

Atomic Energy Optimization for Wireless Sensor Network Clustering (AEOWSNC) Protocol for Energy-Efficient Wireless Sensor Networks

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ABSTRACT

This paper presents AEOWSNC (Atomic Energy Optimization for Wireless Sensor Network Clustering), a novel clustering protocol for Wireless Sensor Networks (WSNs), designed to optimize energy efficiency and extend network lifetime. Inspired by Atomic Energy Optimization (AEO), the algorithm aims to address key challenges in WSNs, such as efficient energy usage, live node maintenance, and ensuring high throughput to the Base Station (BS). AEOWSNC is evaluated through a series of experiments and its performance is compared with the ones of eight well-established meta-heuristic protocols, namely LEACH, LEACH-PWO, GWOC, CGC, LEACH-SAGA, PSO-ECHs, SA-LEACH, and PSCH-CH. The results demonstrate that AEOWSNC outperforms the other protocols in terms of network lifetime, residual energy, live nodes, and throughput at the BS. The protocol achieves superior energy management, prolonging the network's operational life while maintaining a high data transmission rate.

Keywords-WSNs; energy efficiency; network lifetime; clustering protocols; meta-heuristic algorithms; atomic energy optimization

I. INTRODUCTION

In recent years, the widespread adoption of sensor networks in various applications has made them a key technology in the field of wireless communications. The increasing use of sensor networks in fields ranging from environmental monitoring to industrial automation and healthcare has significantly contributed to their growing importance [1]. A sensor network typically consists of a large number of sensor nodes densely deployed over a sensing area, either manually or randomly, depending on the specific application requirements [2-3]. These devices, though inexpensive, serve as the fundamental sensing units in the network. Their primary function is to monitor environmental variables or physical phenomena and transmit the collected data to a central sink node or Base Station (BS)

via wireless communication [4]. The BS acts as the central control unit, which processes the data, sends commands, and integrates relevant information from the sensors. The BS can be a central node or a peripheral node. Regardless of its role, communication between the nodes and the BS tends to be energy-intensive, impacting the overall efficiency of the network [5].

In a typical cluster-based Wireless Sensor Network (WSN) architecture, nodes are grouped into clusters, with each cluster having a designated Cluster Head (CH). The CH is responsible for collecting data from the sensor nodes and forwarding it to the BS, eliminating redundancy and optimizing data transmission. This type of network structure is widely adopted due to its adaptability and simplicity in data collection and

management [6]. By segmenting the network into clusters, the lifetime of the network is extended, as the CHs reduce the number of direct transmissions to the BS, effectively conserving energy in individual sensor nodes. Typically, the assignment of CHs is performed using a distributed algorithm, where the CHs are chosen randomly in each round [7-8]. After the CHs are selected, the remaining sensor nodes join the nearest cluster based on signal strength. Once the nodes are assigned to their respective CHs, they begin sensing and transmitting data, which is then collected, compressed, and transmitted to the BS. Despite their simplicity and effectiveness, clustering techniques in WSNs have limitations that can hinder their performance in some applications [9-11]. Some of these limitations include:

- **Energy Imbalance:** High-energy and low-energy have the same probability of becoming CHs, potentially leading to inefficient energy usage and faster depletion of battery life.
- **Uneven Cluster Distribution:** In some protocols like LEACH (Low-Energy Adaptive Cluster Head) [12], the number of CHs is not evenly distributed across the network. Additionally, the positions and quantities of channels in each round may not be optimally determined, leading to inefficient channel distribution and communication.
- **Inefficient Routing:** The lack of consideration for the distance between nodes and the BS during data transmission can lead to unnecessary energy consumption.

To overcome these challenges, researchers have explored various optimization techniques aimed at improving hierarchical clustering. These approaches often use factors like energy levels and distance to reduce energy consumption [13]. Metaheuristic strategies such as Simulated Annealing (SA) [14], Particle Swarm Optimization (PSO) [15], Genetic Algorithm (GA) [16], and Gray Wolf Optimization (GWO) [17] have emerged as promising methods for optimizing clustering protocols and minimizing energy usage [1]. For instance, authors in [18] introduced LEACH-PWO, a novel methodology designed to address routing and aggregation challenges in WSNs. LEACH-PWO integrates PSO and Wolf Search Optimization (WSO) to enable energy-efficient routing and data aggregation. During the initial setup, PSO is crucial in selecting the optimal CH and forming clusters based on energy and distance parameters. PSO then updates node positions and velocities to reflect the best global solution, ultimately determining the CH selection. Interconnections between CHs are established to route information to the BS. WSO is used to select interconnecting nodes that facilitate the relay path within the first cluster. The hybrid PSO-WSO approach enhances energy-efficient data routing and mitigates CH failures through periodic re-selection. However, this protocol may impose a computational burden on relay nodes.

Similarly, authors in [19] introduced SA-LEACH, an innovative integration of the SA algorithm with the LEACH protocol to enhance network lifespan and throughput. The SA-LEACH protocol improves the cluster head selection process in wireless sensor networks. Initially, LEACH selects CHs in each round, but the SA algorithm is used to optimize this selection by exploring better solutions. If improved candidates

are found, the nodes are replaced with the better ones to optimize clusters. The selection process considers factors such as the node's residual energy, which is calculated using a fitness function that accounts for the energy consumed during data transmission to the cluster head and the energy used by the cluster head during data reception.

In [20], the authors introduced a contribution based on SA to enhance the Percentage Selection of CH Simulated Annealing (PSCH-SA) approach, aimed at stabilizing the network and minimizing energy consumption. In each round, a percentage of CHs in the network is calculated. Since the groups are pre-determined, SA is used to select the optimal CHs. The selection process considers the remaining energy of the nodes and the distance between them using a fitness function. The objective function of the SA algorithm is based on the remaining energy of the sensor nodes, accounting for the energy consumed during each round of data transmission. This includes the energy used by sensors to transmit data to the CHs, the energy consumed by CHs during data reception, and the energy expended during data transfer from CHs to the BS. The results show significant improvements in data transmission rates and a reduction in the total energy consumed across the network.

The introduced Atomic Energy Optimization for Wireless Sensor Network Clustering (AEOWSNC) novel protocol is based on the Atomic Energy Optimization (AEO) algorithm. Inspired by natural processes, this optimization technique addresses the shortcomings of traditional clustering approaches, particularly in terms of energy efficiency and network lifetime. By leveraging the principles of atomic energy dynamics, the proposed AEOWSNC protocol aims to enhance energy saving and extend the operational life of WSNs. The paper makes several contributions to the field of WSNs:

- It introduces AEOWSNC, a novel clustering protocol based on the AEO algorithm, inspired by nature, that optimizes energy consumption and extends network lifetime.
- It provides a detailed comparison of AEOWSNC with eight different meta-heuristic-based clustering methods, including LEACH, LEACH-PWO, GWOC, CGC, LEACH-SAGA, PSO-ECHs, SA-LEACH, and PSCH-CH
- It evaluates the performance of the proposed protocol through metrics such as network lifetime, residual energy, live node count, and throughput at the BS, demonstrating its effectiveness over existing methods.
- It identifies and addresses the limitations of traditional clustering techniques, such as energy imbalance and inefficient routing, and explains how AEOWSNC mitigates these issues.

II. ATOMIC ENERGY OPTIMIZATION

The AEO algorithm is a novel metaheuristic optimization technique inspired by the dynamics of atomic energy and electrostatic discharge processes, as explored in [21]. This algorithm simulates the behavior of atoms, particularly the energy dissipation and accumulation processes, to find optimal solutions for complex optimization problems. The foundational

concept is rooted in the physical phenomenon where friction between two materials causes an imbalance, leading to the transfer of charge (electron hopping) between them. As the system seeks to return to a stable state, energy dissipation plays a central role, making this process a perfect analogy for the AEO algorithm's functioning.

In the AEO algorithm, the "atoms" represent potential solutions to the optimization problem, and "electrons" express the energy state of these solutions. The transfer and dissipation of energy between atoms simulate the optimization process, where the system progressively seeks the optimal state. The deviation from the stable state is determined by the energy acquired by the electrons—the greater the deviation, the higher the energy that must be dissipated. Fixed properties of the solution, such as the atom's position, are modeled similarly to protons, maintaining a constant charge throughout the optimization process. Meanwhile, neutrons are represented by factors that preserve the overall structure of the solution, ensuring stability within the system.

At the initialization stage, the algorithm mimics the physical process of rubbing two surfaces together, causing the atoms (solutions) to gain excess energy, furthering their divergence from the ideal state. This energy difference between solutions ensures diversity in the population, allowing for a broader exploration of the search space and optimal solutions. Each atom is initialized with two key features: a solution vector x_i (representing its position in the search space) and its initial energy E_i . This energy difference encourages the solutions to explore various parts of the search space. The optimization process then begins, and the system moves toward the optimal solution by transferring energy among atoms. The strength of interactions between solutions is influenced by their proximity, ensuring that closer solutions exchange information more effectively.

Key to the AEO algorithm's success are several hyperparameters that govern the optimization process:

A. Energy Transfer Coefficient (α)

This parameter controls the rate of energy transfer between solutions. It dictates how fast high-energy solutions (i.e. less optimal solutions) converge to more ideal states. The energy change between two interacting solutions is given by:

$$\Delta E_i(t) = \alpha \times W_{i,j} \times (E_i(t) + E_j(t)) \quad (1)$$

$$W_{i,j} = 1/(1 + distance_{i,j}) \quad (2)$$

where $W_{i,j}$ represents the weight based on the distance between solutions i and j . Solutions that are closer to each other interact more intensely. The change in energy ΔE_i reflects how the solutions evolve during the optimization process.

B. Step Size (β)

The step size defines the extent of changes during the optimization process. This parameter adjusts the movement of solutions in the search space based on the gradient of the objective function (3). Larger values of β accelerate exploration, while smaller values allow for more accurate convergence but with slower exploration.

$$x_{i,k}(t+1) = x_{i,k}(t) - \beta \cdot \Delta E_i(t) \cdot \frac{\Delta f(x)}{\Delta x_{i,k}(t)} \quad (3)$$

where:

- $x_{i,k}(t)$ and $x_{i,k}(t+1)$ are the k^{th} old and new component of an atom x_i ;
- $\frac{\Delta f(x)}{\Delta x_{i,k}(t)}$ is the finite difference of an atom's objective function after applying a small perturbation on the k^{th} component of an atom x_i .

C. Dissipation Factor (γ)

The dissipation factor governs the rate at which energy is dissipated over time, preventing premature convergence. By adjusting the dissipation rate, the algorithm ensures that solutions maintain energy for sufficient iterations, which encourages prolonged exploration and prevents the system from settling prematurely into suboptimal solutions. The energy update equation is (4):

$$E_i(t+1) = E_i(t) - \gamma \times \Delta E_i \quad (4)$$

III. THE PROPOSED ALGORITHM

The proposed method introduces AEOWSNC, a novel method designed to address the fundamental challenges in the deployment of WSNs, particularly focusing on energy efficiency and optimal cluster formation. AEOWSNC leverages principles derived from AEO to dynamically select CHs and minimize network communication costs. The underlying methodology utilizes energy transfer and dissipation processes inspired by atomic interactions, providing an innovative framework for efficiently exploring and exploiting the solution space in WSN clustering. In AEOWSNC, each node is modeled as an atom with a distinct energy level. The algorithm mimics the natural tendency of atoms to reach stable energy states through interaction and energy dissipation, ultimately ensuring optimal cluster configurations and energy-efficient communication within the network. This modeling approach offers a unique perspective on clustering optimization in WSN, where the goal is to minimize energy consumption while maintaining the efficiency of the clustering process.

A. Initialization Phase

The AEOWSNC algorithm begins by receiving as input a set of n nodes in a WSN. The goal is to optimize the clustering of these nodes in a way that minimizes energy consumption while ensuring effective data transmission. The algorithm proceeds by checking if all nodes in the network have consumed their energy. If any nodes are still active, the algorithm continues with the clustering process. If all nodes are dead, the algorithm terminates.

The first step in the process is to generate m V_i vectors, each with length n , where each component of the vector is randomly assigned a value of either 0 (indicating a regular node) or 1 (indicating a CH). These vectors represent different configurations for the clustering problem, with each vector treated as an atom in the network. By treating these vectors as "atoms," we can model each configuration as a possible solution to the problem, where the energy levels associated

with these atoms dictate their potential effectiveness in solving the clustering problem.

B. Clustering Phase using AEO

Next, the algorithm initializes the parameters α , β , and γ , which represent key factors in the optimization process. α controls the energy transfer coefficient, determining how energy is exchanged between nodes based on proximity and energy state. β adjusts the step size, which controls how far nodes move within the solution space, and γ is the dissipation factor that regulates how energy is dissipated from the system, ensuring that exploration and exploitation are balanced throughout the optimization process.

After initializing these parameters, the algorithm generates a random position for each atom in the search space, representing the initial configuration of the network. Each atom's energy state is then checked to determine if all atoms have zero energy. If they do not, the algorithm proceeds with calculating the interaction weights between atoms based on their positions and energy states. These weights are used to model how the atoms interact with each other, with closer atoms interacting more strongly. The energy transfer between these atoms is calculated, and the positions of the atoms are adjusted accordingly to simulate the transfer and dissipation of energy in the network. At this stage, the fitness of each atom is evaluated using the defined objective function (5), which considers the distance between nodes, CHs, and the BS:

$$F = \sum_{i=1}^{CH_n} distance(CH, BS) + \sum_{i=1}^N distance(members, CH) \quad (5)$$

The fitness function helps determine which configuration of atoms is closest to the optimal solution for the network's clustering. The best atom, which represents the most efficient clustering configuration, is saved as A_{best} , guiding the optimization process moving forward. To further refine the clustering solution, the algorithm applies energy dissipation to the atoms, reducing their energy in accordance with the dissipation factor γ . This step ensures that less optimal solutions gradually lose energy, leaving only the most promising configurations to drive the next iteration of the algorithm. Through this process, the algorithm iterates towards the optimal solution, where the energy dynamics and interactions between atoms guide the formation of energy-efficient clusters.

C. Scheduling Phase

Once the best atom is identified, it is used to assign CHs to appropriate nodes. The CHs then broadcast announcements to the other nodes, inviting them to join a cluster. Regular nodes respond by sending accept packets to the nearest cluster head, while the cluster heads distribute a schedule for sensing the environment. This scheduling ensures that each node participates in the sensing process and contributes to the data collection phase.

D. Steady-State Phase

In the steady-state phase, each regular node senses the environment and transmits its data to the respective CH. The

CHs then aggregate the received data from their members and forward the combined data to the BS for further processing. The algorithm then checks if re-clustering is needed based on energy consumption and the overall efficiency of the network. If re-clustering is necessary due to high energy consumption or imbalanced clusters, the process begins anew. Otherwise, the system continues to operate until all nodes deplete their energy.

IV. EXPERIMENTAL PROCEDURE, RESULTS, AND DISCUSSION

Simulations were conducted in MATLAB. We considered sensor nodes based on a network model, while the energy consumption of individual nodes, as well as the network as a whole, is analyzed through the radio energy model. A set of n sensor nodes is randomly deployed within the search space. These nodes collect and exchange information regularly within the area, with the gathered data transmitted to the BS for processing after being relayed by the CHs. The CHs collect data from their respective nodes and forward it to the BS for further processing.

A. Network Model Specifications

Several assumptions were made to define the proposed simulation model (Table I). Firstly, the nodes or sensors are considered stationary and do not move within the network during the simulation. Secondly, the BS is located at the center of the search area, and its position is known to all the member nodes. Additionally, the energy of the BS is considered unlimited, whereas the energy of the nodes is limited and identical at the beginning of the simulation. Each node in the network is responsible for collecting data and transmitting it only to its respective cluster head during its designated Time Division Multiple Access (TDMA) period. Communication between the sensor nodes, CHs, and the BS follows standard routing rules, where the number of hops plays a crucial role in the energy consumption of the system.

In WSNs, routing algorithms are designed to optimize energy usage throughout the system. For this paper, we adopt the energy model proposed in [8], which considers the energy dissipation of sensor nodes during their tasks. Specifically, the energy consumption is split into two major components: the transmitter energy, which is used for operating the radio electronics during data collection and transmission to another node, and the receiver energy, which is used for operating the radio electronics during data reception. The energy dissipation is also affected by the distance between the transmitter and the receiver. The threshold distance d_0 is defined as the point where energy attenuation begins to differ for short and long distances. This threshold value is given by (6), where d_0 is proportional to d^2 for short distances and inversely proportional to d^4 for long distances:

$$d_0 = \sqrt{\frac{E_{fs}}{E_{amp}}} \quad (6)$$

where E_{fs} represents the free space energy and E_{amp} is the amplification energy.

For a given distance d , the energy consumed to transmit a B-bit packet from the transmitter is calculated according to (7):

$$E_{tx}(B, d) = \begin{cases} E_{elec} \times B \times E_{fs} \times d^2, & d < d_0 \\ E_{elec} \times B \times E_{amp} \times d^4, & d \geq d_0 \end{cases} \quad (7)$$

$$E_{rx} = B \times E_{elec} \quad (8)$$

where E_{elec} represents the energy consumed by the electronics during the transmission of one bit, E_{tx} is the energy consumed by the transmitter during the transmission of one bit. Similarly, the energy consumption of the receiver is given by (8), where E_{rx} is the energy consumed by the receiver during the reception of B-bit packet.

TABLE I. SIMULATION PARAMETERS.

Parameters	Ranges/Values
Network Size	10000 m ²
Number of Sensor nodes	100
Initial Energy	0.5 J
Packet Size	500 bytes
Transmission Energy (E_{elec})	50 nJ/bit
Amplifier Energy (E_{fs})	10 pJ/bit/m ²
Free Space Energy (E_{amp})	0.0013 pJ/bit/m ²

B. Optimization of α , β , and γ for Network Lifetime

This section presents a series of experiments aimed to determine the optimal values of the key parameters α , β , and γ for maximizing the network lifetime in WSNs. These parameters play a critical role in the clustering process and energy efficiency of the network. The experiments were designed to assess the individual and combined effects of these parameters on the network's energy consumption, clustering performance, and overall longevity. By varying the values of α , β , and γ , we aim to identify the settings that offer the best balance between efficient energy use and prolonged network operation.

Figure 1 illustrates the impact of α on the network lifetime across different rounds in the experiment. When $\alpha = 0.8$, the network lifetime is the shortest, lasting 350 rounds. This suggests that a higher α value leads to faster energy depletion, possibly due to a higher rate of energy transfer between nodes. This increased energy transfer could result in higher energy consumption, causing the network to deplete its resources more quickly. At $\alpha = 0.4$, the network lifetime improves slightly, reaching 366 rounds. This appears to be the optimal balance between energy transfer and network longevity. A moderate α value helps maintain energy efficiency without causing excessive energy depletion, resulting in a more stable and longer-lasting network. When $\alpha = 0.1$, the network lifetime is 357 rounds. While this indicates an improvement in terms of longevity, it also suggests that lower α values reduce the interaction and energy transfer rate between nodes. This could lead to a slower convergence to optimal clustering and may reduce the overall effectiveness of the network.

Figure 2 illustrates the impact of β on network lifetime across different rounds in the experiment. When $\beta = 0.8$, the network lifetime is the longest, lasting 355 rounds. This suggests that a higher β value, which influences the degree of movement in the solution space, allows the network to explore more efficient configurations, resulting in an extended

operational lifetime. The larger β value appears to facilitate better exploration and quicker convergence to an optimal network configuration. At $\beta = 0.6$, the network lifetime decreases to 338 rounds. This reduction indicates that while moderate β values allow some degree of exploration, they may not be as effective as higher β values in optimizing the clustering and energy consumption. The moderate exploration might limit the efficiency of the overall process. When $\beta = 0.1$, the network lifetime is 346 rounds. This value represents a slower exploration process, which results in slightly better network lifetime compared to the $\beta = 0.6$ setting. However, the slower movement within the solution space may hinder the network's ability to converge to optimal configurations in a timely manner, although it still performs better than the $\beta = 0.6$ setting.

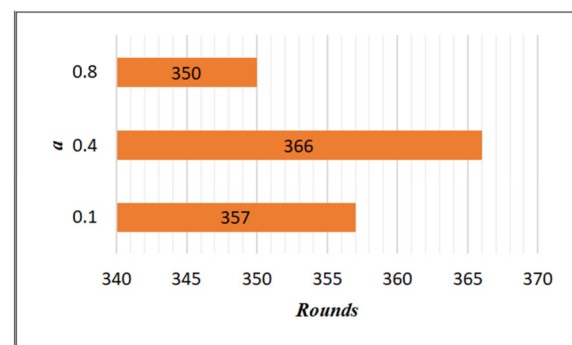
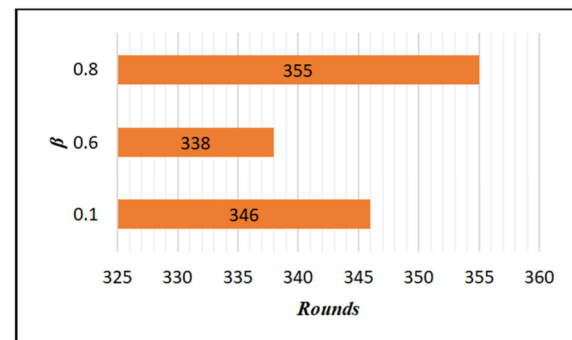
Fig. 1. Effect of varying α values on the network lifetime.Fig. 2. Effect of varying β values on the network lifetime.

Figure 3 illustrates the impact of parameter γ on the network lifetime across different rounds. When $\gamma = 0.9$, the network lifetime is the shortest at 331 rounds. This suggests that a higher value of γ leads to a quicker energy dissipation rate, which results in faster depletion of the network's energy reserves. The high dissipation rate may prevent the network from maintaining energy balance, causing it to reach its end-of-life sooner. At $\gamma = 0.6$, the network lifetime increases to 341 rounds. While this setting improves the network lifetime over $\gamma = 0.9$, it still results in a relatively short lifespan. The moderate dissipation rate may strike a balance between energy usage and dissipation, but it is still not as efficient in terms of energy conservation when compared to lower values of γ . When $\gamma = 0.2$, the network lifetime is the longest at 366 rounds. This indicates that a lower γ value, which reduces the rate of energy

dissipation, helps in preserving the network's energy for a longer period. The slower dissipation rate allows the network to maintain energy balance and prolongs its operational lifetime.

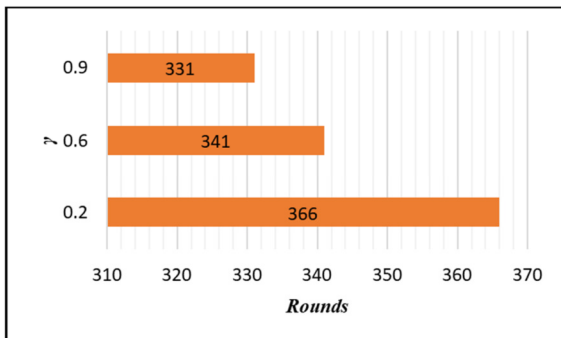


Fig. 3. Effect of varying γ values on the network lifetime.

In summary, moderate values of α (such as 0.4) were found to provide the best balance between energy transfer and network lifetime, with higher values leading to faster energy depletion and lower values reducing interaction efficiency. In terms of β , higher values (like 0.8) contributed to longer network lifetimes by facilitating effective exploration of the solution space, whereas smaller values (0.1) slowed down the exploration process, leading to reduced network performance. For γ , lower values (such as 0.2) resulted in the longest network lifetime by reducing the energy dissipation rate, thus preserving the energy reserves of the network for a longer duration.

C. Simulation Results and Comparison with Peer Protocols

The performance of routing algorithms in WSNs is primarily determined by two key factors: the energy efficiency of the sensor nodes and the data transfer rate between the CHs and the BS. These factors directly influence the overall efficiency and longevity of the network. In this section, we compare the proposed method to other well-established meta-heuristic approaches. In addition to the widely used LEACH protocol, we include comparisons with other nature-inspired algorithms. LEACH-PWO [18] and GWOC [22] are based on the Gray Wolf Optimizer, while CGC [23] and LEACH-SAGA [24] utilize GA for clustering optimization. We also consider PSO-ECHs [25], as well as two approaches derived from annealing algorithms: SA-LEACH [19] and PSCH-CH [20].

Figure 4 compares different clustering protocols in terms of FDN (First Dead Node), HDN (Half Dead Nodes), and LDN (Last Dead Node) over the course of the simulation rounds.

The FDN values show how quickly the first node depletes its energy. We can see that LEACH and GWOC protocols have the earliest FDN, indicating faster energy depletion in these networks. This suggests that these protocols may not efficiently balance energy consumption among nodes, leading to early failure. On the other hand, AEOWSNC and PSCH-CH protocols show a delayed FDN, indicating better energy management and a more balanced distribution of energy across nodes.

The HDN parameter provides insight into the round at which half of the nodes in the network die. AEOWSNC again

performs well, maintaining a longer duration before half of the nodes are dead. It outperforms many other protocols like LEACH-SAGA and PSO-ECHs, which experience earlier HDN values. This indicates that AEOWSNC maintains a more balanced energy consumption strategy, leading to a slower depletion of nodes. Conversely, protocols like LEACH and GWOC see their nodes depleting faster, which could be a result of inefficient energy distribution or suboptimal clustering strategies.

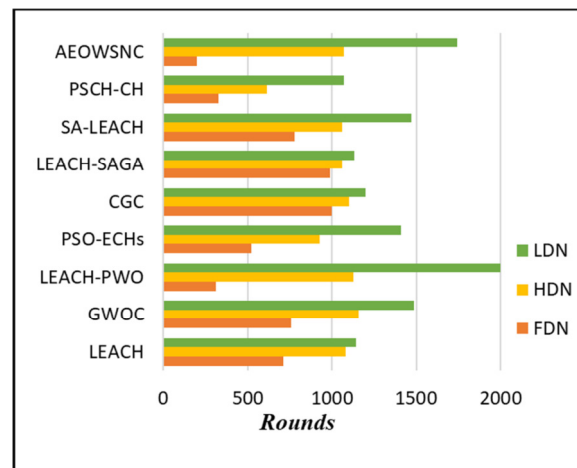


Fig. 4. FDN, HDN, and LDN comparison.

The LDN is a crucial metric for evaluating the overall network lifetime. The graph shows that AEOWSNC and PSCH-CH perform the best, with the last node dying after the most rounds. This suggests that these protocols manage energy efficiently across the entire network, prolonging the lifetime of the last node. On the other hand, protocols such as LEACH and GWOC show earlier LDN values, indicating that the network's overall lifespan is shorter. A later LDN indicates that the protocol is able to distribute energy more effectively, ensuring that the last node survives for a longer period and contributing to the overall longevity of the network.

Figure 5 illustrates the network lifetime of various clustering protocols in terms of residual energy over a series of rounds. AEOWSNC and LEACH-PWO show the best performance in terms of network lifetime. They maintain a relatively high level of residual energy through the first 1000 rounds, with a slower drop-off after that. By round 2000, AEOWSNC still has a noticeable amount of energy left compared to other protocols. The residual energy of AEOWSNC starts at 50 J and only drops to around 0.7 J by round 2000, showing its ability to extend the network's operational life effectively. LEACH and GWOC experience a sharp decline in residual energy early in the simulation, with both dropping to zero energy by round 1200. As shown in the graph, their curves steeply decline, indicating that their clustering methods do not optimize energy usage well, leading to faster energy depletion across nodes. LEACH-SAGA, PSO-ECHs, and PSCH-CH also show a noticeable drop in residual energy, but their decay is not as rapid as those in LEACH and GWOC. LEACH-SAGA, for example, holds around 34.0 J at

round 400 and 20.0 J at round 600, showing a moderate but still significant energy loss. PSO-ECHs follows a with a steeper decline in residual energy.

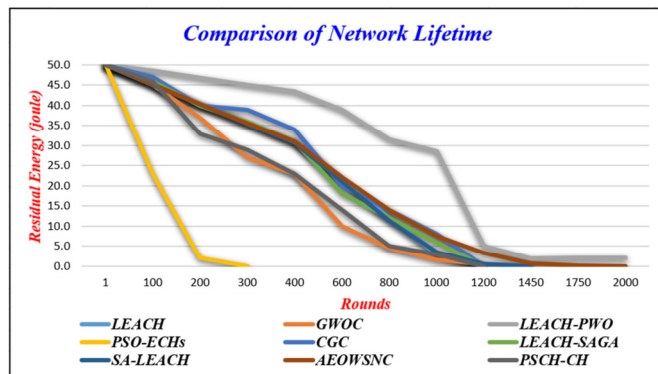


Fig. 5. Comparison of network lifetime over multiple rounds.

Figure 6 shows the comparison of live nodes across different protocols during the simulation. AEOWSNC shows good performance in terms of maintaining a high number of live nodes. In the first 1000 rounds, the protocol maintains almost all nodes active, with only a slight drop. By round 1200, AEOWSNC still has a significant number of live nodes, showing its ability to prolong the network's operational life. The protocol only reaches a very low number of live nodes (around 30) by round 1450, which suggests its effectiveness in preserving node activity and energy efficiency over an extended period.

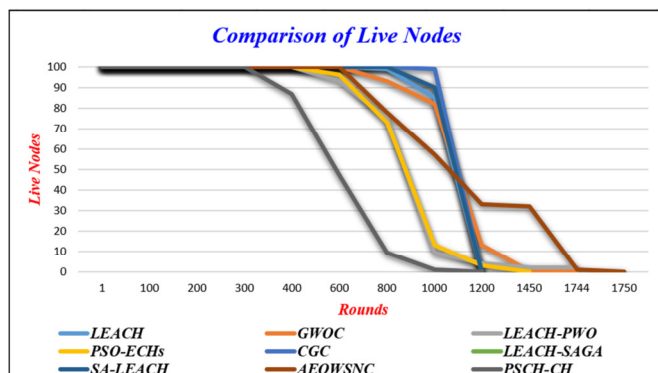


Fig. 6. Comparison of the number of alive nodes over multiple rounds.

LEACH, GWOC, and PSO-ECHs exhibit rapid depletion of the live nodes by round 1200. The other protocols show varying levels of performance.

Figure 7 shows the comparison of throughput at the BS in terms of number of packets transmitted by different clustering protocols. From the graph, AEOWSNC achieves a high throughput with 298,596 packets transmitted to the BS. This indicates that AEOWSNC not only excels in prolonging the network lifetime but also efficiently manages data transmission, ensuring that a large number of packets are sent and successfully received by the BS. This performance can be

attributed to the optimized clustering and energy management strategies that help maintain high data throughput over an extended period. SA-LEACH performs just slightly above AEOWSNC. LEACH-PWO, CGC, and LEACH-SAGA also perform well, indicating a reasonably high throughput, but still significantly lower than AEOWSNC and SA-LEACH. This suggests that these protocols have reasonable data transmission performance but lack the energy-efficient enhancements that AEOWSNC provides. The PSCH-CH's performance indicates a lower data throughput. This suggests that PSCH-CH may be more focused on other performance aspects, such as energy efficiency, but it compromises on throughput. The LEACH protocol has the lowest throughput, which is expected given its well-known limitations in terms of energy efficiency and network management. GWOC performs slightly better packets, but still falls far behind the more optimized protocols like AEOWSNC.

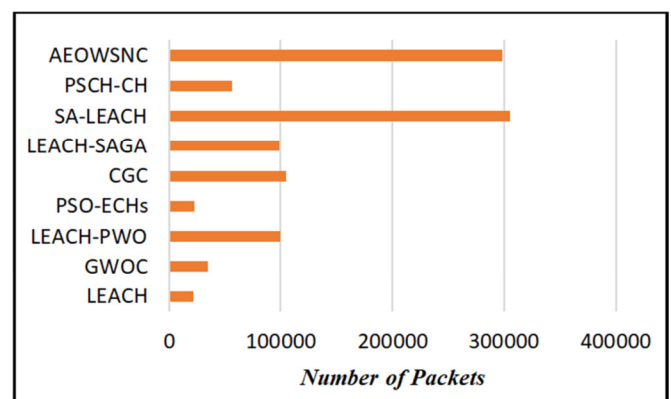


Fig. 7. Comparison of network throughput.

D. Discussion

The analysis of the experimental results for the different protocols reveals significant differences in their ability to balance energy efficiency, network lifetime, and data throughput. AEOWSNC stands out as a top-performing protocol across all metrics, including FDN, HDN, LDN, residual energy, live nodes, and network throughput. It consistently demonstrates superior performance by maintaining a high number of live nodes and residual energy, ensuring that the network operates for the longest period. AEOWSNC's ability to sustain energy and extend network lifetime also translates to better throughput at the BS, indicating that it not only preserves the network's operational life but also supports a higher volume of data transmission.

SA-LEACH and LEACH-SAGA also show good performance in terms of maintaining live nodes and residual energy, though they do not match AEOWSNC in terms of throughput and overall network longevity. These protocols maintain node activity for a considerable time, but they face a sharper decline in residual energy and a faster depletion of live nodes compared to AEOWSNC. Their throughput performance is also lower, indicating that although they are relatively energy-efficient, they are not as optimized for sustaining high data transmission rates.

In contrast, protocols like LEACH, GWOC, and PSO-ECHs perform poorly in several aspects, particularly in terms of energy efficiency and network throughput. These protocols exhibit a rapid drop in residual energy, a steep decline in live nodes, and significantly lower throughput at the BS, suggesting that their energy management strategies are less effective. This results in faster failure of nodes and a shorter network lifetime, which limits their practical applicability in long-term WSNs scenarios.

The findings from this analysis confirm that AEOWSNC offers a balanced performance, effectively managing energy consumption while maximizing network lifetime and throughput. It outperforms the other protocols, making it the most suitable option for applications that require both long-term operation and efficient data transmission. In contrast, while protocols like SA-LEACH and LEACH-SAGA perform reasonably well in terms of node longevity, they still fall short in comparison to AEOWSNC's comprehensive performance across all metrics.

V. CONCLUSION

This paper introduces AEOWSNC, an innovative clustering approach for WSNs designed to optimize energy efficiency and network lifetime. Inspired by the metaheuristic method AEO, the algorithm has been rigorously evaluated through experiments and compared with several well-established metaheuristic approaches, including LEACH, LEACH-PWO, GWOC, CGC, LEACH-SAGA, PSO-ECHs, SA-LEACH, and PSCH-CH. The results consistently show that AEOWSNC outperforms the other methods in key performance metrics such as network lifetime, residual energy, live node count, and throughput at the BS. Its ability to maintain high energy efficiency while sustaining throughput and reducing early resource depletion underscores its practical applicability for long-term deployment in real-world scenarios. By managing energy effectively and optimizing clustering, AEOWSNC ensures that the network operates efficiently for extended periods, avoiding the rapid energy depletion observed in protocols like LEACH and GWOC.

Several potential avenues exist for enhancing AEOWSNC. One direction is the integration of machine learning techniques to dynamically adjust key parameters α , β , and γ , based on network conditions or environmental changes. This could further optimize the clustering process and improve the network's adaptability in diverse settings. Additionally, exploring hybrid approaches that combine AEOWSNC with other optimization techniques, such as genetic algorithms or particle swarm optimization, may improve scalability and robustness, especially for large-scale networks.

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