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Original Research Article

ARRANGEMENT OF AIR POLLUTION SENSORS IN A LOWLAND TOWN

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Abstract

Air pollution is one of the most pressing environmental challenges to public health worldwide. Investigating this problem requires recognizing the distribution of pollution composition and intensity. Therefore, air monitoring systems become more common in big cities worldwide. However, smaller urban centers are frequently overlooked in the literature despite facing similar health risks. The main purpose of this work is to bridge this gap by providing a cost-effective, replicable framework applicable to any lowland town with a limited budget. The proposed monitoring system is a scalable, hybrid network of sensors integrated into the internet of things. The article describes the components of this system and the mathematical method of sensor distribution. The latter is the coarse-graining procedure implemented by weighted k-means clustering based on household emission data. Finally, the application of the proposed system is described by the example of air monitoring in Żary — a lowland town in western Poland. The main results demonstrate the model's high effectiveness: the clustering algorithm successfully identified 15 representative measurement zones, and the subsequent deployment confirmed that combining theoretical spatial optimization with IoT infrastructure yields an accurate, highly representative, and economically viable real-time air quality monitoring system.

Keywords: air quality monitoring, pollution sensors, k-means clustering

1. INTRODUCTION

This article describes a method for designing an air quality monitoring system in a lowland town or a town-size suburb disconnected from a city center by a rural area (e.g. a large park). The meaning of the town in this article is related to the Eurostat definition [1] of a medium (5000-50000 inhabitants) urban cluster surrounded by a rural cluster. It is also assumed that the town is not coastal, located on lowlands, and without high-rise buildings or different high structures.

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Focusing on air quality monitoring restricted to a lowland town aims to contribute significantly to the air quality monitoring literature. This literature is concentrated mainly on big city centers' problems [2–5], neglecting smaller urban populations and suburbs [6]. Focusing on towns is essential, especially regarding the European Union (EU). In 2021, 24.6% of the EU population lived in rural areas [7], not affected, in general, by air pollution. 51.8% of the remaining population lived in a city, while 48.2% in towns and suburbs. The latter, almost half of the EU population, live in areas with a potential risk of air pollution but have limited financial possibilities to tackle the problem (compared to cities' populations). Another weakness of the towns' and suburbs' populations is the smaller number of well-described solutions to monitor air quality and react to detected pollution. This article aims to improve the mentioned drawback by describing one of the possible approaches to designing an air quality monitoring system in a town.

Air pollution remains one of the most pressing public health and environmental challenges worldwide. The International Agency for Cancer Research has classified outdoor air pollution and particulate matter (PM) as Group 1 carcinogens due to their strong association with lung cancer and other health issues [8]. Scientific studies confirm that exposure to air pollution leads to respiratory diseases, heart conditions, chronic bronchitis, and premature death [9–11]. The World Health Organization (WHO) estimates that air pollution is responsible for approximately 7 million deaths per year, with $PM_{2.5}$ alone contributing to 4.2 million premature deaths in 2016 [12,13]. Alarmingly, in the same year, 91% of the global population lived in areas with pollution exceeding WHO air quality standards [13], where the greater the air quality index (AQI), the greater the pollution. Developing countries, particularly in South and East Asia, suffer the most, with pollution-related deaths making up as much as 15% of total fatalities in some regions [14]. Even as some nations work to reduce air pollution-related deaths, places like India have experienced a 14% rise in such fatalities from 1990 to 2017 [14]. In addition to respiratory and cardiovascular diseases, research links air pollution to neurodegenerative disorders like Alzheimer's and Parkinson's, as well as developmental issues such as fetal growth problems, autism, and low birth weight [15,16].

Governments and international organizations have implemented various measures to combat air pollution. Regulations such as the European Parliament's Directive 2008/50/EC, China's Ministry of Ecology and Environment policies, and U.S. Environmental Protection Agency standards aim to mitigate pollution levels and their effects on human health [17–20]. However, despite these efforts, many regions still experience dangerously high pollution levels, requiring stricter enforcement and improved air quality monitoring [21–23]. Beyond health concerns, pollution has far-reaching environmental consequences. Major pollutants, including sulfur dioxide (SO_2) and nitrogen oxides (NO_x), contribute to global warming, with nitrogen dioxide (N_2O) having a global warming potential 298 times greater than carbon dioxide (CO_2) [24]. These pollutants also reduce crop yields, threatening global food security and economic stability [24]. Given the severe health, environmental, and economic implications, urgent action is required to strengthen pollution control policies and improve monitoring technologies [25].

Polluted air is a concern for many large cities and urban agglomerations [26,27]. For instance, in the case of India, air quality monitoring network that operates since 2004 [4], consists of 966 stations in 419 cities and bigger towns, where $PM_{2.5}$ is monitored at 611 stations in 277 cities as of November 2024 [28]. At the same time, there are only 26 stations in 26 villages in this network.

In the past 20 years, several hundred low-cost air monitoring systems have been developed in large urban areas around the world. Gateshead sensor network [29] is an example of early air quality monitoring in this period. During the next five years, various systems were tested, for instance, in Oslo [30], Seoul [31], and São Paulo [32]. This trend continued for the last decade with a growing number of low-cost networks. For instance, in 2016-2020, various low-cost air monitoring systems were studied in

Auckland [33], Southampton [2], Los Angeles [3], and Athens [11,34]. A recent example of a low-cost network is the network in Lisbon [5].

Low-cost air monitoring systems are modular. They consist of sensors, communication protocols, telecommunication devices, servers, and power sources. The sensors are different pollutant detectors and meteorological stations. This architecture of a low-cost network demonstrates that similar systems in small urban areas are easy to design by downscaling analogous networks in big cities. Therefore, the economic potential of towns for creating air quality monitoring is not significantly worse than the potential of cities. If citizens of a town are aware of the danger of air pollution and suppose that the air pollution in their town exceeds safety norms, they can install a monitoring system. All they need to know is how to design the low-cost air monitoring system on a scale smaller than in the case of a well-described big city network. This article aims to present a possible solution.

The manuscript is organized as follows. The next section presents a study of various air pollution monitoring systems, which convinced the authors of the benefits of a hybrid approach — combining an IoT-based monitoring system with reference sensors. The subsequent sections describe the elements of the hybrid solution and the method of its implementation. The components of the IoT air monitoring system are detailed in Sec. 3. Then, the challenges of integrating these components into a functional system are discussed in Sec. 4. The theoretical problem of their placement is addressed using a clustering method. Finally, the implementation of the proposed system is illustrated by the example of air monitoring in Żary — see Subsec. 4.1., and the results of this implementation are described in Sec. 5.

2. LOWLAND TOWN PERSPECTIVE

Air quality monitoring in small towns can be carried out using various technologies that differ in measurement accuracy, implementation costs, and application flexibility. The choice of the appropriate solution depends on available financial and infrastructural resources, as well as the specifics of local emission sources. Among the most commonly used methods are reference systems, low-cost sensors, mobile systems, and hybrid approaches that combine features of several technologies. Each of these approaches has advantages and limitations, which affect their effectiveness in monitoring air quality in smaller urban centers.

Typical reference systems, based on stationary measurement points, are a key component of national and international air quality monitoring networks. They have high accuracy and measurement precision, which enables long-term trend analysis and the assessment of the effectiveness of actions aimed at improving air quality. Examples of such networks include systems implemented by the U.S. Environmental Protection Agency [19] and monitoring conducted by the requirements of the European Union Directive 2008/50/EC [17]. Data collected this way is standardized, allowing for comparisons between regions and the years. However, the use of reference systems in small towns faces significant limitations. The high costs of purchasing, installing, and maintaining measurement stations often result in an insufficient number of such points to capture spatial variations in air quality, especially in areas with dynamic atmospheric conditions and local emission sources [35]. As a result, alternative technologies, such as low-cost sensor networks or mobile measurement systems, are playing an increasingly important role in air quality monitoring in smaller towns.

An alternative to reference systems is the solution based on low-cost sensors, often integrated with wireless internet of things (IoT) technology. Due to its relatively low cost, these solutions enable the deployment of many measurement points within a small area, resulting in high spatial resolution and real-time data recording. Such systems allow for the rapid identification of changes in pollution levels. However, their main limitations include lower measurement precision, susceptibility to interference from atmospheric conditions, and the need for frequent calibration by reference devices [20]. For instance, the implementation of a network of 129 sensors across 15 municipalities in Serbia has confirmed the effectiveness of this approach, enabling precise monitoring of seasonal variations in pollution levels [23]. Additionally, the integration of the IoT technology with monitoring systems allows for the development of flexible and operationally efficient solutions that, despite certain measurement limitations, ensure effective air quality monitoring [22].

Another solution involves mobile air quality monitoring systems that use sensors mounted on vehicles, drones, or other platforms. These systems enable dynamic pollution mapping, particularly in areas where installing stationary sensors is challenging. Studies conducted in Cambridge, MA, have shown that sensors placed on garbage trucks allow for the identification of areas with high pollution concentrations [36]. However, the mobility of these systems comes with challenges, such as the lack of continuous measurements in a single location, the influence of weather conditions, and the potential distortion of results due to exhaust emissions from the vehicle on which the sensors are mounted [37].

In response to the limitations of both traditional reference stations and low-cost sensors, hybrid systems are being developed. Integrating reference stations with a network of low-cost sensors allows for cost optimization and an increase in the spatial resolution of measurements. Research indicates that the calibration of sensors concerning reference stations improves measurement accuracy and enables better coverage of the monitored area [38], while integration with IoT systems and edge computing enhances data management efficiency [22]. Despite the challenges associated with integrating various technologies, the hybrid approach significantly improves the effectiveness of air quality monitoring.

In conclusion, each of the discussed air quality monitoring technologies has advantages and limitations, and their effectiveness in small towns depends on factors such as costs, terrain specifics, accuracy requirements, and the availability of infrastructure. The integration of different solutions, particularly within hybrid approaches, allows for cost optimization and increased monitoring efficiency, which is a significant step towards better air quality management and public health protection. The following sections focus on a simple example of this hybrid system.

3. IOT TECHNOLOGY-BASED MONITORING SYSTEM WITH REFERENCE SENSORS

The air quality monitoring system is based on precisely selected components. Its functions and interconnections enable continuous data collection and analysis. The key components in this system are measuring devices, network elements, and server infrastructure. The latter consists of reference sensors, low-cost (non-referential) sensors, weather stations, LoRaWAN base stations, WAN routers, and LTE modems.

3.1 Infrastructure Components

Reference sensors are the most precise components of the air quality monitoring system. They serve as calibration devices for other sensors. They use approved measurement methods, ensuring compliance with environmental standards [17,19]. The proper functioning of these devices does not require elaborate technologies. The reference sensor has to be installed in the right location to ensure constant access to power and easy maintenance. It must utilize methods that comply with regulatory directives to guarantee high accuracy. Its maintenance and calibration have to be performed regularly. This procedure includes both automatic (e.g., using zero air generators) and manual calibration to maintain data reliability.

Another network component is a non-reference sensors system, which, although less precise, allows increasing measurement points at relatively low costs. However, their effectiveness depends on several key factors. The choice of the appropriate measurement technology is crucial, as non-reference sensors can use various detection methods, including electrochemical measurement cells, which operate based on chemical reactions generating a signal corresponding to the concentration of a measured gas (e.g., carbon monoxide or nitrogen dioxide), or optical dust sensors, which analyze light scattering to determine the concentration of PM_1, $PM_{2.5}$, and PM_{10} particles. The selected technology must be carefully matched to the specific pollutants being monitored and the measurement conditions. Strategic placement of the sensors in the field is also essential, considering local emission sources, terrain characteristics, and other environmental factors influencing pollution distribution to ensure representative data collection. Their reliability depends on a stable power supply and consistent communication; these devices must be equipped with systems ensuring continuous power — such as long-life batteries or direct connection to the power grid — to guarantee ongoing operation and real-time data transmission.

The following elements are meteorological stations, which can be an integral part of the system, as atmospheric conditions significantly influence the dispersion of pollutants. These stations collect meteorological data, including temperature, humidity, atmospheric pressure, wind speed, and direction. They are installed in locations that minimize local interference, often powered by photovoltaic panels and batteries.

LoRaWAN base stations, integral to the network infrastructure, facilitate communication between sensors and the central management system. They receive signals from distributed measurement devices and transmit collected data to the server, ensuring continuous and consistent data transfer. To achieve optimal efficiency, these stations must be installed in locations that guarantee maximum communication range with the sensors. It is also vital to provide a constant power source, whether through a direct connection to the power grid or alternative solutions such as solar panels. Their placement should allow for easy access for maintenance and calibration, which helps maintain high-quality data transmission. Additionally, built-in diagnostic mechanisms enable remote monitoring of operational parameters, allowing for quick detection and response to any malfunctions.

The efficient data transmission to servers is facilitated by WAN routers and LTE modems, which utilize both wired and cellular networks. These devices enable the seamless transfer of information from sensors to the central system, supporting real-time monitoring and analysis. Data transmission security is upheld through mechanisms like VPNs and encryption, while emergency modes ensure uninterrupted operation even when access to the wired network is restricted.

3.2 System Architecture

A sensor network based on LoRa technology and WAN routers provides a comprehensive solution for real-time monitoring and data analysis (see Fig. 1). The system starts with sensors deployed in various locations, measuring key parameters and transmitting the data using LoRa technology. The collected data is then sent to base stations (LoRa gateways), which receive sensors' signals. These gateways feature long-range communication and high sensitivity, enabling effective data collection from hundreds of distributed devices.

The next stage involves transmitting data to the central management system. WAN routers or LTE modems are used for this purpose, enabling data transfer via wired or cellular networks. In emergencies, when traditional network access is limited, these devices can automatically switch to an alternative connection. This switch ensures uninterrupted communication.

Data security is ensured through protection mechanisms such as VPN and encryption, facilitating the secure transmission of information between sensors, gateways, and the central system. Ultimately, the central management system collects, stores, and analyzes the transmitted data, enabling continuous monitoring and rapid responses to any changes or irregularities.

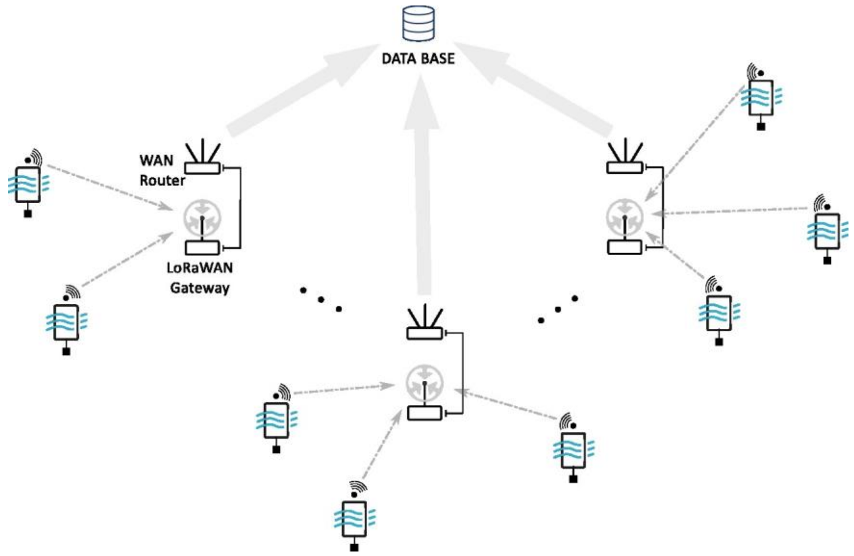

Fig. 1. Integrated Sensor Network Architecture

3.3 System Benefits and Scalability

The proper selection and integration of reference and non-reference sensors, weather stations, LoRaWAN base stations, WAN routers (with PoE support), and server infrastructure form the foundation of an effective air quality monitoring system. The scope and configuration of such a system should be tailored to the budget and specific user needs, meaning not all components mentioned are necessary for every implementation. This solution's flexibility allows for gradual expansion and integration with environmental management automation systems.

As a result, the air quality monitoring system enables real-time data analysis, allowing for the rapid detection of pollution level changes. Users can respond immediately to concerning values, taking appropriate actions to improve air quality. Additionally, the system's infrastructure is flexible and can be gradually expanded by adding more sensors and measurement stations. Integration with IoT systems and edge computing technology enhances data management efficiency, enabling local processing of measurements and optimizing response times.

4. DATA-BASED SENSOR PLACEMENT AND THE CLUSTERING METHOD

Sensors' arrangement should be based on the spatial distribution of pollution emissions in a considered area. However, this distribution has to be specified a priori. The positions of sensors must be selected before their installation. This obstacle leads to the question of planning their arrangement before getting data. The problem is even more demanding due to the limited number of sensors, denoted by k. It prevents an optimal design of devices' distribution as a fine lattice. Therefore, the structure of coarse lattice must be well-planned.

The solution described in this article is based on the regulations in Poland, which are similar to many European countries' regulations. Each owner and administrator of a building is obligated to provide a declaration specifying heating sources. These declarations are handed to the Central Register of Emissivity of Buildings (CEEB) . By checking the data in this register, it is possible to estimate the mean emissions of different pollutants dependent on the types of energy sources and building sizes. This estimation allows the subsequent assessment of the average annual emission of particular contaminants in specific areas. These areas are arranged by the clustering method applied to household distributions, which are bunched according to their similarities in pollution emissions.

The clustering method is defined as a theoretical model of a space constructed as follows. Let n be the number of households (sources of pollution). Then, using the data obtainable from CEEB, the characteristics of each source can be simplified by the pair

$$(\mathbf{x}_i, \mathbf{P}_i), \text{where } i = 1, \cdots, n.$$

The variable $\mathbf{x}_i$ is the vector in the three-dimensional Cartesian frame. Its coordinates are defined in the Earth-centered, Earth-fixed coordinate system (ECEF). Quantity $\mathbf{P}_i \coloneqq (p_{i,1}, p_{i,2}, \cdots, p_{i,s})$ is the vector, describing the mean annual emissions of different pollutants as its coordinates. For instance, the internal indices $1,2, \dots, s$ correspond to CO, CO_2, PM_{10}, $PM_{2.5}$, NO_2, SO_2, etc.

The individual distribution of sensors, separate for each pollutant, is neither economically nor operationally effective. Therefore, the selective strategy is assumed. It optimizes the locations of sensors by focusing on a pivotal pollutant. A more sophisticated approach is almost as easy as the selective. The consideration of several pollutants requires the definition of a linear combination of pollutants' concentrations. The coefficients in this combination should be normalized,

$$w_i = \sum_{j=1}^{s} q_j \, p_{i,j}\,, \qquad \text{where} \quad \sum_{j=1}^{s} q_j = 1 \quad \text{and} \quad q_j \geq 0\,.$$

As a result, each will represent the weight w_i, measuring the significance of a pollutant in the combination.

The key step in the clustering procedure is the k-means algorithm [39,40], applied to n sources of air pollution. These sources are bunched together into k groups of similar pollution intensities and characteristics. In the case of the weighted linear combination of pollutants' concentrations, the weighted Euclidean distance,

$$d(\mathbf{x}_i, \mathbf{c}) = w_i \parallel \mathbf{x}_i - \mathbf{c} \parallel,$$

replaces the Euclidean distance $\parallel \mathbf{x}_i - \mathbf{c} \parallel$ in the standard clustering method. As a result of the clustering, the considered distribution of sources is divided into k groups. Each group represents the region in which air pollution emitters have similar characteristics. From geometrical perspective, the grouped sources are the vectors that became clustered into k three-dimensional cells. The centroids of these cells, $\mathbf{c}_1, \mathbf{c}_2, \dots, \mathbf{c}_k$, are the optimal locations for sensors. However, these points, most accurately representing the average emission in clusters, often cannot be selected for precise locations of sensors.

Real-world urban infrastructure differs from the distribution of pollution emitters known from the governmental register. Moreover, the estimated centroids indicate only approximate localizations for sensors. The margin of error depends on several inestimable factors — for instance, the polluters not listed in the register. Furthermore, sensor installation can be impossible or forbidden in preferred localizations. Therefore, the model should also estimate neighborhoods of tolerance around the centroids. One of the simplest solutions is the quantified margin of uncertainty related to the distance from each centroid and its characteristics. This uncertainty is estimated by the ellipsoidal confidence region for each vector c_j, representing a centroid, where $j \in \{1, \dots, k\}$ [39,40].

4.1. Example: air pollution monitoring in Żary

The method for designing an air quality monitoring system in a lowland town has practice implementation. The approach described in this article took place in Żary — a lowland town in western

Poland with 34591 inhabitants in 2024[2]. The budget for the pilot project allowed for buying 15 sensors, including a reference one, and the necessary telecommunication infrastructure.

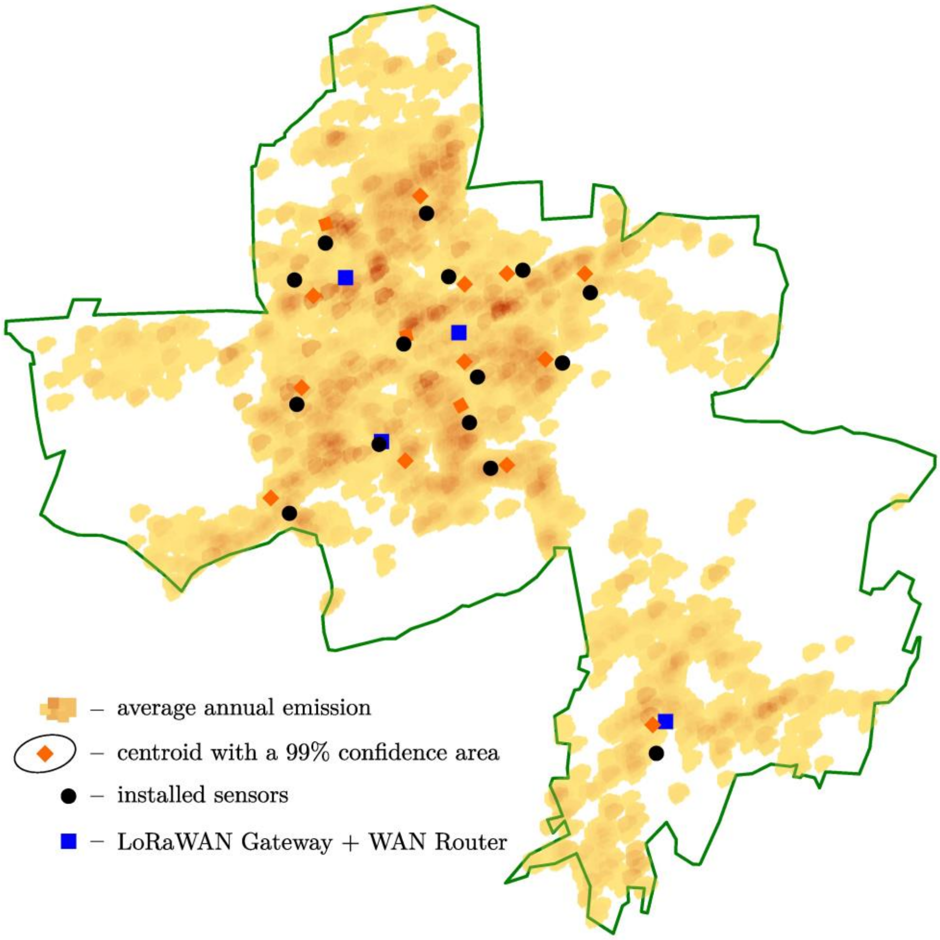

Fig. 2. Sensor deployment in Żary based on CEEB data and k-means clustering

The mathematical model of spatial pollution distribution intensity has been supported by data. The declarations of inhabitants in the CEEB register led to estimating the mean annual air pollution from households. The clustering method by the k-means algorithm provided 15 representative regions of similar pollution intensities within the town boundaries — see Fig. 2. It turned out that all of these regions have relatively low vertical diversity, which justified the simplification of the three-dimensional model to the planar problem. As a result, the spatial regions of clustering became surfaces. These surfaces are represented by their centroids, surrounded by confidence regions. The latter are no longer ellipsoids but ellipses.

The location of the sensors depended on the technical aspects of their installation. In particular, the accessibility of power supply, the possibility of data transmission, and the size, type, and ownership of infrastructure influenced the final localization. Advantageously, all sensors have been placed close to the centroids indicated by the theoretical model — compare Fig. 2. Therefore, the realization of the project obtained accurate measuring representativeness.

[2] Central Statistical Office (GUS), Bank Danych Lokalnych, accessed 2025 Apr 15, https://bdl.stat.gov.pl.

5. DISCUSSION OF THE RESULTS

The proposed theoretical framework was implemented as a continuous air quality monitoring system in Żary in May 2024. The final network configuration consists of 15 sensors—a number strictly determined by the project's budget limit—with real-time data publicly accessible via a dedicated web platform[3].

This methodology presents practical advantages over complex heuristic optimization algorithms or geostatistical models frequently discussed in the literature. While mathematically robust, such existing methods often require extensive historical measurement datasets for spatial calibration or exhibit high computational complexity. In contrast, the applied weighted k-means clustering framework is computationally efficient (scaling linearly with the number of emission sources and sensors) [39] and operationally feasible. By leveraging a priori household emission data from the CEEB register, the algorithm partitions the target area into k spatial clusters that maximize monitoring representativeness without requiring expensive pre-deployment measurement campaigns [23, 25].

Furthermore, the proposed sensor network design exhibits strong universality. Based on the parameter k, the method unambiguously designates ellipses of uniform immission concentrations relying directly on building emissivity data. Although demonstrated in a lowland town, the model is applicable to larger urban centers, provided that the spatial distribution of traffic and industrial emissions is relatively uniform or negligible. Finally, while simplified to a planar problem in Żary, the mathematical model can be easily generalized to three dimensions, extending its applicability to cities with varied topography or high-rise architecture.

6. SUMMARY

The article presents an integrated air quality monitoring system for small towns and lowland suburbs. The proposed solution combines high-precision reference sensors with cost-effective non-reference sensors, achieving both exceptional measurement accuracy and a higher density of monitoring points. A central innovation of the methodology is the optimization of sensor placement, which relies on the analysis of pollutant emission sources (e.g., CEEB) and employs a clustering technique by the weighted k-means algorithm. This strategy identifies representative locations that accurately reflect the spatial distribution of pollutant emission sources.

In addition, the system integrates meteorological stations, LoRaWAN base stations, and WAN/LTE routers to ensure reliable, continuous data transmission to a centralized management platform. The pilot implementation in the town of Żary confirms the system’s effectiveness and scalability, allowing for the gradual expansion of the monitoring network in response to evolving operational demands.

Furthermore, the proposed mathematical model of sensor placement is highly universal. Dictated by the budget limit, it can be easily adapted to larger urban centers with relatively uniform traffic emissions, or generalized to three dimensions to accommodate cities with complex topographies and high-rise architecture.

Overall, this approach provides a practical method for implementing air quality monitoring networks in medium-sized urban areas where traditional, costly systems often prove impractical. The model not only enables precise, continuous monitoring but also supports rapid responses to fluctuations in pollution levels — an essential factor for protecting public health and the environment.

[3] ZAiRY – Air Monitoring, accessed 2025 Apr 15, https://app.zairymon.pl.

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