Proceedings of the 20th Conference on Computer Science and Intelligence Systems (FedCSIS) pp. 369–374 DOI: 10.15439/2025F3919 ISSN 2300-5963 ACSIS, Vol. 43

Enhancing Low-Cost Air Quality Sensors with AI for Smart Green Routing

Laura Po, Federica Rollo, Martina Casari
0000-0002-3345-176X, 0000-0002-3834-3629, 0000-0003-0406-3036
”Enzo Ferrari” Engineering Department
University of Modena and Reggio Emilia
Modena, Italy

Matteo Angelinelli, Giorgio Pedrazzi, Roberta Turra
0000-0002-3382-1900, 0000-0001-8896-3044, 0000-0001-5973-3805
HPC Department, Cineca
Casalecchio di Reno, Bologna, Italy

Chiara De Pascali, Luca Nunzio Francioso
0000-0002-2673-4593, 0000-0002-4500-0421
National Research Council, CNR
Institute for Microelectronics and Microsystems
IMM Lecce, Italy

***Abstract*—Urban air pollution poses severe health risks, demanding accurate monitoring and exposure-reducing solutions. Low-cost air quality sensors (LCS) provide high spatial resolution but suffer from accuracy limitations that hinder their reliability. This paper presents the AIQS project (AI-enhanced air quality sensor for optimizing green routes), an ongoing initiative that combines artificial intelligence, sensor hardware optimization, and pedestrian routing innovation to address these challenges. AIQS applies machine learning techniques, including Multilayer Perceptrons and fuzzy logic, to correct sensor readings. In parallel, hardware-level optimizations, such as fluid dynamics simulations and pre-treatment modules, are explored to enhance sensor performance. The corrected AQ data is then incorporated into a configurable routing tool capable of estimating pollutant exposure and computing low-exposure pedestrian paths in urban environments. First evaluations, shows that our correction models achieve up to 0.92 R^2 against reference data across diverse urban environments. The corrected data drives a configurable routing tool that computes paths minimizing cumulative pollution exposure while balancing user preferences (e.g., proximity to green spaces). Preliminary validation in Modena, Italy demonstrates viable ”green routes”.**

***Index Terms*—Air quality monitoring, Low-cost sensors, Artificial Intelligence, Machine Learning, Data correction, Fuzzy logic, Green routing, Urban mobility, Pollution exposure.**

I. Introduction

URBAN air pollution remains one of the most pressing environmental health risks worldwide, contributing to respiratory illnesses, cardiovascular diseases, and premature deaths, particularly in densely populated areas [1]. Monitoring air quality (AQ) is therefore crucial for supporting mitigation strategies and informing public health interventions. In recent years, low-cost air quality sensors (LCS) have emerged as a promising tool for expanding AQ monitoring coverage, especially in urban environments where spatial resolution is key [2]. However, despite their affordability and ease of deployment, LCS suffer from significant limitations, including low measurement accuracy, susceptibility to environmental conditions such as humidity, and a lack of standardized calibration procedures [3].

To address these challenges, data correction algorithms have been introduced to improve the accuracy of sensor measurements, with growing interest in applying artificial intelligence (AI) and machine learning (ML) techniques to this task [4], [5]. Concurrently, urban navigation systems are increasingly being explored as tools for reducing human exposure to pollution by suggesting ”green routes”—paths that prioritize air quality rather than shortest time or distance [6]. Yet, these systems are only as reliable as the data they consume; inaccurate AQ measurements from low-cost sensors risk undermining the effectiveness of health-oriented routing recommendations.

In this paper we present the AIQS project (AI-enhanced air quality sensor for optimizing green routes) that directly addresses this gap by combining hardware improvements, AI-driven data correction methods, and routing algorithm integration to enhance the trustworthiness and usability of AQ data in real-world applications. Building upon the open-source MitH framework for humidity correction [5], the project aims to raise the technology readiness level (TRL) of the solution to TRL 7, demonstrating its applicability across various urban environments through partnerships with environmental agencies and industrial stakeholders. In doing so, AIQS represents a comprehensive, interdisciplinary effort to bring together environmental sensing, machine learning, and human-centered navigation in support of healthier, more sustainable cities.

The paper is structured as follows. Section II reviews existing approaches to improve the accuracy of LCS through AI-driven data correction techniques and discusses urban navigation systems designed to reduce exposure to air pollution. Section III presents the integrated strategy of the AIQS project, that combines AI-based data correction, hardware optimization, and pollution-aware routing. Section IV reports preliminary results from data correction experiments highlighting improvements in sensor accuracy achieved through transformer-based models and validating the approach across multiple datasets from both Italian and international sources, moreover the pollution-aware routing system and an evaluation in a real urban context is shown. These findings support the development of health-conscious routing systems within the broader vision of sustainable smart cities. Finally, Section V offers concluding remarks and suggests directions for future work.

II. Related Work

A. AI for Air Quality

Recent advances in ML for air quality monitoring have demonstrated promising approaches to enhance low-cost sensor accuracy. Hybrid models combining multiple algorithms consistently outperform single-technique approaches for AQI prediction [7], while neural networks have shown significant improvements in PM10 calibration [8]. Practical implementations of end-to-end IoT pipelines for sensor data acquisition and cleaning have also been demonstrated in real-world deployments [9].

For short-term forecasting, deep learning models like LSTM have proven to be effective when integrated with meteorological data. Arsov et al. [10] showed that LSTM networks outperform traditional ARIMA models for PM_{10} prediction (+3 hours) with MSE as low as 0.01. These approaches collectively highlight the importance of data preprocessing and multi-source integration to address LCS limitations.

B. Green Navigation Systems

The integration of air quality data into urban navigation systems is emerging as a key strategy for reducing pollution exposure. IoT technologies enable smart city solutions that combine heterogeneous data sources to support sustainable mobility [11]. Recent frameworks leverage traffic-aware predictions and routing algorithms like Dijkstra's to reduce pedestrian PM2.5 exposure by 11-15% [12], while prototypes in cities like Barcelona demonstrate the feasibility of real-time green routing [13]. Despite these advances, most navigation systems still lack robust environmental health considerations.

III. Integrated Approach

The AIQS project adopts an interdisciplinary approach that combines AI-based data correction, sensor hardware optimization, and the development of a pollution-aware routing tool. Its goal is to deliver a validated, open-source system that enhances LCS reliability and supports healthier, user-configurable pedestrian navigation in urban environments.

The main goals are:

- Improving sensor data accuracy: Develop and apply AI and ML techniques, to dynamically correct sensor readings and improve reliability in various environmental contexts.
- Optimize sensor hardware: Enhance the physical design and operation of low-cost AQ sensors through fluid dynamics simulations and the development of pre-treatment modules, such as air dehydration systems and anti-coalescence components.
- Deliver a validated demonstrator: Advance the MitH framework to TRL 7 by integrating AI algorithms and hardware improvements into a real-world demonstrator, tested in an urban pilot and released as an open-source tool for broad adoption.
- Develop a green routing tool: Design and implement a flexible routing tool that integrates air quality data to compute pollution-aware pedestrian routes. It will estimate individual exposure to pollutants based on real-time AQ levels along each road segment, and compute routes that minimize cumulative exposure. The tool will be adaptable to different urban contexts and configurable by users, who will be able to tune preferences such as avoiding polluted areas, favoring proximity to green spaces, or prioritizing walking routes over other options.

A. Data Collection & AI Correction

To enhance the accuracy of low-cost air quality sensors, we apply AI-based correction techniques using data collected from co-located low-cost sensors and regulatory reference stations (e.g., ARPA) across multiple Italian and international cities. These co-located datasets allow us to calibrate sensor readings by learning correction functions that map raw low-cost measurements to validated reference values under shared environmental conditions. Meteorological variables are also included to improve model robustness. Our approach combines dynamic correction functions to mitigate humidity effects, anomaly detection to filter spurious data, and machine learning algorithms, such as Multilayer Perceptrons and fuzzy logic systems, to refine sensor outputs. These components are being integrated into the open-source MitH framework [5], which we aim to advance to Technology Readiness Level (TRL) 7. Model training and evaluation are supported by a high-performance computing infrastructure with GPU capabilities.

B. Pollution-Aware Routing

LCS measurements provide local PM concentrations. Through spatial interpolation strategies [14], we generate city-wide air quality maps that enable health-conscious navigation by estimating pollution levels across urban areas.

These AQ datasets drive our configurable routing system, which computes pedestrian paths minimizing cumulative pollutant exposure using OpenStreetMap networks. The tool supports user-customizable preferences:

- Minimizing pollution exposure
- Prioritizing proximity to green spaces
- Selecting pedestrian-only segments

Currently being validated in Modena through stakeholder partnerships, the open-source implementation[1] represents an adaptable framework for human-centered, pollution-aware navigation in diverse urban contexts.

[1] https://github.com/federicarollo/GRAFMOVE

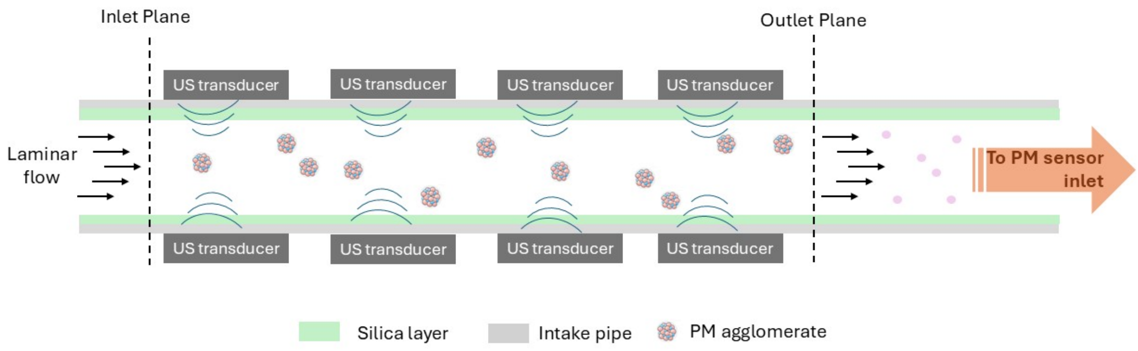

Fig. 1: Low-power air preconditioning module for particulate matter.

C. Hardware Optimization for Humidity Mitigation

A compact pretreatment module is being developed to minimize humidity-induced artifacts in LCS sensors. As shown in Figure1, ambient air enters through an intake pipe whose inner surface is coated with a thin silica aerogel layer acting as a passive desiccant. Along the pipe, ultrasonic (US) transducers are mounted transversely and driven in phase to generate localized oscillations and mild heating. This action promotes de-aggregation of PM agglomerates and accelerates moisture desorption from particles, while simultaneously regenerating the silica layer by enhancing vapor transport. The laminar flow then reaches the PM sensing chamber with reduced aggregation and humidity effects.

Finite-Element simulations guide the optimization of acoustic and thermal fields to achieve these effects with low power consumption, and a PWM-controlled heater can be added if ultrasonic energy alone is insufficient. Ongoing evaluation quantifies the reduction of humidity-related artifacts by comparing sensor responses with and without the module under controlled conditions.

IV. Results

A. Data Collection

Several key activities were carried out to enhance the accuracy and reliability of low-cost air quality sensors using artificial intelligence and high-performance computing resources.

We completed a comprehensive dataset collection [15] that includes:

- 4 Italian air quality datasets (e.g., ARPA regional agencies),
- 10 international datasets across various urban environments,
- Meteorological variables, including temperature, relative humidity, atmospheric pressure, and wind speed/direction, collected specifically for each city to support model robustness and correction accuracy.

All datasets include measurements from co-located low-cost sensors and regulatory reference stations, which is a critical requirement for developing accurate correction models. Co-location ensures that both LCS and RS measure the same environmental conditions at the same time and place, enabling a direct comparison between the two. This alignment is essential for calibrating LCS readings, as RS data provide a validated high-quality ground truth against which LCS measurements can be adjusted. The availability of synchronized data supports the development of reliable correction algorithms that significantly enhance the accuracy and trustworthiness of LCS output. Furthermore, all datasets feature at least an hourly measurement frequency, ensuring adequate temporal resolution for both real-time applications and time series analysis.

B. AI-Based Sensor Data Correction

In the preliminary phase of our study, we conducted evaluations of various anomaly detection and correction algorithms using some of the air quality datasets collected. The goal was to improve the quality of the sensor data and improve the performance of the model in subsequent prediction and correction tasks. These initial experiments provided insight into the effectiveness of both statistical and AI-based methods in identifying and correcting anomalies, as well as in accurately modeling time series data.

a) Anomaly Detection: To identify anomalous patterns in the AQ time series data, we applied a range of traditional outlier detection techniques. These included density-based spatial clustering of noise applications (DBSCAN), the inter-quartile range (IQR) method, and the three-sigma rule. Each method contributed to detecting noise and irregularities across different temporal contexts. For time series repair, we employed K-Nearest Neighbors (KNN) interpolation, which proved effective in reconstructing missing or corrupted values. Our preliminary results indicate that the inclusion of these anomaly detection and repair steps in the pre-processing pipeline leads to measurable improvements in model performance. In particular, we observed increases of up to 0.1 in the coefficient of determination (R^2) in some cases, highlighting the value of robust data preparation.

b) AI Algorithms for Correction: To correct and calibrate sensor readings, we tested a wide spectrum of traditional and advanced machine learning models. Among traditional

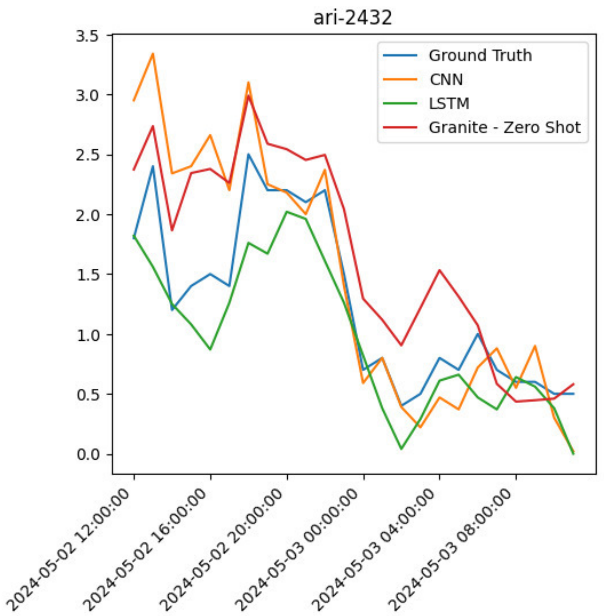

Fig. 2: A 24-hour forecast produced using different deep learning approaches on a randomly chosen AQ sensor.

regression techniques, we employed Linear Regression, Lasso, Ridge, and Elastic Net, all of which served as baseline models for evaluating correction accuracy.

We then explored supervised machine learning models, including Support Vector Regression (SVR), Decision Trees (DT), Random Forest (RF), XGBoost, and LightGBM. These models demonstrated varying degrees of effectiveness in correcting sensor data, with ensemble methods generally outperforming simpler approaches.

In addition to these methods, we investigated a fuzzy logic-based correction strategy using the Adaptive Neuro-Fuzzy Inference System (ANFIS) [16]. ANFIS achieved performance levels comparable to those of neural network models, obtaining a value R^2 of approximately 0.68 on the primary test dataset. Further experimentation with ANFIS on five additional datasets, focusing on model interpretability, yielded Pearson correlation coefficients exceeding 0.75 in all cases and reaching up to 0.97 in the best scenario.

Neural network models, particularly Multilayer Perceptrons (MLPs) [17], were also tested. These models achieved strong performance, with an R^2 value of 0.92 in one of the urban scenarios. Moreover, we implemented dynamic correction functions to account for the hygroscopic effect of humidity using both empirical and data-driven approaches. These corrections led to improvements of up to 0.3 in R^2 values during the autumn period, demonstrating the importance of incorporating environmental factors in correction models.

c) Deep Learning Architectures:: We also performed a series of preliminary tests using deep learning architectures, evaluating their potential in modeling AQ time series. These included Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, Gated Recurrent Units (GRUs), Temporal Convolutional Networks (TCNs), and Transformer-based models. These architectures were trained and tested on domain-specific AQ datasets, with particular attention to their ability to reproduce both general trends and specific point values.

Among these, the CNN and LSTM models showed the most promise in accurately modeling the observed behaviors. Our early results suggest that, while these models are capable of capturing overall trends, fine-grained prediction of individual values remains challenging in cases of high temporal variability. Further optimization, particularly in terms of network architecture and hyperparameter tuning, is necessary to enhance performance and potentially surpass the results obtained from simpler models.

In addition, we evaluated the performance of foundation models designed for time-series analysis. Two such models, TimesFM [18] and Granite [19], were tested. TimesFM was evaluated in zero-shot mode, while Granite was tested both in zero-shot and fine-tuned settings. Initial findings suggest that these foundation models can achieve performance comparable to traditional deep learning models without requiring extensive training. Notably, fine-tuning Granite on specific AQ datasets further improved its accuracy, indicating the potential for transfer learning in environmental sensing applications. However, further investigation is needed to draw definitive conclusions, as specific metrics are still under analysis.

Figure 2 illustrates an example of 24-hour time series from one AQ sensor. In these examples, both the trained architectures and the foundation model successfully capture the ground truth trend. While sharp variations (left panel) present challenges in reproducing point values, smoother patterns (right panel) are more accurately modeled. Figure 3 provides a comparative overview of the R^2 values obtained from all tested deep learning models. It is worth emphasizing that preliminary tests highlight the critical importance of defining appropriate training, validation, and test sets, as their configuration significantly impacts model performance. Ongoing experiments aim to systematically address this issue and validate the robustness of the observed results.

Among the traditional architectures, *LSTM*, *GRU*, and *CNN* demonstrate exceptionally high performance with R^2 values approaching 1.0, suggesting that these models are highly capable of capturing temporal dependencies and nonlinear patterns in the data. The *Transformer*, despite its theoretical strengths, shows comparatively lower performance ($R^2 \sim 0.87$), possibly due to the need for more extensive hyperparameter tuning or larger datasets to fully leverage its self-attention mechanisms.

The *TCN* model performs well with an R^2 of 0.95, slightly below the recurrent models but still in a strong range. This suggests TCNs can be a competitive alternative.

Regarding foundation models, *TimesFM - Zero Shot* achieves an R^2 of 0.93, which is notable given that it was used without any fine-tuning. Similarly, *Granite - Zero Shot* performs slightly better ($R^2 \sim 0.96$), indicating strong out-of-the-box generalization capabilities. However, the *Granite -*

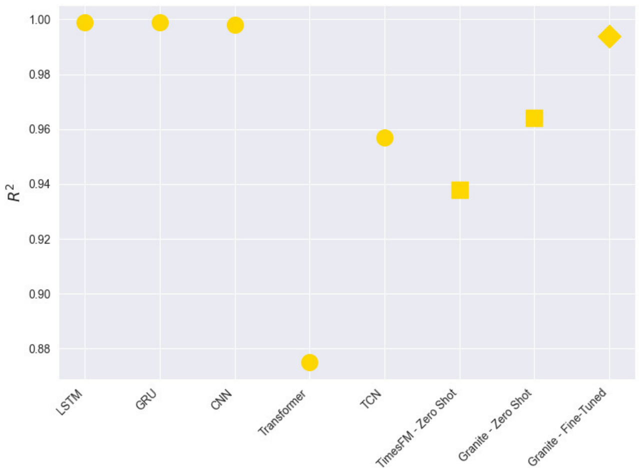

Fig. 3: Comparison of R^2 metrics computed over several deep learning architectures on a test set includes all the available AQ sensors.

Fine-Tuned model outperforms all other approaches with an R^2 of 0.99, highlighting the significant boost in performance that can be gained from domain-specific fine-tuning.

C. Pollution-Aware Routing System

We extracted and analyzed cycleway and footpath data from OpenStreetMap (OSM) and Open Data portals, focusing on the city of Modena. The data was modeled as a directed graph, where $Nodes$ represent OSM-defined junctions or road shape points, with properties such as the OSM identifier and the GPS coordinates, $Edges$ correspond to roads, with properties including: *geometry* representing the shape of the road, *distance*, i.e., the geometric length of the road, *green_area* indicating whether the segment traverses a green space (e.g., parks).

Only pedestrian-accessible roads (e.g., sidewalks, footpaths) and cycleways were included. The graph was implemented in Neo4j, using the spatial plugin.

To enable pollution-aware routing, we sourced open air quality data for Modena. Due to the absence of hyperlocal measurements (e.g., particulate matter sensors), we generated synthetic PM_{10} data by analyzing historical measurements from ARPAE's two regulatory stations in Modena, applying Inverse Distance Weighting (IDW) interpolation using the GDAL library[2] to estimate PM_{10} levels across the road network, assigning each edge an air_quality property, calculated as the average PM_{10} concentration within a configurable buffer around the road.

Using the enriched graph, we developed a routing algorithm to prioritize low-pollution pedestrian paths leveraging on the routing algorithms (Dijkstra and A*) of the APOC library[3].

Preliminary tests were performed using randomly selected locations within the urban area of Modena, computing optimal routes based on edge properties including *distance*, *green_area*, and *air_quality*. Figure 4 presents a comparison between two routes connecting the San Paolo kindergarten and the "Fontana dei due fiumi". The left route represents the distance-optimized solution (shortest path), while the right route maximizes green space exposure along the path.

[2]https://gdal.org/en/stable/programs/gdal_grid.html
[3]https://github.com/neo4j-contrib/neo4j-apoc-procedures

V. Conclusion

This paper presented the AIQS project, an integrated approach to enhance the reliability of low-cost air quality sensors (LCS) using AI-driven correction and to enable pollution-minimizing "green routing" for pedestrians.

The AI-based sensor correction ca be performed using Multilayer Perceptrons (MLPs), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), or foundation models (e.g., TimesFM, Granite), and achieves up to 0.92 R^2 accuracy against reference data across diverse urban environments. The configurable routing tool leveraging OpenStreetMap and Dijkstra/A* algorithms to compute paths minimizing cumulative pollution exposure while balancing user preferences has been validated in Modena and confirmed the opportunity to generate actionable green routes.

Upcoming efforts will focus on finalizing the integration of the AI models into the open source MitH framework. The framework will be validated on at least 6 real AQ datasets to ensure robustness across diverse conditions. On the hardware side, planned field trials will rigorously assess the effectiveness and durability of the proposed pre-treatment module in real environments. In parallel, the routing system will evolve into a deployable web application with multi-objective optimization, adaptable to different urban contexts. By addressing both data accuracy and usability, AIQS contributes to the development of healthier, cleaner, and more sustainable cities.

By addressing both data accuracy and application usability, AIQS aims to contribute to the development of healthier, cleaner, and more sustainable cities through AI-enhanced environmental monitoring and decision-making tools.

Acknowledgment

This work was carried out as part of the AIQS project (AI-enhanced Air Quality Sensor for Optimizing Green Routes), under the project code `DIP_AIQS_PO_2025_PNRR_ECOS_SK4AF_E93C22001100001`. AIQS was funded through a closed call within the initiative "Ecosystem for Sustainable Transition in Emilia-Romagna" (ECOSISTER), financed under the National Recovery and Resilience Plan (PNRR) – Mission 4 "Education and Research", Component 2 "From Research to Business", Investment 1.5 "Creation and strengthening of innovation ecosystems, building territorial R&D leaders" – funded by the European Union – *NextGenerationEU* (Grant Agreement No. 0001052, dated 23/06/2022 – Project ECS_00000033 – CUP E93C22001100001).

We gratefully acknowledge the Regional Agency for Environmental Protection of the Aosta Valley, Arpae Emilia-Romagna, and the Provincial Agency for Environmental Protection of Trento for providing data from their reference

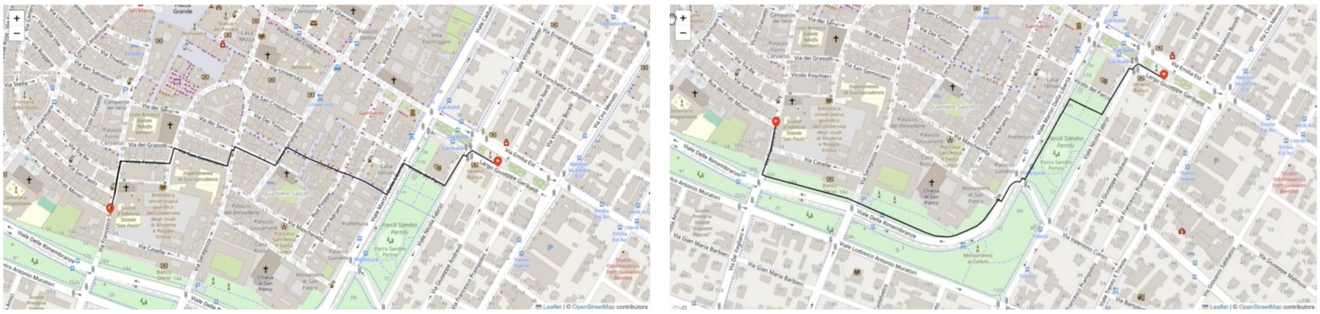

Fig. 4: Comparison of optimized routes based on shortest path (left) and greenest path (right) sharing the same origin and destination points.

monitoring stations. These stations were co-located with low-cost sensors donated by Wiseair Srl, whose contribution of sensors is also sincerely appreciated.

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