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OPTIMISING THE NETWORK OF AIR QUALITY MONITORING STATIONS

Abstract. This study explores the application of genetic algorithms (GAs) for optimizing the network of air quality monitoring stations. Recognizing the complexity of accurately assessing air pollution levels across diverse urban and rural landscapes, the research focuses on finding the most effective station placements to maximize coverage and data fidelity while minimizing costs.

The methodology entails simulating natural selection processes, including selection, crossover, and mutation, to evolve a population of potential solutions. Each candidate solution in the population represents a unique configuration of monitoring stations. A fitness function evaluates the efficiency of each configuration based on criteria such as population coverage, proximity to pollution sources, and installation and operational expenses.

The research employs a genetic algorithm developed in Python, which iteratively refines the population of solutions over thousands of generations. The algorithm's performance is assessed through experimental validation, with an emphasis on the adaptability of the approach to accommodate various environmental, economic, and regulatory constraints.

Results indicate that GAs can effectively balance multiple optimization objectives, leading to a network design that is both cost-efficient and comprehensive in its monitoring capabilities. The outcome of the study is an optimized network that significantly improves upon the initial state in terms of coverage and cost-effectiveness.

The study concludes that genetic algorithms offer a promising avenue for addressing the challenges of air quality monitoring network design. The flexibility and global search capabilities of GAs make them suitable for the complex, multi-objective nature of the task. Moreover, the findings suggest potential for further improvements and applications of GAs in environmental monitoring and other complex systems optimization scenarios.

Keywords: genetic algorithms, air quality monitoring, optimization, station siting, environmental management, network design, data analysis, pollution control, sensor deployment, machine learning.

Introduction

Air quality monitoring stands as a vital component in the endeavour to safeguard environmental integrity and public health. The strategic deployment and optimization of air quality monitoring stations are essential to gather accurate and representative data on atmospheric pollutants. These stations track the concentrations of various contaminants, including particulate matter PM10 and PM2.5. The efficiency of the data collected hinges on the thoughtful placement and efficient operation of the monitoring network.

The optimization of the network of air quality monitoring stations is a multifaceted challenge that encompasses scientific, technical, and policy-driven factors. It necessitates a comprehensive grasp of atmospheric dynamics, urban structures, emission sources, and demographic distributions, alongside the deployment of sophisticated statistical methodologies and computational technologies. The objective is to achieve expansive spatial and temporal coverage, utilize resources judiciously, and provide high-calibre data that serves as a foundation for environmental protection and public health measures.

Additionally, the optimization process must remain adaptable to the fluid nature of urban development and industrial activities that influence the dispersion of air pollutants. It should be sufficiently versatile to accommodate new pollutants, shifting regulatory frameworks, and the changing needs of communities.

This article examines the array of tactics and methodologies employed in optimizing the network of air quality monitoring stations. It delves into the considerations for station siting, the application of mathematical and computational models for network design, the significance of emerging technologies, and the critical role of community involvement in the monitoring process. Through a balanced approach to optimization, the aim is to ensure that air quality monitoring networks are not only effective and economical but also resilient and attuned to the dynamic aspects of air pollution.

Implementation

Implementing an optimized air quality monitoring network involves several steps, each of which requires careful planning and execution to ensure that the network is effective and meets the needs of the community it serves. The following sections describe the key steps in the implementation process:

Site selection criteria

The first step in creating an optimized network is to establish clear criteria for selecting monitoring sites. These criteria typically include:

- Proximity to emission sources: Stations should be in such a way as to monitor areas with high emissions, such as industrial areas, heavy traffic corridors and power plants.
- Population density: To assess the impact of pollutants on a larger number of people, areas with higher population densities may be prioritized.
- Geographical representation: Ensure a variety of geographical areas, including urban, suburban and rural areas, to reflect variability in air quality.
- Meteorological conditions: Consideration of prevailing wind directions, temperature, humidity and other meteorological factors that may affect the dispersion of pollutants.
- Topographic features: Consideration of local topography, such as hills, valleys and water bodies, which can affect air flows and pollutant concentrations.
- Compliance with regulatory requirements: Compliance with the requirements set by environmental regulations and standards for air quality monitoring.

Modelling and simulation

Advanced modelling and simulation techniques are used to predict the spread of pollutants and identify potential hotspots of air quality problems. These models can help to:

- Simulate different scenarios based on emissions data and meteorological information.
- Predict the impact of changes in industrial activity or traffic patterns on air quality.
- Optimize the placement of monitoring stations to maximize coverage and data accuracy.

Technology integration

Integrating the latest technologies is crucial to modernizing and improving air quality monitoring networks:

Sensor technologies: Deploying state-of-the-art sensors that can detect a wide range of pollutants with high accuracy and reliability.

- Data analytics: Using big data analytics to process and interpret the huge amounts of data generated by monitoring stations.
- Remote sensing: The use of satellite imagery and other remote sensing tools to supplement ground-based monitoring data.
- Continuous evaluation and adaptation
- An optimized network is not static; it needs to be continuously evaluated and adapted to remain effective:
- Regularly reviewing monitoring data to assess the effectiveness of the network and identify areas for improvement.
- Adapting the network in response to new developments, such as urban expansion or changes in industrial activity.
- Keeping abreast of advances in monitoring technology and scientific understanding of air pollution to improve the network accordingly.

After identifying problem areas, criteria can then be set for the placement of new stations, considering factors such as demographics, industrial activity, traffic, and even natural features of the landscape, Figure 1 shows the current stations in Ukraine for 2024 (342 stations).

The application of geostatistical methods, which include mathematical techniques for analysing spatial data, will help determine how pollutants are distributed over the territory. These methods will help not only to select locations for new stations, but also to optimize their number and location for the best coverage. Google Maps allows you to see the level of pollution in most countries of the world, see Figure 2, but data from Ukrainian stations are not considered due to high inaccuracy and low coverage.

Determining the criteria for the location of air quality monitoring stations requires a process that requires a thorough understanding of both the environmental and social aspects of the area. Above all, representativeness is a key criterion. Stations should be in such a way that they can provide data that accurately reflects the overall air pollution situation in different environments, from densely populated urban areas to remote rural areas. This allows for a holistic view of air quality and identifies problem areas that require special attention. Accessibility and security of the locations also play an important role. Stations should be easily accessible for regular maintenance and calibration, but at the same time located in secure locations to ensure that the equipment

is protected from potential damage or tampering. When choosing locations for monitoring stations, it is important to avoid excessive proximity to large sources of pollution, such as industrial plants or major transport routes, to ensure the objectivity of the data collected.

Topographical features and meteorological conditions also have a significant impact on the distribution of pollutants in the air. Altitude, topography, and wind directions and speeds can significantly change local pollution levels, and these parameters should be considered when planning a monitoring network.

The socio-economic context also plays a critical role in determining the location of stations. It is important to ensure that data are collected in locations where their impact on the health and well-being of local communities is maximized, especially in areas where vulnerable populations live.

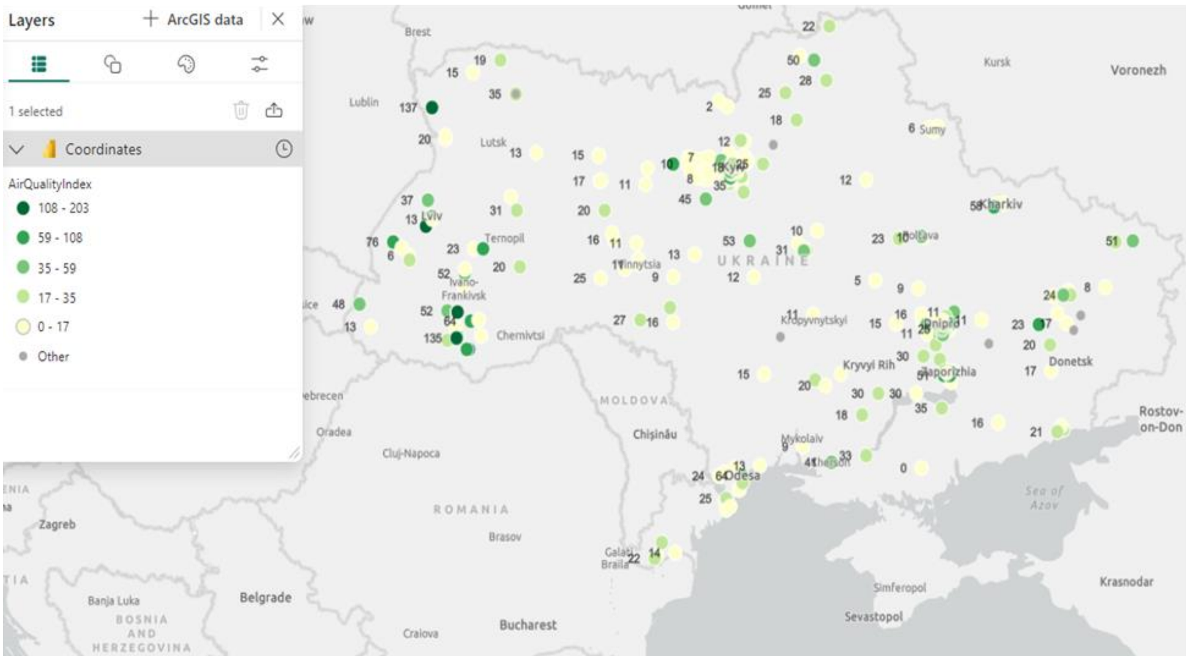

Fig. 1. Current active stations on the territory of Ukraine

All these criteria are interrelated and interdependent, and their use allows for a monitoring network that not only collects important data but also contributes to the health of communities and the environment. At the same time, the criteria must be dynamic, able to adapt to changes in technology, pollution conditions and socio-economic realities to ensure the monitoring system's long-term and effective operation.

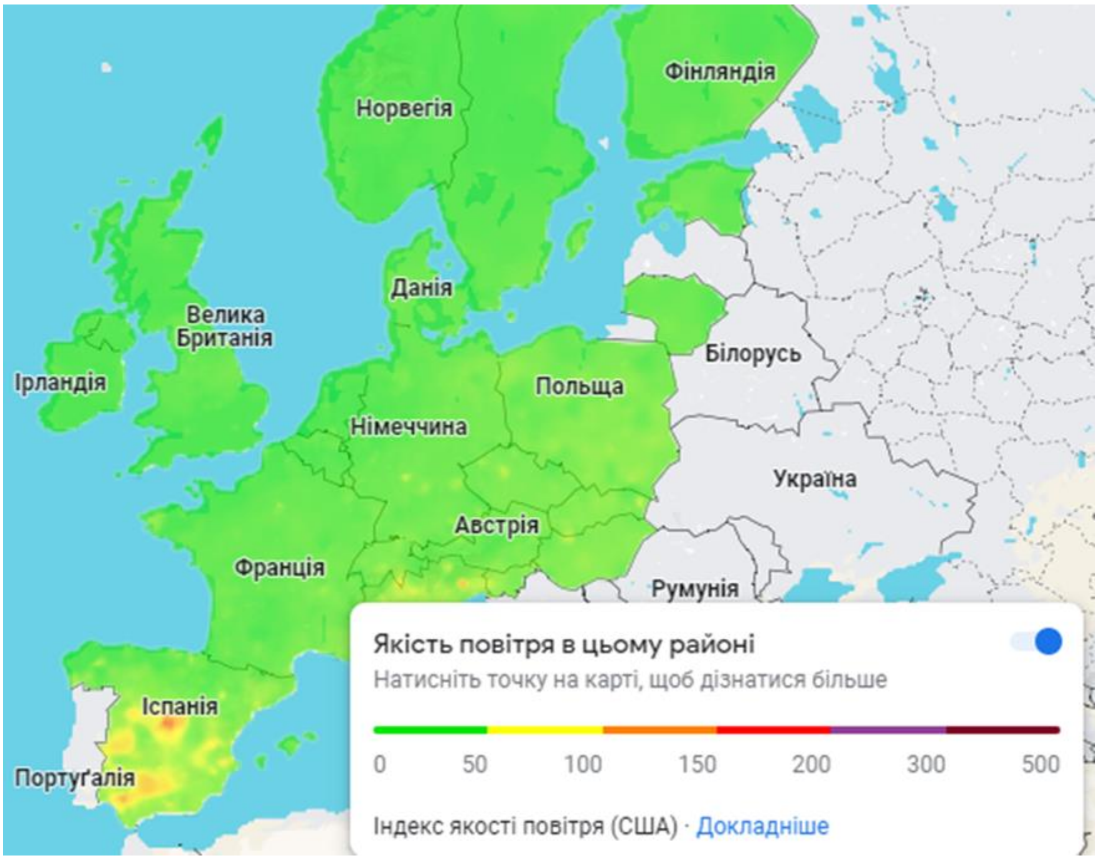

Fig. 2. Coverage of the world's territory by stations

The use of atmospheric pollutant distribution models is another tool that allows you to simulate different scenarios and determine how changes in emission sources or weather conditions can affect air quality. This helps in predicting pollution levels and selecting locations where monitoring will be most effective.

Optimization algorithms, such as genetic algorithms or artificial intelligence techniques, can be used to automate the process of selecting station locations. These techniques allow for many variables to be taken into account and for optimal solutions to be found quickly.

It is also important to consider socio-economic aspects, such as the impact of pollution on public health and the economic feasibility of station locations. This ensures that the monitoring system is not only technically efficient but also socially responsible.

The problem of optimizing the placement of air quality monitoring stations is multifaceted and includes numerous aspects, ranging from geographical location to economic feasibility. Existing research in this area can be classified into different areas.

Various approaches have been proposed to solve the problem of optimizing the location of air quality monitoring stations. Comparative Table 1 below provides an overview of five key methodologies: statistical methods, machine learning, genetic algorithms, ant colony methods and hybrid methods.

Table 2 evaluates the key characteristics of each method, including their accuracy, computational speed, implementation complexity, scalability, training data requirements, and ability to interpret results. These characteristics make it possible to understand which methods are best suited to solve the specific optimization problem considered in this study.

The comparison table for optimization methods provides a general picture of the best approaches to optimizing the location of air quality monitoring stations. Statistical methods are simplified and fast data processing tools, but they may not consider the full complexity of the optimization problem. They are best suited for basic analysis but may not be effective for detailed planning.

Table 1. Overview of existing methods

Method	Description	Advantages	Disadvantages	Suitability for Station Optimization
Statistical Methods	Utilize universal statistical models for data processing.	Simplicity of use, speed, possibility of result interpretation	May be less precise for complex optimization tasks	Suitable for preliminary data analysis and identifying correlations between factors.
Machine Learning	Automatically detects patterns in large datasets using prediction and classification methods.	Capable of identifying complex nonlinear patterns, online learning capability	Requires large volumes of data for training, difficulties with result interpretation	Suitable for detecting subtle dependencies and predicting trends.
Genetic Algorithms	Employ mutations, crossover, and selection to create generations of solution candidates.	Effective for global search in solution space	Computational speed may be low, requires extensive computation	Excellent for multi-criteria optimization tasks, such as station placement.
Ant Colony Methods	Mimic the behavior of ant colonies to solve optimization problems.	Good for optimization tasks involving pathfinding.	Not always efficient for tasks with large solution spaces.	Can be useful for solving problems similar to the traveling salesman, when determining the optimal path between stations.
Hybrid Methods	Combine various methods in one system to leverage the advantages of each.	Can be extremely effective, provide more accurate and reliable solutions.	Complex to implement and require deep understanding of each used method.	Great when a single method cannot effectively address the entire problem.

Table 2. Comparison of existing methods

Method	Accuracy	Computational Speed	Implementation Complexity	Scalability	Data Requirement for Training	Result Interpretation
Statistical Methods	High	High	Medium	High	Low	High
Machine Learning	High	Medium	High	High	High	Low
Genetic Algorithms	Medium	Low	Medium	Medium	Low	Medium
Particle Swarm	Medium	Medium	Medium	Medium	Low	Medium
Ant Colonies	Medium	Medium	High	High	Low	Low
Hybrid Methods	High	Variable	High	High	Variable	Variable

Machine learning methods can account for complex dependencies in data but require large volumes of data for training. Moreover, the results of machine learning can be difficult to interpret.

Genetic algorithms utilize principles of natural selection to search for optimal solutions and can be effective in considering multiple optimization criteria. However, they can be more demanding in terms of computational resources and require careful tuning.

Ant colony methods are effective for optimization tasks involving route planning, but they may be less efficient for the primary task of optimizing the placement of stations.

Finally, hybrid methods attempt to combine the advantages of different approaches but can be more complex to implement.

Modelling the air quality monitoring system is an important step in the optimization process. It allows for an objective assessment of the current situation and the development of forecasts and strategies for system improvement. Modelling can be performed at different levels, from models of pollutant dispersion in the atmosphere to models of monitoring station placement.

Pollutant dispersion models consider factors such as pollution sources, pollutant characteristics, meteorological conditions, and the topography of the area to predict the distribution of pollutants in the air. They are an important basis for identifying critical zones requiring enhanced monitoring. Equation 1 demonstrates a model of environmental pollution dispersion for most pollutants.

The statement provided explains that both molecular diffusivity (D) and turbulent diffusivity (K) depend on temperature (T), and that this relationship can be expressed through correlations and physical principles as functions D(T) and K(T), respectively. Similarly, density (ρ) can also be expressed as a function of temperature, ρ(T).

$$\frac{\partial \rho(r,t)}{\partial t} + \nabla \cdot (\rho u) = \nabla \cdot \left(\rho D(r,t)\nabla c + \rho K\big(T(r,t), RH(r,t)\big)\nabla c\right) + S\big(T(r,t), RH(r,t)\big) \quad (1)$$

Monitoring station placement models aim to find the optimal location of monitoring stations based on various criteria, such as air pollution, population centres, site accessibility, and other constraints. They can include theoretical and empirical methods, including operations analysis, statistical methods, and machine learning algorithms.

Monitoring station operation models describe the working processes of monitoring stations, such as the process of data collection, processing, and transmission. They take into account factors such as station capacity, data collection frequency, measurement accuracy, and device reliability. The developed system, which includes means for monitoring its own condition and making necessary corrective actions in case of defects or problems with the prediction process, is depicted in Figure 3.

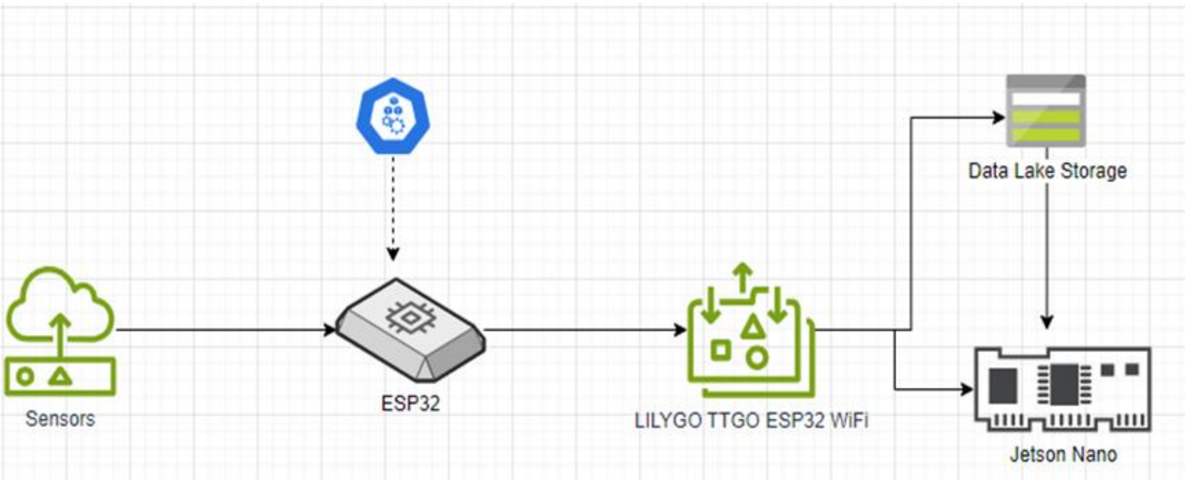

Fig. 3. Architecture of the microcontroller hardware and software system

All these models are important components in the process of optimizing the air quality monitoring system. They allow for the consideration of many different factors and conditions, leading to the selection of the best solution for specific circumstances. Modelling results are used for planning the expansion of existing systems, developing new monitoring systems, and adapting to changing air pollution conditions.

The initial stage of this process includes identifying key criteria that should be considered during the placement of stations. These are the geographic distribution of the population, the location of pollution sources, geographical and meteorological conditions, as well as budget constraints.

With these criteria, the next step is to develop a mathematical model that can be used to calculate the optimal placement of stations.

This model can be formulated as an optimization task, where the objective function represents the desired outcomes, and the constraints reflect real-world limitations.

To solve the arising optimization task, optimization algorithms such as genetic algorithms, particle swarm algorithms, simplex methods, and others are applied. The choice of a specific algorithm depends on the nature of the task, computational resource capabilities, and other factors.

After optimization, it is important to evaluate and verify the obtained results. This may involve comparison with existing real data, cross-validation, or using other methods to check the reliability of the modelling results.

Based on the obtained results, opportunities for model refinement are identified. This includes changing the criteria definitions, revising the mathematical model, or applying other optimization algorithms.

Thus, building an effective model for the placement of air quality monitoring stations is an important component of the overall monitoring system optimization process. It requires an understanding of the basic principles of modelling, as well as the specifics of the task.

Determining the optimal parameters is a key stage in the process of modelling the air quality monitoring system. These parameters include the number and placement of monitoring stations, their technical characteristics, monitoring intervals, and other factors that can affect the system's efficiency.

The first step in the process of determining optimal parameters is to create an objective function that reflects the optimization goals. Typically, this function aims to maximize several criteria, such as coverage area, measurement accuracy, and minimize the costs of installation and operation of stations.

After defining the objective function, optimization algorithms can be applied to search for the optimal solution. Typically, this search involves exploring different combinations of parameters and evaluating their effectiveness through the objective function. The final optimal parameters are those that score highest according to the objective function.

Finally, the optimal parameters must be tested and validated to ensure their relevance and effectiveness in real-world conditions. This may include procedures such as cross-validation, testing on new data, or comparison with other optimization methods.

It is important to note that in the process of determining optimal parameters, several iterations may be performed to account for new information or changes in air monitoring conditions. This requires flexibility in the methodology and the ability to quickly adapt to new circumstances.

Optimization algorithms play a crucial role in solving the task of placing air quality monitoring stations. These methods seek the optimal balance between various goals and constraints, individually considering different factors that affect the system's efficiency.

One of the key properties of optimization algorithms is their method of searching for a solution. Some methods, such as gradient.

Model Implementation

For the task of optimizing the placement of air quality monitoring stations, a genetic algorithm was chosen. This method simulates natural selection processes, including selection, crossover, and mutation, to evolutionarily develop a population of potential solutions, with the algorithm's workflow depicted in Figure 4.

In the context of creating an optimal network for air quality monitoring, each solution or "individual" represents a potential placement of stations in space. The fitness function, or fitness score, calculates the effectiveness of each placement, taking into account criteria such as population coverage, distance to pollution sources, and the cost of installation and maintenance of stations.

The genetic algorithm uses these mechanisms to evolve the population of solutions until a stopping criterion is reached, such as after a certain number of generations or when no further improvements are observed. The final solution or outcome then represents the optimal or most effective placement of monitoring stations for the given task.

The use of genetic algorithms in research is central to the process of determining the optimal parameters of a monitoring system. Genetic algorithms are search and optimization methods that replicate the principles of evolution and natural selection to find the best solutions to complex problems.

A crucial step in applying the genetic algorithm is defining the individual (or solution) that will represent the current state of the monitoring system. In this study, everyone represents a set of system parameters, such as the location and number of monitoring stations.

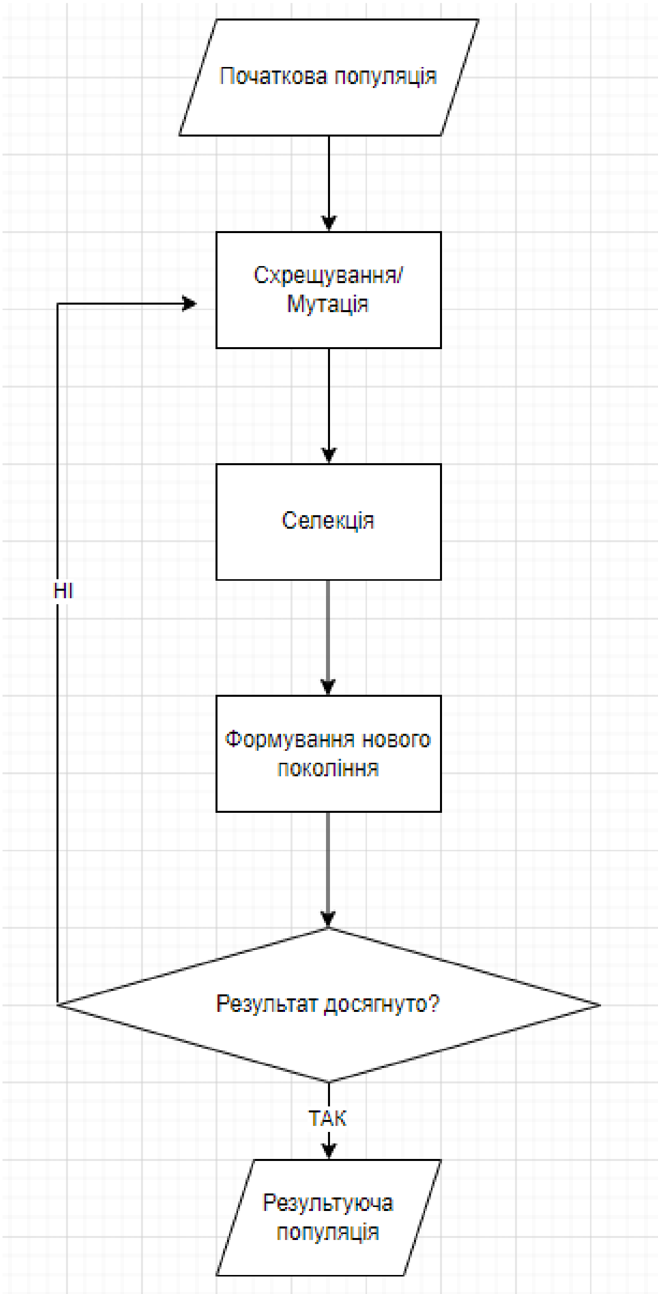

Fig. 4. Scheme of the genetic algorithm

Defining the fitness function, which evaluates how well each solution solves the task, is also critically important. A highly adaptive fitness function was developed, which assesses the population covered by the stations, considering the cost of placing each station. In the context of searching for an optimal network of air quality measurement stations in Ukraine, the fitness function may consider a range of different parameters.

Optimality is determined by several criteria - coverage efficiency, economic benefit, availability of infrastructure, location of pollution sources, population density, and others. Criteria to be considered in the fitness function:

- Territory coverage: One of the goals is to maximize the coverage of the country's territory with an optimal number of stations.
- Cost: The establishment and maintenance of air quality measurement stations require expenses. The fitness function should.
- Minimize the cost of installing monitoring stations while maintaining their effectiveness.
- Population density: Stations should be located closer to population centres, especially cities, as they are more vulnerable to air pollution.
- Location of pollution sources: It is important to place measurement stations close to major sources of pollution, such as industrial zones, highways, etc. Taking all criteria into account, a map of station placements was developed, depicted in Figure 5.

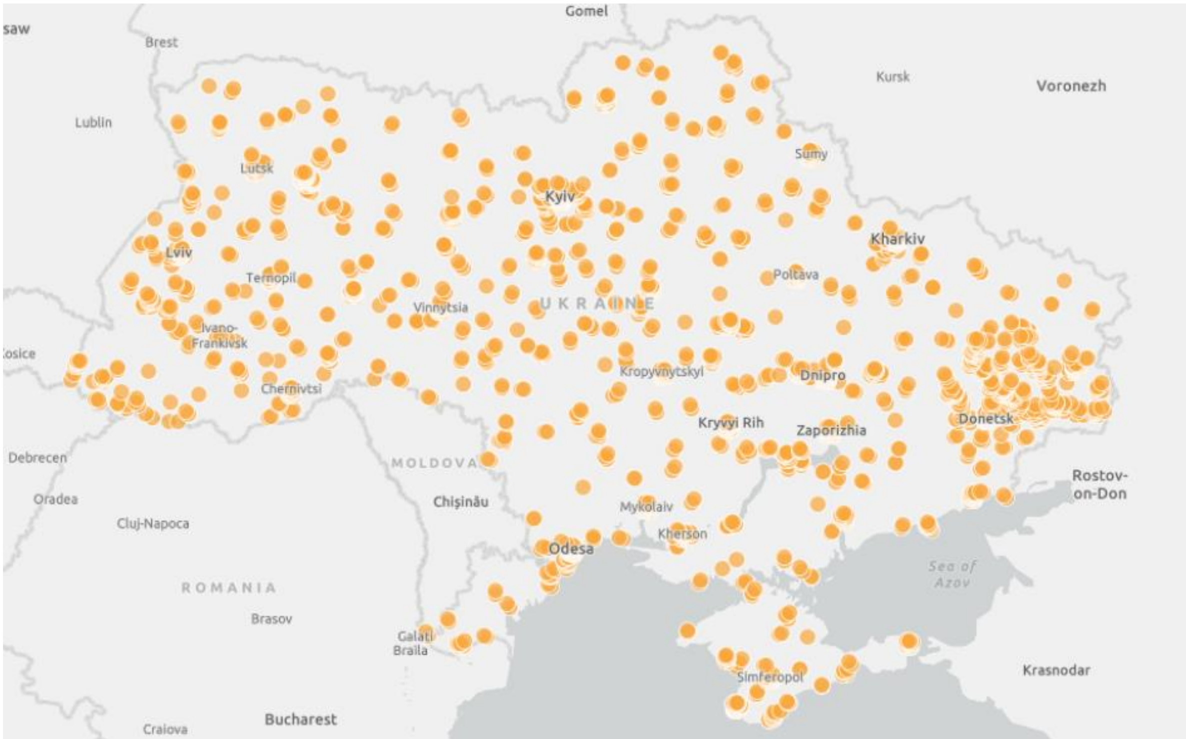

Fig. 5. Map of possible station locations (3044)

Using a genetic algorithm developed in Python, an initiated population of current station locations, totaling 3044, was created to cover all conditions, and the population was evolved through thousands of generations using mutation and crossover mechanisms. The results of the algorithm's work are shown in Figure 6.

This process continued for 5000 generations, during which the population evolved by selecting the best solutions. The result is the best-found solution from the network, consisting of 1746 depicted in Figure 5, which was preserved for further analysis and validation.

This method demonstrates potential in solving the task of optimizing the placement of air quality monitoring stations, allowing for a balance between different tasks, such as maximizing coverage and minimizing costs. The results obtained from this process not only show how well the algorithm works but also provide important information that can be used for further improvement of the algorithm. Moreover, experimental validation also allows comparing different methods with each other and determining which one is most effective in specific situations.

Thus, experimental validation determined how effectively the algorithm finds the best solution. The results of such validation can serve as a basis for further optimization of the algorithm and for comparing its effectiveness with other methods.

The analysis of the results assesses how successfully the research objectives were achieved. This includes evaluating the quality of the obtained solution, i.e., its effectiveness in terms of coverage and cost, as well as its compliance with regulatory requirements and budget constraints.

The optimization process for the placement of air quality monitoring stations is an important task that affects the efficiency of the monitoring system both now and in future. This work has explored various computational methods, including practically implemented genetic algorithms, to solve this task.

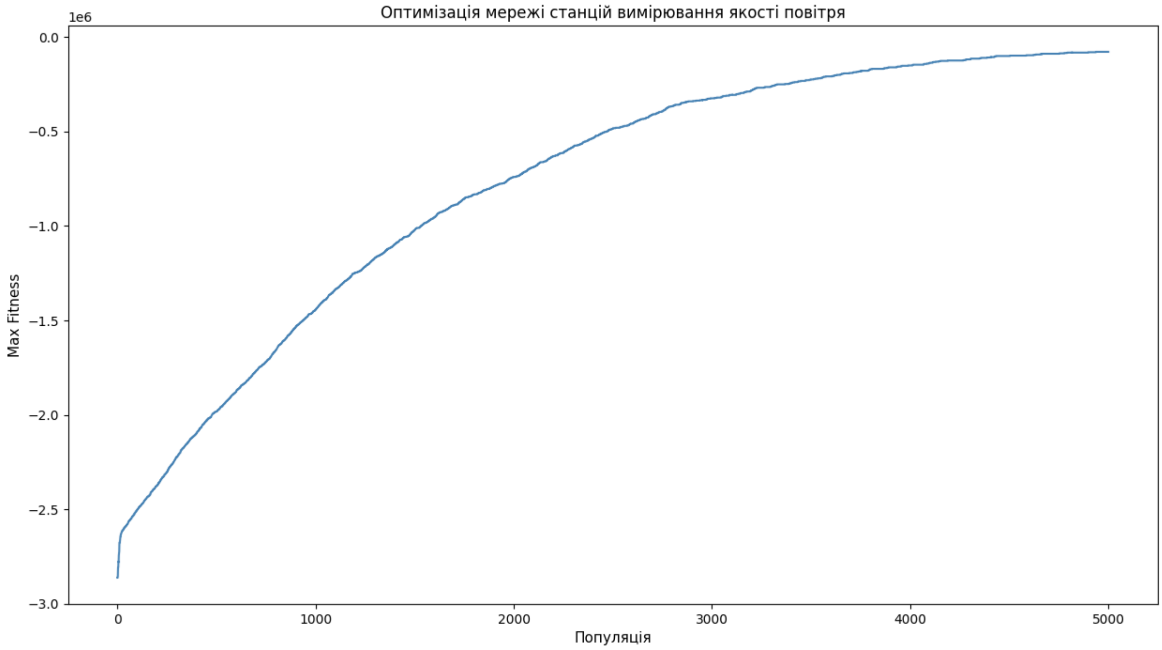

Fig. 6. Scheme of the genetic algorithm

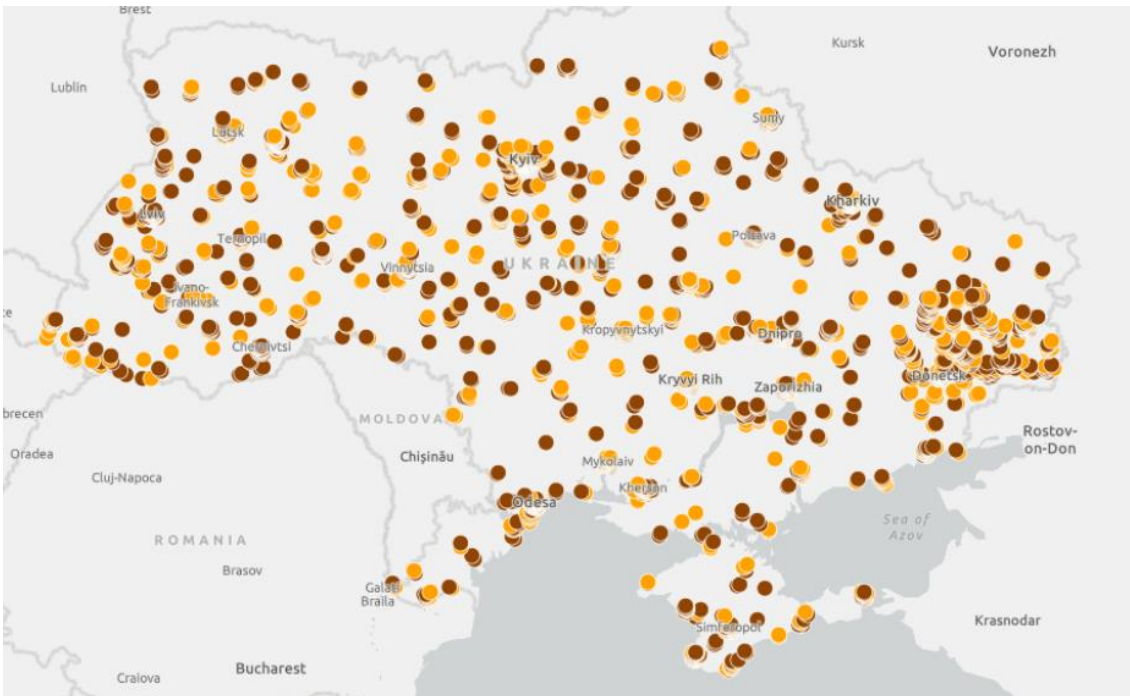

Fig. 7. Optimized network of stations (1746)

The basis of the research used modelling methods designed to describe the monitoring system based on real data. Based on these models, a fitness function was created that allowed determining the optimal parameters using genetic algorithms.

The results of experimental validation showed that the genetic algorithm-based approach can be effective in solving the optimization task. The obtained solutions provide a high level of coverage, considering cost constraints and other factors. Figure 7 shows how optimized network looks for Ukraine. Network contains only 1746 station to cover all needs.

As a result of optimizing the placement of air quality monitoring stations in the city of Lviv using a genetic algorithm, it was found that optimally 10 stations should be placed. Figure 8 shows how optimized network looks for Lviv.

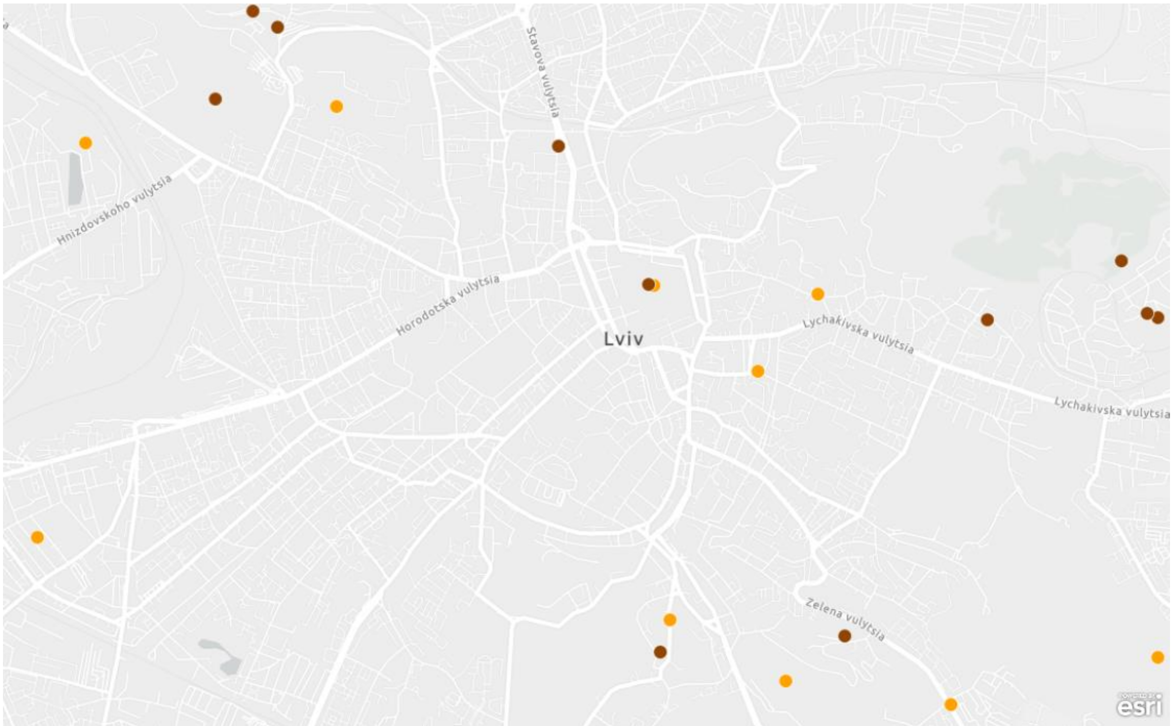

Fig. 8. Optimized network of air quality stations for the city of Lviv

The optimization was performed with the following input parameters:

- Population size: 50
- Crossover probability (P_CROSSOVER): 0.8
- Mutation probability (P_MUTATION): 0.2
- Maximum generation (MAX_GENERATIONS): 5000
- "HALL OF FAME" size: 5
- Cost of installing one station (COST_PER_STATION): 2000 UAH.
- Total budget (BUDGET): 2000000 UAH.
- Coverage radius of one station (COVERAGE_RADIUS): 5 km

Considering the output constraints and using the genetic algorithm with the specified parameters, a station placement was obtained that maximizes coverage within the given constraints. Under these conditions, the optimal number of monitoring stations that can be installed in the city of Lviv is 10. A final fitness function score of 0 and a final generation value of 5000 were obtained.

Conclusion

In conclusion, the optimization of the air quality monitoring network should be flexible and adaptive, capable of responding to changes in pollution conditions and technological innovations. It is an iterative process that requires constant review and updating to ensure that the monitoring system remains relevant and reliable.

We analyse methods for optimising air quality monitoring systems, from developing criteria for selecting station locations to applying advanced algorithms to improve the efficiency of these systems. Our research has shown that the integration of different scientific approaches and technologies is key to addressing the complex challenges associated with air quality monitoring and management.

It was found that accurate and representative measurement of pollutants requires not only careful planning of station locations, but also attention to details such as topography, meteorological conditions, and local emission sources. In addition, socio-economic and environmental aspects must be considered to ensure that monitoring systems not only accurately reflect the state of the environment, but also serve the interests of communities.

The use of genetic algorithms has proved particularly promising in finding optimal solutions for the placement of monitoring stations. These algorithms, which effectively use natural selection processes for optimisation, demonstrate the ability to search globally and solve multi-objective problems, making them ideal for solving the complex problems that arise in the context of air quality monitoring.

Experimental verification and analysis of the results confirmed that the developed methods are effective and can identify solutions that meet the established constraints and requirements. The results obtained not only indicate the high reliability of the method, but also open up opportunities for its practical application.

Given the potential for further research and improvement, it is safe to say that genetic algorithms and other optimisation methods discussed provide a solid foundation for the development of more efficient air quality monitoring systems. This study highlights the need for continued work in this area, as the goal of creating a healthy environment for living remains important to us all.

Throughout this chapter, we have explored how genetic algorithms can be applied to solve these optimisation problems. Genetic algorithms, which mimic the processes of natural selection and evolution, have proven to be particularly powerful in solving problems where traditional analytical methods are ineffective or insufficient.

Using genetic algorithms, we developed a model that allows us to determine the optimal locations for monitoring stations. The model is based on the calculation of a fitness function that includes criteria such as coverage of the territory, the cost of installing and maintaining stations, and the priority of locating stations in populated areas.

Experimental validation of the model confirmed that genetic algorithms are able to identify effective solutions that take into account the established constraints and requirements. The analysis of the results showed that the method is reliable and can be used for practical applications as well as for research purposes.

However, the study also revealed opportunities for further improvement. Improvements can be achieved by fine-tuning the parameters of the genetic algorithm, developing more complex fitness functions, and integrating with other optimisation methods.

Our conclusions confirm that genetic algorithms are of considerable interest as a tool for solving complex optimisation problems. They open new perspectives for improving air quality monitoring systems, which is important for ensuring a healthy living environment and reducing the negative impact of pollution on the population.

An analysis of the methods used has shown that genetic algorithms have significant potential for finding effective solutions to such optimisation problems. Their ability to search globally and perform multi-objective optimisation makes them suitable for complex tasks such as optimising monitoring stations.

The developed model, based on genetic algorithms, determines the optimal locations for monitoring stations by calculating a fitness function that includes criteria for coverage, cost, and location of settlements.

Experimental verification and analysis of the results showed that the developed methodology can identify effective solutions for the installation of monitoring stations, considering the identified constraints and requirements. The analysis reflects the reliability of the method, which indicates the possible suitability of the algorithm for use in practical applications, as well as for research purposes.

At the same time, several areas for further research have been identified. Improvements can be achieved by adjusting the parameters of the genetic algorithm, developing more complex fitness functions, and integrating with other optimisation techniques.

The conclusions drawn from this study confirm that genetic algorithms can be an effective tool for solving complex optimisation problems such as this one. Although further research is needed to fully understand all the possible applications and limitations of this technique, the results already indicate its great potential to improve the efficiency of air quality monitoring systems.

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