

Article

An Innovative Multi-Parameter Environmental Sensor System for Real-Time Indoor Air Quality Monitoring in Industrial Facilities

Pedro Catalão Moura ^{1,2,*}, Vladyslav Alieksieiev ³, Hugo Domingues ², Sofia Pessanha ^{1,2}
and Valentina Vassilenko ^{1,2,3,*}

- ¹ Laboratory for Instrumentation, Biomedical Engineering and Radiation Physics (LIBPhys-UNL), Associated Laboratory in Translation and Innovation Towards Global Health (LA-REAL), NOVA School of Science and Technology, NOVA University of Lisbon, Campus FCT-UNL, 2829-516 Caparica, Portugal; sofia.pessanha@fct.unl.pt
- ² Department of Physics, NOVA School of Science and Technology, NOVA University of Lisbon, Campus FCT-UNL, 2829-516 Caparica, Portugal; h.domingues@campus.fct.unl.pt
- ³ NMT, S. A., Madan Parque, Rua dos Inventores, 2825-182 Caparica, Portugal; vla@nmt.pt
- * Correspondence: pr.moura@fct.unl.pt (P.C.M.); vv@fct.unl.pt (V.V.)

Abstract

Ensuring adequate indoor air quality (IAQ) in industrial environments is essential for protecting worker health, particularly in facilities characterized by chemical emissions and complex layouts, such as automotive painting lines. This study presents the implementation and field evaluation of a low-cost multisensory electronic system prototype designed for continuous, long-term monitoring of six key environmental parameters: temperature, relative humidity, atmospheric pressure, carbon dioxide equivalent (CO₂ eq), total volatile organic compounds (VOC), and an overall Indoor Air Quality (IAQ) index. The system consists of autonomous sensing stations with integrated multi-parameter MEMS sensors and a centralized data aggregation hub. The system was engineered to ensure metrological stability across power cycles, adaptive energy management, and robust long-range wireless communication, thereby addressing common limitations of conventional industrial monitoring solutions. The prototype was deployed in an operational automotive manufacturing plant, where seven sensing stations were installed along the painting line for a two-week continuous monitoring campaign, identifying process-dependent peaks in CO₂ and VOC concentrations and corresponding reductions in IAQ values. The system was able to identify CO₂ peaks as high as 2997.7 ppm (Sensor 3) in localized industrial zones, significantly exceeding standard indoor thresholds. At the same time the system demonstrated the ability to detect VOC fluctuations with a resolution capable of capturing peaks up to 144.1 ppb (Sensor 3) during high-activity shifts. All sensors provided continuous and reliable data over an extended monitoring period. The measured trends and value ranges were consistent with expected industrial conditions, indicating satisfactory system performance under real operating conditions. Overall, the results demonstrate that the developed multisensory prototype is a promising, portable, and economically sustainable solution for distributed continuous IAQ assessment in complex industrial environments, with strong potential for scalable large-scale implementation in occupational health protection and environmental sustainability frameworks.

Academic Editor: Luca Stabile

Received: 5 March 2026

Revised: 5 July 2026

Accepted: 6 July 2026

Published: 10 July 2026

Copyright: © 2026 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

Keywords: electronic nose; indoor air quality; industrial sustainability; environmental monitoring; VOC detection; CO₂ monitoring; multi-sensor systems; automotive painting Line

1. Introduction

One of the most important concerns of any employer whose employees are exposed to potentially dangerous environments during work shifts should be the preservation of those employees' health and safety, and the overall improvement in working conditions. In the specific cases of work locations like factories and production lines, where the labourers are often exposed to hazardous compounds and poor air quality, stricter regulations and more precise monitoring systems should be mandatory to control the air toxicity and prevent the degradation of working conditions [1,2].

As mentioned, one of the main factors for the increased health risks that the workforce of a factory often faces during work shifts is the lack of air quality. This is often caused by the common presence of toxic compounds in the indoor environment of the factories and production lines, which are often released into the air by all types of chemicals, coatings, rubbers, disinfectants, and overall fabrication steps like heating, burning, or drying stages [3,4].

Among the most common and hazardous compounds present in the air of industrial sites are volatile organic compounds (VOCs), carbon oxides, sulfur oxides, ozone, and particulate matter. VOCs are frequently emitted from coatings, solvents, and chemical solutions used in production lines [5,6]. While VOCs comprise a wide range of chemicals, some individual compounds have well-established health-based limits. For example, the WHO recommends short-term indoor exposure to formaldehyde not exceed approximately 0.1 mg/m³ ($\approx$ 0.08 ppm) to prevent sensory irritation, while OSHA sets an 8 h permissible exposure limit of 0.75 ppm, with a short-term excursion limit of 2 ppm [7]. Carbon oxides, including carbon monoxide (CO) and carbon dioxide (CO₂), are emitted by boilers, furnaces, engines, and generators [8,9]. The WHO's guideline for CO in ambient air sets a 24 h average of 4 mg/m³ to avoid adverse health effects, whereas CO₂, though not regulated as a pollutant by the WHO, is monitored in occupational settings because concentrations above 1000 ppm can indicate inadequate ventilation and may impair cognitive function and comfort [10]. Sulphur dioxide (SO₂), generated by combustion in furnaces, kilns, and incinerators [11,12], has a WHO-recommended 24 h mean concentration limit of 40 µg/m³, while ozone (O₃), formed during combustion and sterilization processes [13,14], should not exceed 100 µg/m³ over an 8 h period to prevent respiratory irritation [15]. Finally, particulate matter, including PM₁₀ and PM_{2.5}, originates from dust in ceramics, cement, glass, and metal production [16,17]. The WHO recommends that PM_{2.5} levels not exceed 5 µg/m³ annually and 15 µg/m³ over 24 h, and that PM₁₀ levels remain below 15 µg/m³ annually and 45 µg/m³ over 24 h [18,19]. These limits underscore the critical need for continuous monitoring in industrial environments to ensure that pollutant concentrations remain within safe levels and to protect workers' health from chronic and acute exposure.

Regarding the health impacts caused by constant exposure to the aforementioned pollutants, the employees face serious pathological risks that extend from simple health conditions to serious threats to life [20]. VOCs, for example, are well-known for their capacity to traverse biological tissues and for leading to oxidative stress [21,22]. Consequently, compounds like methanol, ethanol, toluene, xylenes, acetaldehyde, formaldehyde, chloroform, benzene and ethylene, among others, have been linked to the development of pathologies that include simple allergic reactions, cutaneous pruritus and

ocular irritation [23,24], asthma and overall chronic pulmonary conditions [25,26], and even carcinogenic pathologies like pulmonary, breast, oral and other forms of cancer [27,28]. Carbon oxides, in their turn, are responsible for health conditions like dizziness, headaches, unconsciousness and, in extreme cases, death by intoxication [29,30]. SO₂ can cause loss of pulmonary function, bronchoconstriction and chronic coughing [31,32]. O₃ is responsible for several types of irritation (ocular, cutaneous and pulmonary tract), breath shortness, reduced lung function, and even exacerbation of asthma and chronic obstructive pulmonary disease [33,34]. Finally, PM has been widely linked to pulmonary, cardiovascular and neurological effects due to its capacity to penetrate deep into lungs and bloodstream [35,36].

Due to all the issues described, industrial sites must be equipped with technology capable of controlling and monitoring air quality and working conditions as a way of preventing the exposure of employees to hazardous compounds and protecting them from potential pathologies. To do so, it is necessary that the factories not only support the development of accurate and precise protocols for air monitoring, but also the implementation of analytical systems that allow them to continuously monitor the toxicity of the compounds present in the air of the indoor environment and surrounding areas.

Several analytical methods are used in air quality monitoring, including chromatographic and spectrometric techniques such as mass spectrometry (MS) [37,38], ion mobility spectrometry (IMS) [39,40], gas chromatography (GC) [41,42], and infrared spectroscopy (IR Spectr.) [43,44]. These technologies offer high sensitivity, wide detection ranges, and strong analytical flexibility [45,46]. However, they also have drawbacks, including high cost (both spectrometric-based devices or electrochemical-type sensors often rise to thousands of euros) [47,48], need for skilled operators (due to the complexity of the devices), complex sample preparation (complex/rich matrices are often a challenge to the established methods), and limited portability (heavy hardware in the majority of the cases) [49–51].

Another approach that has been gaining attention due to recent advances in electronic nose (e-nose) technologies based on metal oxide semiconductor (MOS) and thin-film sensors produced with thin films of graphene oxide (GO), copper oxide (CuO), titanium dioxide (TiO₂), or even zinc oxide (ZnO) [52,53]. These sensors are generally sensitive to low gas concentrations, but accurate identification and quantification of specific toxic compounds often require multi-sensor e-nose systems and proper calibration. Their industrial use may also be limited by sensor drift, reproducibility issues, calibration instability, fabrication costs, and system complexity, while energy management can be a concern mainly in portable or battery-powered applications [54–56].

Within the framework of sustainable environmental monitoring, there is a growing need for systems that combine the following features:

- Continuous real-time monitoring;
- Energy-efficient operation;
- Reduced maintenance requirements;
- Low total cost of ownership (TCO);
- Scalability across large infrastructures.

In response to these technological and operational challenges, a significant body of research has focused on the development of sensor-based systems for continuous air quality monitoring. In particular, the emergence of low-cost sensing technologies has enabled the deployment of distributed monitoring solutions as an alternative to conventional analytical instrumentation. Early studies have primarily addressed the performance and limitations of commercially available sensors under real environmental conditions. For example, Spinelle et al. (2017) demonstrated that although low-cost

sensors provide a viable and economically attractive solution, their measurements are strongly influenced by environmental conditions and long-term drift [57]. Similar findings were reported by Kang et al. (2022), which highlighted issues related to cross-sensitivity, calibration stability, and reproducibility [58]. In addition, Wang et al. (2010) emphasized the influence of temperature and humidity on MOS-based sensors, reinforcing the need for robust compensation and calibration strategies [59].

Alongside sensor performance studies, several integrated indoor air quality monitoring systems have been proposed, combining multiple sensing elements into unified platforms. A representative example is the work of Kim et al. (2014), which introduced a real-time monitoring system capable of measuring environmental parameters and gas concentrations within a centralized architecture [60]. More recent developments have leveraged Internet of Things (IoT) technologies to enhance connectivity and data accessibility. For instance, Jo et al. (2020) and Sai et al. (2019) proposed systems enabling continuous monitoring, remote visualization, and cloud-based data processing [61,62]. While these approaches improve accessibility and data handling, they often rely on continuous connectivity and may exhibit increased energy consumption, limiting their applicability in long-term autonomous deployments.

Another important research direction involves the use of distributed sensor networks to capture spatial and temporal variations in pollutant concentrations. The study of Coleman et al. (2018) demonstrated that multi-point measurements are essential to accurately characterize heterogeneous air quality conditions, particularly in complex indoor environments [63]. Additional works, such as the results reported by Mansour et al. (2014) and Rescio et al. (2023), have explored distributed architectures for environmental sensing [64,65]. Wireless communication technologies have further enabled scalable deployments, as shown by Christakis et al. (2023) [66]. Despite these advances, challenges related to communication reliability, synchronization, and data integrity persist, especially in environments with physical obstructions and electromagnetic interference.

More recently, attention has shifted toward improving system robustness, energy efficiency, and long-term sustainability. Kumar et al. (2016) discussed the main barriers to large-scale deployment, including maintenance requirements, sensor degradation, and calibration needs [67]. In addition, Saini et al. (2020) emphasized the importance of energy-aware architectures and scalable solutions [68]. Despite the progress achieved, the application of such systems in industrial environments remains comparatively limited. Industrial settings introduce additional constraints, including complex airflow dynamics, process-dependent emissions, and harsh operating conditions. Furthermore, many existing systems lack integrated strategies for persistent calibration, adaptive energy management, and robust long-range communication. These limitations highlight the need for reliable, scalable, and energy-efficient sensing platforms specifically tailored for industrial applications, motivating the development of the system presented in this work.

In response to these needs, this work presents the development and validation of a distributed Environmental Condition Monitoring System (ECMS). The system leverages commercially available MEMS sensors combined with custom firmware to ensure persistent calibration, adaptive energy management, and robust wireless communication, even in metal-dense, challenging industrial environments.

The primary aim of this study is to demonstrate and evaluate the performance of the ECMS under extreme operational conditions, specifically within an automotive factory painting line. By deploying the system in this demanding scenario, we assess its suitability, robustness, and sustainability for continuous indoor air quality (IAQ) monitoring.

This article details the design, implementation, and testing of an innovative electronic nose based on commercial sensors, capable of remotely monitoring and controlling air quality in industrial sites. The platform is designed to be low-cost, minimally complex, and largely independent of user intervention, making it a practical solution for long-term environmental monitoring in harsh industrial settings.

2. Materials and Methods

2.1. System Architecture and Deployment

The Environmental Condition Monitoring System (ECMS) utilizes a custom-engineered firmware stack designed to overcome the traditional limitations of autonomous, low-power environmental sensing. By prioritizing metrological continuity and dynamic energy orchestration, the system maintains high data integrity in challenging industrial environments. The ECMS consists of autonomous sensing stations and a centralized data aggregation hub. Each station integrates multi-parameter MEMS sensors capable of measuring:

- Temperature;
- Relative humidity;
- Atmospheric pressure;
- CO₂ equivalent (CO₂) concentration;
- Total volatile organic compounds (VOC);
- IAQ index (algorithm-based composite metric).

As seen, both CO₂ equivalent and total volatile organic compounds are respectively represented by their simplified versions of CO₂ and VOC.

Table 1 summarizes lists the main measured variables, nominal resolution, accuracy, and operating range for the developed system (EMS) based on BOSCH sensors (Stuttgart, Germany) and derived from BSEC 2 algorithm (Stuttgart, Germany).

Table 1. Parameters measured by the developed system and respective measurement range, resolution, accuracy/tolerance, and additional notes.

Parameter	Measurement Range	Resolution	Nominal Output Characteristics (BSEC2)	Notes
Indoor Air Quality (IAQ)	0–500	1	±15 points or ±15%	Proprietary Bosch Index
CO ₂ Equivalent (CO ₂ eq)	400–65,000 ppm	1 ppm	±15% (typical)	Derived from VOC gas scan
Total VOC (TVOC)	0–1000 ppb	0.01 ppb	±15% (typical)	Derived from VOC gas scan
Temperature	−40–+85 °C	0.01 °C	±0.5 °C (at 25 °C)	Without self-heating
Relative Humidity	0–100% RH	0.008% RH	±3% RH	Hysteresis: ±1.5% RH
Pressure	300–1100 hPa	0.18 Pa	±0.6 hPa	Absolute accuracy

The prototype utilizes the Bosch 4-in-1 sensor with the following manufacture guarantee for precision and accuracy: Temperature (±0.5 °C), Humidity (±3% RH), Pressure (±0.12 hPa) and IAQ (Index 0–500, ±15%). The CO₂ (resolution of 1 ppm and accuracy of ±5%) was tested against the calibrated Telaire 7001 CO₂ Sensor (Amphenol Advanced Sensors, St. Marys, PA, USA). Only the CO₂ equivalent output was

experimentally compared with a calibrated reference instrument. IAQ and VOC values correspond to algorithm-derived outputs from the Bosch BSEC2 library and were not independently validated against laboratory reference instruments. For the wireless communication the LoRa protocol with developed proprietary “functional optimization” was used.

Installation Height: In line with IAQ standards, the sensors were mounted at the “breathing zone” level (approx. 1.5 m) to accurately reflect worker exposure, except for the reference unit.

Seven stations were strategically deployed along the painting line of an operational automotive manufacturing facility. The deployment period extended from April 1st to April 12th under normal production conditions.

The system architecture was designed according to three core sustainability principles, such as (i) Energy efficiency; (ii) Maintenance minimization; (iii) Scalable wireless deployment.

2.1.1. Persistent Sensor Calibration and Baseline Retention

Gas sensor drift and baseline loss following power interruptions represent major limitations in low-power environmental systems.

To mitigate this issue, the ECMS implements a persistent calibration strategy using the BSEC2 state memory. Before entering low-power mode, the firmware stores the internal calibration state and environmental compensation parameters in non-volatile memory. Upon wake-up, these parameters are restored instantaneously, eliminating the need for extended re-stabilization periods. This “digital memory” approach has an important feature as follows:

- Preserves long-term measurement consistency by maintaining the BSEC2 baseline;
- Reduces warm-up energy consumption;
- Minimizes recalibration frequency;
- Enhances data continuity across deployment cycles.

2.1.2. Adaptive Energy Management

Energy optimization is critical for large-scale distributed sensing.

The ECMS dynamically adjusts operational modes based on the following environmental requirements:

- High-frequency sampling during critical production stages;
- Low-power background monitoring during stable periods.

This adaptive strategy significantly extends battery lifespan while preserving analytical responsiveness. The system manages its energy budget through a tiered strategy that scales performance based on real-time requirements.

The nodes are powered by 3.7 V 1200 mAh LiPo batteries. Given the 300s deep-sleep cycle and an average current draw of $\sim 20\mu\text{A}$ in sleep, the calculated operational lifespan exceeds 21 days on a single charge, confirming true portability for temporary “hot-spot” monitoring in factories.

The proposed system demonstrates strong low-energy performance and scalability, with a deep sleep current of only $22\mu\text{A}$, an active measurement current of 12 mA for 2 s , and a LoRa transmission current of 120 mA for just 50 ms . These operating characteristics result in an average hourly energy consumption of less than 0.5 mAh , enabling long-term autonomous operation while supporting scalable deployments of multiple sensor nodes.

The firmware can dynamically toggle between high-frequency sampling for detailed event tracking and ultra-low-power sampling for background monitoring. This adaptive

approach is recognized as a key method for extending the lifespan of distributed sensor networks [69].

Operational parameters can be reconfigured remotely via secure bidirectional communication with the central hub, eliminating the need for physical access to sensing nodes.

2.1.3. Long-Range Communication Optimization

To ensure reliable data delivery in metal-dense industrial infrastructures, the wireless protocol has been functionally optimized:

- **Payload Compaction:** A custom data-stripping algorithm compresses outbound telemetry by removing redundant metadata. Shorter transmission windows, or “Time-on-Air,” significantly reduce energy consumption and the risk of signal collisions in high-interference environments [70].
- **Industrial Link Reliability:** The use of spread-spectrum communication, combined with a dedicated listening window for hub-based acknowledgments, ensures high penetration through the physical obstructions found in manufacturing facilities [71].

2.1.4. Temporal Synchronization

Accurate data logging across a distributed network requires all stations to share a common clock. Following each transmission, the station performs a temporal handshake to synchronize its internal clock with the Master Hub. This keeps the entire fleet of stations aligned within a narrow margin, enabling precise correlation of environmental events across different areas of the plant [72].

2.1.5. Performance Optimization, Economic Viability, and Scalability

Beyond technical robustness, the ECMS was designed according to principles of economic and operational sustainability.

Integrated MEMS Architecture: The use of high-density MEMS sensors integrating temperature, humidity, pressure, and dual gas metrics into a single module reduces hardware redundancy and system complexity. This integration lowers production costs and simplifies maintenance logistics. In fact, the total 7-node system expenditure in EMS was <\$1200, compared to approximately \$6000–\$15,000 for other commercially equivalent industrial monitoring networks.

Reduced Infrastructure Requirements: The long-range wireless topology eliminates the need for industrial cabling, conduit installation, and network contractors. Deployment follows a “drop-and-detect” strategy, reducing capital expenditure (CAPEX) and installation time.

Edge Intelligence and Maintenance Reduction: The system implements edge-level diagnostic logic, triggering alerts only when predefined environmental thresholds are exceeded (“management by exception”). This approach reduces manual data inspection, minimizes technician intervention and avoids frequent recalibration procedures.

Reliability: We measured reliability using the Packet Delivery Ratio (PDR). Over the 30-day trial, the system maintained a PDR of 98.2%, despite the electromagnetic interference (EMI) from industrial zones. Furthermore, we monitored the BSEC Accuracy Status (0–3); the system reached Status 3 (High Accuracy) within 4–7 days and maintained it consistently. The BSEC algorithm requires a “burn-in” period. Accuracy levels are only guaranteed after the sensor has been powered for at least 20 min (Run-in) and has experienced “clean air” and “polluted air” cycles to establish a baseline.

Calibration/Baseline Retention: The system utilizes the BSEC2 “Memory Factor” logic. The BSEC2 algorithm state is stored in Non-Volatile Storage (NVS) every 6 h and

restored after wake-up. Upon wakeup, the previous calibration baseline is restored, preventing temporary baseline loss after power cycling.

Digital preservation of the BSEC2 baseline reduces the need for repeated baseline stabilization after power interruptions, thereby decreasing maintenance effort. Figure 1 summarizes, in a simplified manner, the architecture diagram of the system.

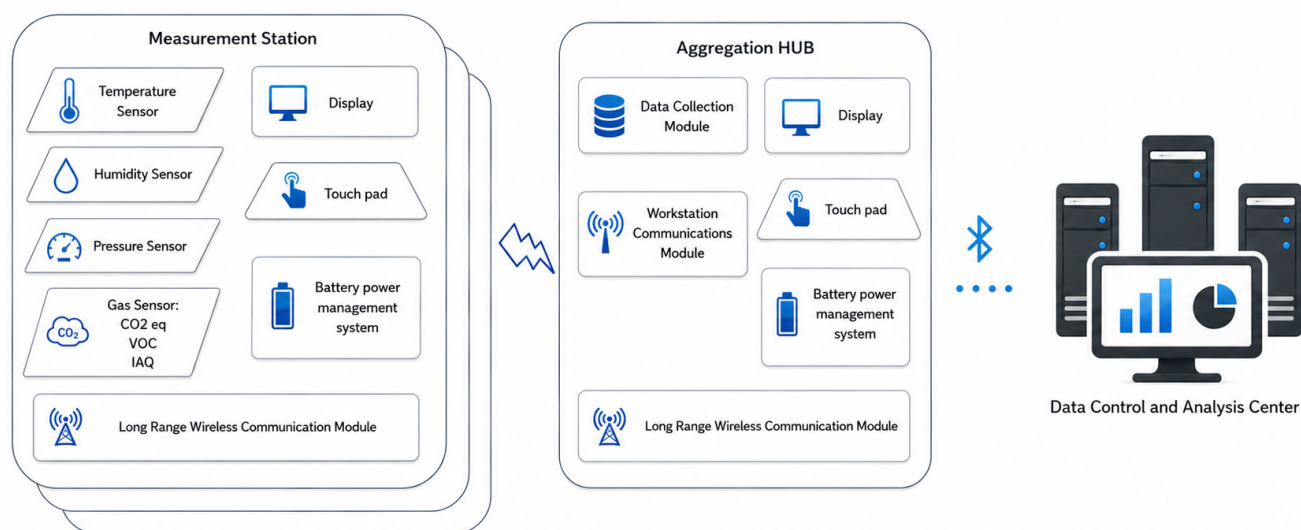


Figure 1. Architecture Diagram of the developed system.

2.2. Testing Protocol

As a way of testing the suitability of the developed prototype for long-term in situ air quality monitoring, one established a partnership with a car factory of one of the largest international manufacturing brands that allowed us to perform analyses at several locations of its painting line.

The painting line of a car factory is of special concern regarding air quality monitoring and control as it involves heavy utilization of chemicals, coatings and overall toxic pollutants [73,74]. In fact, painting a car body is a complex and multi-stage process whose steps require the use of products that are potential VOC-emitting sources [75,76]. It is even estimated that per produced vehicle, the total emission of VOCs ranges between 1.18 and 4.30, a very dangerous and hazardous amount [77].

In the initial step, the car chassis is immersed in two chemical baths using large tanks filled with the respective solutions. The phosphatizing bath contains a phosphoric acid solution saturated with metallic phosphate, which protects the metal from corrosion and improves coating adhesion. The cataphoresis bath then applies a thin, electrically charged epoxy layer over the entire metal surface, ensuring a uniform coating application across the chassis. After drying in industrial ovens, the chassis moves to the next stage, where robotic arms apply the primer and ink. These automated processes generate coating clouds that adhere to the pre-treated metal surface. Subsequently, high-pressure jets spray varnish onto the coloured chassis, followed by manual polishing with wax using rotary tools and cloths by a team of employees. Finally, line workers perform a visual inspection of each chassis to detect any imperfections or inconsistencies in the paint [74–76,78].

2.2.1. Locations

The studied car factory corresponds to the largest facility of automotive production in Portuguese territory, employs near 5.000 employees, and produces cars for one of the largest international brands. Its production can reach up to 1.000 units per day meaning

that a humongous amount of chemicals, coatings and overall toxic solutions are used on a regular basis, leading to large emissions of pollutants possibly hazardous to both the environment and human health. Due to these reasons, it is of extreme relevance to explore the air quality and overall indoor air characteristics in order to protect both fauna and flora of the surrounding areas of the factory as well as to ensure the best life quality for the painting line employees.

A total of seven sensors, numbered from 1 to 7, were placed at specific locations of the painting line, which were selected based on their intrinsic characteristics, namely:

- 1—Head of the Painting Line's Office;
- 2—Cataphoresis Bath;
- 3—Primer Application/Coating;
- 4—Ink/Paint Application/Coating;
- 5—Varnish Application;
- 6—Wax Application and Final Verification;
- 7—Ceiling of the Factory.

The cataphoresis (Sensor 2) bath was considered a relevant location due to the large amount and diversity of chemicals used in this coating stage, even though their exact composition is not fully known. The primer application/coating (Sensor 3), the ink/paint application/coating (Sensor 4), the varnish application (Sensor 5), and the wax application and final verification (Sensor 6) locations, in their turn, were considered of special interest for air analyses due to the common exposure that the employees face during work shifts at these sites. Finally, the air of ceiling of the factory (Sensor 7) was studied since the extractors and air purification systems are assembled here, making it of special interest to assess the presence of VOCs near these systems.

2.2.2. Procedure

To not disrupt the normal working routines of the employees and to not expose the devices to possibly damaging or destructive scenarios, in the interior of the painting line, the sensors were placed at safe but central places, for all the seven studied locations. The central hub, in its turn, was left at the Head of the Painting Line's Office. All sensors were turned on at the respective locations and, once verified that they were communicating with the central hub, they were left to measure continuously.

The measuring cycle was initiated on 1 April and completed on 12 April, totalizing 12 days of continuous and uninterrupted air quality monitoring and control. As previously described, each one of the seven sensors communicate every five minutes the values of all the six under-study variables (temperature, humidity, pressure, CO₂, VOC and IAQ) to the central hub, which stored all the data in an internal memory card. The collected data was saved in one comma-separated values (CSV) file per day of measurement and was equally exhibited in real-time at a portable computer in which the developed application was previously installed.

All the collected data was processed a posteriori. To do so, all the eight columns of each CSV file, containing respectively information regarding the number of the sensor (1–7), temperature (°C), relative humidity (%), pressure (kPa), CO₂ (ppm), VOC (ppb), IAQ and time and date of each measurement, were promptly separated into individual columns. Then, their values were plotted in scatter plots in order to one visualize the behaviour and alterations of each variable throughout the period of collection. Finally, the data was studied regarding behaviour through time and putative direct correlations between distinct variables.

Across the large number of measurements collected by each sensor during the analysis period, no statistical outliers were detected in the dataset. The only exception corresponded to six records on 9 April, which were identified as erroneous due to a

timestamping issue, where the measurements from the beginning of the day (00:00) were incorrectly recorded with a shifted time (06:00). These records were therefore considered invalid and were manually removed from the dataset. No additional outliers were detected or excluded during the data processing and analysis.

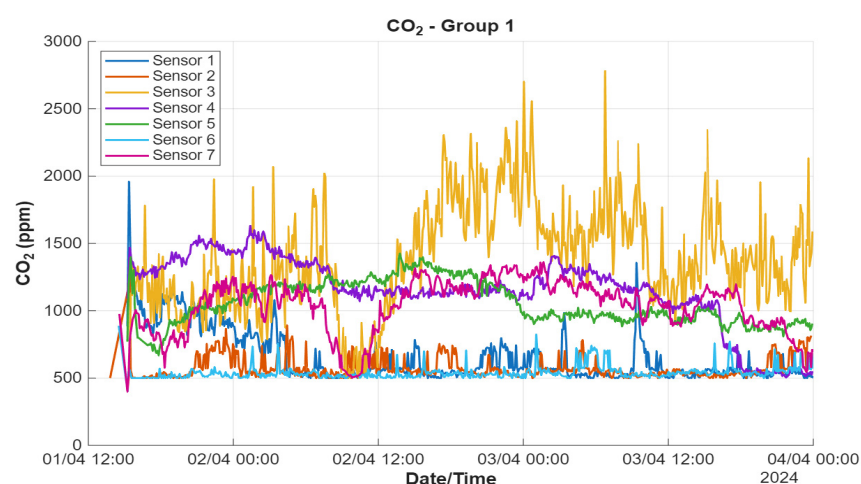
3. Results and Discussion

As addressed, a total of six variables (temperature, humidity, pressure, CO₂ eq, VOC and IAQ) were continuously (measurement performed each five minutes) explored for a total of seven locations (1—Head of the Painting Line's Office, 2—Cataphoresis Bath, 3—Primer Application/Coating, 4—Ink/Paint Application/Coating, 5—Varnish Application, 6—Wax Application and Final Verification, 7—Ceiling of the Factory) during 12 consecutive days. Considering these sensors, a comparative analysis for the six explored variables was performed with the goal of finding direct relationships between the behavior of two or more variables through time, assessing the potential suitability of the developed prototype for continuous air quality monitoring. To do so, the evolution of each variable (CO₂, VOC and IAQ) was plotted as function of time and compared with the behavior of the remaining and most generic variables (Temperature, Humidity and Pressure). A total of six groups of graphs were plotted. In each group, four graphs were plotted per variable; each graph containing the data of three consecutive days: first period—data from 1 April to 3 April; second period—data from 4 April to 6 April; third period—data from 7 April to 9 April; fourth period—data from 10 April to 12 April. In this way, a total of 24 graphs were analyzed.

3.1. CO₂ Equivalent Monitoring

The potential relationship between the concentrations of CO₂ equivalent (ppm), simplified to CO₂, in the analyzed air with the humidity (%) levels, with temperature (°C), and with pressure (kPa) was assessed for each one of the four periods. It is relevant to mention that due to being very constant throughout the entire period of the study, the graphs of temperature and pressure were omitted from all the datasets here discussed; however, for purposes of illustration, the average, maximum and minimum values of these variables were included in Table 1, addressed in due time. In addition, no significant relationship was observed between these two variables and the evolution of CO₂, VOC or IAQ, as discussed in due time. Therefore, temperature and pressure plots are not presented.

Figure 2 represents the variation in CO₂ concentration (top), and humidity (bottom) registered for the seven sensors between 1 April and 3 April.



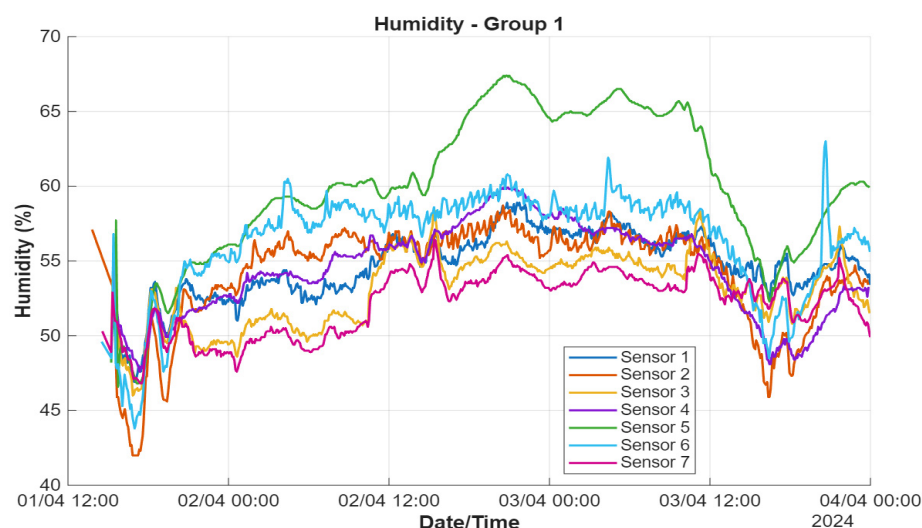


Figure 2. Variation of (top) CO₂ concentration (ppm) and (bottom) humidity (%) between April 1st and April 3rd for sensors 1—Head of the Painting Line’s Office (dark blue), 2—Cataphoresis Bath (orange), 3—Primer Application/Coating (yellow), 4—Ink/Paint Application/Coating (purple), 5—Varnish Application (green), 6—Wax Application and Final Verification (light blue) and 7—Ceiling of the Factory (pink).

Here, the CO₂ plot shows substantial variability across sensors, both in magnitude and temporal dynamics. Sensor 3 stands out with consistently elevated CO₂ levels, frequently exceeding 1500 ppm and peaking near 3000 ppm, suggesting proximity to a local emission source, reduced ventilation, or higher occupancy. In contrast, Sensors 1, 2, and 6 remain relatively stable, hovering close to 500–800 ppm for most of the period, indicating better air exchange or lower occupancy influence in those zones.

The temporal evolution of CO₂ reveals clear episodic spikes across several sensors, particularly on the second and third days of this group. These peaks likely correspond to periods of higher occupancy or reduced ventilation efficiency. Sensors 4, 5, and 7 show moderate but sustained elevations (approximately 900–1400 ppm), with gradual rises and falls that appear synchronized, implying shared environmental conditions or similar room usage patterns. The distinct behavior of Sensor 3 from the rest suggests spatial heterogeneity within the monitored environment, emphasizing the importance of distributed sensing rather than relying on a single measurement point.

The humidity plot, by contrast, displays much tighter clustering among sensors, generally ranging between 45% and 67%. All sensors exhibit a similar overall trend, specifically an initial dip around 1 April, followed by a gradual increase toward the second and third days, and then a decline approaching midday of April 3rd before partial recovery. Sensor 5 records the highest humidity values, peaking at nearly 67%, while Sensors 2 and 7 tend to report slightly lower values.

When comparing both variables, CO₂ demonstrates far greater spatial variability than humidity, indicating that CO₂ levels are more sensitive to localized occupancy and ventilation patterns. Humidity appears to respond more uniformly across the monitored area, implying more independent behavior. Interestingly, both CO₂ and humidity tend to follow similar broad time patterns. When CO₂ rises (especially around 2 April and 3 April), humidity also generally increases. This suggests an apparent relationship between them, consistent with previous reported observations [79].

The observed parallel behavior is most likely explained by occupancy and human activity. Humans exhale CO₂ and release moisture through breathing and perspiration. In enclosed environments, higher occupancy typically leads to simultaneous increases in

both CO₂ concentration and relative humidity. The synchronized gradual rise seen across several sensors supports this explanation. However, the relationship is not proportional. CO₂ shows large spikes and strong spatial variability (e.g., Sensor 3 reaching very high levels), while humidity remains comparatively stable and clustered between ~45–65%. Additionally, during some periods (e.g., around 03/04 midday), humidity drops across sensors while certain CO₂ levels remain elevated or fluctuate independently. This suggests that the factor impacting CO₂ have a stronger effect on CO₂ concentrations than on relative humidity, and that humidity is also influenced by external weather conditions or mechanical dehumidification.

Figure 3 represents the variation in CO₂ concentration (top), and humidity (bottom) registered for the sensors between 4 April and 6 April.

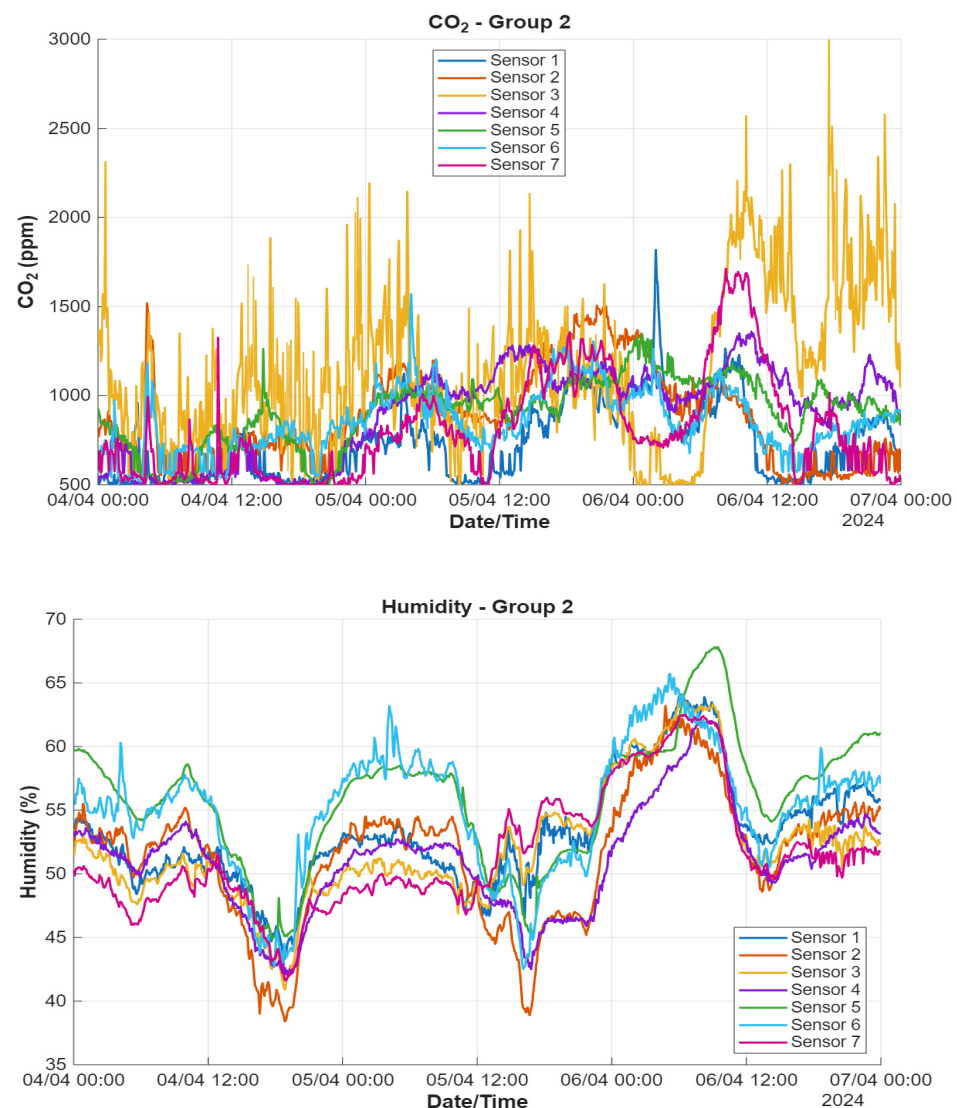


Figure 3. Variation of (top) CO₂ concentration (ppm) and (bottom) humidity (%) between April 4th and April 6th for sensors 1—Head of the Painting Line’s Office (dark blue), 2—Cataphoresis Bath (orange), 3—Primer Application/Coating (yellow), 4—Ink/Paint Application/Coating (purple), 5—Varnish Application (green), 6—Wax Application and Final Verification (light blue) and 7—Ceiling of the Factory (pink).

For Group 2, CO₂ concentrations again show strong temporal variability and clear spatial differences among sensors. Sensor 3 exhibits the largest fluctuations and highest peaks, frequently exceeding 2000 ppm and approaching 3000 ppm toward 6 April and 7

April, indicating localized accumulation. Other sensors follow similar daily cycles, i.e., rising through 5 April and 6 April and dropping sharply over a certain interval.

Humidity exhibits greater consistency across sensors, generally ranging between ~40% and 68%. All sensors display synchronized dips around 5 April and a marked increase toward 6 April midday, followed by a decline and partial recovery. The strong alignment between sensors implies that humidity is governed mainly by shared environmental controls.

In terms of relationships, there is a noticeable but not perfectly linear association between CO₂ and humidity. Periods of rising CO₂ often coincide with increasing humidity, supporting the idea that occupancy contributes to both variables. However, humidity changes appear smoother and more uniform, while CO₂ spikes are sharper and more sensor-specific. This suggests that although both variables may share common drivers, CO₂ is more sensitive to localized emission sources, whereas humidity reflects broader ambient conditions.

Figure 4 represents the variation in CO₂ concentration (top), and humidity (bottom) registered for the communicative sensors between 7 April and 9 April.

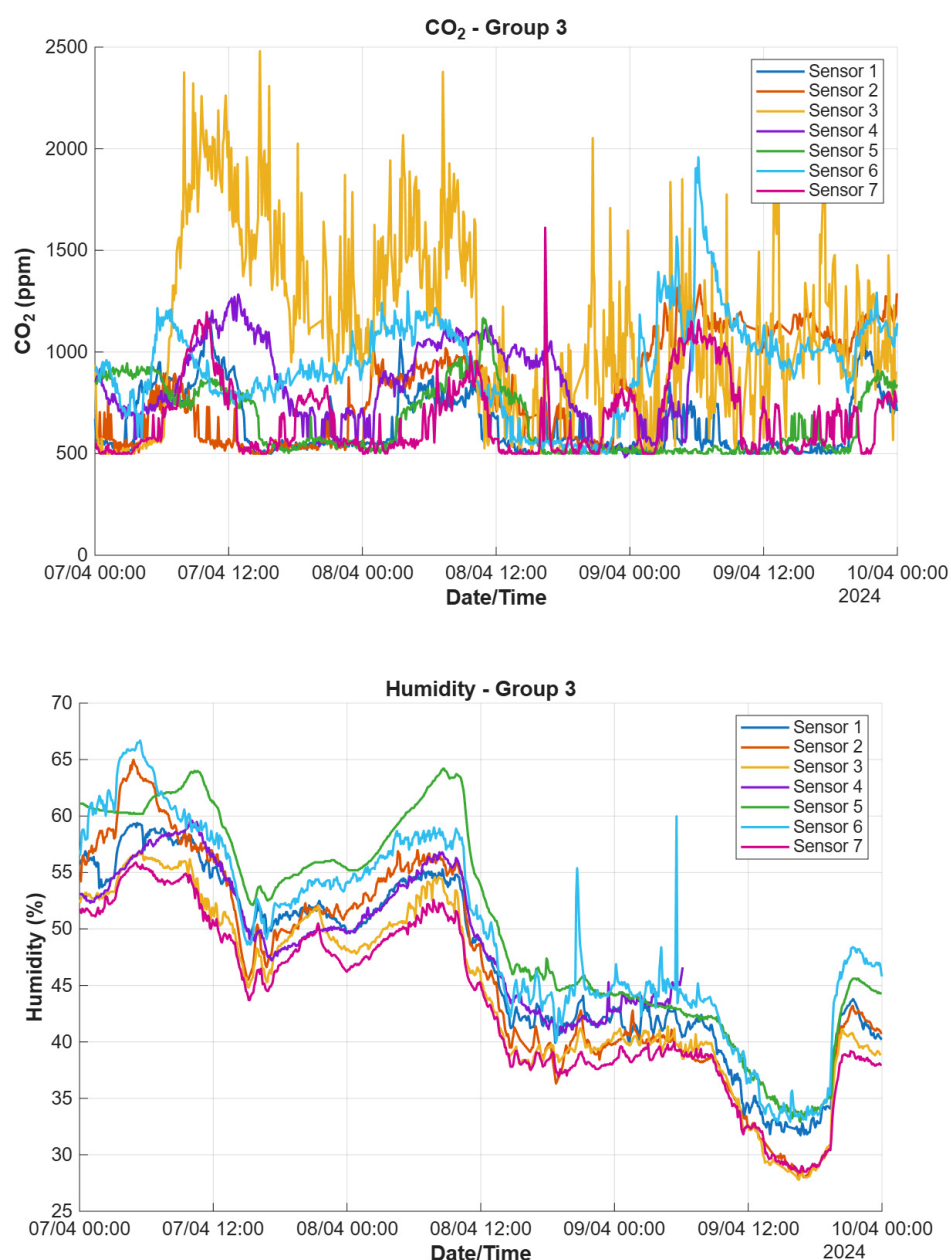
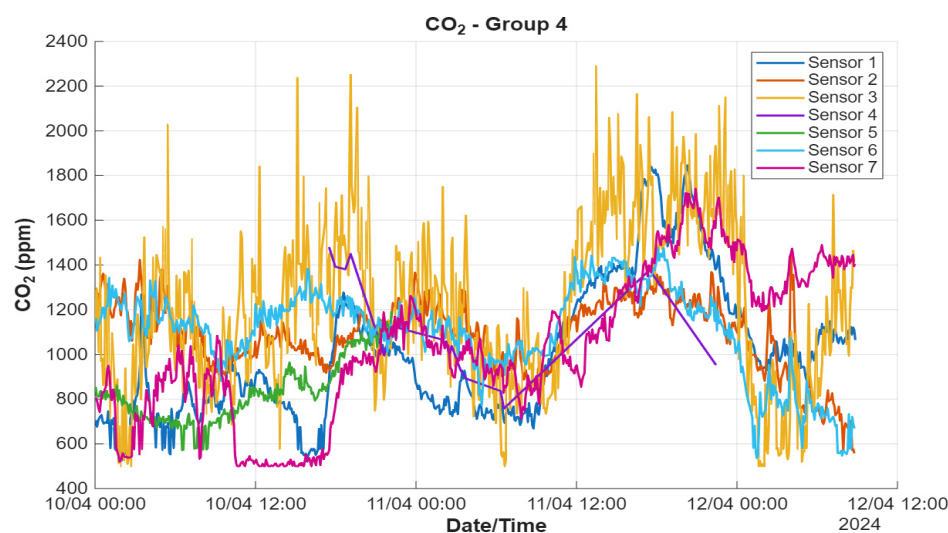


Figure 4. Variation of (top) CO₂ concentration (ppm) and (bottom) humidity (%) between April 7th and 9 April for sensors 1—Head of the Painting Line’s Office (dark blue), 2—Cataphoresis Bath (orange), 3—Primer Application/Coating (yellow), 4—Ink/Paint Application/Coating (purple), 5—Varnish Application (green), 6—Wax Application and Final Verification (light blue) and 7—Ceiling of the Factory (pink).

In Group 3, CO₂ concentrations display pronounced temporal fluctuations and marked differences between sensors, indicating strong spatial variability within the monitored area. Sensor 3 again records the highest and most erratic values, frequently exceeding 2000 ppm, particularly on 7 April and 8 April, suggesting localized accumulation or limited ventilation. Other sensors generally range between 500 and 1200 ppm, with noticeable daily cycles characterized by rises during likely occupied periods and sharp drops back toward baseline (~500 ppm), consistent with ventilation events or unoccupied intervals. Around 9 April, several sensors show synchronized increases, implying a shared occupancy or common emission effect, though the magnitude still differs by location. Overall, the pattern reinforces the presence of heterogeneous air distribution, with some zones experiencing significantly higher CO₂ buildup than others. A similar temporal association between humidity and CO₂ can again be observed.

Some abnormal peaks observed in sensors 5 and 6 are likely measurement artefacts rather than real humidity variations. These anomalies may be caused by temporary communication errors, timestamp misalignment, or interpolation during data processing, which can produce inclined spikes in the time series. Therefore, these values were not considered representative of actual environmental changes.

Figure 5 represents the variation in CO₂ concentration (top) and humidity (bottom) registered for the sensors between 10 April and 12 April.



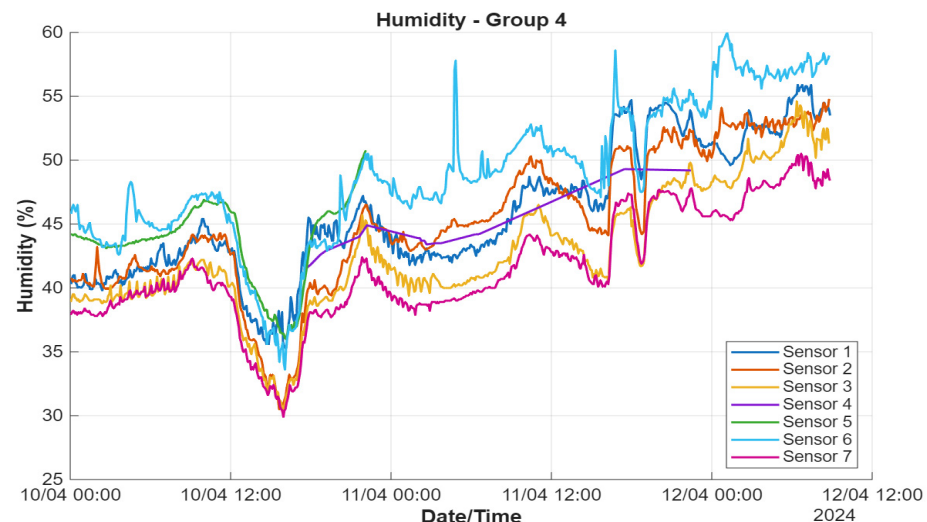


Figure 5. Variation of (top) CO₂ concentration (ppm) and (bottom) humidity (%) between 10 April and 12 April for sensors 1—Head of the Painting Line’s Office (dark blue), 2—Cataphoresis Bath (orange), 3—Primer Application/Coating (yellow), 4—Ink/Paint Application/Coating (purple), 5—Varnish Application (green), 6—Wax Application and Final Verification (light blue) and 7—Ceiling of the Factory (pink).

A temporal association between CO₂ and humidity can again be observed, and the variation in temperature (25 ± 5 °C) appears to have limited influence on CO₂ concentration. Interestingly, sensor 5 stopped working by the end of 10 April, most likely due to battery depletion. Sensor 4 also exhibited unstable operation (i.e., a lower number of measurements and periods of inactivity), most likely due to battery depletion. The moment at which the sensor completely stopped working can be observed at the end of 11 April, indicating the end of the battery life.

After exploring the evolution of four variables throughout the entire period of analysis, and after observing temporal associations between some variables, it was also observed that some locations exhibited a constantly similar behavior. Sensors 1, 2, and often 5 tend to behave more similarly within each group since they show moderate CO₂ levels, comparable daily cycles, and relatively synchronized rises and drops, frequently returning to baseline values during low-occupancy or ventilation periods. Sensor 3 stands out in every group as the most distinct, consistently recording the highest peaks and the greatest variability. Its behavior is less aligned with the others, suggesting either a location closer to emission sources, poorer ventilation, or a microenvironment with limited air mixing. Meanwhile, Sensors 4, 6, and 7 generally display intermediate similarity, i.e., they often follow the main temporal trends observed in the more stable sensors but exhibit stronger fluctuations or occasional spikes. Overall, the strongest similarity across all groups is observed among Sensors 1, 2, and 5, while Sensor 3 is consistently the most dissimilar.

3.2. VOC Monitoring

Once explored the evolution of CO₂ concentrations throughout the entire period of study, similar approach was employed to explore potential relationships between VOC concentration (ppm) in the analyzed air and humidity (%) levels, temperature (°C), and pressure (kPa), to further assess the performance of the developed sensing system for continuous air quality monitoring.

Figure 6 represents the variation in VOC concentration (ppb) registered for the seven sensors for the periods of (top left) 1 April–3 April, (top right) 4 April–6 April, (bottom

left) 7 April–9 April, and (bottom right) 10 April–12 April. For logistic reasons, the graphs of humidity, temperature and pressure were not included here, nonetheless, the relationship with humidity is properly addressed, and both temperature and humidity were stable throughout the entire study, not exhibiting any relevant impact on VOC variation.

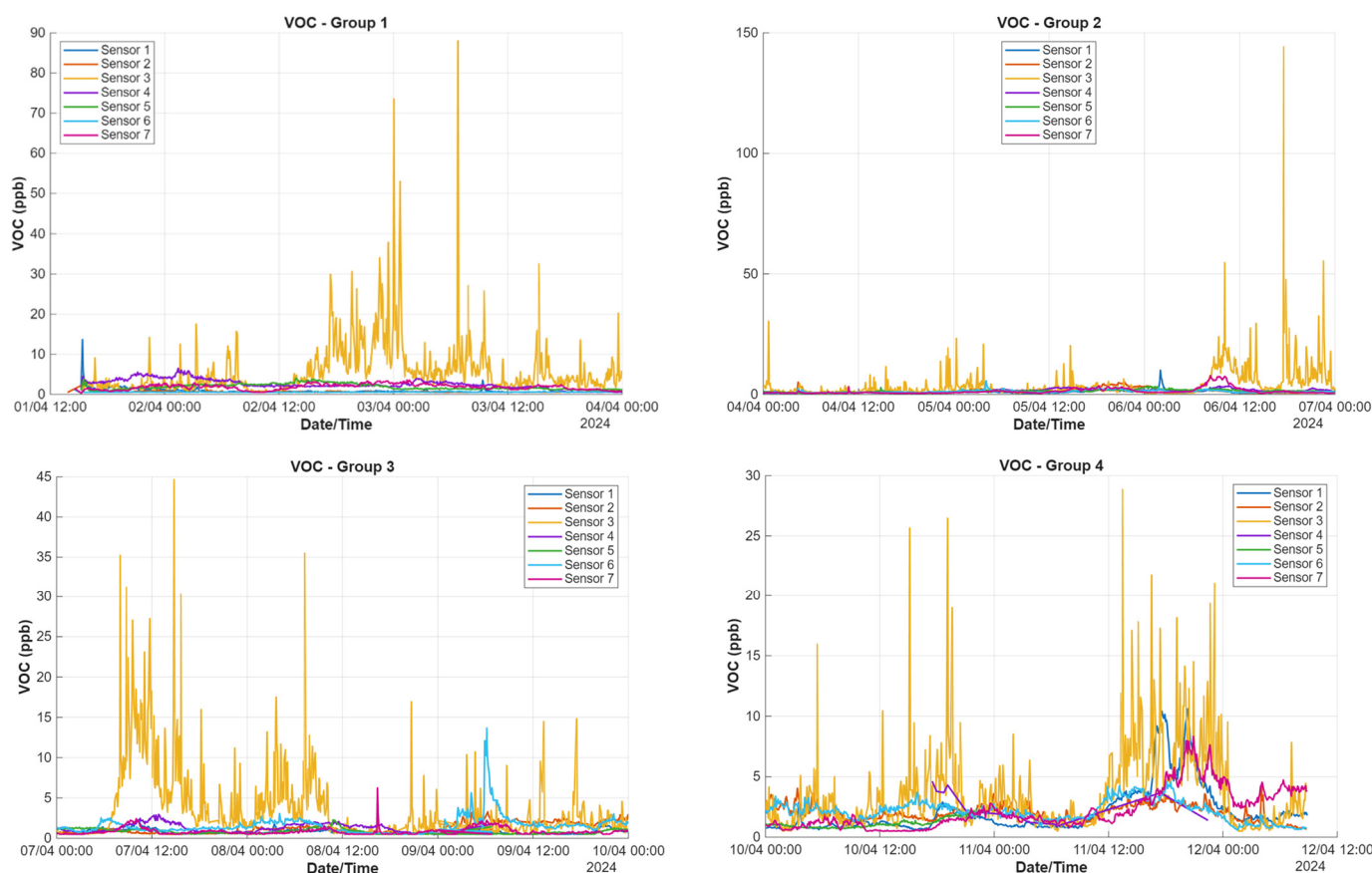


Figure 6. Variation in VOC concentration (ppb) for the periods of (top left) 1 April–3 April, (top right) 4 April–6 April, (bottom left) 7 April–9 April, and (bottom right) 10 April–12 April, for sensors 1–Head of the Painting Line’s Office (dark blue), 2–Cataphoresis Bath (orange), 3–Primer Application/Coating (yellow), 4–Ink/Paint Application/Coating (purple), 5–Varnish Application (green), 6–Wax Application and Final Verification (light blue) and 7–Ceiling of the Factory (pink).

The recorded VOC profiles reveal several noteworthy observations. Sensor 3, similar to observations from the previous datasets, exhibits markedly different behavior compared to the other sensors. Specifically, the concentration of VOCs at Location 3—the primer application/coating area—is significantly higher than the levels recorded at the other sites throughout the study. These elevated levels are most likely due to the presence and use of solvent-based coatings in this area. Indeed, most primers are VOC-rich, as discussed elsewhere [5], which explains the high concentrations detected. At other locations, VOC concentrations remain below 5 ppb; however, occasional peaks occur at certain points during the study period. These transient increases likely result from the use of VOC-rich compounds, causing temporary spikes in emissions.

The measured concentrations also highlight the potential health hazards of this environment. According to the literature, air containing up to 220 ppb of VOCs is generally considered to be of good quality. Levels between 0.22 and 0.66 ppm are classified as moderate quality, 0.66 and 22 ppm as poor quality, and above 2.2 ppm as unhealthy [80]. Since the maximum VOC concentration measured was approximately 150

ppb, the recorded values remained within the range generally considered to represent good indoor air quality according to the adopted classification.

Regarding temperature, despite the often-reported dependence between temperature and humidity [81], no clear correlation was observed between VOC concentration and temperature variation. This may be due to the relatively narrow temperature range studied (approximately 25 ± 5 °C). Similarly, no relationship was found between VOC concentration and atmospheric pressure, which remained steady at 100.5 ± 0.5 kPa over time.

3.3. IAQ Monitoring

The third variable assessed in this study was the IAQ (Indoor Air Quality) index, which provides a quantitative measure of air quality on a scale from 0 to 100, considering the overall composition of the environment. Unlike CO₂ and VOC levels, which showed noticeable fluctuations across the monitored locations, the IAQ values remained remarkably stable throughout the measurement periods. Due to this limited variation, the IAQ graphs are not presented, as they would offer little additional insight.

The modest variation observed can be explained by the fact that IAQ is influenced by multiple environmental factors, not solely by CO₂ or VOC concentrations. In the spaces analyzed, VOC levels never exceeded the thresholds previously established for “good” conditions, and CO₂ concentrations remained moderate. Consequently, even during moments of transient increases in these pollutants, the overall air quality, as represented by the IAQ index, remained constant, indicating generally continuous conditions throughout the study.

Unlike CO₂ and VOC, IAQ does not appear to be directly affected by, nor partially correlated with, variations in humidity, temperature, or pressure. Its values reflect the combined impact of multiple environmental factors and are therefore less sensitive to abrupt changes in any single variable. Additionally, the BSEC2 algorithm establishes an internal baseline during the initial stabilization period. The baseline conditions recorded at the start are used as a reference for subsequent readings, so even if local fluctuations in CO₂ or VOC occur, these variations are measured relative to the sensor’s initial baseline and do not lead to substantial decreases in the IAQ value. This behavior reflects the characteristics of the BSEC2 algorithm, which is designed to reduce sensitivity to short-term fluctuations and supports the potential applicability of the developed sensing system for low-cost continuous indoor air quality monitoring in complex industrial environments.

3.4. Measurements Range

Table 2 summarizes the maximum, average, and minimum values of CO₂ concentration, VOC concentration, IAQ index, relative humidity, temperature, and atmospheric pressure measured at seven sensor locations within the factory.

Table 2. Maximum, average, and minimum values registered for CO₂ eq concentration (ppm), VOC concentration (ppb), IAQ, humidity (%), temperature (°C), and pressure (kPa) at the locations of sensors 1—Head of the Painting Line’s Office, 2—Cataphoresis Bath, 3—Primer Application/Coating, 4—Ink/Paint Application/Coating, 5—Varnish Application, 6—Wax Application and Final Verification and 7—Ceiling of the Factory.

Sensor	CO ₂ eq (ppm)	VOC (ppb)	IAQ	Hum. (%)	Temp. (°C)	Press. (kPa)
Maximum Values						
1	1958.2	13.6	76.2	64.1	29.0	101.0
2	1518.4	5.0	93.0	65.0	28.0	101.0

3	2997.7	144.1	97.0	63.6	32.0	101.0
4	1631.8	6.5	100.0	62.0	31.0	101.0
5	1424.6	4.1	71.0	67.8	25.0	101.0
6	1959.3	13.7	90.0	66.7	27.0	101.0
7	1741.1	8.3	71.0	62.5	31.0	101.0
—	Average Values					
1	749.8	1.1	100.0	50.1	26.5	100.5
2	843.1	1.3	68.5	49.7	24.9	100.5
3	1211.0	4.2	71.2	48.6	27.1	100.5
4	962.4	1.7	93.2	51.7	26.9	100.5
5	856.1	1.3	48.4	53.9	23.1	100.5
6	857.9	1.4	65.5	52.7	23.9	100.5
7	871.5	1.5	49.4	47.1	27.8	100.5
—	Minimum Values					
1	500.0	0.5	58.0	31.7	23.0	100.0
2	500.0	0.5	47.0	28.0	22.0	100.0
3	400.0	0.2	53.0	27.8	23.0	100.0
4	481.1	0.5	72.0	40.8	23.0	100.0
5	500.0	0.5	0.0	32.9	22.0	100.0
6	400.0	0.3	47.0	32.9	22.0	100.0
7	400.0	0.3	5.0	28.4	23.0	100.0

The measured CO₂ concentrations exhibited notable spatial variability across the monitored areas, though temporal fluctuations were generally moderate. Maximum CO₂ values ranged from 1424.6 ppm at the Varnish Application area (Sensor 5) to 2997.7 ppm at the Primer Application/Coating area (Sensor 3). These peaks are consistent with process-related emissions rather than persistent ventilation deficiencies. It is interesting that in the Head of the Painting Line's Office (Sensor 1), some relatively high CO₂ peaks were also observed, which could be associated with worker density in this location. Average CO₂ concentrations remained below 1300 ppm at all locations, with Sensor 3 recording the highest mean value of 1211 ppm. Minimum values, between 400 and 500 ppm, correspond closely to outdoor background levels, indicating effective air renewal during low-activity periods. These results suggest that while episodic increases occur, they are generally transient and do not compromise overall indoor air quality [82,83].

VOC concentrations demonstrated a strong dependence on location, corresponding to the nature of the industrial processes performed in each area. Sensor 3 exhibited the highest maximum VOC concentration (144.1 ppb), likely associated with solvent-based coating applications. Other areas, including the Wax Application and Final Verification area (Sensor 6), recorded lower maximum VOC concentrations (up to 13.7 ppb). Average VOC values remained low across all sensors (0.2–4.2 ppb), indicating that high VOC events were short-lived and largely process-dependent. These findings suggest that, under normal operating conditions, occupational exposure limits are not exceeded.

The IAQ index remained consistently high across all monitored locations, with maximum values often reaching 100. Average IAQ varied between 48.4 at the Varnish Application area (Sensor 5) and 93.2 at the Ink/Paint Application area (Sensor 4), reflecting generally good indoor air quality throughout the factory. Notably, even in areas with elevated CO₂ or VOC concentrations, the IAQ did not decrease substantially. This stability is likely related to the integrative nature of the IAQ metric, which accounts for multiple environmental factors beyond just CO₂ and VOCs. Additionally, the IAQ sensor establishes its own baseline during the initial measurements, using the initial conditions as a reference. As a result, transient or localized changes in pollutant concentrations have

a limited impact on the IAQ value. Unlike CO₂ and VOC, IAQ showed no direct or partial correlation with humidity, temperature, or pressure variations, further reflecting its integrative nature.

Relative humidity values across all sensors remained within acceptable industrial comfort ranges, with average values between 47.1% and 53.9%. Maximum humidity reached up to 67.8%, while minimum values ranged from 27.8% to 32.9% depending on location. These variations are typical of large industrial facilities and are unlikely to substantially affect workers' comfort or material stability. Temperature measurements were similarly consistent, with average values close to 25 °C and a narrow range between 22 °C and 32 °C. The relatively stable thermal conditions may have reduced the influence of temperature on the perceived differences in air quality across locations. Atmospheric pressure remained effectively constant at approximately 100.5 kPa across all sensors, indicating stable atmospheric conditions throughout the monitoring period [84].

Among the monitored areas, the Primer Application/Coating area (Sensor 3) represented the location with the highest localized emissions of CO₂ and VOCs, whereas the Wax Application and Final Verification area (Sensor 6) and other sites exhibited lower pollutant levels and maintained high IAQ. The Varnish Application area (Sensor 5) showed slightly lower IAQ values, consistent with moderate CO₂ and VOC concentrations. These observations suggest that while overall indoor air quality is acceptable, process-specific areas may require targeted attention to mitigate transient emissions.

Overall, the results indicate that the developed sensing system is suitable for continuous monitoring of indoor air quality in complex industrial environments, such as an automotive painting line. Despite structural obstacles, metallic elements, and large inter-sensor distances, the sensing system was able to capture spatial differences and temporal trends in CO₂, VOC, IAQ, and thermal parameters. The observed consistency of recorded trends, the realistic magnitude of measured values, and the clear differentiation between process-specific areas indicate satisfactory system performance and practical applicability of the system. These findings suggest potential applications of such sensors for occupational health assessment, ventilation optimization, and real-time air quality management in challenging industrial settings.

3.5. Identified Limitations

Despite the promising performance demonstrated during the monitoring study here described, some limitations of the developed sensor system should be acknowledged. First, although the sensors provided stable and coherent measurements through time, low-cost sensing technologies often present lower absolute accuracy as well as higher long-term drift when compared to certified or reference-grade industrial instrumentation. While calibration procedures were implemented prior and during the development of the prototype, periodic recalibration is necessary to ensure long-term reliability, particularly in environments with sustained chemical exposure.

Second, the IAQ index used in this study is an integrative and sensor-dependent metric that establishes its own internal baseline during the initial measurement period. Although this approach improves stability while reducing sensitivity to short-term fluctuations, it may reduce sensitivity to gradual background changes over extended time scales. Consequently, IAQ values should be interpreted as relative indicators of air quality variation rather than absolute standardized air quality classifications.

Additionally, VOC measurements reflect total volatile organic compound equivalents (and are often impacted by the levels of humidity, temperature and even CO₂) rather than compound-specific identification. The developed sensors are therefore unable to distinguish between different VOC species, some of which may present varying

toxicological relevance. Nonetheless, it is important to emphasize that this prototype was not intended to be a replacement for chromatography- or spectrometry-based techniques, but rather a practical, analytically simple, sustainable and low-cost alternative for air quality monitoring.

Finally, communication constraints were observed in certain factory areas due to structural obstacles, metallic interference, and large inter-sensor distances. Although the sensors provided usable monitoring data throughout the study, future system optimization should include improved network architecture and signal robustness to ensure full spatial coverage in highly obstructed industrial environments.

4. Conclusions

This study investigated the potential suitability of a low-cost sensor-based prototype for continuous indoor air quality monitoring in a complex industrial environment, specifically an automotive painting line. The system continuously monitored six environmental variables (CO₂ equivalent, VOC, IAQ, relative humidity, temperature, and atmospheric pressure) using seven strategically positioned sensing stations over a 12-day period. The collected data showed that CO₂ and VOC concentrations were generally higher in process-intensive areas, particularly in the Primer Application/Coating zone (Sensor 3), whereas the IAQ index remained relatively stable across all monitored locations. This behavior is consistent with the integrative nature of the IAQ metric and suggests that short-term increases in CO₂ and VOC concentrations had a limited influence on the overall IAQ index. In addition, no clear relationship was observed between IAQ and variations in humidity, temperature, or atmospheric pressure during the monitoring period.

The monitoring campaign also demonstrated stable operation of the sensing network throughout the study period. The prototype was able to capture spatial variability and process-related emission patterns while recording temporal trends in the monitored environmental variables. Peak CO₂ and VOC concentrations remained below commonly adopted occupational exposure limits, whereas minimum CO₂ values were close to expected outdoor background concentrations, suggesting adequate ventilation during periods of lower activity. These observations indicate that the proposed sensing system may support data-driven interventions, such as localized ventilation optimization, with the potential to reduce unnecessary ventilation while improving environmental awareness in industrial facilities.

The developed multi-sensor system also shows potential as an early-warning tool for industrial environments by enabling the identification of localized increases in CO₂ equivalent and VOC concentrations that may not be captured by conventional fixed monitoring strategies. One of the distinguishing features of the proposed approach is its combination of low-cost MEMS sensing technology with the Bosch BSEC2 algorithm, enabling high spatial deployment density while providing continuous IAQ-related information across complex industrial layouts.

From a sustainability perspective, the proposed sensing system was designed as a low-energy and scalable alternative to conventional industrial environmental monitoring solutions. Under the operating conditions evaluated in this study, the system reduced energy consumption by approximately 90% compared with continuous-sampling Wi-Fi-based sensing systems and achieved an estimated tenfold reduction in deployment cost relative to conventional industrial monitoring stations, while maintaining the ability to detect localized CO₂ peaks (up to 2997.7 ppm) and VOC increases in process-specific areas. These characteristics support the widespread deployment of sensing nodes capable of providing spatially and temporally resolved environmental information with relatively low installation and operating costs. The prototype also operates at a substantially lower

cost than spectrometric and many electrochemical monitoring systems, potentially enabling broader adoption in industrial applications.

Overall, the results suggest that the developed prototype is a promising and potentially cost-effective solution for continuous industrial environmental monitoring. The system demonstrated its ability to identify spatial differences and temporal trends in indoor air quality under real operating conditions, supporting its potential application in occupational exposure assessment, ventilation management, and industrial environmental monitoring. Nevertheless, additional long-term studies under different industrial conditions and further comparison with reference-grade instrumentation would strengthen the evaluation of the proposed system and support its broader implementation.

Author Contributions: Conceptualization, V.A. and V.V.; methodology, P.C.M.; software, P.C.M. and H.D.; validation, V.A. and V.V.; formal analysis, P.C.M. and H.D.; investigation, P.C.M. and H.D.; resources, S.P. and V.V.; data curation, P.C.M. and H.D.; writing—original draft preparation, P.C.M. V.A. and S.P.; writing—review and editing, V.A., S.P. and V.V.; visualization, P.C.M. and V.V.; supervision, S.P. and V.V.; project administration, V.V.; funding acquisition, V.V. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Fundação para a Ciência e Tecnologia (FCT–Portugal), grants number UID/FIS/04559/2020 (LIBPhys) and LA/P/0117/2020 (LA-REAL).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available on request from the corresponding author due to privacy matters.

Acknowledgments: The authors express their gratitude to Carlos Fujão and Eng. Fausto Santos, from Volkswagen AutoEuropa, for facilitating the development of this study.

Conflicts of Interest: Author Vladyslav Aliexsieiev is employed by NMT, S.A. Author Valentina Vassilenko serves as a scientific advisor to NMT, S.A., but has not received any salary, grant, or other financial compensation from the company. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest. Volkswagen AutoEuropa was merely a partner of the study and there are no commercial interest or other potential conflicts involved.

References

1. Tomassoni, A.J.; French, R.N.E.; Walter, F.G. Toxic Industrial Chemicals and Chemical Weapons: Exposure, Identification, and Management by Syndrome. *Emerg. Med. Clin. N. Am.* **2015**, *33*, 13–36. <https://doi.org/10.1016/J.EMC.2014.09.004>.
2. Liu, Z.; Yan, Y.; Lv, T.; Huang, Z.; Liu, T.; Huang, Q.; Yang, J.; Chen, Y.; Zhao, Y.; Zhou, T. Comprehensive Understanding the Emission Characteristics and Kinetics of VOCs from Automotive Waste Paint Sludge in a Environmental Test Chamber. *J. Hazard. Mater.* **2022**, *429*, 128387. <https://doi.org/10.1016/J.JHAZMAT.2022.128387>.
3. Moura, P.C.; Santos, F.; Fujão, C.; Vassilenko, V. In Situ Indoor Air Volatile Organic Compounds Assessment in a Car Factory Painting Line. *Processes* **2023**, *11*, 2259. <https://doi.org/10.3390/pr11082259>.
4. Omanga, E.; Ulmer, L.; Berhane, Z.; Gatari, M. Industrial Air Pollution in Rural Kenya: Community Awareness, Risk Perception and Associations between Risk Variables. *BMC Public Health* **2014**, *14*, 377. <https://doi.org/10.1186/1471-2458-14-377>.
5. Moura, P.C.; Santos, F.; Fujão, C.; Vassilenko, V. Towards the Identification of the Volatile Organic Compounds Emitted by the Coatings Used in a Car Factory Painting Line. *J. Coat. Technol. Res.* **2024**, *21*, 665–682. <https://doi.org/10.1007/S11998-023-00847-7>.

6. Mu, J.; Zhang, Y.; Xia, Z.; Fan, G.; Zhao, M.; Sun, X.; Liu, Y.; Chen, T.; Shen, H.; Zhang, Z.; et al. Two-Year Online Measurements of Volatile Organic Compounds (VOCs) at Four Sites in a Chinese City: Significant Impact of Petrochemical Industry. *Sci. Total Environ.* **2023**, *858*, 159951. <https://doi.org/10.1016/J.SCITOTENV.2022.159951>.
7. Tsai, W.T. An Overview of Health Hazards of Volatile Organic Compounds Regulated as Indoor Air Pollutants. *Rev. Environ. Health* **2019**, *34*, 81–89. <https://doi.org/10.1515/REVEH-2018-0046>.
8. Chen, W.; Wu, F.; Geng, W.; Yu, G. Carbon Emissions in China's Industrial Sectors. *Resour. Conserv. Recycl.* **2017**, *117*, 264–273. <https://doi.org/10.1016/J.RESCONREC.2016.10.008>.
9. Geng, Y.; Wei, Y.M.; Fishedick, M.; Chiu, A.; Chen, B.; Yan, J. Recent Trend of Industrial Emissions in Developing Countries. *Appl. Energy* **2016**, *166*, 187–190. <https://doi.org/10.1016/J.APENERGY.2016.02.060>.
10. Hill, R.J.; Smith, P.A. Exposure Assessment for Carbon Dioxide Gas: Full Shift Average and Short-Term Measurement Approaches. *J. Occup. Environ. Hyg.* **2015**, *12*, 819–828. <https://doi.org/10.1080/15459624.2015.1053894>.
11. Landim, A.A.; Teixeira, E.C.; Agudelo-Castañeda, D.; Schneider, I.; Silva, L.F.O.; Wiegand, F.; Kumar, P. Spatio-Temporal Variations of Sulfur Dioxide Concentrations in Industrial and Urban Area via a New Statistical Approach. *Air Qual. Atmos. Health* **2018**, *11*, 801–813. <https://doi.org/10.1007/s11869-018-0584-2>.
12. Srivastava, R.K.; Miller, C.A.; Erickson, C.; Jambhekar, R. Emissions of Sulfur Trioxide from Coal-Fired Power Plants. *J. Air Waste Manag. Assoc.* **2004**, *54*, 750–762. <https://doi.org/10.1080/10473289.2004.10470943>.
13. Domínguez-López, D.; Adame, J.A.; Hernández-Ceballos, M.A.; Vaca, F.; De La Morena, B.A.; Bolívar, J.P. Spatial and Temporal Variation of Surface Ozone, NO and NO₂ at Urban, Suburban, Rural and Industrial Sites in the Southwest of the Iberian Peninsula. *Environ. Monit. Assess.* **2014**, *186*, 5337–5351. <https://doi.org/10.1007/s10661-014-3783-9>.
14. Mohan, S.; Saranya, P. Assessment of Tropospheric Ozone at an Industrial Site of Chennai Megacity. *J. Air Waste Manag. Assoc.* **2019**, *69*, 1079–1095. <https://doi.org/10.1080/10962247.2019.1604451>.
15. Schenk, L.; Hansson, S.O.; Rudén, C.; Gilek, M. Occupational Exposure Limits: A Comparative Study. *Regul. Toxicol. Pharmacol.* **2008**, *50*, 261–270. <https://doi.org/10.1016/J.YRTPH.2007.12.004>.
16. Yang, Q.; Liu, G.; Falandysz, J.; Yang, L.; Zhao, C.; Chen, C.; Sun, Y.; Zheng, M.; Jiang, G. Atmospheric Emissions of Particulate Matter-Bound Heavy Metals from Industrial Sources. *Sci. Total Environ.* **2024**, *947*, 174467. <https://doi.org/10.1016/J.SCITOTENV.2024.174467>.
17. Zhang, H.; Sun, W.; Li, W.; Wang, Y. Physical and Chemical Characterization of Fugitive Particulate Matter Emissions of the Iron and Steel Industry. *Atmos. Pollut. Res.* **2022**, *13*, 101272. <https://doi.org/10.1016/J.APR.2021.101272>.
18. WHO. Executive Summary—WHO Guidelines for Indoor Air Quality: Selected Pollutants—NCBI Bookshelf. Available online: https://www.ncbi.nlm.nih.gov/books/NBK138699/?utm_source=chatgpt.com (accessed on 31 March 2026).
19. Organización Mundial de la Salud (OMS). *WHO Global Air Quality Guidelines: Particulate Matter (PM_{2.5} and PM₁₀), Ozone, Nitrogen Dioxide, Sulfur Dioxide and Carbon Monoxide*; World Health Organization: Geneva, Switzerland, 2021; pp. 1–360.
20. Khoshakhlagh, A.H.; Yazdanirad, S.; Saberi, H.R.; Liao, P.C. Health Risk Assessment of Exposure to Various Vapors and Fumes in a Factory of Automobile Manufacturing. *Heliyon* **2023**, *9*, e18583. <https://doi.org/10.1016/j.heliyon.2023.e18583>.
21. Wang, F.; Li, C.; Liu, W.; Jin, Y. Oxidative Damage and Genotoxic Effect in Mice Caused by Sub-Chronic Exposure to Low-Dose Volatile Organic Compounds. *Inhal. Toxicol.* **2013**, *25*, 235–242. <https://doi.org/10.3109/08958378.2013.779767>.
22. Drabińska, N.; Flynn, C.; Ratcliffe, N.; Belluomo, I.; Myridakis, A.; Gould, O.; Fois, M.; Smart, A.; Devine, T.; Costello, B.D.L. A Literature Survey of All Volatiles from Healthy Human Breath and Bodily Fluids: The Human Volatilome. *J. Breath Res.* **2021**, *15*, 034001. <https://doi.org/10.1088/1752-7163/ABF1D0>.
23. Moon, C.S. Estimations of the Lethal and Exposure Doses for Representative Methanol Symptoms in Humans. *Ann. Occup. Environ. Med.* **2017**, *29*, 44. <https://doi.org/10.1186/s40557-017-0197-5>.
24. Bevan, R.J.; Slack, R.J.; Holmes, P.; Levy, L.S. An Assessment of Potential Cancer Risk Following Occupational Exposure to Ethanol. *J. Toxicol. Environ. Health Part B* **2009**, *12*, 188–205. <https://doi.org/10.1080/10937400902894160>.
25. Nurmatov, U.B.; Tagiyeva, N.; Semple, S.; Devereux, G.; Sheikh, A. Volatile Organic Compounds and Risk of Asthma and Allergy: A Systematic Review. *Eur. Respir. Rev.* **2015**, *24*, 92–101. <https://doi.org/10.1183/09059180.00000714>.
26. Wang, J.; Janson, C.; Gislason, T.; Gunnbjörnsdóttir, M.; Jogi, R.; Orru, H.; Norbäck, D. Volatile Organic Compounds (VOC) in Homes Associated with Asthma and Lung Function among Adults in Northern Europe. *Environ. Pollut.* **2023**, *321*, 121103. <https://doi.org/10.1016/J.ENVPOL.2023.121103>.
27. Xiong, Y.; Du, K.; Huang, Y. One-Third of Global Population at Cancer Risk Due to Elevated Volatile Organic Compounds Levels. *NPJ Clim. Atmos. Sci.* **2024**, *7*, 54. <https://doi.org/10.1038/S41612-024-00598-1>.

28. Hussain, M.S.; Gupta, G.; Mishra, R.; Patel, N.; Gupta, S.; Alzarea, S.I.; Kazmi, I.; Kumbhar, P.; Disouza, J.; Dureja, H.; et al. Unlocking the Secrets: Volatile Organic Compounds (VOCs) and Their Devastating Effects on Lung Cancer. *Pathol. Res. Pract.* **2024**, *255*, 155157. <https://doi.org/10.1016/J.PR.P.2024.155157>.
29. Guais, A.; Brand, G.; Jacquot, L.; Karrer, M.; Dukan, S.; Grévilot, G.; Molina, T.J.; Bonte, J.; Regnier, M.; Schwartz, L. Toxicity of Carbon Dioxide: A Review. *Chem. Res. Toxicol.* **2011**, *24*, 2061–2070. <https://doi.org/10.1021/TX200220R>.
30. Kinoshita, H.; Türkan, H.; Vucinic, S.; Naqvi, S.; Bedair, R.; Rezaee, R.; Tsatsakis, A. Carbon Monoxide Poisoning. *Toxicol. Rep.* **2020**, *7*, 169–173. <https://doi.org/10.1016/J.TOXREP.2020.01.005>.
31. Ye, L.; Li, C.; Qin, K.; Xu, L.; Jin, P.; Wang, Z.; Zhang, C.; Yin, C.; Liu, Y.; Fang, Z.; et al. Associations between Long-Term Exposure to Air Pollutants and Mortality Risk of Critically Ill Patients: A Multi-Center Cohort Study in Central China. *Ann. Intensive Care* **2025**, *15*, 165. <https://doi.org/10.1186/S13613-025-01527-Y>.
32. Gokirmak, M.; Yildirim, Z.; Hasanoglu, H.C.; Koksall, N.; Mehmet, N. The Role of Oxidative Stress in Bronchoconstriction Due to Occupational Sulfur Dioxide Exposure. *Clin. Chim. Acta* **2003**, *331*, 119–126. [https://doi.org/10.1016/S0009-8981\(03\)00117-7](https://doi.org/10.1016/S0009-8981(03)00117-7).
33. Gerosa, A.; Wang, Q.; Yang, C.; Liu, M.; Yan, R. Research on the Distribution Characteristics and Health Effects of O₃ in the Fenwei Plain. *Atmosphere* **2025**, *16*, 1219. <https://doi.org/10.3390/ATMOS16101219>.
34. Salah, H.; Xiong, Y.; Partha, D.; Mariscal, N.; Wang, L.; Tilmes, S.; Tang, W.; Huang, Y. Impact of Anthropogenic Emission Estimates on Air Quality and Human Health Effects. *Geohealth* **2025**, *9*, e2024GH001223. <https://doi.org/10.1029/2024GH001223>.
35. Paterson, C.A.; Sharpe, R.A.; Taylor, T.; Morrissey, K. Indoor PM_{2.5}, VOCs and Asthma Outcomes: A Systematic Review in Adults and Their Home Environments. *Environ. Res.* **2021**, *202*, 111631. <https://doi.org/10.1016/J.ENVRES.2021.111631>.
36. Geto, A.K.; Feleke, S.F.; Yimer, A.; Kidie, A.A.; Tesfa, N.A.; Mislu, E.; Yesuf, H.A.; Hailu, M.; Ayal, B.G. The Association between Air Pollution and Cognitive Impairment: A Systematic Review and Meta- Analysis of Global Studies. *BMC Public Health* **2025**, *25*, 3548. <https://doi.org/10.1186/S12889-025-24560-9>.
37. Zhang, W.; Xu, L.; Zhang, H. Recent Advances in Mass Spectrometry Techniques for Atmospheric Chemistry Research on Molecular-Level. *Mass Spectrom. Rev.* **2024**, *43*, 1091–1134. <https://doi.org/10.1002/MAS.21857>.
38. Schripp, T.; Etienne, S.; Fauck, C.; Fuhrmann, F.; Märk, L.; Salthammer, T. Application of Proton-Transfer-Reaction-Mass-Spectrometry for Indoor Air Quality Research. *Indoor Air* **2014**, *24*, 178–189. <https://doi.org/10.1111/INA.12061>.
39. Moura, P.C.; Vassilenko, V. Long-Term in Situ Air Quality Assessment in Closed Environments: A Gas Chromatography–Ion Mobility Spectrometry Applicability Study. *Eur. J. Mass Spectrom.* **2023**, *29*, 231–239. <https://doi.org/10.1177/14690667231187502>.
40. Arnanthigo, Y.; Anttalainen, O.; Safaei, Z.; Sillanpää, M. Sniff-Testing for Indoor Air Contaminants from New Buildings Environment Detecting by Aspiration-Type Ion Mobility Spectrometry. *Int. J. Ion Mobil. Spectrom.* **2016**, *19*, 15–30. <https://doi.org/10.1007/s12127-016-0189-0>.
41. Moura, P.C.; Vassilenko, V. Gas Chromatography–Ion Mobility Spectrometry as a Tool for Quick Detection of Hazardous Volatile Organic Compounds in Indoor and Ambient Air: A University Campus Case Study. *Eur. J. Mass Spectrom.* **2022**, *28*, 113–126. <https://doi.org/10.1177/14690667221130170>.
42. Marć, M.; Tobiszewski, M.; Zabiegała, B.; de la Guardia, M.; Namieśnik, J. Current Air Quality Analytics and Monitoring: A Review. *Anal. Chim. Acta* **2015**, *853*, 116–126. <https://doi.org/10.1016/J.ACA.2014.10.018>.
43. Kim, J.; Kim, J.-H.; Jang, S.H. Infrared Spectra in Air Pollution Research and Monitoring from Space: A Review. In *Proceedings of SPIE SPIE Smart Structures and Materials + Nondestructive Evaluation*; SPIE: Bellingham, WA, USA, 2021; Volume 11590, pp. 50–59. <https://doi.org/10.1117/12.2584500>.
44. Druckenmüller, K.; Günther, K.; Elbers, G. Near-Infrared Spectroscopy (NIRS) as a Tool to Monitor Exhaust Air from Poultry Operations. *Sci. Total Environ.* **2018**, *630*, 536–543. <https://doi.org/10.1016/J.SCITOTENV.2018.02.072>.
45. Moura, P.C.; Vassilenko, V.; Ribeiro, P.A. Ion Mobility Spectrometry Towards Environmental Volatile Organic Compounds Identification and Quantification: A Comparative Overview over Infrared Spectroscopy. *Emiss. Control Sci. Technol.* **2023**, *9*, 25–46. <https://doi.org/10.1007/s40825-022-00220-x>.
46. Günzler, H.; Williams, A. *Handbook of Analytical Techniques*; Wiley: Weinheim, Germany, 2008; Volumes 1–2, pp. 1–1182. <https://doi.org/10.1002/9783527618323>.
47. Karagulian, F.; Barbiere, M.; Kotsev, A.; Spinelle, L.; Gerboles, M.; Lagler, F.; Redon, N.; Crunaire, S.; Borowiak, A. Review of the Performance of Low-Cost Sensors for Air Quality Monitoring. *Atmosphere* **2019**, *10*, 506. <https://doi.org/10.3390/ATMOS10090506>.
48. Alberti, G.; Zaroni, C.; Magnaghi, L.R.; Biesuz, R. Disposable and Low-Cost Colorimetric Sensors for Environmental Analysis. *Int. J. Environ. Res. Public Health* **2020**, *17*, 8331. <https://doi.org/10.3390/IJERPH17228331>.

49. Moura, P.C.; Vassilenko, V. Contemporary Ion Mobility Spectrometry Applications and Future Trends towards Environmental, Health and Food Research: A Review. *Int. J. Mass Spectrom.* **2023**, *486*, 117012. <https://doi.org/10.1016/J.IJMS.2023.117012>.
50. Hübschmann, H.J. *Handbook of GC-MS: Fundamentals and Applications*, 3rd ed.; Wiley-VCH: Weinheim, Germany, 2015; pp. 1–863. <https://doi.org/10.1002/9783527674305>.
51. Lundanes, E.; Reubsaet, L.; Greibrokk, T. *Chromatography: Basic Principles, Sample Preparations and Related Methods*; Wiley-VCH: Weinheim, Germany, 2014; p. 207.
52. Moura, P.C.; Pivetta, T.P.; Vassilenko, V.; Ribeiro, P.A.; Raposo, M. Graphene Oxide Thin Films for Detection and Quantification of Industrially Relevant Alcohols and Acetic Acid. *Sensors* **2023**, *23*, 462. <https://doi.org/10.3390/S23010462>.
53. Catalão Moura, P.; Raposo, M. Thin-Films–Based Sensors: Physics Contribution to Medicine, Environment and Food. *Europhys. Lett.* **2025**, *151*, 66001. <https://doi.org/10.1209/0295-5075/AE02BF>.
54. Moura, P.C.; Sério, S. Recent Applications and Future Trends of Nanostructured Thin Films-Based Gas Sensors Produced by Magnetron Sputtering. *Coatings* **2024**, *14*, 1214. <https://doi.org/10.3390/COATINGS14091214>.
55. Sakthinathan, S.; Meenakshi, G.A.; Vinothini, S.; Yu, C.L.; Chen, C.L.; Chiu, T.W.; Vittayakorn, N. A Review of Thin-Film Growth, Properties, Applications, and Future Prospects. *Processes* **2025**, *13*, 587. <https://doi.org/10.3390/PR13020587>.
56. Bulowski, W.; Knura, R.; Socha, R.P.; Basiura, M.; Skibińska, K.; Wojnicki, M. Thin Film Semiconductor Metal Oxide Oxygen Sensors: Limitations, Challenges, and Future Progress. *Electronics* **2024**, *13*, 3409. <https://doi.org/10.3390/ELECTRONICS13173409>.
57. Spinelle, L.; Gerboles, M.; Villani, M.G.; Aleixandre, M.; Bonavitacola, F. Field Calibration of a Cluster of Low-Cost Commercially Available Sensors for Air Quality Monitoring. Part B: NO, CO and CO₂. *Sens. Actuators B Chem.* **2017**, *238*, 706–715. <https://doi.org/10.1016/J.SNB.2016.07.036>.
58. Kang, Y.; Aye, L.; Ngo, T.D.; Zhou, J. Performance Evaluation of Low-Cost Air Quality Sensors: A Review. *Sci. Total Environ.* **2022**, *818*, 151769. <https://doi.org/10.1016/J.SCITOTENV.2021.151769>.
59. Wang, C.; Yin, L.; Zhang, L.; Xiang, D.; Gao, R. Metal Oxide Gas Sensors: Sensitivity and Influencing Factors. *Sensors* **2010**, *10*, 2088–2106. <https://doi.org/10.3390/S100302088>.
60. Kim, J.Y.; Chu, C.H.; Shin, S.M. ISSAQ: An Integrated Sensing Systems for Real-Time Indoor Air Quality Monitoring. *IEEE Sens. J.* **2014**, *14*, 4230–4244. <https://doi.org/10.1109/JSEN.2014.2359832>.
61. Jo, J.; Jo, B.; Kim, J.; Kim, S.; Han, W. Development of an IoT-Based Indoor Air Quality Monitoring Platform. *J. Sens.* **2020**, *2020*, 8749764. <https://doi.org/10.1155/2020/8749764>.
62. Kumar Sai, K.B.; Mukherjee, S.; Parveen Sultana, H. Low Cost IoT Based Air Quality Monitoring Setup Using Arduino and MQ Series Sensors with Dataset Analysis. *Procedia Comput. Sci.* **2019**, *165*, 322–327. <https://doi.org/10.1016/J.PROCS.2020.01.043>.
63. Coleman, J.R.; Meggers, F. Sensing of Indoor Air Quality—Characterization of Spatial and Temporal Pollutant Evolution through Distributed Sensing. *Front. Built Environ.* **2018**, *4*, 285098. <https://doi.org/10.3389/fbuil.2018.00028>.
64. Mansour, S.; Nasser, N.; Karim, L.; Ali, A. Wireless Sensor Network-Based Air Quality Monitoring System. In *2014 International Conference on Computing, Networking and Communications (ICNC)*; IEEE: Piscataway, NJ, USA, 2014; pp. 545–550. <https://doi.org/10.1109/ICCNC.2014.6785394>.
65. Rescio, G.; Manni, A.; Caroppo, A.; Carluccio, A.M.; Siciliano, P.; Leone, A. Multi-Sensor Platform for Predictive Air Quality Monitoring. *Sensors* **2023**, *23*, 5139. <https://doi.org/10.3390/S23115139>.
66. Christakis, I.; Tsakiridis, O.; Kandris, D.; Stavarakas, I. Air Pollution Monitoring via Wireless Sensor Networks: The Investigation and Correction of the Aging Behavior of Electrochemical Gaseous Pollutant Sensors. *Electronics* **2023**, *12*, 1842. <https://doi.org/10.3390/ELECTRONICS12081842>.
67. Kumar, P.; Skouloudis, A.N.; Bell, M.; Viana, M.; Carotta, M.C.; Biskos, G.; Morawska, L. Real-Time Sensors for Indoor Air Monitoring and Challenges Ahead in Deploying Them to Urban Buildings. *Sci. Total Environ.* **2016**, *560–561*, 150–159. <https://doi.org/10.1016/J.SCITOTENV.2016.04.032>.
68. Saini, J.; Dutta, M.; Marques, G. Indoor Air Quality Monitoring Systems Based on Internet of Things: A Systematic Review. *Int. J. Environ. Res. Public Health* **2020**, *17*, 4942. <https://doi.org/10.3390/IJERPH17144942>.
69. Jin, X.; Chieng, D.; Kar, P.; Kwong, C.F.; Li, Y.; Wang, Y. Large-Scale Continuous Monitoring of Greenhouse Gases with Adaptive LoRaWAN in CN470–510 MHz Band. *Sensors* **2025**, *25*, 5349. <https://doi.org/10.3390/s25175349>.
70. Casals, L.; Gomez, C.; Vidal, R. Efficiency of Temporal Sensor Data Compression Methods to Reduce LoRa-Based Sensor Node Energy Consumption. *Sens. Rev.* **2022**, *42*, 503–516. <https://doi.org/10.3390/s21196478>.
71. Tamang, D.; Pozzebon, A.; Parri, L.; Fort, A.; Abrardo, A. Designing a Reliable and Low-Latency LoRaWAN Solution for Environmental Monitoring in Factories at Major Accident Risk. *Sensors* **2022**, *22*, 2372. <https://doi.org/10.3390/s22062372>.

72. Wang, Z.; Lyu, D.; Zhou, P.; Ge, Y.; Hu, Y.; Zhu, R.; Wang, W.; Yang, X. Robust High-Precision Time Synchronization for Distributed Sensor Systems in Challenging Environments. *Remote Sens.* **2025**, *17*, 3715. <https://doi.org/10.3390/rs17223715>.
73. Li, J.; Gutierrez-Osuna, R.; Hodges, R.D.; Luckey, G.; Crowell, J.; Schiffman, S.S.; Nagle, H.T. Using Field Asymmetric Ion Mobility Spectrometry for Odor Assessment of Automobile Interior Components. *IEEE Sens. J.* **2016**, *16*, 5747–5756. <https://doi.org/10.1109/JSEN.2016.2568209>.
74. Kim, B.R. VOC Emissions from Automotive Painting and Their Control: A Review. *Environ. Eng. Res.* **2011**, *16*, 1–9. <https://doi.org/10.4491/EER.2011.16.1.001>.
75. Singgih, I.K.; Yu, O.; Kim, B.I.; Koo, J.; Lee, S. Production Scheduling Problem in a Factory of Automobile Component Primer Painting. *J. Intell. Manuf.* **2020**, *31*, 1483–1496. <https://doi.org/10.1007/s10845-019-01524-6>.
76. Bysko, S.; Krystek, J.; Bysko, S. Automotive Paint Shop 4.0. *Comput. Ind. Eng.* **2020**, *139*, 105546. <https://doi.org/10.1016/J.CIE.2018.11.056>.
77. Salihoglu, G.; Salihoglu, N.K. A Review on Paint Sludge from Automotive Industries: Generation, Characteristics and Management. *J. Environ. Manag.* **2016**, *169*, 223–235. <https://doi.org/10.1016/J.JENVMAN.2015.12.039>.
78. Baumann, W.; Dingleiter, U. Method for Reprocessing and Recycling of Aqueous Rinsing Liquids from Car Painting with Water-Based Paints in Automobile Industry. *Heat Mass Transf.* **2011**, *47*, 1043–1049. <https://doi.org/10.1007/s00231-011-0861-1>.
79. Golkar, F.; Al-Wardy, M.; Saffari, S.F.; Al-Aufi, K.; Al-Rawas, G. Using OCO-2 Satellite Data for Investigating the Variability of Atmospheric CO₂ Concentration in Relationship with Precipitation, Relative Humidity, and Vegetation over Oman. *Water* **2020**, *12*, 101. <https://doi.org/10.3390/w12010101>.
80. Umweltbundesamt. Beurteilung von Innenraumluftkontaminationen Mittels Referenz- Und Richtwerten. *Bundesgesundheitsblatt-Gesundheitsforschung-Gesundheitsschutz* **2007**, *50*, 990–1005. <https://doi.org/10.1007/s00103-007-0290-y>.
81. Nguyen, J.L.; Schwartz, J.; Dockery, D.W. The Relationship between Indoor and Outdoor Temperature, Apparent Temperature, Relative Humidity, and Absolute Humidity. *Indoor Air* **2014**, *24*, 103–112. <https://doi.org/10.1111/ina.12052>.
82. Honan, D.; Gallagher, J.; Garvey, J.; Littlewood, J. Indoor Air Quality in Naturally Ventilated Primary Schools: A Systematic Review of the Assessment & Impacts of CO₂ Levels. *Buildings* **2024**, *14*, 4003. <https://doi.org/10.3390/buildings14124003>.
83. Mendell, M.J.; Chen, W.; Ranasinghe, D.R.; Castorina, R.; Kumagai, K. Carbon Dioxide Guidelines for Indoor Air Quality: A Review. *J. Expo. Sci. Environ. Epidemiol.* **2024**, *34*, 555–569. <https://doi.org/10.1038/s41370-024-00694-7>.
84. Wernecke, J.; Wernecke, R. *Industrial Moisture and Humidity Measurement: A Practical Guide*; Wiley-VCH: Weinheim, Germany, 2014.

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.