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Taking Flight for a Greener Planet: How Swarming Could Help Monitor Air Pollution Sources

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Abstract: As the world grapples with the pressing challenge of environmental sustainability, the need for innovative solutions to combat air pollution has become paramount. Air pollution is a complex issue that necessitates real-time monitoring of pollution sources for effective mitigation. This paper explores the potential of swarm algorithms applied as a novel and efficient approach to address this critical environmental concern. Swarm algorithms offer a promising framework for coordinating fleets of drones to collaboratively monitor and analyze air pollution sources. The unique capabilities of drones, including their agility, accessibility, and versatility, make them ideal candidates for aerial data collection. When harnessed in a swarm, these drones can create a dynamic and adaptable network that provides a more comprehensive and fine-grained understanding of air pollution dynamics. This paper delves into the conceptual foundations of using swarm algorithms in drone-based air pollution monitoring.

Keywords: computer science; swarm optimization; green transformation; sustainability

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1. Introduction

In the current day, the global community confronts numerous environmental obstacles, one of the most significant being the preservation of the air we collectively inhale. A prominent issue is air pollution [1], which arises from the expansion of factories, urban areas, and human activities that have detrimental effects on air quality.

Air pollution is a constant source of concern in modern cities and has been linked to numerous health problems. Pollutants are present in every area of our atmosphere, ranging from harmful gasses to minute particle matter, and they directly endanger our circulatory and respiratory systems. Using knowledge from a large corpus of research, we investigate the complex ways various contaminants present harmful impacts on human health.

One of the most noticeable and immediate effects of air pollution is its assault on the respiratory system. Inhaling polluted air can result in a range of respiratory issues, from persistent wheezing and coughing to potentially fatal dyspnea. The aggravation of symptoms can put those who already have a medical condition like asthma or chronic obstructive pulmonary disease (COPD) at risk. Air pollution damages the cardiovascular system by entering the bloodstream and not just affecting the lungs. Research has revealed a concerning connection between cardiovascular illnesses, such as heart attacks and strokes, and air pollution. Particulate matter, particularly tiny PM2.5, works as a sneaky collaborator to undermine the health of the heart and blood vessels. These are just two instances of the wide range of effects on human health. Long-term exposure to high air pollution levels has negative effects on mortality rates. Due to the negative effects that air pollution can have on fetal development, pregnant women are particularly vulnerable, as well as several other groups [2].

This study examines swarm algorithms [3] as a powerful and economical approach to identifying the root cause of problems in instances when standard methods such as camera feeds or human investigation are not feasible.

The integration is built on the conceptual foundations that explore the theoretical principles of swarm algorithms and fuzzy systems [4] used for monitoring air pollution with drones. The distinct characteristics of swarm algorithms are examined, highlighting their adaptability and effectiveness in coordinating groups of drones for collaborative analysis of pollution sources. In addition, fuzzy systems play a crucial role in enhancing the decision-making capabilities of the monitoring system. Fuzzy logic, a mathematical framework that deals with uncertainty and imprecision, allows for incorporating human-like reasoning into the system. In the context of air pollution monitoring, fuzzy systems can assist in handling complex and ambiguous data, providing a more nuanced understanding of environmental conditions. This integration of swarm algorithms and fuzzy systems creates a comprehensive approach that leverages the strengths of both methodologies for robust and intelligent air pollution monitoring with drones.

Factories, automobiles, and diverse human activities collectively generate a combination of pollutants in the atmosphere. This matter transcends particular locations and impacts both metropolitan centers and serene rural regions. Given the escalating severity of air pollution, it is imperative to develop more effective methods for monitoring and regulating it continuously. The conventional techniques for monitoring air pollution are subject to constraints, particularly when considering the dynamic nature of pollution levels over time. Therefore, it is imperative we adopt novel and inventive methodologies.

An effective approach involves employing swarm algorithms, which draw inspiration from the cooperative behavior observed in animal groupings. These algorithms provide a versatile method for monitoring and analyzing pollution sources. An essential aspect of transforming our approach to air pollution is integrating swarm algorithms with drone technology [5,6]. Drones are valuable instruments due to their agility, user-friendliness, and ability to gather aerial data [7]. However, their computing capabilities are rather restricted, making them an ideal match for swarm behavior. Their capabilities are highly suitable for effectively monitoring air pollution, as evidenced by their increasing utilization for this specific purpose in recent years [8].

Integrating swarm algorithms with drones offers the capacity to provide immediate and comprehensive observations of the dynamic variations of air pollution. This study seeks to investigate the potential utilization of swarm algorithms in conjunction with drones to monitor air pollution sources more efficiently. An important objective is to achieve this without requiring constant human intervention. Additionally, the study aims to address the challenge of parameterizing swarm algorithms, which is typically a complex task.

An area of particular emphasis is a swarm algorithm that draws inspiration from the behavior of Carthaginian war elephants [9]. This technique has the potential to greatly enhance pollution source detection by increasing accuracy efficiency, and yielding superior results and improving simplicity of usage. The study plan entails incorporating swarm behavior with deliberate adaptations to accommodate wind patterns and establish a resilient scanning system. Supplementary agents positioned at the periphery of the search region have a vital function in verifying pollution's origins, enhancing the entire system's dependability. This study is located at the convergence of environmental science, artificial intelligence, and drone technology.

The next section of the study will provide a thorough explanation of the theoretical underpinnings of swarm algorithms, specifically focusing on the approach inspired by Carthaginian war elephants. This project endeavors to integrate swarm algorithms with drone technology to provide a contemporary and precise solution for monitoring air pollution in real-time. Additionally, it attempts to establish a theoretical basis for scalable and flexible pollution management techniques by utilizing swarm algorithms. The objective of this comprehensive investigation extends beyond immediate considerations of air pollution. Its objective is to establish a detailed plan for a future in which cutting-edge technologies like drones and heuristic approaches collaborate to tackle the pressing environmental issues of our era.

As we investigate swarm algorithms and their incorporation for air pollution scanning, it is evident that this work extends beyond a mere scientific quest; it represents a dedication to the environment. Addressing air pollution involves more than technological solutions; it requires comprehending and minimizing the issues most effectively. By employing ingenuity, cooperation, and mindful effort, we can discover the appropriate measures to achieve a future where air pollution could become a remote recollection.

2. Material and Methods

The Carthaginian War Elephant Swarm Optimization (CWESO) algorithm, introduced in the paper "The Elephant in the Room: Swarm Algorithms Inspired by Warfare", is a custom-designed algorithm created with the explicit goal of being highly adaptable to different input functions and with a simple approach to parameterization. The following is an examination of the distinctive qualities of this algorithm and its derivation from the cooperative actions witnessed in historical battlefields.

The CWESO is based on the cooperation and strategic actions of Carthaginian war elephants. These elephants, renowned for their coordinated locomotion across many landscapes, serve as a paradigm for an algorithm that surpasses traditional adaptation. Instead, it transforms the process of identifying pollution sources. The system emulates the synchronized movements and communication observed in Carthaginian war elephants. It utilizes ideas of collaboration, adaptability, and strategic decision-making to enhance the precision and effectiveness of identifying pollution sources. Just like how elephants on the battlefield can be used to make coordinated decisions, the algorithm promotes teamwork among the individual pieces, which in this case are the drones. The program facilitates instantaneous connection and exchange of information, allowing drones to collaboratively navigate and adapt to evolving air pollution patterns. The system enables drones to adapt to different settings, drawing inspiration from the battlefield behavior of Carthaginian war elephants. The versatility of the monitoring system guarantees its continued effectiveness in response to variations in wind patterns, meteorological conditions, and dynamics of pollution sources. The program integrates tactical movement patterns influenced by how Carthaginian war elephants navigate intricate terrains. By adhering to these patterns, drones optimize their routes to methodically cover large areas, hence improving the overall efficiency of identifying pollution sources. This section examines the potential benefits of the Carthaginian War Elephant Swarm algorithm in monitoring air pollution. The algorithm offers a hopeful foundation for effectively monitoring pollution sources by improving source identification accuracy and adapting efficiently to changing environmental conditions.

In short, the Carthaginian War Elephant algorithm is a swarm algorithm that draws inspiration from the coordinated movement and strategic actions exhibited by Carthaginian war elephants. Now, let us analyze the functioning of this algorithm:

1. Initialization:
    - The algorithm begins by initializing a data frame ('result_data') to store outcomes, x-coordinates ('x'), and y-coordinates ('y');
    - Unique positions for virtual elephants are generated randomly distanced from each other within a specified range ('lb' to 'ub');
    - Each elephant position is associated with a random movement capability.
2. Elephant movement and outcome evaluation:
    - For each elephant position, the algorithm iterates through the y-coordinates based on the elephant's movement capabilities;
    - Outcomes are evaluated for each position, and the results are stored in the 'result_data' data frame;
    - Additionally, the algorithm implements a lance attack direction, adding further outcomes to the data frame.
3. Variability in elephant movement:

- The algorithm introduces variability in elephant movement by considering different types of ranges for lance attacks;
- For each type of range, the algorithm calculates outcomes for the current position with varying offsets.

4. Removing duplicates and sorting:
    - Duplicate positions are removed from the result data frame to ensure unique configurations;
    - The data frame is then sorted based on the evaluated outcomes.
5. Selection of top positions:
    - The algorithm retains only the top 'criter' number of positions from the sorted result data frame.
6. Troop movement simulation:
    - For each selected position, the algorithm simulates troop movements;
    - Unique random positions for troops are generated around the selected position;
    - The troop positions are sorted for systematic movement.
7. Line of attack and outcome evaluation:
    - For each troop position, a line of attack is generated;
    - Outcomes are evaluated for each attack position along the line of attack.
8. Final selection and return:
    - The algorithm selects the top outcome from all evaluated positions and returns the corresponding x and y coordinates.

In summary, the Carthaginian War Elephant Algorithm emulates the collaborative and strategic behaviors of Carthaginian war elephants between each elephant, and in the final stage, it scans the battlefield using much more precise agents called "troops". It evaluates outcomes based on various positions, introduces variability in movement, and selects optimal troop positions for attacks. The algorithm aims to find the most favorable positions that maximize the overall outcome, making it a dynamic and adaptive swarm algorithm without passing function-specific parameters other than criter, representing how many outcomes we want to store.

To better represent the behavior of each agent, the whole algorithm can be divided into two steps, discussed below.

After an initial investigation, it became clear that using this approach showed very promising results when applied in a simulated environment in a fictional domain. The simulation was built with a blend of Python-based tools and a tailor-made benchmarking tool for monitoring the values calculated by microcontrollers. Python, known for its vast array of libraries and frameworks, enabled the development of a dynamic simulation environment. A dedicated program was developed in Python to replicate the movements of drones and implement the influence of wind factors. The CWESO algorithm, which formed the foundation of the simulation, was tasked with creating stochastic movements, computing results, and developing movements in accordance with the specified criteria, which was initially proposed in R and had to be rewritten to Python to allow for the use in MicroPython controller boards with replacement of official Numpy module with ulab module, for the same reason the fuzzy logic had to be simplified as the official fuzzy logic modules are not yet ported to microcontrollers. In addition, a customized benchmarking tool was created to assess and illustrate the algorithm's performance using plotly. The purpose of this tool is to monitor and assess the algorithm's efficiency and efficacy in different simulated scenarios. We were able to evaluate the algorithm's capacity to adjust and discover optimal solutions in a changing environment, yielding significant insights into its performance. However, after careful examination and further analysis, we have reached a clear and certain conclusion that translating this achievement into real-life situations may be difficult due to external circumstances. The primary difficulty is the widespread influence of the wind, a powerful force that significantly affects the feasibility of this technique. Our examination uncovered a crucial relationship between the wind's intensity and the resulting data spread within the assigned search area. The complicated link between these factors adds a high level of complexity, which greatly reduces the practicality of implementing the proposed approach in real-world, non-simulated environments. As the wind intensity increases, the previously positive results reported in the controlled, artificial environment become more scattered and, as a result, make the methodology less dependable.

Essentially, although the initial exploration of the simulated realm showed promising signs, the shift to real-world implementation requires a reassessment of the technique's effectiveness. The significant impact of external factors, particularly the wind component, highlights the necessity of adjusting and improving the methods to match the complexities and unpredictability of real environmental conditions. This marks a significant milestone in our continuous pursuit of novel solutions that connect theoretical potential with real-world application.

The influence of wind dynamics on drone-based air pollution monitoring is a crucial component that greatly affects the precision and dependability of the findings. The presence of wind, a dynamic and unpredictable factor, adds intricacies that need to be meticulously taken into account to guarantee the efficiency of pollution detection approaches. As air currents transport pollutants away from their origin, the levels and dispersion of these pollutants might differ in terms of space and time. The scattering of pollutants can provide difficulties in precisely determining the precise origin and accurately evaluating the concentration of pollutants at specific locations. The wind's influence introduces fluctuations in pollutant concentrations, particularly in outdoor settings, leading to variability. This variability can be significant at various elevations and distances from sources of pollution. Drones, equipped with pollution level measuring sensors, may face difficulties in accurately capturing these fluctuations, resulting in potential mistakes in the gathered data. Wind conditions also directly affect the navigational skills of drones [10]. Powerful gusts can impact the stability and maneuvering capabilities of drones, perhaps causing them to deviate from their intended flight paths. This divergence can lead to an uneven distribution of data collecting, which can impact the thoroughness of the pollution mapping process.

The displacement of contaminants in the atmosphere, directed by air currents, might alter the manner in which sensors on unmanned aerial vehicles measure and analyze pollution levels. Fluctuations in sensor readings caused by the dynamic nature of wind-induced pollution dispersion necessitate meticulous calibration and consideration of wind-related variables to guarantee the accuracy of air quality assessments.

The complex movement of wind presents substantial difficulties in precisely determining the origins of pollution. Pollutants can form intricate and interrelated dispersion patterns when they travel across long distances. Drones that depend on conventional algorithms for identifying pollution sources may have challenges in differentiating between nearby and faraway sources, affecting the accuracy of determining the source. Adaptive techniques are crucial for addressing the influence of wind on air pollution measurements. Incorporating up-to-date weather information into the drone's operational framework enables flexible modifications in flight routes and sampling techniques.

Furthermore, the integration of edge drones strategically placed at the boundaries of the search region acts as stationary markers, assisting in capturing alterations in environmental dynamics caused by wind. When it comes to using drones for monitoring air pollution, it is crucial to prioritize the comprehension and reduction of the impacts caused by wind dynamics. The study showcases a complete strategy for addressing wind-related difficulties by integrating advanced algorithms, real-time weather data, and strategic drone deployment. As technology advances, it will be essential to consider the complex relationship between wind and pollutant measurements to improve the precision and dependability of environmental evaluations carried out using drone-based techniques.

To tackle potential issues arising from environmental conditions, we implemented a strategic improvement to the algorithmic framework. This improvement entailed deploying either four or eight additional drones strategically positioned at the edges of the actively surveyed search plane. The major purpose of integrating these edge drones was to establish fixed reference points within the spatial domain. The drones remained stationary at a constant height, acting as stable reference points to counteract extrinsic factors such as changes in wind patterns. The immobile characteristics of these boundary drones played a crucial role in collecting the nuanced fluctuations in environmental circumstances. When exposed to the force of prevailing winds, these immobile drones served as dependable indicators of alterations in the environmental dynamics over the designated search area. The real-time data on wind perturbations played a crucial role in making algorithmic adjustments, allowing our system to react dynamically to changing conditions. Through careful placement of drones along the periphery of the search region, we successfully converted them into sentinel nodes that detected changes in the surroundings. This enabled us to consider and incorporate these modifications into our algorithmic decision-making process. The agile relocation of our drones, guided by the knowledge obtained from the stationary edge drones, resulted in a search approach that was more prompt and adaptable, hence improving the overall strength and effectiveness of our exploratory endeavors.

The incorporation of edge drones into our system is distinguished by its inherent simplicity, utilizing easily accessible sensors [11] to assess both the initial value and wind intensity. This efficient method enables quickly gathering crucial information, establishing the basis for a strong operational structure. The primary operations of these edge drones encompass the computation of wind intensity, ongoing refreshes of the pertinent data, and a flexible placement mechanism to synchronize with the mean values obtained from initial measurements.

In order to control these drones efficiently, we have incorporated a fuzzy system [12] that reacts appropriately only when the wind speed surpasses a specific threshold, requiring a modification in the drone's course. This allows us to represent variable values within the 0 to 1 range, indicating the degree to which an element belongs to a specific set. By adopting this methodology, we emulate human reasoning [13] while simultaneously accounting for the imperfect and subjective nature of real-world pollution measurements. Fuzzy logic finds extensive application in control systems [14], artificial intelligence, and decision-making processes that involve substantial ambiguity and uncertainty [15–17]. The tool's capacity to manage intricate, practical situations renders it a significant asset in diverse applications, enhancing the development of computer systems that are more adaptable and reminiscent of human behavior [18,19]. Specifically, we utilize fuzzy logic to govern the actions of the drones based on the prevailing wind force and direction. This strategic implementation is particularly valuable due to wind conditions' inherently "fuzzy" nature. Winds, by their very nature, exhibit variability and uncertainty. Fuzzy logic provides an ideal solution in this context, allowing for nuanced and adaptive responses to the dynamic environmental factors affecting drone navigation. The decision to incorporate fuzzy logic stems from its ability to effectively handle imprecise and uncertain information. In the context of wind management, the fuzzy system reacts discerningly only when the wind speed surpasses a predefined threshold, indicating the need for a course modification. Fuzzy logic, as a mathematical framework, excels in capturing and addressing the uncertainty inherent in decision-making processes. Unlike classical binary logic, fuzzy logic introduces degrees of membership, enabling a more nuanced representation of truth that aligns with the inherently imprecise nature of environmental variables.

By strategically employing fuzzy logic, we were able to reduce the effects of wind while maintaining a satisfactory level record of particle density. This method allows us to achieve a well-rounded balance between our aims. When there is a notable decrease in the number of particles and the direction of the wind is identifiable, our system smartly adapts its trajectory to align with the accurate route. The collective decision-making process among the drones is crucial in optimizing the effectiveness of the search operation. By ensuring that all drones autonomously align with a consensus direction, we can fully exploit the capabilities of our search field without incurring any inefficiencies. On the other hand, in the event of a lack of agreement among the drones, they respond as a group by increasing the area being searched. Expanding the area under examination has the benefit of maintaining the coverage of prospective sources inside the field but at the cost of speeding up the search for solutions.

In order to fix this problem and improve the flexibility and effectiveness of our system, we are introducing a supplementary group of drones called "scout" drones. These entities imitate the actions of scout bees, exploring their surroundings to find the best options and communicating with each other to coordinate the entire group toward a better outcome. This scout drone mechanism incorporates advanced techniques inspired by nature's effective scouting procedures to enhance the search process and direct the collective intelligence of the drone swarm toward optimal results. The seamless combination of edge drones and scout drones demonstrates a comprehensive strategy for tackling search and reconnaissance operations, utilizing both simplicity and complexity to achieve improved performance.

3. Results

After successfully incorporating both edge drones and scout drones into our system, the results generated by our advanced code show great potential in a simulated environment based on real-world collected data. Our approach efficiently identified the global optimum, the main source of pollution, without the need for extensive scanning of the whole search area or reliance on traditional camera feeds. The seamless cooperation between edge drones and scout drones has greatly improved the efficiency and precision of our detecting process. Our solution combines complex algorithms and state-of-the-art drone technology to efficiently identify targets while reducing the time and resources typically needed for such tasks. The nimbleness and independence of our edge drones were crucial in accelerating the detection process, allowing us to quickly pinpoint the origin of pollution. This innovative approach, characterized by cleverness and accuracy, signifies a fundamental change in how environmental monitoring and resource utilization are conducted.

Moreover, removing the need for exhaustive search patterns and camera feeds is a significant advancement in optimizing our system. By using the distinct capabilities of edge and scout drones, we have successfully surpassed the restrictions of traditional approaches, providing a stronger and more efficient solution to the task of detecting and resolving environmental pollution at its source. Essentially, the effective execution of our combined drone system signifies a significant achievement in the field of pollution-detecting technology. The results obtained not only confirm the effectiveness of our method but also establish the foundation for a more sustainable and efficient future in the field of environmental monitoring and repair.

The fusion of the Carthaginian War Elephant Swarm Optimization algorithm with a fuzzy decision system and drone technology has produced encouraging outcomes in the pursuit of effective and instantaneous air pollution surveillance.

3.1. Implementation of the Carthaginian Elephant Swarm Optimization Algorithm

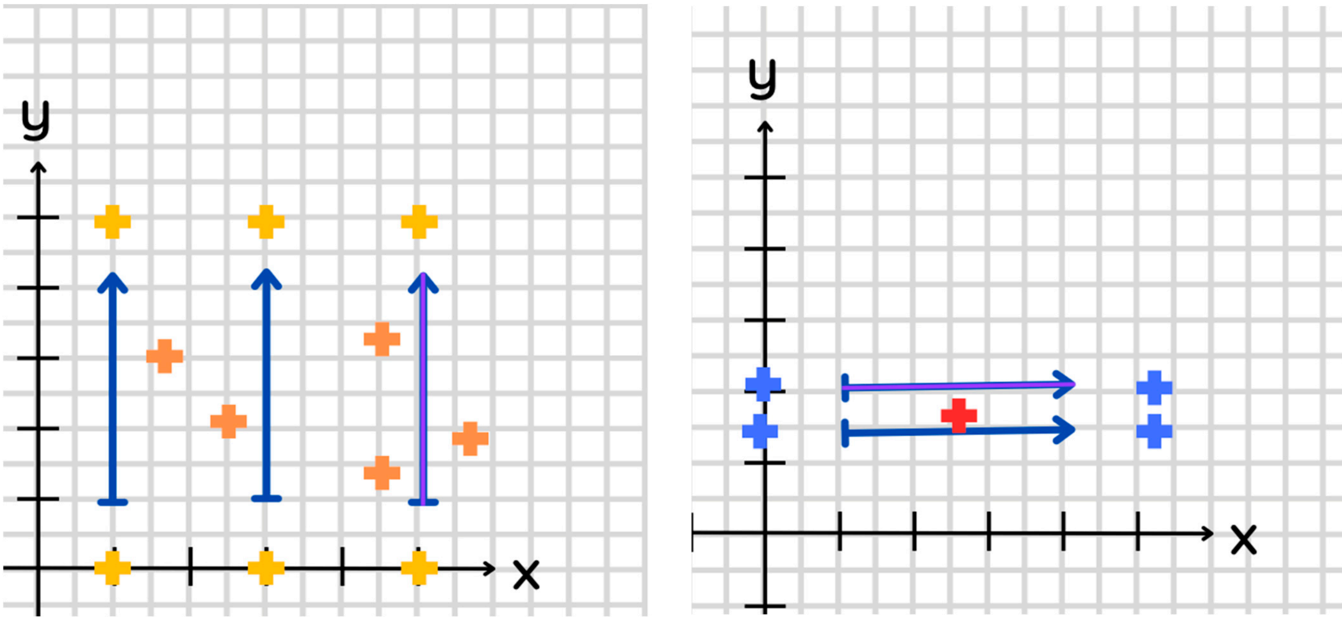
The CWESO algorithm, which draws inspiration from the coordinated movements and strategic actions of Carthaginian Elephants, has been effectively implemented in a virtual setting. The algorithm showcased its versatility by adjusting to several input functions with minimum parameterization. The program employs a distinctive strategy by imitating the cooperative behaviors witnessed in elephants during military conflicts, promoting instantaneous communication and exchange of information among unmanned aerial vehicles.

The CWESO algorithm consists of several crucial parts. Firstly, virtual elephants are initialized with random positions and movement capabilities. Then, the outcomes for each position are evaluated. Next, there is variability in movement, followed by the removal of duplicates. The top positions are selected, and a troop movement simulation is conducted.

The algorithm, as illustrated in Algorithm 1 and Figure 1, is both simple and adaptable, making it a highly promising choice for identifying pollution sources of different kinds. It has minimal impact on computational power while significantly improving the speed of obtaining results. This is particularly advantageous considering the limited battery storage of smaller and more affordable drones.

Algorithm 1. CWESO algorithm

Initialize *result_data with columns outcome, x, and y*
Generate *unique elephant positions within the specified range*
for each *elephant position in elephant positions*
    Generate *random movement capabilities for the elephant*
    for each y *value based on elephant movement capabilities*
        Calculate outcome *of the current position and add to result_data*
        Generate random *value of lance_direction*
        for each *range in {5, 10}*
            Calculate outcome *of lance_direction * range point and add to result_data*
Remove duplicate *positions and sort result_data by outcome*
Select *the top criter number of positions in result_data*
for each row *in result_data*
    Generate *random positions for troops around the given position with precision*
    for each troop *position*
        Generate a line of attack around the troop position
        for each attack *position on the line*
            Check if the attack is within range
            If within range, calculate outcome and add to result_data
    Order *result_data by outcome*
    Select *the top row of result_data*
Return a list containing result_data



(**a**) (**b**)

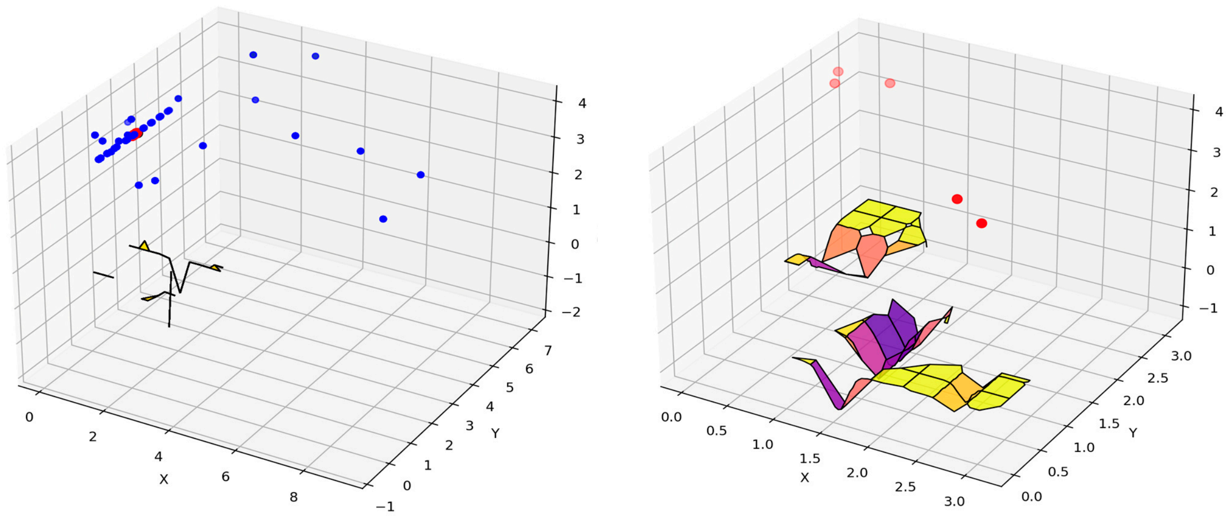
Figure 1. Graphical representation of actions done by agents (drones) at each step. (**a**) In the first part of the algorithm, the drones behave like elephants when they scan over one axis while diverging to random left or right by the amount of "lance distance" and direction chosen at random. (**b**) In the second part, the drones adapt the behavior of troops where they are concentrated much narrowly, and they scan across the second axis based on the best results from the previous iteration.

3.2. The Influence of Wind Factor on Algorithm Performance

The introduction of real-world measurement settings into simulated systems revealed the significant influence of external elements, namely wind dynamics. The wind's intensity displayed a crucial association with the spread of data throughout the search area. The previously encouraging outcomes observed in controlled settings became sporadic and less dependable as wind strength escalated, underscoring the want for adaptable approaches.

3.3. Incorporation of Edge Drones

To address the difficulties presented by wind dynamics, a strategic improvement was implemented by integrating edge drones. The drones, strategically placed at the edges of the search aircraft, functioned as fixed reference points to counteract external forces. The edge drones supplied instantaneous data on wind-induced environmental disturbances, allowing for adaptive modifications to the algorithm. The findings, depicted in Figures 2–4, showcase the system's capacity to adjust to varying wind conditions.



(**a**) (**b**)

Figure 2. Graphical representation of results when applied to the simulated environment. (**a**) This represents each stage of best points in each run and the troops stage. In blue, we see all points considered best by each agent. The red point is the outcome, which is also the global known resolution. (**b**) Graph B represents the results after including the "wind" factor in our simulation, which unfortunately scatters the best solution towards "local optimums".

3.4. Application of Fuzzy Logic

Implementing a fuzzy logic system was incorporated into the swarm algorithm [19] to guide the scout drones and control edge drones, ensuring a well-balanced approach to objectives in the presence of different wind conditions. In addition, scout drones were introduced to improve adaptability and efficiency. These drones, which were influenced by the scouting techniques of bees, were deployed to identify the most favorable conditions and communicated with each other to coordinate the swarm towards an optimal outcome. Incorporating edge and scout drones demonstrated a comprehensive strategy for tackling obstacles in search and reconnaissance operations while implementing fuzzy logic, which facilitates nuanced decision-making by drones, enabling adaptation to the variability and uncertainty of wind conditions. Because wind is a very dynamic factor, using typical binary logic in code was impossible. The fuzzy system considers wind force and its direction, introducing degrees of membership based on each sensor measurement to represent environmental parameter variations. Based on that membership, the drones communicate the wind influence between each agent, and the swarm is effectively steered to adjust to wind influence. Adjusting the single drone and communicating its position contributes to improving the position of the whole swarm and provides a well-balanced approach by guiding drones through decision-making that first considers primary mission objectives and then simplifies dynamic environmental factors. Degrees of membership in fuzzy logic effectively weigh factors, allowing drones to prioritize objectives based on prevailing wind conditions without losing sight of wind influence on the source of pollution. This replicates the imprecise and subjective nature of environmental conditions, enabling drones to make decisions aligned with real-world scenarios' fuzzy and uncertain nature (Figures 5 and 6).

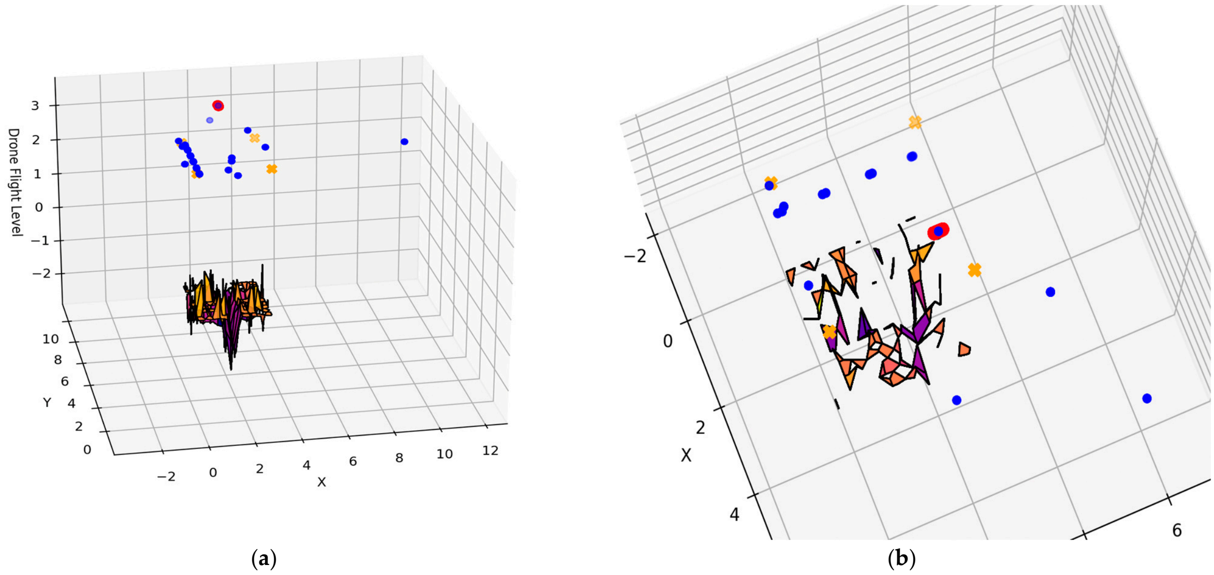


Figure 3. Graphical representation of results when applied to the simulated environment after implementing wind factor and static edge drones. (**a**) In this graph, we can see how the field of search was adjusted after the first agent calculated the values, after which the wind factor was increased. Which resulted in the movement of the search plane towards a different scope. (**b**) This graph shows the path individual drones took to follow the edge drones accordingly.

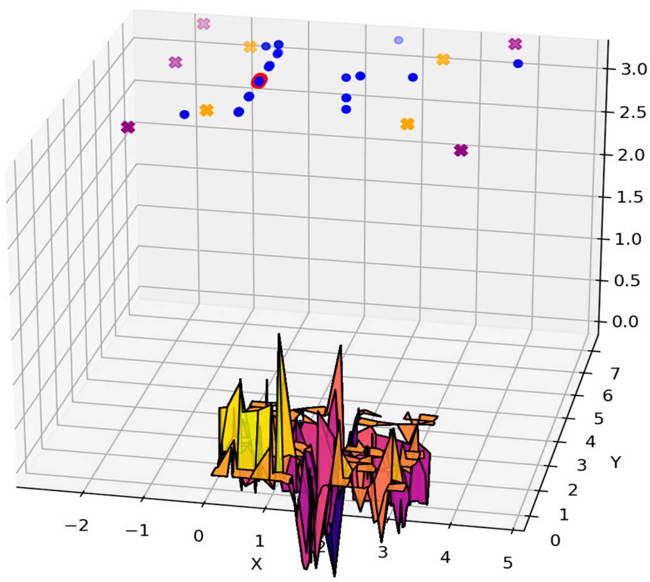


Figure 4. Graphical representation of results when applied to the simulated environment after implementing wind factor and edge (yellow) and scout (purple) drones. After implementing the edge drones and scout drones, we can see that the whole swarm very quickly achieves the goal when the search plane is bigger than expected.

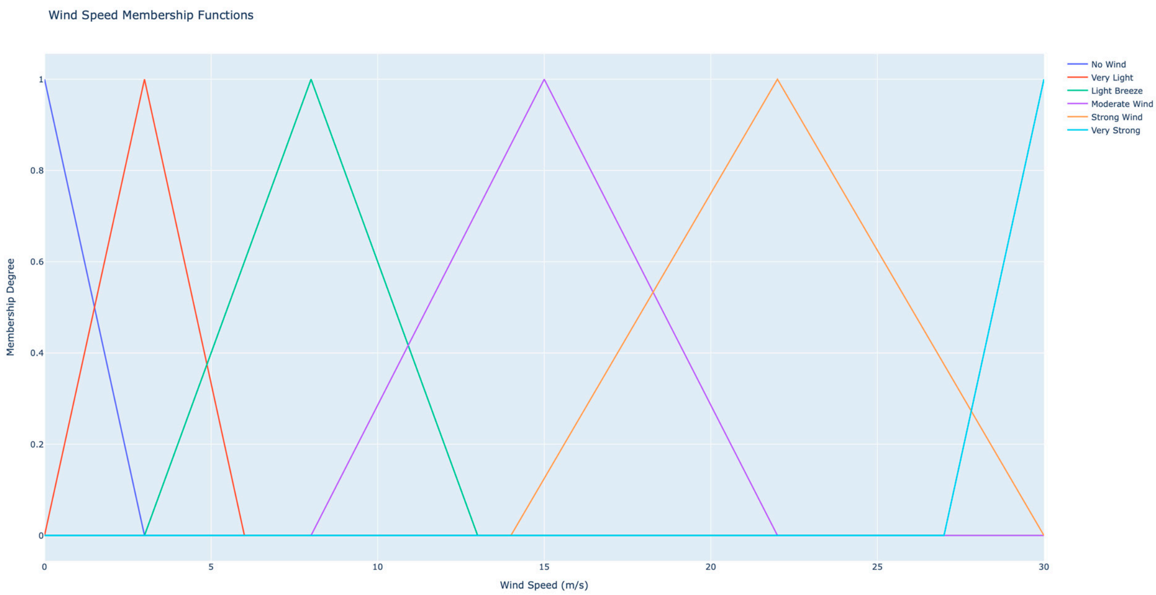


Figure 5. Graphical representation for simplified fuzzy membership for wind speed used by the outer ring drones.

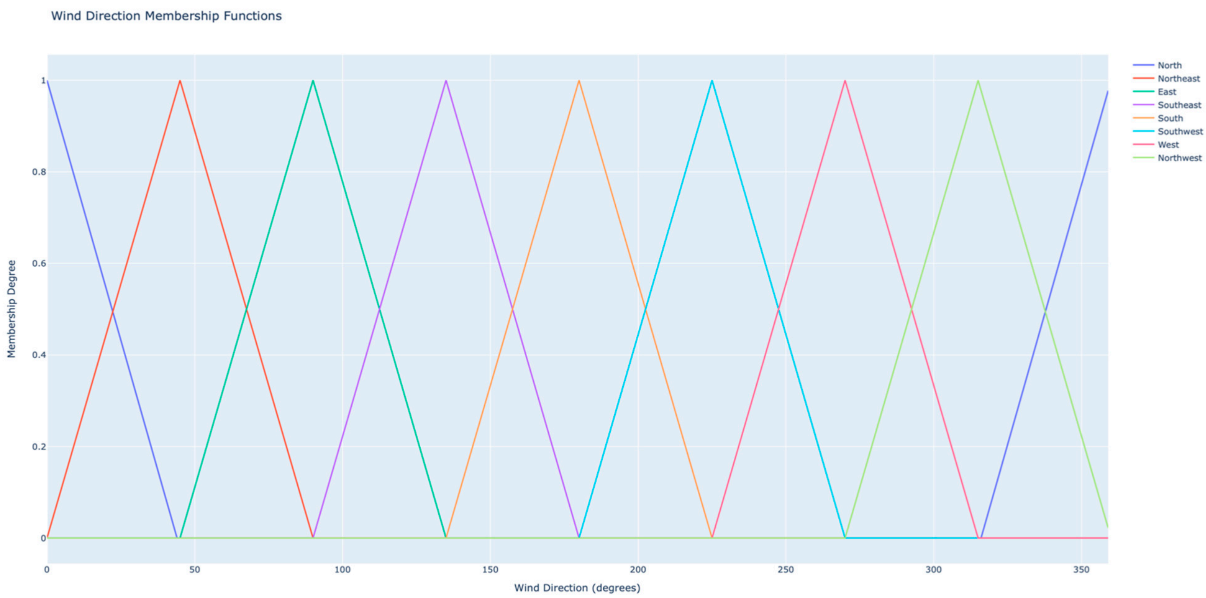


Figure 6. Graphical representation for simplified fuzzy membership for wind direction used by the outer ring drones.

Drones in the outer ring (scouts and outer edge)have been bundled with a simplified software fuzzy logic controller, an essential element that converts unprocessed wind speed and direction data into practical and useful observations. The fuzzy logic controller operates by performing the fuzzification process, in which accurate wind condition readings are classified into fuzzy values. Wind speed is categorized into specific levels, from 'No Wind' to 'Very Strong Wind', while wind direction is divided into sectors, such as 'North-Northeast' or 'Southwest'. It is, however, important to mention that the wind speeds could also be easily adjusted to follow the well-known Beaufort scale, despite it being known to be usually a very human-based fuzzy system that easily allows for such implementations and could be even further specified if needed but it was simplified due to simulation restraints.

The calculation procedure during our simulations incorporates membership functions that are simple linear representations but could also be built to precisely depict the nuances and fluctuations of wind behavior in following regions influenced by natural factors such as the presence of mountains or different atmospheric pressures. For example, a wind speed measurement of 15.1 m/s can be classified as both Moderate and Strong Wind' to different degrees, reflecting the inherent uncertainty in environmental conditions. After the wind data is subjected to fuzzification, the fuzzy logic controller employs a predetermined set of rules constructed based on pre-established guidelines. According to a system rule, when encountering a 'Moderate Wind' blowing from the southwest, the drone should increase its height and slightly adjust its formation towards the northeast. These rules are flexible and adjustable, refined by continuous observations and feedback from the environment, improving the system's accuracy and ability to respond.

The main advantage of the fuzzy logic system is its capacity to provide a range of potential actions, effectively handling the uncertainty present in real-life situations. Our swarm technique involves decision-making that goes beyond the boundaries of individual drones, creating a collaborative environment where the actions of one drone impact the collective movement of the entire flock. This collaboration guarantees that modifications made by individual drones in reaction to specific wind conditions are seamlessly incorporated into the collective movement plan of the drone flock. By employing fuzzy logic, wind measuring drones are capable of not only responding to immediate fluctuations in wind conditions but also of proactively predicting and adapting their actions to include the wind factor.

The rule set of the fuzzy logic system of the wind measurement drones is precisely crafted manually to handle diverse wind situations effectively. These criteria, derived from drone flight dynamics, are crucial in ensuring that the drones adjust their movements properly to uphold the integrity of the air pollution monitoring mission. However, those dynamics must be different based on the hardware used. The system has principles that adapt to variations in wind velocity, ranging from calm to strong winds. For example, if the system detects a 'Strong Wind' report, it will instruct the drone to ascend to reduce the effects of turbulence and maintain stable circumstances for precise sensor measurements.

In addition, rules based on wind direction are designed to enhance the drone's positional adjustments according to the identified wind direction. A directive may instruct a drone to make a modest adjustment in its location towards the southwest when it detects a northeastern wind. This adjustment would counteract the wind's effect and stabilize the drone's position, allowing for efficient pollution monitoring. The rule set has advanced protocols that consider both the velocity and orientation of the wind. These regulations offer subtle and detailed answers to intricate wind situations. If a 'Moderate Wind' is identified coming from the south, a rule may be triggered, instructing the drone to maintain its present height but move slightly northward. This will optimize the drone's capacity to monitor areas with concentrated pollution caused by wind patterns.

In addition, the regulations also consider the potential influence of wind conditions on the spread of pollution, which is vital for drones operating within urban areas to measure pollution levels accurately. There are numerous additional uses of those rule sets that are easier to write thanks to fuzzification and easier to maintain. For example, the drones on the outer edges could be directed to maintain their position on a given side of the group, considering specific wind patterns while moving to adjust the position of the flock on the other side. This would ensure that the drones collectively concentrate their efforts on locations with the highest pollution levels. In situations of very strong wind conditions, the system may incorporate emergency and safety processes as well. An established regulation may require drones to lower their height and limit their lateral motions in the presence of strong winds. This precaution significantly reduces the likelihood of destabilization or damage.

These regulations guarantee that the wind-measuring drones not only promptly react to current wind conditions but also adjust their actions to maximize the collective capacities of the entire group in monitoring air pollution. Each drone effectively contributes to the collective aim of identifying pollution sources with precision and dependability by addressing a wide range of environmental circumstances. Due to wind conditions being hard to specify in a single binary category, fuzzification of those input values into a fuzzy logic system, despite it being simplified, yields very satisfactory results.

It is important to note that the fuzzy system in this approach was implemented in a simplified form due to a lack of official modules available for microcontrollers, and scikit-fuzzy (also known as kfuzzy) modules rely on Numpy and SciPy modules, which are currently being ported towards microcontrollers, in case that this effort will be completed it is important to note that the implementation could yield even further benefits as we could implement reactions to measurements also based on fuzzy logic improving the precision of adjustments greatly.

3.5. System Performance

The successful incorporation of both edge drones and scout drones into the environmental monitoring system was crucial in swiftly and accurately identifying the sources of pollution. The cooperative interaction between these two categories of drones, coordinated by advanced algorithms, led to a remarkably effective and resource-efficient method for identifying pollution. This successful fusion was a significant turning point in the field of pollution detection technology, introducing a new era of adaptable and intelligent systems. The edge drones were deliberately placed at the boundaries of the search plane to serve as active guards that provide important fixed reference points against external factors, namely the unpredictable movements of the wind. Their stationary placements at uniform elevations allowed them to stabilize the entire system, acting as dependable indications of environmental disturbances produced by changing wind conditions. The real-time data on environmental changes played a crucial role in adapting the behavior and decision-making of the drone swarm.

4. Discussion

This study represents a notable advancement in the field of air pollution monitoring by combining swarm algorithms, notably the Carthaginian War Elephant Swarm Optimization (CWESO) method, with fuzzy system and drone technology. The favorable results and inventive approaches derived from this study create opportunities for future advancements in the realm of ecological preservation. The incorporation of edge drones played a crucial role in tackling the difficulties presented by ever-changing climatic conditions, such as wind dynamics. Nevertheless, further investigation could explore the optimization of edge drone deployment more extensively by taking into account variables such as altitude modifications, alternative positioning tactics, or the integration of supplementary sensors to improve data gathering.

Investigating the interaction between edge drones and other technologies, such as sophisticated weather prediction models, can enhance the algorithm's ability to adapt to practical situations [20]. Moreover, the utilization of fuzzy logic in controlling scout drones demonstrates the possibility of integrating more advanced decision-making systems. Potential future research might investigate the application of machine learning methodologies [21] to facilitate the acquisition and adjustment of strategies by drones, leveraging historical data and dynamic environmental circumstances. Implementing this adaptive learning strategy has the potential to improve the overall effectiveness and self-governance of the swarm system [22].

The effective amalgamation of swarm algorithms and drone technology in this work necessitates contemplating expanding the implementation. Examining the practicality of using bigger groups of drones in various geographical locations or urban settings could offer valuable information on the potential to expand and the strength of the suggested approach. Furthermore, the comprehensive understanding of global air pollution dynamics could be enhanced by investigating the potential combination of satellite data and widely accessible ground-based sensor networks in public areas. Recent research, such as the study "Boundary layer structure characteristics under the objective classification of persistent pollution weather types in the Beijing area" [23], sheds light on the importance of classifying persistent pollution weather types. This classification provides a framework for objectively characterizing atmospheric conditions, including the structure of the pollution boundary layer. The pollution boundary layer serves as a dynamic interface between the Earth's surface and the atmosphere, acting as a reservoir for various pollutants. The intricate interplay between meteorological factors and pollutant behavior within this layer can significantly influence the efficacy of air pollution algorithms. Therefore, a comprehensive discussion on the impact of pollution boundary layer structure is paramount to refining and optimizing algorithmic performance.

In the long term, by incorporating an in-depth analysis of pollution boundary layer characteristics into algorithms, we can enhance the adaptability of these models to diverse environmental conditions. Variations in boundary layer structure under different persistent pollution weather types in the Beijing area can offer valuable insights into how algorithms respond to specific atmospheric contexts. Understanding the influence of pollution boundary layer structure on algorithm performance is not merely an academic exercise; it holds practical implications for refining predictions and mitigating the impact of air pollution. As we dissect the intricacies of boundary layer dynamics, we pave the way for algorithms that are robust and responsive to the ever-changing atmospheric conditions they aim to model.

In conclusion, acknowledging and addressing the impact of pollution boundary layer structure in future work could play a pivotal role in advancing the capabilities of air pollution algorithms. By incorporating insights from studies on persistent pollution weather types, we aim to refine our understanding of how algorithms navigate the complexities of the boundary layer. This, in turn, will contribute to the development of more accurate and adaptable models for predicting and managing air pollution in urban landscapes, with implications extending beyond the Beijing area to global contexts.

Although this research's primary emphasis has been monitoring air pollution, the methods proposed in this study could be applied to tackle more extensive environmental issues. Potential future research could investigate using swarm algorithms and drone technology to monitor additional pollutants, evaluate ecological well-being [24], or assist in catastrophe response endeavors [25].

4.1. Limitations

Despite the many advantages of swarm intelligence, such as robustness, adaptability, and scalability, it also has limitations in its application to air pollution monitoring, as listed in Table 1. Overcoming or bypassing these will be a challenge for researchers in the years to come.

Table 1. Limitations and challenges (own analysis) [26,27].

Limitation	Scope of Limitation
Low data quality and quantity	Sensors may have limitations in terms of the types of contaminants they can detect and their sensitivity, plus some contaminants may require specialized and expensive sensors that may not be easily integrated into a swarm system.
	Sensor calibration is essential to ensure reliable and accurate measurements, which, with a large number of sensors, can lead to challenges in maintaining consistent calibration of a large number of sensors and inaccuracies in the data collected.
	The effectiveness of swarm intelligence depends on the spatial distribution and density of sensors, while in some areas, it can be difficult to achieve adequate coverage, especially in remote or inaccessible locations. The resulting gaps in spatial coverage can lead to incomplete and biased data, affecting the overall accuracy of pollution monitoring.
	In real-world environments with obstacles (e.g., terrain), signal interference or limited communication range, maintaining reliable communication links between swarm members can be challenging—this can result in delayed responses to changes in contamination levels and even data loss.

Table 1. *Cont.*

Limitation	Scope of Limitation
Vulnerability	Swarm systems can be susceptible to external factors (e.g., weather conditions), which can adversely affect sensor performance and reduce the reliability of data collected by the swarm.
Integration	Integrating data from multiple sensors can be challenging when handling different data sources and accurately representing overall air quality.
Energy and cost constraints	Energy limitations may restrict the duration of monitoring or the frequency of data transmission, impacting the ability to provide continuous and real-time monitoring.
	The initial investment in setting up a large-scale swarm intelligence system can still be significant (cost of sensors, communication infrastructure and maintenance); hence, budget constraints may limit the deployment of swarm systems in some areas.

Addressing the above constraints requires a coherent strategy and an interdisciplinary approach.

4.2. Future Research Directions

By exploring the directions listed in Table 2, scientists and engineers can contribute to the development of more robust, efficient and practical swarm intelligence solutions for monitoring air pollution, improving our understanding of air quality and supporting efforts to mitigate environmental impacts and improve air quality, particularly during the winter months.

Table 2. Directions for further research (own concept) [28–31].

Direction	Detailed Subsequent Tasks
Community awareness	• Stimulate the involvement of local communities in the implementation of swarm systems as part of promoting community participation in monitoring and tackling air pollution.
Development of technical solutions	• More advanced sensor technologies • Efficient communication protocols • Calibration issues • Energy-efficient solutions • Spatial optimization • Multi-modal data integration
Integration and interoperability	• Develop a framework for interoperability and cooperation between traditional monitoring methods and swarm systems to create a more comprehensive and reliable monitoring network.
Better decision-making processes	• Novel methods to enhance real-time decision-making in swarm systems. • Rapid response to changes in pollution levels, timely alerts or interventions.
Standardization and legal issues	• Explore the regulatory and policy implications of integrating swarm intelligence into air pollution monitoring. • Evaluate how swarm systems can contribute to evidence-based decision-making. • Identify desirable, from a strategic point of view, research directions.

Air quality monitoring will remain key to improving air quality for many years to come, especially in areas that require a calculated assessment of change and consistency to stimulate even small but continuous changes for the better [32–34].

5. Conclusions

This research serves as a scientific investigation and demonstrates a dedication to continuously seeking sustainable and effective resolutions for environmental obstacles. Through the integration of state-of-the-art technology and inventive algorithms, our objective is to tackle the current issues surrounding air pollution and provide the groundwork for a future in which technology plays a crucial part in fostering a more pristine and healthier environment. As we begin our efforts to create a more environmentally friendly globe, working together and consistently coming up with new ideas will be crucial in defining a future where we actively prevent environmental problems and make the dream of clean skies a reality.

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