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Improvement of Calibration Techniques and Data Quality for Personal Space Air Monitoring using a Platform of Fixed and Mobile Low-Cost Devices

Doctoral Thesis – Summary

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Air quality monitoring (AQM) is essential for mitigating environmental pollution by measuring and analyzing atmospheric pollutants. Traditional monitoring systems, while highly accurate, are costly and require frequent maintenance, limiting their large-scale deployment [1]. In contrast, low-cost air quality sensors provide a scalable and accessible alternative, offering improved spatial and temporal resolution. However, these sensors face challenges related to measurement accuracy, calibration complexity, and environmental influences, which requires further research to enhance their reliability [2].

Real-time air quality data are crucial for public health, especially vulnerable groups such as children, the elderly, and individuals with respiratory diseases [3]. Air quality indices simplify complex pollutant measurements, enabling communities to make informed decisions, such as reducing outdoor activities during periods of high pollution [4]. Despite their advantages, low-cost sensors exhibit key limitations, including measurement errors, environmental interference, sensor drift, and cross-sensitivity to multiple pollutants [5]. To address these issues, advanced calibration techniques, machine learning models, and novel sensor materials are being explored to improve precision and stability over time [2].

Currently, AQM in Europe is based on high-precision reference stations, which despite their precision, suffer from sparse spatial coverage, high installation and maintenance costs, and data availability delays [1]. Low-cost sensors can complement these systems by providing greater coverage and real-time data availability.

This research focuses on improving the performance of low-cost air quality sensors by addressing key sources of error and developing efficient calibration methodologies. The study proposed three primary objectives:

- O1 Enhance Personal AQM Confidence: Measure and display air quality accurately in the immediate vicinity of individuals. Ensure data reliability is sufficient for meaningful health assessments and actionable insights.
- O2 Optimizes Calibration Efficiency for Low-Cost Sensors: Streamline calibration processes for low-cost air quality monitors, reducing both time and cost. Maintain or enhance the accuracy of the data produced by these sensors while enabling scalable deployment.
- O3 Implement a standardized testing and measurement platform that integrates a rigorous evaluation methodology to assess data quality with high accuracy and reliability.

To achieve the objectives of this thesis, we outline several contributions as output aligned with each objective. The primary contributions are as follows.

- C1 Extensive state of the art of research initiatives in the direction of air quality, sensors calibration and data visualization
- C2 Development of an iterative process for sensor selection, evaluate and conlude the final sensors list using real low-cost sensor devices.
- C3 Development of an IoT and a wearable device with estimates/indicative data quality objective (DQO) levels: These devices balance affordability with data reliability, making them accessible for personal and widespread use.
- C4 Proposal and validation of calibration models for low-cost sensors, thus reducing the cost of calibration and maintainability.
- C5 On-the-Fly Calibration Algorithm for Immediate Deployment: Design of a real-time calibration algorithm to enable rapid and automated calibration of newly deployed low-cost sensors. This minimizes setup time and enhances scalability, ensuring cost-effective and efficient sensor integration.
- C6 Integrated mobile application for comprehensive air quality information: Development of a mobile application that integrates the Air Quality Index (AQI) for standardized air quality reporting. Body Pollution Index (BPI) for personalized health impact assessments. The Data Fusion Algorithm for detailed spatial insights. These applications will provide users with actionable and comprehensible data to make informed decisions about their exposure and health.
- C7 Design, implement, and evaluate a series of three iterations of IoT prototypes and one wearable prototype device.

By advancing calibration techniques, data fusion methodologies, and machine learning-based corrections, this study aims to bridge the gap between traditional and low-cost AQM systems. Enhancing sensor accuracy, scalability, and accessibility will facilitate widespread adoption of AQM solutions. The findings contribute to the decentralization of air quality information, the support of public health initiatives, and the improvement of environmental decision making, laying the foundation for future innovations in AQM on a global scale [2].

To support the work presented in this thesis, several papers were published during the research period, the first three of which are published in ISI journals.

- Petruc, S.-I.; Bogdan, R.; Ionascu, M.-E.; Nimara, S.; Marcu, M. An IoT Framework for Assessing the Correlation Between Sentiment-Analyzed Texts and Facial Emotional Expressions. *Electronics* 2025, **14**, 118. (WOS:001393618000001)
- Ionascu, M.-E.; Marcu, M.; Bogdan, R.; Darie, M. Calibration of NO, SO_2, and PM using Airify: A low-cost sensor cluster for air quality monitoring, *Atmospheric Environment*, Volume **339**, 2024, 120841. (WOS:001343585000001)

- Ionascu, M. E.; Castell, N.; Boncalo, O.; Schneider, P.; Darie, M.; Marcu, M. Calibration of CO, NO_2, and O_3 Using Airify: A Low-Cost Sensor Cluster for Air Quality Monitoring, *Sensors*, **21**(23), 7977, 2021. (WOS:000743308100001)
- Gruicin, I.; Ionascu, M. E.; Popa, M. Evaluation of air quality variability in Timișoara, Romania, *SACI 2020 - IEEE 14th Int. Symp. Appl. Comput. Intell. Informatics*, Proc., pp 179-182, 2020. (WOS:000610510000029)
- Ionascu, M. E.; Gruicin, I.; Marcu, M. Variance Analysis of Signals from Four Electrode Electrochemical Sensors, *2019 29th Telecommun. Forum, TELFOR 2019 - Proc.*, 2019. (WOS:000568618700081)
- Blagoiev, M.; Gruicin, I.; Ionascu, M. E.; Marcu, M. A Study on Correlation between Air Pollution and Traffic, *2018 26th Telecommun. Forum, TELFOR 2018 - Proc.*, pp. 2–5, 2018. (WOS:000459714200175)
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- Gruicin, I.; Ionascu, M. E.; Popa, M. A solution for air quality monitoring and forecasting, *SACI 2018 - IEEE 12th Int. Symp. Appl. Comput. Intell. Informatics*, Proc., pp. 503–507, 2018. (WOS:000448144200087)
- Ionascu, M. E.; Marcu, M. Energy Profiling for Different Bluetooth Low Energy Designs, in *IDAACS'2017*, 2017, pp. 1032–1036. (WOS:000425870400084)

Next, we present the summary of each chapter of the thesis highlighting the main contributions to each of them. Thus, Chapter 1 provides a comprehensive foundation for this study, beginning with the importance of AQM and its vital role in protecting public health, mitigating environmental impacts, and informing policy decisions. Reviews the evolution of AQM technologies, transitioning from traditional high-cost, limited-coverage systems to low-cost sensors that offer improved spatial and temporal resolution. The chapter then identifies key challenges and limitations associated with these sensors, such as environmental sensitivity, cross-sensitivity, sensor drift, and calibration complexity. Building on this, the research questions are framed to address these challenges, focusing on improving sensor accuracy, reliability, and integration into scalable networks.

Chapter 2 is the main state-of-the-art part and presents the evolution of AQM platforms, focusing on the challenges and advances in the deployment of low-cost sensors for environmental monitoring. The state-of-the-art study has been divided into the identified research projects, but also presenting other independent studies that are not grouped into any larger project. These projects include CitiSense [6], OpenSense [7], ENEA, [8], AirSenseEur [9], SNAQ Heathrow [10], and US-based projects [11], highlighting their strategies for calibration, sensor integration, and addressing environmental interferences. The analysis underscores the transformative potential of low-cost sensors in democratizing AQM while emphasizing the need for standardized protocols and interdisciplinary collaboration to achieve reliable and scalable solutions.

Chapter 3 presents the methodology used to select low-cost air quality sensors for integration into IoT and wearable devices. The selection process is guided primarily by user specifications and the intended application scenarios. Two use cases are considered: monitoring city-level air quality with fixed or mobile IoT devices and monitoring personal exposure using wearable units. Each use case introduces distinct challenges that influence sensor choice and system design.

An iterative approach was adopted for sensor selection, beginning with a comprehensive review of datasheets from multiple manufacturers. Several test devices were developed, each incorporating different sensor types. An important observation was that many electrochemical sensors share similar characteristics, in particular those with three and four electrodes. This allowed for a standardized circuit design capable of accommodating sensors from multiple manufacturers. In the end, all IoT prototypes were designed to support electrochemical sensors of four electrons. In contrast, for wearable devices, priority was given to sensors with a smaller form factor and lower power consumption, even at the expense of accuracy drop.

Table 1: Proposed sensor specifications of IoT and Wearable devices. (* as of august 2022)

Device type	**Sensor Type**	**Manufacturer**	**Sensitivity**	**Estimation cost***
Iot	CO-A4	Alphasense	220 to 410 nA/ppm	$68
	NO-A4	Alphasense	350 to 550 nA/ppm	$68
	NO2-A43F 003I	Alphasense	-175 to -500 nA/ppm	$68
	SO2-A4	Alphasense	320 to 500 nA/ppm	$68
	Ox-A431	Alphasense	-200 to -650 nA/ppm	$68
	IRC-A1	Alphasense	1 ppm	$80
Wearable	BME680	MEMS	ppb/ °C/ %/ mBar	$15
	10Dx-SO2-1000	Spec-Sensors	6 ± 4 nA/ ppm	$30
	10Dx-O3-1000	Spec-Sensors	6 ± 4 nA/ ppm	$30
	10Dx-NO2-1000	Spec-Sensors	6 ± 4 nA/ ppm	$30
	PMSA 003I	Plantower	1 $\mu g/m^3$	$30
Both	PMSA 003I	Plantower	1 $\mu g/m^3$	$30
	BME680	Bosch	ppb/ °C/ %/ mBar	$10

To ensure reliability, selected sensors were integrated into test platforms and deployed in various environmental conditions. Sensor performance was assessed through calibration procedures, comparing collected data with reference stations where available. Metrics such as mean absolute error (MAE) and coefficient of determination (r^2) were employed to quantify accuracy. The process involved multiple iterations of devices, with successive improvements made to sensor selection and system design. The final step consisted of developing wearable and IoT prototypes, which underwent laboratory and colocation validation, followed by real-world deployment.

Table 1 outlines the final sensor configuration for the latest IoT and wearable devices. Based on this set-up, five IoT devices and more than twenty wearable units were assembled. These devices serve as the foundation for the calibration strategies presented in the following chapters.

Chapter 4 presents the evaluation and calibration of a low-cost air monitoring platform designed to measure a wide range of air pollutants, including CO, NO_2, NO, O_3, SO_2, CO_2, PM_{10}, $PM_{2.5}$, and PM_1, along with temperature, relative humidity, and atmospheric pressure. The study explores the challenges associated with calibrating the platform, developed based on a review of existing methodologies and advances in low-cost AQM. Previous research [12], [13] has analyzed the sensors integrated into our system, demonstrating their feasibility for real-world applications. Our contribution focuses on the development and validation of calibration models using multivariate linear regression (MLR) and random forest (RF) techniques [11], [12], [14]–[16], ensuring that the sensor platform meets Data Quality Objectives (DQO).

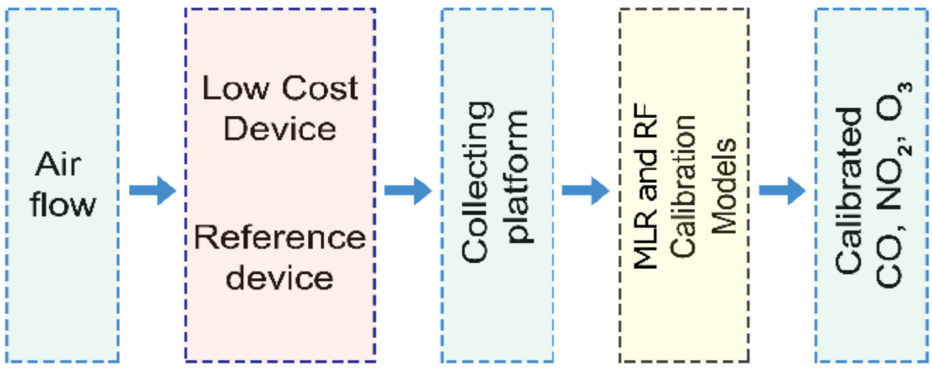

Figure 1: Main calibration methodology

The calibration process, described in Figure 1, involves colocating our devices with reference instruments in a controlled environment to collect parallel datasets. These datasets are stored separately and later used to develop and apply calibration models. This methodology enables the generation of device-specific models for each pollutant, which are used to adjust the measurements in real time.

The evaluation used multiple performance metrics, including mean absolute error (MAE), mean square error (MSE), root mean square error (RMSE), normalized mean bias (NMB), and normalized mean error (NME). In addition, the uncertainty of the measurement was assessed using orthogonal regression [17], and the reliability of the model was quantified using the coefficient of determination (r^2). These metrics provide a comprehensive assessment of calibration accuracy, allowing performance comparisons across different models.

The results indicate substantial improvements in the calibration techniques for low-cost air sensors. Our models outperformed previous work, achieving 60% improvement in r^2 for SO_2, a 10% higher determination coefficient for CO and O_3, and accuracy comparable to the state-of-the-art methods for PM_x and NO_2. However, the NO models performed poorly due to the low concentration levels present during the tests. Despite this, the introduction of custom equations and RF models with additional predictors significantly enhanced the calibration accuracy.

The evaluation confirmed that the proposed calibration models meet the DQO estimative level for all measured parameters, and the RF model achieved this threshold more rapidly than the MLR approach. Although both techniques achieved indicative level accuracy for PM_x and CO, RF models proved more effective for O_3, NO, NO_2, and SO_2. The models for NO_2, NO, and SO_2 did not reach indicative levels during validation, but their accuracy improved at higher pollutant concentrations, suggesting their suitability for monitoring industrial environments.

To further validate the platform, a colocation study was conducted in which five units were deployed alongside a reference station in Petrosani for a one-month period (6 January 2021 - 2 February 2021). The results confirmed that the platform functions as a reliable indicative monitoring tool for PM and CO, particularly in urban settings. For other pollutants, its accuracy is enhanced in industrial regions with higher concentrations of pollutants, where reduced uncertainty improves measurement reliability.

In Chapter 5, we evaluate the feasibility of transferring calibration models to newly deployed AQM units. The primary objective is to determine whether it is possible to bypass traditional calibration procedures while preserving measurement accuracy, thus reducing the time and cost of individual unit calibration.

To validate this approach, two additional colocation campaigns were conducted in collaboration with the Norwegian Institute for Air Research (NILU). These campaigns included laboratory and field measurements in different seasons. Laboratory calibration presents new challenges, as it requires controlled environmental chambers and precisely prepared gas mixtures, increasing complexity and costs. In contrast, colocation calibration provides a more practical and scalable alternative by colocating low-cost devices with reference monitoring stations. These stations, equipped with high-precision sensors, offer a reliable benchmark for calibrating low-cost AQM devices, ensuring consistency of performance in diverse environmental conditions.

Recalibration on new datasets collected in laboratory experiments confirmed the effectiveness of this calibration for the proposed devices. However, while the results met the indicative DQO level, laboratory calibration did not fully account for environmental variability. In particular, colocation based calibration exhibited reduced accuracy at lower concentration levels typically observed in outdoor environments, highlighting the limitations of in-lab calibration when applied to real-world conditions.

Model transferability plays a crucial role in reducing the costs and effort required to calibrate newly deployed devices. Although the initial deployment of an AQM network requires a critical mass of calibrated units, the transfer of models between devices improves long-term scalability and operational efficiency. Two transfer scenarios were examined:

- **Scenario 1:** Transfer of calibration models trained in a controlled laboratory environment.
- **Scenario 2:** Transfer of models trained on collocation data under real-world conditions.

These scenarios provide a comprehensive framework for assessing model transferability under both controlled and real-world conditions. The first scenario explores the potential of using laboratory-trained models for device calibration, while the second scenario demonstrates the effectiveness of leveraging collocation-trained models for improved accuracy in real-world applications.

As expected, model transferability results in a trade-off between accuracy and error. The direct application of laboratory-trained models produced unreliable results, with negative r^2

values and high errors, highlighting the need for greater environmental variability in training datasets. In contrast, models transferred from the colocation based calibration exhibited significantly better performance.

In general, the findings indicate that the calibration models trained and validated on the same device consistently outperform the transferred models. Although certain pollutants, such as PM_{10} and $PM_{2.5}$, retain acceptable accuracy after model transfer, volatile gases such as NO and SO_2 experience substantial performance degradation. This highlights the sensitivity of calibration models to changes in environmental conditions and sensor-specific factors, reinforcing the necessity of recalibration or domain-specific adaptation for effective deployment in large-scale AQM networks.

In Chapter 6, we introduce an algorithm for calibrating low-cost sensors using an on-the-fly approach. Our methodology categorizes the monitoring stations into three levels:

- **Reference stations:** High-precision monitoring stations used for calibration.
- **IoT devices:** Fixed or mobile units equipped with more accurate sensors, deployed in public transportation or stationary locations.
- **Wearable devices:** Portable air quality monitors carried by individuals, which dynamically interact with IoT devices and reference stations.

We evaluated this framework at the city level, demonstrating its potential to enhance large-scale AQM. To support this approach, we developed compact and energy efficient wearable devices capable of continuous monitoring for up to 16 hours. These devices balance accuracy and power efficiency, making them suitable for real-world deployment and integration with proposed calibration models.

Given that only an initial calibration is insufficient to maintain measurement accuracy over time, we implemented an autocalibration mechanism. This mechanism ensures that wearable devices adapt to changing environmental conditions, while maintaining dynamic calibration performance. Our on-the-fly calibration method follows a three-step process designed for flexibility and adaptability. The key contributions of this work include improving calibration models for low-cost sensors and testing a mechanism for real-time model updates. By enabling the transfer of calibration models between devices, this approach aims to provide consistent and reliable air quality measurements in various deployment scenarios.

One of the main challenges in model transfer is the accumulation of noise over time, which requires frequent recalibration. To mitigate this, our methodology strictly enforces the calibration hierarchy rules.

- **Wearable devices (Level 3)** are not calibrated in colocation with other wearable devices, even if they have recently been calibrated.
- **IoT devices (Level 2)** are calibrated using data from reference stations or other calibrated IoT devices with a high trustworthiness factor.

To assess the feasibility of this methodology, we conducted experiments using one wearable device equipped with the smallest electrochemical sensors available. To our knowledge, we are the first to successfully propose calibration models for these sensors. The calibration models introduced in Chapter 4 were applied to the datasets collected with this wearable device, and the performance of the algorithm was evaluated. The initial results demonstrated that our approach could achieve an estimative DQO level, validating the effectiveness of the training phase. Subsequently, we proposed an autocalibration algorithm incorporating vicinity principles, device hierarchy, and a newly introduced trustworthiness factor. A real-world test scenario was designed to evaluate the feasibility of this method.

The results highlight both the potential and challenges of autocalibration for low-cost air quality sensors. RF models significantly outperformed traditional MLR models, improving the accuracy of the calibration. For CO and PM_x, autocalibration algorithms demonstrated high r^2 values and low error metrics in controlled testing scenarios. However, performance degradation was observed when applied to unseen data, as indicated by decreasing r^2 values and increased RMSE in the new results of the RF model. These findings suggest that, while autocalibration can achieve reasonable accuracy under controlled conditions, real-world reliability remains influenced by environmental variability.

A conclusive assessment of autocalibration algorithms suggests that they offer estimation measurements and reduce the dependence on manual calibration. However, achieving reliable and scalable solutions for AQM remains a challenge. For pollutants such as SO_2 and O_3, where the accuracy of the calibration was consistently low, improved training datasets and pollutant-specific calibration strategies are required. Additionally, while machine learning models enhance calibration performance, hybrid approaches that integrate ML with physics-based models or contextual data (e.g., meteorology, traffic patterns) could further improve robustness.

In Chapter 7 we explore four potential applications of the proposed AQM platform, which integrates public AQM stations, fixed and mobile calibrated IoT devices, and wearable sensors. The platform is designed to deliver air quality measurements at different levels of DQO, allowing comprehensive environmental mapping within personal and urban spaces. The combination of these devices, along with tailored calibration models and an on-the-fly calibration algorithm, enhances the ability to dynamically monitor air pollution.

- **Calibration Scheme Integration:** The initial calibration models are updated in real time based on the colocation of multiple devices over a specific period. This approach improves the accuracy and adaptability of deployed sensors.
- **Mobile Application for Air Quality Mapping:** A dedicated mobile application allows users to visualize their personal exposure to air pollution. This application can function with or without a wearable device, aggregating data from multiple sources, including public reference stations, meteorological data, and traffic conditions.
- **Body Pollution Index (BPI):** A novel index designed to quantify the health impact of air pollution on individuals. By correlating air quality exposure with potential health risks, BPI provides actionable insights for users to minimize exposure.
- **Data Fusion for Large-Scale Air Quality Estimation:** A predictive model that uses localized sensor data to extrapolate air quality trends across urban areas. This method integrates real-time sensor readings with external datasets to enhance spatial coverage and prediction accuracy.

In Chapter 8, we conclude the thesis by summarizing the key contributions and outlining potential future research directions. This research has significantly advanced AQM by improving low-cost sensors, developing calibration techniques, and proposing innovative data visualization methods. The results of this work pave the way for reliable, scalable, and cost-effective AQM networks.

- *Investigation of Existing Research:* A thorough analysis of current AQM initiatives, sensor calibration techniques, and data visualization strategies laid the foundation for this study.

By consolidating insights from various research efforts, this work bridges the gap between theoretical advances and practical implementation.

- *Sensor Selection Empirical Analysis:* An iterative approach was adopted to select and evaluate sensors, ensuring a balance between cost and reliability of the data. This process involved prototyping and testing three IoT devices and one wearable device before finalizing the sensor list.
- *Calibration Models for IoT Devices:* A major challenge in the deployment of low-cost air quality sensors is their need for frequent calibration. To address this, calibration models were developed and validated specifically for these sensors, ensuring reliable data accuracy across deployments.
- *Reduction of Calibration Time and Cost:* The transferability of proposed calibration models significantly reduces the cost and complexity of sensor calibration, facilitating large-scale deployment without the logistical constraints of traditional calibration methods.
- *On-the-Fly Calibration for Wearable Devices:* A novel real-time calibration algorithm was developed to enable automated calibration of new sensors, reducing setup time and improving scalability. This dynamic calibration approach improves sensor integration into urban and rural monitoring networks.
- *Application and Enhancement Proposals:* To complement sensor and calibration advancements, a mobile application was developed to present air quality data in an accessible format. This application integrates multiple features, including: Air Quality Index (AQI) for standardized reporting, Body Pollution Index (BPI) for personalized health assessments, and Data Fusion algorithms for enhanced spatial insight.

In addition, several promising areas for further exploration have been identified.

- *Body Pollution Index:* Further refinement of the BPI metric could involve integrating physiological data such as heart rate variability and respiratory patterns of wearable devices. In addition, correlating BPI values with long-term health outcomes may establish its use as a predictive tool.
- *Data Fusion Techniques:* Advanced data fusion methods can improve spatial and temporal AQM. Future efforts may explore the integration of diverse datasets, such as traffic patterns, meteorological data, and satellite imagery. Methods such as federated learning and graph-based models could be employed for robust data fusion.
- *Sensor Degradation Over Time:* Predictive maintenance models using machine learning could detect early signs of sensor drift or failure. Research on environmental impacts on sensor longevity, automatic recalibration mechanisms, and material advancements could enhance sensor durability and reduce operational costs.
- *Edge-Based Sensor Calibration:* Implementing real-time calibration directly on IoT and wearable devices using edge computing could reduce the reliance on centralized models. Future work could explore lightweight machine learning algorithms for device calibration, distributed edge architectures for collaborative model refinement, and security measures to prevent data manipulation.

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