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Improving the Lifetime of Wireless Sensor Networks for Air Quality Monitoring Using Metaheuristic Algorithms

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ABSTRACT

Wireless sensor networks (WSNs) are crucial for environmental monitoring, particularly for assessing air quality. However, optimizing energy consumption remains a significant challenge due to the limited energy resources of the sensor nodes, which adversely affects the network's performance and lifespan. This study aims to enhance the longevity and efficiency of WSNs by implementing metaheuristic algorithms, specifically Ant Lion Optimization (ALO) and Cheetah Optimization (CO), for effective energy management through clustering strategies. Utilizing simulations, we compared the performance of ALO against CO in terms of energy efficiency, network lifespan, and resilience within heterogeneous network conditions. The results indicate that ALO optimizes data transmission by reducing network traffic through efficient cluster communication. Additionally, ALO's scalability enables the network to adapt to changing sensor deployments, while data aggregation at the cluster head level further minimizes energy consumption. This load balancing ensures a more even distribution of energy usage, further ALO outperforms CO by extending network lifespan, improving energy management, and providing better scalability. The findings suggest that ALO is a robust approach for optimizing clustering and energy consumption in WSNs.

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INTRODUCTION

Air quality is one of the essential aspects in maintaining the health of society. Air pollution can lead to various health problems for humans, including respiratory diseases, cardiovascular diseases, cancer, and more (Kim et al., 2015). Pollution sources can be classified into two groups: natural and man-made. Natural sources, for example, can include dust and plant pollen, while human sources involve activities such as transportation, industry, and commercial activities (Santos et al., 2019). One of the main sources of air pollution in the country is emissions from mobile sources, especially vehicles (Pio et al., 2020). Various studies have examined the contribution of pollutant sources to air pollution (Abbas et al., 2021). Transportation plays a significant role in the emission of nitrogen dioxide (NO_2) and particulate matter (PM) (Monjardino et al., 2018). Emissions from industrial facilities include pollutants such as sulfur dioxide (SO_2), NO_2, and PM, which lead to a decrease in air quality.

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Studies indicate that there is a relationship between population density and air pollution in urban areas, but the findings are varied and often depend on the specific location and conditions (Chen et al., 2020). For example, researchers have shown that population density is generally associated with lower levels of air pollution and greenhouse gas emissions due to the more efficient transportation systems and reduced use of personal vehicles (Muñiz and Galindo, 2005; Yang et al., 2021). On the other hand, some studies suggest that higher population density in urban areas leads to increased air pollutant emissions (Schweitzer and Zhou, 2010; Wang et al., 2017). A review of the literature on the subject indicates that there are many complexities and challenges in studying pollutant sources and pollution emissions, which may be due to limited access to extensive information given the lack of recorded data in this field (Abdelzaher and Awad, 2022; Abdelzaher et al., 2023).

An effective approach to reduce this challenge is the use of online data monitoring networks, which are continuously developing with the advancement of technology (Rayalu et al., 2023). Due to advancements in wireless communication technology, the design and development of small and economic smart sensors, easy deployment of sensor nodes, wireless sensor networks (WSNs) have become an essential part of monitoring systems (Hassan et al., 2020). This is due to the ability of sensor nodes to operate in harsh environments, inaccessible areas without supervision, and the availability of various types of sensors such as chemical, optical, magnetic, thermal sensors, etc., leading to the emergence of wireless sensor networks of various sizes and even networks consisting of thousands of sensor nodes and multiple base stations (Amutha et al., 2022; Itaya et al., 2023).

Wireless sensor networks have been utilized in various fields such as environmental pollution monitoring stations, agriculture, surveillance of pollution levels in seas and rivers, and so on (Ketshabetswe et al., 2019). Despite all the applications, sensors have important limitations. The energy limitation is the most important challenge of sensor networks, which affects the overall performance and network lifetime (Kandris et al., 2020). Sensors usually have limited energy sources; however, technological advancements in this area have also contributed to energy supply from various methods such as solar energy (Fahmi et al., 2022). Nevertheless, considering the energy limitation constraint for monitoring networks is considered a logical matter. Therefore, the useful lifetime of the network can be a fundamental criterion for evaluating the network. This criterion depends on two factors: energy consumption during network operations and remaining energy in the network after operation (Sharmin et al., 2023).

One of the methods proposed to reduce the impact of challenges is the use of clustering approaches. Clustering mechanisms improve energy efficiency by grouping sensors into clusters with designated cluster heads that manage data collection and transmission. This enhances network performance by optimizing energy consumption, reducing traffic, balancing loads, and extending network lifespan. This approach, by utilizing a hierarchical structure, has the capability to manage the energy consumption of wireless sensor networks (Pal et al., 2024). In the hierarchical structure, the network is divided into different clusters. Each cluster consists of cluster member nodes and a cluster head (CH). The cluster head is a node responsible for collecting data from cluster members and transmitting the aggregated data to the base station (Sinde et al., 2020).

In most designed networks, the cluster head node sends information in a single step. However, other strategies have also been proposed to optimize energy consumption, where data can be sent to the base station in multiple stages (via auxiliary cluster head nodes) depending on the strategy used (Vijayan et al., 2024). The most important issue in clustering strategy is the selection of optimal cluster heads, which, based on the nature of the mathematical model, becomes an NP-hard problem (Gupta et al., 2022). Solving NP-hard problems requires searching in a vast space. Assuming N sensor nodes exist in the network, if there is a need to form K optimal clusters in the network, a combination of n and K search operations is required, which will be very time-consuming. Additionally, with the network expansion, challenges may arise.

Metaheuristic optimization algorithms have emerged as effective tools for enhancing network lifetime in IoT-based sensor networks by addressing energy constraints and optimizing routing (Malik et al.).

Kim et al. (2014) introduced the Ant Colony Optimization (ACO) algorithm called IC-ACO to improve the efficiency of wireless sensor networks. The proposed IC-ACO algorithm uses ant colony for data packet routing in wireless sensor networks. Furthermore, they compared the results of the IC-ACO algorithm with the LEACH protocol. Simulation results showed that the IC-ACO algorithm has a longer stability period compared to the LEACH protocol and performs better in energy efficiency in dense environments. Especially when the number of nodes increases from 100 to 200 or 300, the performance of the LEACH protocol decreases, while the performance of IC-ACO improves or remains stable. These two algorithms were compared based on parameters such as stability period and network lifetime.

Dixit and Jindal (2020) conducted a study on cluster-based routing protocols for air pollution monitoring using WSN. They utilized the (Clustering Protocol of Air Sensor System) CPAS method for clustering wireless sensor networks. This article explains how the use of a random controller for selecting each cluster, determining the cluster head (CH), the process of selecting sensor data, and communication distances. They also synchronize sensor performance in clusters and sensor cycle synchronization based on sensor types. The article examines the protocol for data aggregation based on data measurement distances, LEACH, designed for air quality monitoring. The goal of LEACH is to minimize data transmission for energy savings and improve network lifetime by reducing data communications and optimizing power consumption based on air quality conditions. Finally, they highlight the importance of efficient protocols such as CPAS and LEACH in monitoring air quality, reducing energy consumption, and enhancing network performance in wireless sensor networks.

A stable and intelligent energy-efficient pollution monitoring protocol using wireless sensor networks (IEESEP) was proposed by (Dixit and Jindal, 2022). The main goal of this research is to improve energy efficiency and reduce end-to-end delay in information transmission to the destination node in these networks. The proposed protocol (Intelligent Energy Efficient Stable Election Routing Protocol) IEESEP forms an optimal path in the network using the feedforward neural network algorithm with error backpropagation. This method improves by using an air pollution monitoring system (Intelligent Energy Efficient Stable Election Routing Protocol) trained on a large dataset. IEESEP protocol increases network stability using advanced and ordinary nodes and determines an effective threshold value for selecting the optimal path. The results showed that the packet delivery rate of the IEESEP protocol reaches 78%, while the delivery rates of other protocols such as SEP (Stable Election Protocol) and ELDC (Energy-Efficient and Robust Routing Scheme) are 50% and 27% respectively. The proposed protocol outperforms existing protocols in terms of energy consumption, packet delivery ratio, end-to-end delay, number of live nodes in each round of clustering, and overall performance efficiency.

Lin et al. (2020) introduced a novel approach for inter-cluster routing in wireless sensor networks aiming to enhance network lifetime. This method is designed based on Compressive Sensing (CS) theory and Economic Welfare Theory. During the intra-cluster phase, data is collected using Compressive Sensing theory to reduce the extra energy consumption caused by spatiotemporal correlation. The inter-cluster phase utilizes Economic Welfare Theory to balance energy consumption among different clusters. This article introduces a new concept called "energy welfare" and an inter-cluster routing method named EIREC. Comparison of results with existing strategies demonstrates the effectiveness of this approach in improving energy efficiency and increasing network lifetime through reducing energy consumption in the intra-cluster phase and establishing energy balance in the inter-cluster phase.

In this research, we explore advanced clustering algorithms, particularly ALO and CO, aimed at improving the energy consumption of Wireless Sensor Networks (WSNs). The main objectives ar as follow:

· To assess the potential of these algorithms to prolong the operational lifespan of WSNs by implementing effective energy management techniques that extend sensor functionality. A

· To systematically compare the performance of ALO and CO with traditional methods, such as the LEACH protocol, focusing on metrics like network stability, energy usage, and sensor durability in both homogeneous and heterogeneous environments.

Therefore, the research aims to create a comprehensive framework for the selection of optimal cluster heads, thereby enhancing cluster management strategies within WSNs. Additionally, to assess the efficacy of the proposed algorithms relative to previous research, the initial network configurations were derived from the work of (Kim et al., 2014), and the results were compared with those obtained in our study.

MATERIAL AND METHODS

This study investigates the application of innovative algorithms i.e. Iranian Cheetah Optimization (ICO) and Ant Lion Optimization (ALO) to enhance the performance and lifespan of wireless sensor networks (WSNs). The proposed approach integrates these algorithms within an energy consumption model and sensor clustering framework. Initially, it is assumed that the WSN nodes are randomly and uniformly distributed in the environment, with fixed positions and initial energy levels. The optimal number of clusters is calculated, and the network is clustered accordingly. The type of cluster (large or normal) is determined, and the optimal cluster head for each cluster is selected based on factors such as remaining energy, distance to the cluster center, and distance to the base station. In large clusters, primary and secondary cluster heads are identified, and network information is updated by calculating the energy of nodes and determining active and inactive nodes. The iteration process is stopped when the network energy is depleted (Figure 1). In the next phase, the study shifts to a heterogeneous WSN scenario, where sensors have different initial energy levels. The simulation follows the same steps as in the homogeneous case, allowing for a comparative analysis with the model presented by J.-Y. Kim et al. (2014).

• *Energy model*

The principles involved in designing clustering protocols include considering the sensing range, transmission, and neighbor set. In this study, we assume that the monitored area is a circle with a diameter of M meters. The following sections will define the fundamental concepts and present a commonly used energy model applicable in most protocols.

The sensing range of a sensor node s_i is represented as a circle or disk with a radius di, which includes its boundary. The sensor node is positioned at the center χ_i and is defined by a set of points (Xiuwu et al., 2019).

$$D(\chi_i, d_i) = \{\chi : |\chi_i - \chi| \le d_i\} \tag{1}$$

where $|\chi_i - \chi|$ denotes the Euclidean distance between the locations χ_i (the position of sensor s_i) and χ. The transmission range of a sensor node s_i is also a circle or disk with a radius R_i, including its boundary, where the sensor node is located at the center χ_i and is defined by a set of points.

$$D(\chi_i, R_i) = \{\chi : |\chi_i - \chi| \le R_i\} \tag{2}$$

The sensing and communication ranges in randomly distributed nodes are determined by

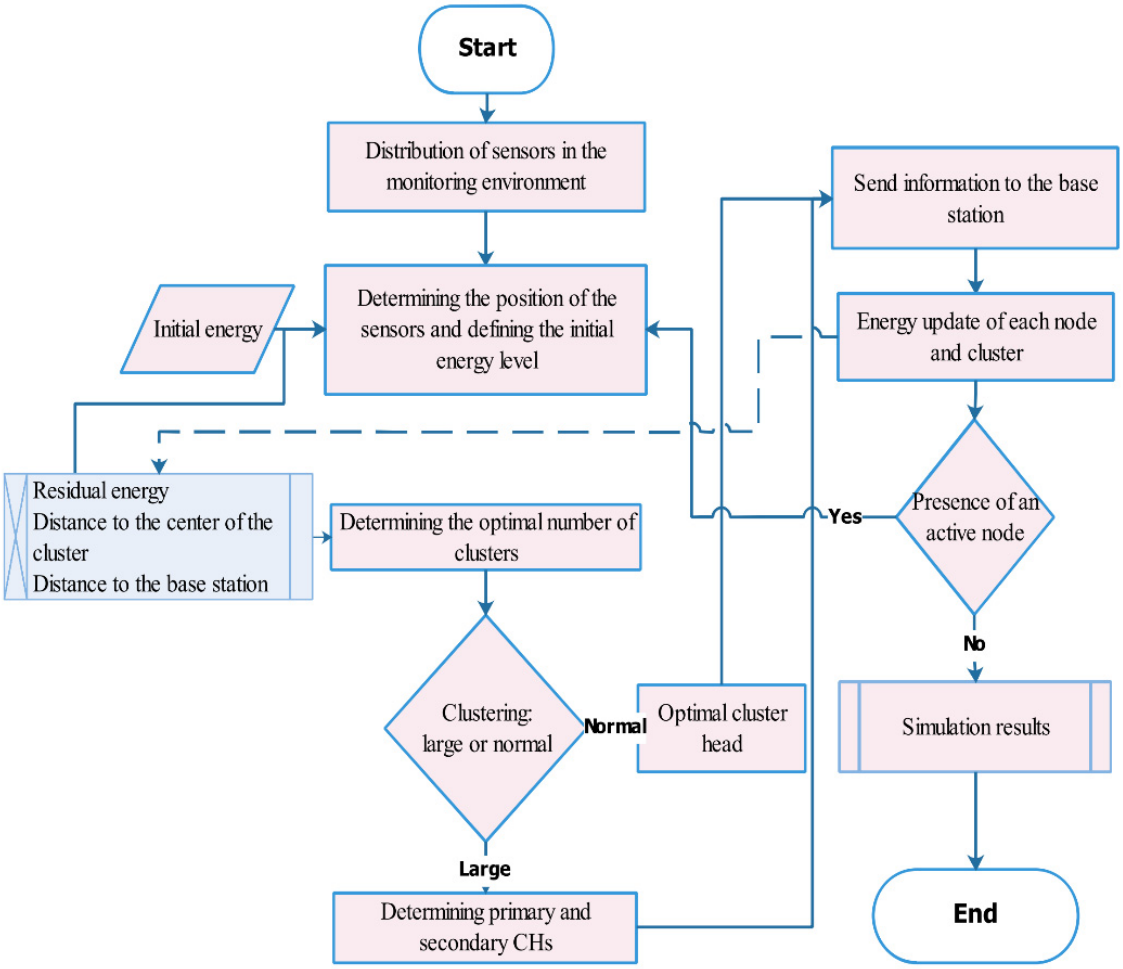

Fig. 1. Flowchart of simulation and problem solving process

the maximum distance between any two neighboring sensor nodes within a specified area. The distance between node i and node j is denoted by D(i,j), which is defined as:

$$D(i,j)=\sqrt{\left(x(i)-x(j)\right)^2+\left(y(i)-y(j)\right)^2} \quad (3)$$

where i,j = 1,2,3,…,N with i = j, and the terms (x(i), y(i)) and (x(j), y(j)) represent the coordinates of nodes i and j, respectively.

It can be assumed that energy consumption in sensors primarily relates to the transmission and reception of data. The energy expended in transmitting an n-bit message over a distance l, known as the transmission distance, is given by the following equation:

$$\Gamma_T=\left(\delta_{amp}l^{\kappa}+\Gamma_{elec}\right)n \quad (4)$$

In this equation, Γ_{elec} represents the energy consumed by the transmitter/receiver's electronic circuitry. Additionally, $\delta_{amp} \in \{\delta_{fs}, \delta_{mp}\}$ is the transmitter amplifier factor in free space δ_{fs} or the multi-path model δ_{mp}, and κ is the path loss exponent.

If $l \le l_0$, then κ =2; if $l > l_0$, then κ =4. Considering the energy consumption model, it can be expressed as follows (Matin, 2012):

$$\begin{cases} \Gamma_{\mathrm{T}}(n,l) = n\delta_{amp} l^2 + k\Gamma_{elec}, & if \quad l \le l_0 \\ \Gamma_{\mathrm{T}}(n,l) = n\delta_{mp} l^4 + k\Gamma_{elec}, & if \quad l > l_0 \end{cases} \tag{5}$$

Furthermore, the received energy is given by:

$$\Gamma_{\mathrm{R}} = n\Gamma_{\mathrm{elec}} \tag{6}$$

• *Clustering protocol*

In this section, the optimal number of clusters is determined through the proposed combined clustering algorithm with energy consumption-based optimization, and then the optimal cluster heads are identified. If the number of nodes in a cluster exceeds a certain value (large cluster), a secondary mechanism is activated to determine the cluster head with the aim of reducing active energy consumption. Subsequently, after data transmission, the energy update process takes place. The simplest method for clustering is to initially consider each sensor as a cluster, then calculate the distance between them, and based on the proximity of the sensors to each other, the process of combining and forming a new cluster occurs. This process continues until the number of clusters becomes equal to the optimal k clusters. The simplicity of this method is its most important advantage, and its disadvantages include being time-consuming and requiring extensive calculations in high-dimensional and large datasets. One way to reduce this challenge is to use the k-means clustering algorithm. In the k-means clustering method, a number of k optimal clusters are considered as centers. Then, sensors are assigned to a center based on their proximity to randomly selected centers. Subsequently, by averaging the position of each cluster's coordinates.

• *Cluster Head selection*

The concept of a "large cluster," defined by its energy consumption relative to the average energy consumed by other clusters, is explored in this research with the goal of reducing overall network energy consumption. The process of selecting a cluster differs between general clusters and large clusters. Generally, for a node to be selected as the Cluster Head (CH), it must satisfy three criteria: proximity to the cluster center, a short distance from the base station, and having more remaining energy compared to most other nodes. If we consider C as a hypothetical cluster, the optimal node for the cluster head is chosen based on the following objective function (Sharmin et al., 2023).

$$Z_{CH}\left(\Gamma r_{(i)},\ l_C^i,\ l_B^i\right) = \frac{\Gamma r_{(i)}}{\alpha\ l_C^i + \beta\ l_B^i} \tag{7}$$

where, $\Gamma r_{(i)}$ represents the residual energy of node i, l_C^i denotes the distance from node i to the center, l_B^i represents the distance from node i to the base station, and the coefficients α and β are corrective factors that sum to one. A higher value of Z_{CH} for node i increases the probability of it being selected as the cluster head.

For large clusters, the energy balance strategy involves selecting both a primary cluster head (F_{CH}) and a secondary cluster head (S_{CH}). A cluster is classified as a large cluster if the energy consumption of its cluster head exceeds one and a half times the average energy consumption of network cluster heads. The average energy consumption of cluster heads is calculated using equation 8.

$$\overline{\Gamma_{CH}} = \frac{N}{k}.n\left(\Gamma_{elec} + \Gamma_{DA}\right) + A.n$$
$$A = \frac{2\delta_{fs} l_0^4}{M^2} + \frac{\delta_{mp} M^4}{48} - \frac{4\delta_{mp} l_0^6}{3M^2} \tag{8}$$

Assuming that there are x nodes in each cluster, the energy consumption of the cluster is calculated from the following equation.

$$\Gamma = xn\left(\Gamma_{elec} + \Gamma_{DA}\right) + A.n \tag{9}$$

By determining the energy of each cluster and the average energy, the large clusters are identified. Then, the main cluster and the auxiliary clusters are selected. For example, in Figure 2, the sensor network consists of 5 clusters (2 large clusters and 3 general clusters). Compared to the general cluster, the member nodes in the large cluster collect environmental data and send it to the primary cluster. After sending the data to the secondary cluster, they are combined. The final data is sent to the base station for decision-making.

• *k-means algorithm*

The k-means method is an iterative clustering algorithm that involves partitioning a set of n elements into k clusters, where k is greater than or equal to 2. The members within a cluster exhibit similar characteristics, distinguishing them from members of other clusters. Let O = {x1,…,xn} represent a collection of n sensors that need to be clustered in the real number space based on a distance metric. Assuming the number of clusters is an integer, K = {1,…, k} denotes

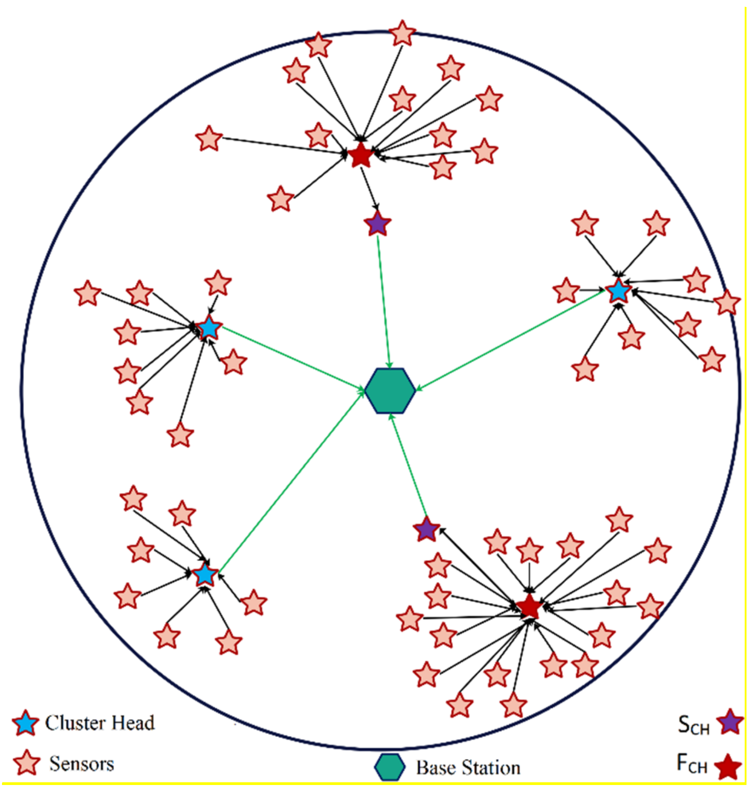

Fig. 2. A schematic representation of the combined strategy for selecting primary and secondary cluster heads (F_{CH} and S_{CH}).

the k clusters, and the clustering is represented as R = {P(1),…, P(k)}, with μj indicating the centroid of cluster P(j). Consequently, the vector of cluster centroids is denoted as M = {μ1,…, μk}, and W = {w11,…,wij} represents the membership vector for each cluster. This implies that wij = 1 indicates that sensor xi belongs to cluster P(j). If l(xi, μj) denotes the Euclidean distance between the sensor and the cluster centroid for i = 1,…,n and j = 1,…,k, the clustering problem can be reformulated as an optimization problem with the following objective function (Sinaga and Yang, 2020).

$$\text{Min } z\left(W,M\right)=\sum_{i=1}^{n}\sum_{j=1}^{k}\mathrm{w}_{\mathrm{ij}}\mathrm{l}\left(x_i,\mu_j\right)$$

St.

$$\left\{\sum_{j=1}^{k}\mathrm{w}_{\mathrm{ij}}=1,\quad \text{for i=1,...,n}\right. \tag{10}$$

A challenge encountered when employing the k-means algorithm is the lack of consideration for cluster size differences. Certain clusters may contain more nodes than others. A suggested strategy for this issue involves optimization through the application of heuristic algorithms. This research incorporates a combination of the k-means and heuristic algorithms to ensure an even distribution of sensors within the clusters.

• *Cheetah Optimizer*

The Cheetah Algorithm is designed based on the hunting behavior of cheetahs to solve optimization problems and resource allocation (Sharma and Kumar, 2023). This algorithm has numerous advantages such as simple modeling of the cheetah hunting process, reducing the number of initial populations, balancing between exploratory search and exploitation, considering below equations, preventing premature convergence in optimization problems (Akbari et al., 2022). The strategies of this algorithm include stalking and waiting for prey, attacking, returning home in case of failure, and using the latest successful hunt. Let χ_i represents the current position of cheetah i (where (i = 1, 2, ..., n)) in dimension (j) (where (j = 1, 2, ..., D)). Here, n is the number of cheetah populations and D is the dimension of the optimization problem.

$$X_{i,j}^{t+1}=X_{i,j}^{t}+r_{i,j}^{\wedge-1}\cdot\alpha_{i,j}^{t} \tag{11}$$

The next and current positions of cheetah in dimension j are indicated by $X_{i,j}^{t+1}$ and $X_{i,j}^{t}$. $r_{i,j}^{-1}$ and $\alpha_{i,j}^{t}$ are randomization parameter and step length for cheetah i in dimension j, respectively. If a cheetah spots prey, it may ambush. Therefore, in this case, the cheetah remains in its position and waits for the prey to come closer. The cheetah uses speed and agility in the attack to catch the prey. Each cheetah can adjust its position based on the fleeing prey and the position of the leader or neighboring cheetah.

$$X_{i,j}^{t+1}=X_{B,j}^{t}+r_{i,j}\cdot\beta_{i,j}^{t} \tag{13}$$

$X_{B,j}^{t}$ is the current position of the prey is in dimension j. In other words, it represents the optimal current position of the population. Additionally, $r_{i,j}$ and $\beta_{i,j}^{t}$ are the rotation factor and the interaction factor associated with cheetah i.

• *Ant Lion Optimizer*

The Ant Lion Optimization (ALO) algorithm is inspired by the hunting behavior of ant lions in nature (Mirjalili, 2015). This algorithm is a heuristic method used to solve complex optimization problems (Behnamfar et al., 2021). In fact, ants move randomly in the search space. The following equation is used to model the movement of ants:

$$X^t = \left[0,\ C(2r^{t_1}-1),...,C(2r^t)\right] \tag{13}$$

where C is the cumulative sum function, n is the maximum number of iterations, t is the random walk step, and r(t) is a random function.

$$r^t = \begin{cases} 0 & if\ \ rand \le 0.5 \\ 1 & if\ \ rand > 0.5 \end{cases} \tag{14}$$

The positions of the ants during optimization are stored in the matrix (M).

$$\mathbf{M} = \begin{bmatrix} \mathrm{A}^{1,1} & \cdots & \mathrm{A}^{1,\,d} \\ \vdots & \vdots & \vdots \\ \mathrm{A}^{n_A,1} & \cdots & \mathrm{A}^{n_{A,d}} \end{bmatrix} \tag{15}$$

where n is the number of ants and d is the number of variables. The random movement function of the ants is as follows:

$$X^{t,i} = \left[\left(\frac{1}{\left(d^{,i}-a^i\right)}\right)\left(\left(X^{t,i}-a^i\right)\left(b^i-c^{t,i}\right)\right)\right]+c^i \tag{16}$$

where a^i is the minimum random step of variable i and b^i the maximum random walk in variable c.

$$\begin{aligned} c^{t,i} &= \mathrm{Al}^{t,j} + c^t \\ \mathrm{d}^{ti} &= \mathrm{Al}^{t,j} + \mathrm{d}^t \end{aligned} \tag{17}$$

RESULTS AND DISCUSSION

We supposed that the network model consists of 100 sensor nodes in a circular area with a diameter of 100 units randomly distributed, with the base station located at the center of the network area. Energy consumption at the base station and the process of transmitting control messages for cluster formation and cluster head identification are not considered. The model is compared for homogeneous and heterogeneous scenarios by comparing the performance of two optimization algorithms introduced. Figure 3 shows the distribution of sensors in the hypothetical monitoring area. Additionally, Table 1 presents the parameters considered for this network.

Figure 4 presents a comparison of the simulation results for the sensor network utilizing the Cheetah and Ant Lion algorithms, focusing on a homogeneous network with an initial energy level of 0.5J.

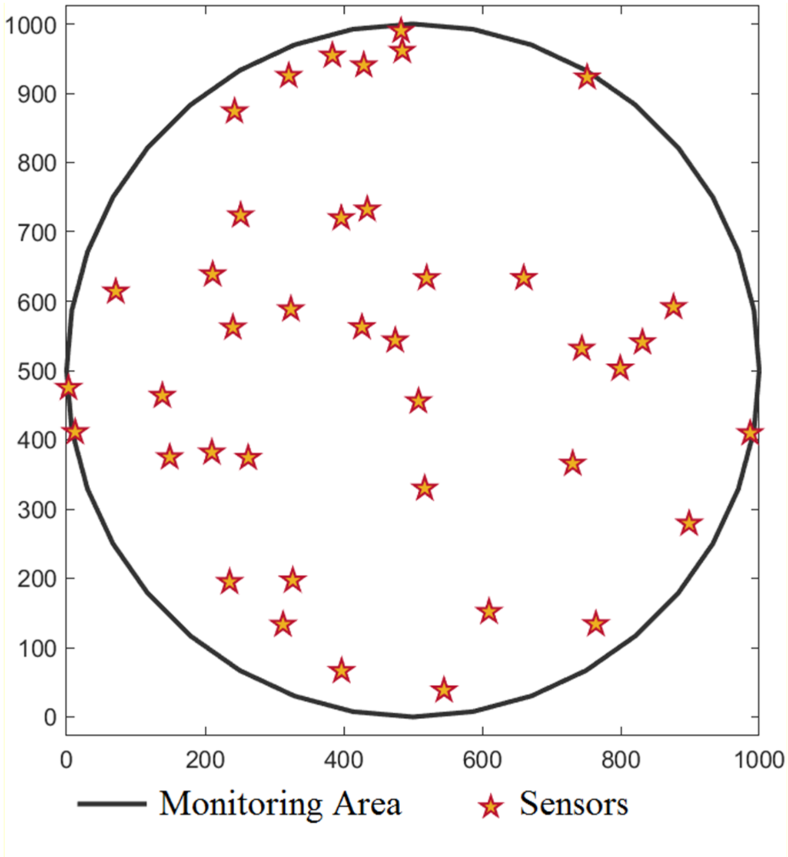

Fig. 3. Distribution of sensors in the monitoring area.

Table 1. Initial Values of Simulation Parameters

Parameter	Value
Γ_{elec}	50 nJ/bit
Γ_{DA}	5 nJ/bit/message
δ_{fs}	10 pJ/bit/m²
δ_{mp}	0.0013 pJ/bit/m⁴
Message Size	4000 bits
Initial Energy	0.4~0.6 J (0.5 J)

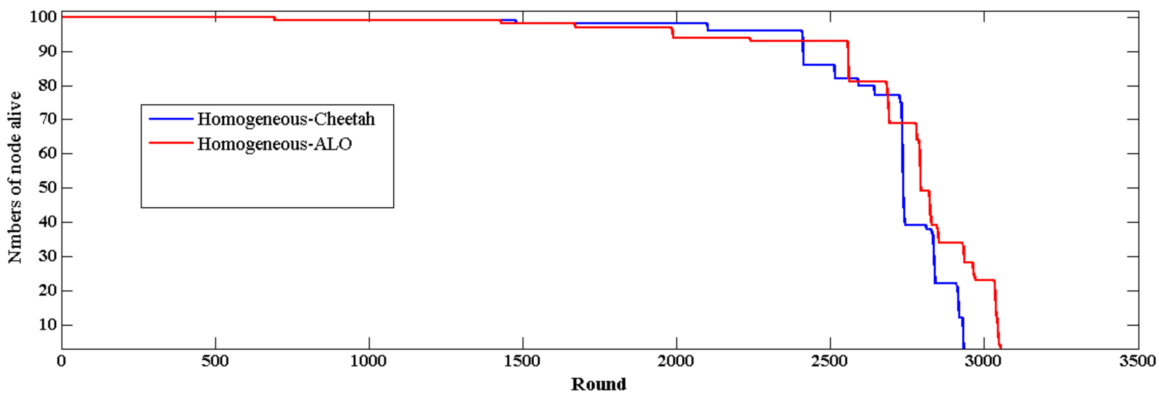

Fig. 4. Performance of the Cheetah (CO) and Ant Lion (ALO) algorithms in terms of the percentage of sensors alive in a homogeneous network.

As can be seen, the Ant Lion algorithm outperforms the Cheetah algorithm in extending the network's longevity by sustaining a greater proportion of active sensors. The performance of both algorithms is relatively comparable during the first 1600 simulation rounds. Furthermore, at approximately the 600th round, both algorithms successfully maintain around 95 percent of the sensors in operation. This level of performance for the Ant Lion algorithm continues until about the 2500th simulation round. In the concluding phases of sensor energy depletion, both algorithms exhibit similar behavior. Figure 5 illustrates the energy consumption pattern of the network throughout the simulation process.

As illustrated in the figure, the Ant Colony algorithm demonstrates superior performance in energy management within the network, effectively controlling energy consumption from round 1000 onwards. Figure 6 presents the performance results of both the Ant Colony algorithm and the Cheetah algorithm in a heterogeneous network. In this heterogeneous scenario, it is assumed that the initial energy of the sensors is randomly distributed uniformly within the range of 0.4 to 0.6 joules.

It is evident from the figure that the Ant Colony algorithm outperforms the Cheetah algorithm in extending the overall lifespan of the network. However, the Cheetah algorithm manages to keep approximately 40 percent of the sensors operational until around round 3000, while the Ant Colony algorithm is only able to maintain about 15 sensors during this iteration. Upon examining Figure 6, it becomes clear that the algorithm's performance in the heterogeneous state is weaker compared to the homogeneous state, with a difference of approximately 150 simulation rounds in the energy depletion of the Cheetah algorithm. In contrast, this difference

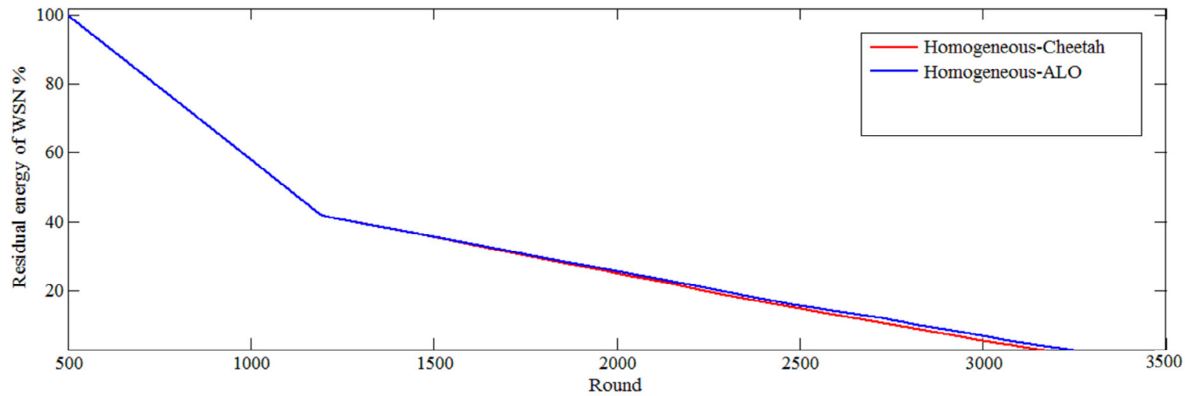

Fig. 5. Performance of the Cheetah (CO) and Ant Lion (ALO) algorithms in terms of the residual energy in the homogeneous network.

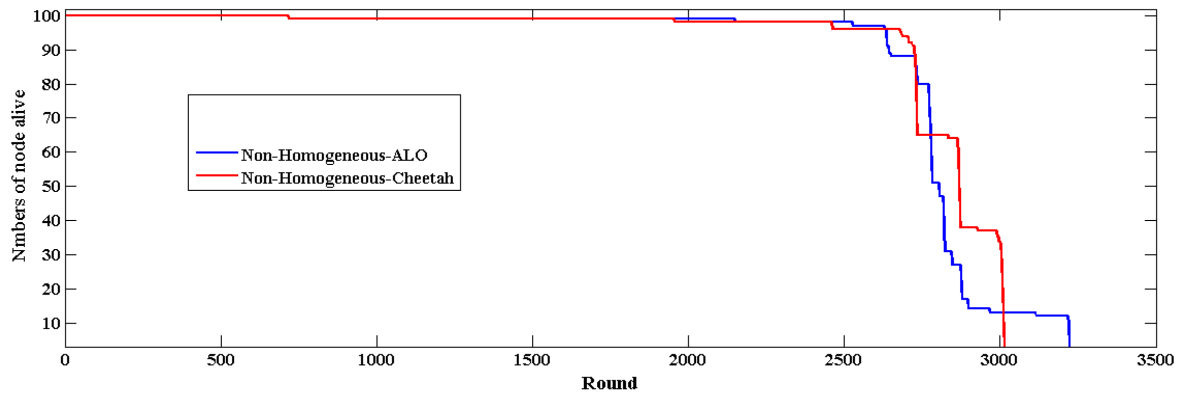

Fig. 6. Performance of the Cheetah (CO) and Ant Lion (ALO) algorithms in the heterogeneous network.

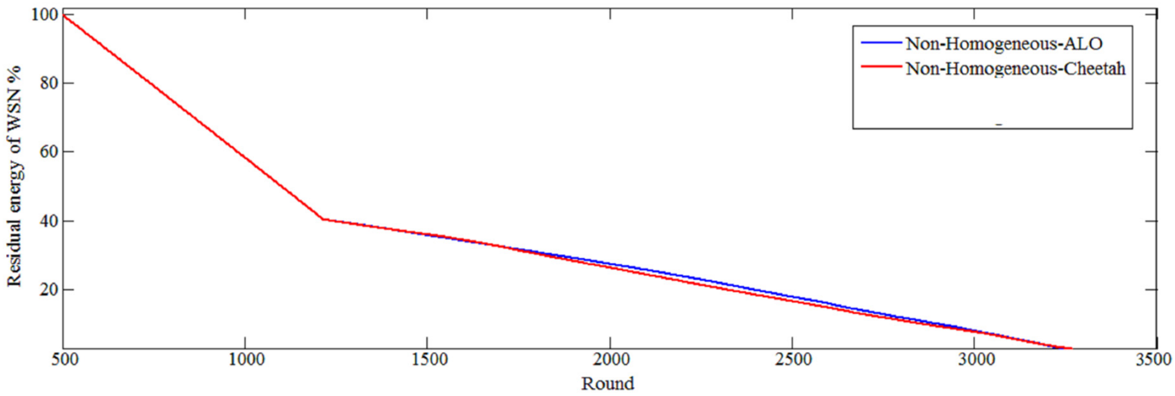

Fig. 7. Performance of the Cheetah (CO) and Ant Lion (ALO) algorithms in terms of the residual energy in the heterogeneous network.

Table 2. Comparison of Algorithm Performance in Network Simulation

round/% / Algorithm	1500 (simulation round)		2500 (simulation round)		60%
	Sensors Alive (%)	Residual Energy (%)	Sensors Alive (%)	Residual Energy (%)	Simulation round
LEACH	2	0.5	0	0	827
IC-ACO	17	6	6	6	1144
Cheetah (CO)	99	39	86	24	2733
Ant Lion (ALO)	99	41	93	25	2789

in the lifespan of the network for the Ant Colony algorithm is around 100 simulation rounds. This observation also holds true for the remaining energy consumption within the network. Regarding the remaining energy, it is noteworthy that the rate of energy reduction in the heterogeneous network is consistent, which may indicate the algorithm's capability.

• *Performance of the proposed algorithms*

The comparison of the performance of the proposed algorithms with the research conducted by J.-Y. Kim et al. (2014) highlights a method for evaluating the efficiency of algorithms in network simulation by examining energy consumption and network stability across various iterations.

One of the methods for comparing the performance of algorithms in network simulation is to examine the energy consumption and network stability in different iterations. Additionally, a threshold of 40 percent energy depletion among sensors is utilized as another criterion for assessing network status. Table 2 presents the results obtained from the simulation of the proposed algorithms alongside the referenced research.

LEACH algorithm demonstrated poor performance in maintaining active sensors and residual energy during both the 1500 and 2500 simulation rounds. Notably, at the 2500 round, no sensors remained alive, and energy was entirely depleted. The IC-ACO algorithm performed better than LEACH; however, it still yielded inferior performance compared to other algorithms. In both the 1500 and 2500 simulation rounds, the percentage of remaining active sensors and residual energy was similarly low. Conversely, the Cheetah algorithm exhibited acceptable performance in preserving active sensors and remaining energy. In the 1500 simulation round, 99 percent of sensors remained operational, with 39 percent of energy still available. In the 2500 simulation rounds, 86 percent of sensors were still active, and 24 percent of energy was retained. The Ant Lion algorithm achieved the best performance among all algorithms tested, with 99 percent of sensors remaining alive and 41 percent of energy available in the 1500 simulation round.

The examination of network stability when 40% of the sensors are lost indicates that the Ant

Colony Algorithm with 2789 simulation rounds performed the best and has the capability to create a stable network by optimizing energy consumption. The IC-ACO algorithm achieves approximately 50% of the performance of the two proposed algorithms in this study.

In this research, the performance of the Ant Lion Optimization (ALO) and Cheetah Optimization (CO) algorithms were assessed in relation to wireless sensor networks (WSNs) designed for air quality monitoring. The findings revealed that ALO consistently has a better performance compared to the CO in terms of network longevity, energy management, and resilience across both homogeneous and heterogeneous sensor environments. The simulations indicated that ALO sustains a greater number of active sensors over time, highlighting its effective energy management strategies. This observation is consistent with existing literature that acknowledges the importance of energy optimization in prolonging the operational lifespan of WSNs (Sharmin et al., 2023). Conversely, the Cheetah algorithm showed limited efficacy, particularly under increased sensor load, underscoring the urgent need for adaptive and robust energy management solutions in WSNs.

A significant observation was the performance difference between homogeneous and heterogeneous network configurations. The ALO algorithm exhibited enhanced scalability and adaptability, which is particularly advantageous in heterogeneous scenarios where sensor energy levels can vary significantly. This finding supports the relevance of adaptive clustering strategies, which have been suggested in previous studies as a means to improve the stability and performance of WSNs (Dixit and Jindal, 2022; Lin et al., 2020). Additionally, clustering protocols were identified as crucial for optimizing energy consumption and enhancing network stability. The results reinforce theories that effective clustering can alleviate energy constraints within the network and improve overall performance (Pal et al., 2024). The careful selection of cluster heads, based on remaining energy and proximity metrics, was found to be vital in minimizing data transmission costs, a phenomenon also noted in the context of metaheuristic optimization in earlier research (Kim et al., 2014).

CONCLUSION

The results of this research significantly enhance the theoretical framework of wireless sensor networks (WSNs) in the context of air quality monitoring. By illustrating that the Ant Lion Optimization (ALO) algorithm substantially surpasses conventional techniques, such as Cheetah Optimization, this study emphasizes on the application of metaheuristic strategies in environmental monitoring. The suitable performance of ALO in managing energy consumption and extending network longevity indicates its potential for real-world applications, driving efficiency in sensor deployments and improving data reliability. A crucial insight derived from this study is the paramount significance of energy optimization within WSNs. The research acknowledges that clustering not only improves energy efficiency but that the careful selection of cluster heads can lead to considerable enhancements in overall network functionality. Furthermore, the adaptability of ALO in diverse environments is another essential takeaway, showcasing how customized algorithms can effectively address prevalent challenges associated with varying sensor node capabilities and environmental conditions. Nevertheless, it is important to recognize several limitations within this study. Primarily, the focus was narrowed to a limited number of metaheuristic algorithms; future investigations could gain from incorporating a wider array of optimization methods for a more comprehensive comparative analysis. Additionally, while the simulations yielded valuable findings, they may not entirely reflect the complexities encountered in real-world scenarios, where factors such as sensor malfunctions and environmental variability could impact results. Lastly, the scalability assessments conducted under different network configurations were limited, necessitating further investigation to evaluate the robustness of the ALO algorithm in larger-scale deployments.

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CONFLICT OF INTEREST

The authors declare that there is not any conflict of interests regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/ or falsification, double publication and/or submission, and redundancy has been completely observed by the authors.

LIFE SCIENCE REPORTING

No life science threat was practiced in this research.

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