WOAAEO: A Hybrid Whale Optimization and Artificial Ecosystem Optimization Algorithm for Energy-Efficient Clustering in Internet of Things-Enabled Wireless Sensor Networks

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***Abstract*—In the Internet of Things (IoT) era, energy efficiency in Wireless Sensor Networks (WSNs) is of utmost importance given the finite power resources of sensor nodes. An efficient Cluster Head (CH) selection greatly influences network performance and lifetime. This paper suggests a novel energy-efficient clustering protocol that hybridizes Whale Optimization Algorithm (WOA) and Artificial Ecosystem Optimization (AEO), called WOAAEO. It utilizes the exploration capabilities of AEO and the exploitation strengths of WOA in optimizing CH selection and balancing energy consumption and network efficiency. The proposed method is structured into two phases: CH selection using the WOAAEO algorithm and cluster formation based on Euclidean distance. The new method was modeled in MATLAB and compared with current algorithms. Results show that WOAAEO increases the network lifetime by a maximum of 24%, enhances the packet delivery rate by a maximum of 21%, and reduces energy consumption by a maximum of 35% compared to related algorithms. The results show that WOAAEO can be a suitable solution to help resolve energy-saving issues in WSNs and can thus be applied to IoT without any issues.**

Keywords—Clustering; Internet of Things; energy efficiency; wireless sensor network; network lifespan

I. INTRODUCTION

The Internet of Things (IoT) has completely changed how data is collected, and how communications are established within industries ranging from agriculture to health and urban infrastructure [1, 2]. WSN captures and sends environmental information via hundreds of tiny sensor nodes under power constraints in each case [3]. Because sensor nodes operate on minimal power, energy efficiency becomes essential for extending the lifetime of these networks and lowering maintenance costs [4].

Moreover, as IoT systems become increasingly pervasive, the need for robust security mechanisms alongside energy optimization becomes more pressing. Recent studies have explored behavior-based intrusion detection frameworks tailored to mobile and dynamic environments, such as mobile social networks, where communication analysis is leveraged to detect malicious activity among ad hoc nodes [5]. Energy consumption in WSNs has to be managed efficiently to make IoT applications sustainable and reliable [6, 7].

Cluster Head (CH) selection is a significant challenge in WSN, significantly reducing redundant data transmission. CHs act as representatives of accumulating data from cluster participants and forwarding it to the Base Station (BS); hence, they are crucial for network efficiency [8]. However, inappropriate CH selection may lead to excessive energy use and energy holes, reducing network performance and lifetime [9]. In this regard, efficient CH selection remains a research focus for solving these issues for optimized network sustainability.

Despite their efficiency, the existing clustering algorithms suffer from long convergence times and energy inefficiency [10]. Most recent clustering methods depend on metaheuristic optimization techniques, which may sometimes get stuck in a local optimum, wasting energy and spoiling network performance [11]. Besides, these algorithms are usually inefficient at trading off the two critical components of exploration and exploitation for efficient CH rotation and maintaining an energy-efficient network [12].

For real-world deployment in geotechnical applications such as landslide monitoring, tunneling, or underground infrastructure, it is essential to model the mechanical behavior of the rock mass accurately. Constitutive models tailored to weak rock formations are crucial to simulate deformation zones, aiding in sensor placement strategies [13].

In this paper, a new hybrid optimization algorithm, WOAAEO, is presented that strategically combines the Whale Optimization Algorithm (WOA) and Artificial Ecosystem Optimization (AEO) with a dynamic phase-shifting mechanism. This mechanism switches between exploration (AEO-based ecological modeling) and exploitation (WOA-based spiral search) based on convergence characteristics. This complementarity combines a mechanism-level innovation by providing fine-grained population diversity and convergence rate control, two inherent shortcomings of single-metaheuristic standalones. The algorithm is optimized for resilient and energy-efficient CH selection in IoT-enabled WSNs, offering enhanced scalability and adaptability.

The remaining sections of the paper are presented as follows: Section II reviews related work. The proposed methodology is presented in Section III. Section IV reports simulation outcomes. Section V concludes the study and outlines possible future directions.

II. Related Work

Mohseni, et al. [14] proposed the Cluster-based Energy-aware Data Aggregation Routing (CEDAR) protocol for IoT networks to solve redundant data transmission and node energy consumption issues. CEDAR features a hybrid strategy that couples the Capuchin Search Algorithm (CapSA), fuzzy logic for forming clusters, and efficient intra-cluster and inter-cluster communication. Simulations indicated that CEDAR gives higher network longevity, packet delivery rate, energy efficiency, and so on compared to existing methods.

Ghamry and Shukry [15] proposed a multi-objective clustering routing strategy based on deep reinforcement learning on IoT-based WSNs. This technique partitions the network into unequal clusters, considering the sensor node data load to avoid node death in advance. It could balance the energy consumption in various clusters, providing better energy efficiency, packet delivery, and network lifetime than any other clustering approach.

Karunkuzhali, et al. [16] developed a QoS-aware routing for IoT-based intelligent city applications with energy efficiency and data reliability. The system adopted chaotic bird swarm optimization of clustering, improved differential search of CH selection, and lightweight encryption for secure data transmission. The simulation findings indicated that the proposed strategy significantly enhanced energy conservation, network lifespan, and latency compared to other methods.

Shah, et al. [17] proposed an energy-aware and reliable clustering protocol for UAV-assisted WSNs in remote IoT applications. The protocol considers wake-up radios and time-division access to avoid excess energy and cluster overlapping. Compared to existing models, this protocol has been proven to exhibit improved energy efficiency, network stability, and data collection efficiency, and it has been validated through extensive simulation.

Sharma and Chawla [18] developed a hybrid data routing protocol called PRESEP for heterogeneous WSNs, combining particle swarm optimization with residual energy-based CH selection. PRESEP calculates the data routing so that the optimization prolongs the network lifetime with a better energy balance. Simulation results outperform other heterogeneous algorithms as per alive nodes and reduced CH selection frequency.

Sennan, et al. [19] proposed a fuzzy-based Harris Hawks Optimization algorithm for CH selection in IoT-enabled WSNs. FHHO evaluates CH nodes in terms of residual energy and node-sink distance and utilizes fuzzy logic to optimize network lifetime and throughput. Comparative analysis indicates that FHHO outperforms other CH selection algorithms, extending network life by 18–44%.

Kumar and Sreenivasulu [20] introduced an energy-efficient node-clustering technique based on the metaheuristic optimization method, the Dingo Optimizer, to elect CHs in IoT-based WSNs. The protocol conserves overhead by minimizing message transmissions between the CHs and the member nodes. Additionally, data compression at the node level further decreases the protocols' power consumption, thereby improving the lifespan of the networks.

As shown in Table I, the discussed papers introduce various techniques for energy-efficient CH selection and routing in WSNs with IoT, leveraging fuzzy logic, metaheuristic algorithms, and reinforcement learning. Despite recent research, several areas for improvement remain. The majority of them take advantage of a faster convergence time or a single optimization technique, which typically affects their adaptability under varying network conditions.

Also, most methods must balance exploration and exploitation appropriately, which may result in suboptimal energy utilization. This work identifies these lacunae and proposes one hybrid optimization combining WOA with AEO, namely WOAAEO. In this regard, WOAAEO has been designed to be more efficient in CH selection, reducing energy consumption while increasing the convergence rate to maintain WSN sustainability in IoT applications.

TABLE I. Recent Cluster-Based Routing Methods

Research	Method	Key components	Primary advantages
[14]	CEDAR protocol	CapSA and fuzzy logic	Enhanced network lifetime, packet delivery, and energy efficiency
[15]	Multi-objective clustering	Deep reinforcement learning	Energy efficiency, balanced energy consumption, and improved network lifespan
[16]	QoS-aware routing	CBSO, IDS, and Signcryption	Energy conservation, network longevity, and reduced latency
[17]	EEUCH protocol	UAV assistance and wake-up radios	Higher energy efficiency, network stability, and data collection efficiency
[18]	PRESEP protocol	PSO and residual energy	Prolonged network life, stable clustering, and balanced energy usage
[19]	FHHO algorithm	Fuzzy logic and harris hawks optimization	Extended network lifespan and increased throughput
[20]	Dingo optimizer-based routing	Modified dingo optimizer and data compression	Reduced energy consumption and eco-friendly network

III. Proposed Methodology

A. Network Model

The network model of WOAAEO consists of several nodes scattered randomly within an area of a predefined network. Each node can be utilized as a CH or a Cluster Member (CM) in this network model. The CMs send their data to the elected CH through local sensing. A CH then gathers this data and sends it to either the sink node or the BS after aggregating these data. The sink node at the network's center analyzes and decides based on the data gathered. This paper will use the WOAAEO optimization algorithm to select the fittest CHs. Once the CH is chosen in the cluster, clusters can be formed by selecting some nodes around each CH. This model structure is illustrated in Fig. 1. The network model takes the following assumptions into account:

- Every node is randomly distributed within the network.
- Nodes each have unique identifiers making them identifiable.
- Each node is equipped with equal computational and power resources.
- The BS is situated in the network's center.
- Nodes know the exact position or coordinates of the BS.
- The BS collects aggregated data from CHs, which collect information from their respective CMs.

B. Energy Consumption Model

Maintaining power at sensor nodes is crucial for various reasons, including ensuring network functionality, keeping nodes active, enabling data processing, transmitting and receiving packets, and performing sensing tasks [21]. Energy consumption while transmitting a packet is directly linked to the packet size and transmission distance [22]. In this research, a first-order radio model, as shown in Fig. 2, is used to calculate the energy. For a packet of size *l* (in bits) to travel a distance *d*, the transmitter's energy consumption E_{TX} *(l,d)* is calculated as follows:

$$E_{TX}(l,d) = \begin{cases} E_{elec} \times l + \varepsilon_{fs} \times l \times d^2, & if\ d < d_0 \\ E_{elec} \times l + \varepsilon_{mp} \times l \times d^4, & if\ d \geq d_0 \end{cases} \quad (1)$$

Where E_{elec} represents the energy consumed by the electronic circuitry per bit, while ε_{fs} and ε_{mp} refer to the energy usage of the amplifier in open-space and multiple-path fading scenarios, respectively. The parameter d indicates the transmission distance between the sender and receiver, and d_0 is a threshold distance defined by:

$$d_0 = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}} \quad (2)$$

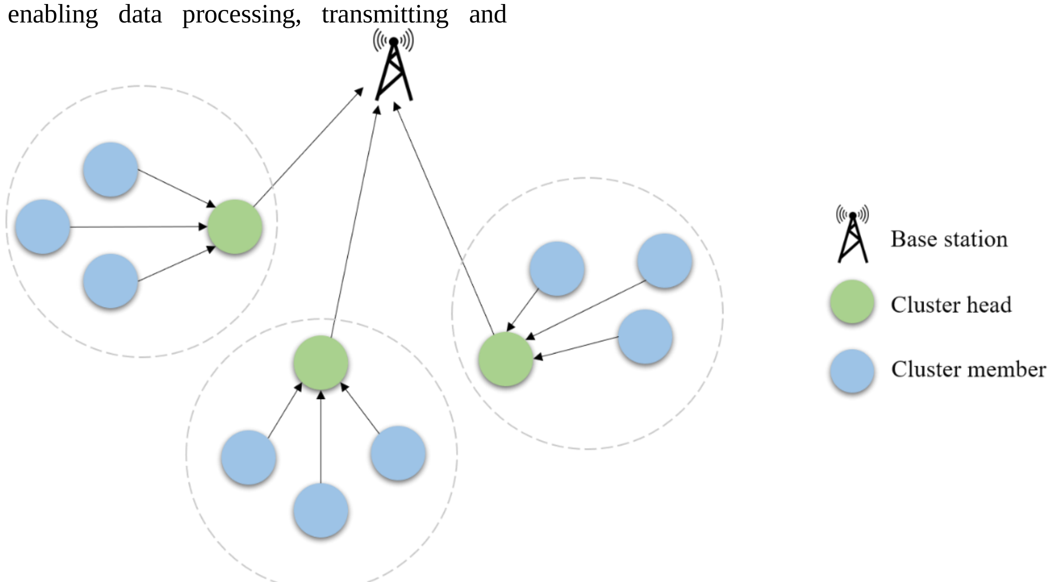

Fig. 1. Network model.

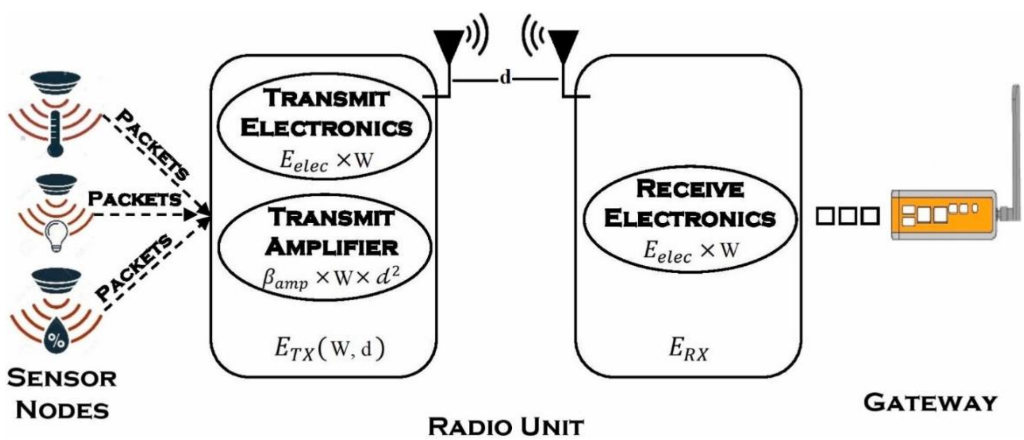

Fig. 2. Energy consumption model.

When receiving a packet of size l, the energy $E_{RX}(l)$ consumed by the receiver's electronics is calculated as:

$$E_{RX}(l) = E_{elec} \times l \quad (3)$$

In addition to the transmission and reception energy, the energy required for data aggregation, denoted as E_{da}, is also considered in the total energy model. This comprehensive approach enables precise assessment of energy consumption in IoT-enabled WSNs, enhancing the model's relevance for sustainable network operations.

C. WOAAEO Algorithm

This work presents the WOAAEO algorithm, which efficiently chooses CHs in WSNs for better network lifetime and minimum end-to-end delay. This approach contributes in two key phases: selecting CHs based on a hybrid algorithm aiming at the network's optimality in determining the fittest nodes to act as CH and cluster formation by grouping nodes around each chosen CH using Euclidean distance. This is achieved through a two-phase process that optimizes communication paths and reduces energy consumption to increase network performance.

WOA is a swarm intelligence-based technique developed for recurrent optimization problems as a derivative of humpback whale hunting strategies. It has been proven to have superior performance over other optimization techniques using two major coupled behaviors from whales: encircling of prey and bubble-net hunting attack. In WOA, each candidate solution is considered a "whale" attempting to reach a target position, represented by the best solution identified so far. At each iteration, whales move toward this reference point as follows:

$$\vec{D} = \left|\vec{C} \cdot \overrightarrow{X^*}(t) - \vec{X}(t)\right| \quad (4)$$

$$\vec{X}(t+1) = \overrightarrow{X^*}(t) - \vec{A} \cdot \vec{D} \quad (5)$$

Here, $\overrightarrow{X^*}(t)$ represents the current best solution, $\vec{X}(t)$ denotes the position of a whale, and $\vec{A}$ and $\vec{C}$ are coefficient vectors. The values of $\vec{A}$ and $\vec{C}$ are calculated as follows:

$$\vec{A} = 2 \cdot \vec{a} \cdot \vec{r} - \vec{a} \quad (6)$$

$$\vec{C} = 2 \cdot \vec{r} \quad (7)$$

The parameter $\vec{a}$, which influences the convergence behavior in WOA, is linearly decreased from 2 to 0 over the course of iterations to gradually transition the algorithm from a global search (exploration) to a local search (exploitation). This adaptive scheduling is essential for avoiding premature convergence in the early stages while refining solutions in later phases. The parameter $\vec{r}$, representing randomness in the whale position update, is re-sampled at each iteration to maintain diversity in the population. WOA models the bubble-net feeding behavior through two main strategies, as shown in Fig. 3.

Shrinking encircling mechanism: As $\vec{a}$ decreases, the values of $\vec{A}$ fluctuate within $[-a, a]$, enabling whales to converge around the best solution by shrinking their search area.

Spiral updating position: This strategy mimics the helical movement of whales as they approach their prey. The position update formula is given by:

$$\vec{X}(t+1) = \overrightarrow{D'} \cdot e^{bl} \cdot \cos(2\pi l) + \overrightarrow{X^*}(t) \quad (8)$$

Here, $\overrightarrow{D'}$ is the distance between the whale and the best solution, b defines a constant defining the shape of the spiral, and l gives a random number in [−1, 1]. WOA alternates between these two behaviors using a probability of 0.5, as represented in Eq. (9), to use either the shrinking encircling or spiral model for each position update.

$$\vec{X}(t+1) = \begin{cases} \vec{X}^*(t) - \vec{A}.\vec{D}, & if\ p \leq 0.5 \\ \overrightarrow{D'} \cdot e^{bl} \cdot cos(2\pi l) + \overrightarrow{X^*}(t), & if\ p \geq 0.5 \end{cases} \quad (9)$$

WOA emphasizes global search (exploration) when $|\vec{A}| > 1$, prompting whales to move toward randomly chosen positions rather than the best-known solution. This feature allows WOA to diversify its search, helping avoid local optima. The equations used for exploration are:

$$\vec{D} = \left|\vec{C} \cdot \overrightarrow{X_{\text{rand}}} - \vec{X}(t)\right| \quad (10)$$

$$\vec{X}(t+1) = \overrightarrow{X_{\text{rand}}} - \vec{A} \cdot \vec{D} \quad (11)$$

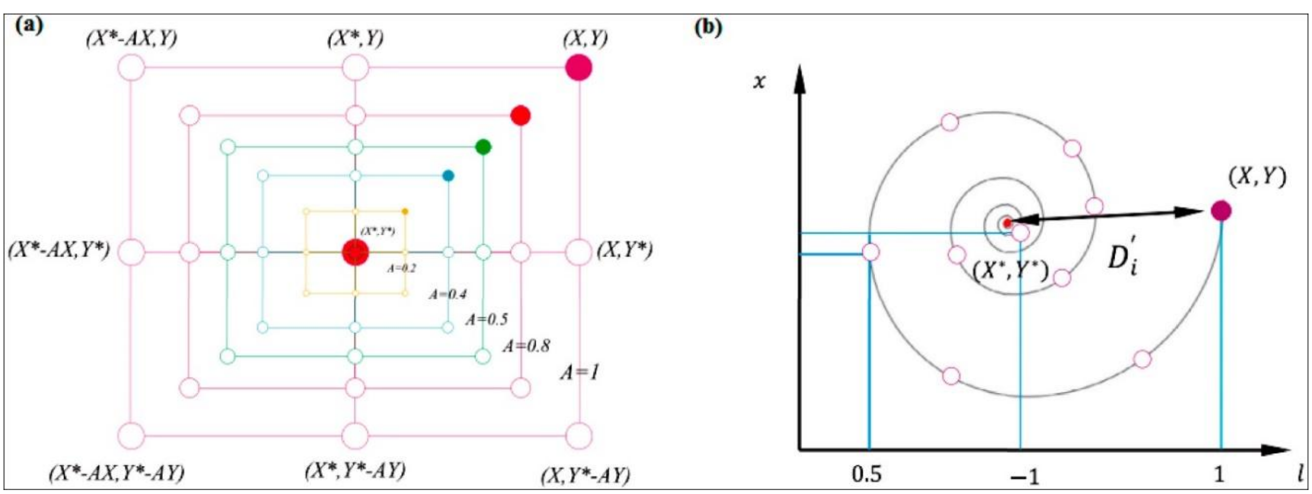

Fig. 3. Bubble-net search adopted by WOA.

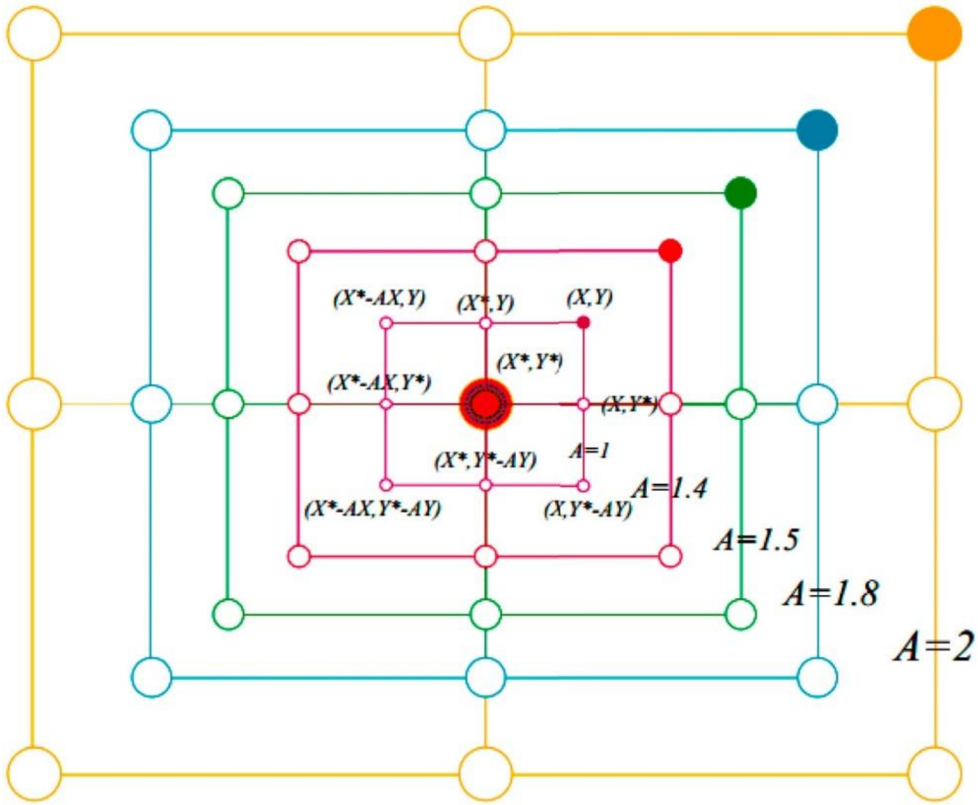

Fig. 4. The exploration process applied to WOA.

$\overrightarrow{X_{\text{rand}}}$ denotes the position of a randomly selected whale, as depicted in Fig. 4, where $|\vec{A}| > 1$ leads to a wider exploration of the search space.

The WOA algorithm initiates with a group of randomly positioned whales (candidate solutions) that renew their positioning at each iteration depending on either the best solution found or a randomly selected whale. A smooth transition between exploration and exploitation is achieved by gradually decreasing $\vec{a}$, thus controlling the search range.

The AEO algorithm is an ecosystem-inspired optimization technique for simulating organism interactions and movements [23]. It involves two main steps: exploration and exploitation, mimicking natural processes such as consumption and decomposition. It carries out the exploration process through random searches in the solution space. In contrast, during the exploitation phase, the solutions are enhanced through ecosystem dynamics. To reconcile these phases, the production process is combined; it draws inspiration from nature's energy flow. The algorithm generates N solutions (agents) in a D-dimensional space where D is the number of parameters. Agent position is initialized randomly within predefined limits:

$$X_{\text{rand}} = X_{i,j}^{\min} + \text{rand}_{i,j} \times \left(X_{i,j}^{\max} - X_{i,j}^{\min}\right), \quad i = 1, \dots, N; \quad j = 1, \dots, D \tag{12}$$

Where $X_{i,j}^{\min}$ and $X_{i,j}^{\max}$ refer to the minimum and maximum bounds for each dimension, and $rand_{i,j}$ is a random value in the range [0, 1]. Each solution's fitness is evaluated using an objective function.

In the production phase, the worst agent (producer) is modified based on the best agent (decomposer) to improve its quality. During this stage, a new solution is generated by blending the best solution X best and a random position X rand , using the following equations:

$$X_{\text{worst}}^{t+1} = (1 - \alpha) \times X_{\text{best}}^{g} + \alpha \times X_{\text{rand}}^{g} \tag{13}$$

$$\alpha = \left(1 - \frac{g}{g_{\max}}\right) \times r_1 \tag{14}$$

Where g stands for the current generation, g_{max} is the maximum generation, r_1 is a random value in [0, 1], and α is a weight coefficient that ensures exploration.

The refinement of the solutions after their generation is carried out at the consumption stage, where the term "consumers" refers to those agents with intermediate fitness that could "eat" either from producers or other agents. In the interest of intensifying diversity in the search, a Levy flight operator is applied, modeled by:

$$C = \frac{\nu_1}{2\pi\nu_2}, \quad \nu_1 \sim N(0,1), \quad \nu_2 \sim N(0,1) \tag{15}$$

The consumption factor C supports local optima escape. Depending on their type, agents follow different update strategies:

- Herbivores: Consume only from the worst agent:

$$X_i^{g+1} = X_i^{g} + C \times \left(X_{\text{worst}} - X_i^{g}\right) \tag{16}$$

- Carnivores: Consume from a randomly chosen agent with higher fitness:

$$X_i^{g+1} = X_i^g + C \times \left(X_j^g - X_i^g\right) \tag{17}$$

- Omnivores: Consume from both producer and consumer in a random position:

$$X_i^{g+1} = X_i^g + C \times \Big(r_2 \times (X_{best} - X_{worst}) + (1 - r_2) \times \left(X_j^g - X_i^g\right)\Big) \tag{18}$$

The decomposition stage, after consumption, is devoted to exploitation, done through breaking down the most promising solutions that have the closest proximity to the optimum to improve the quality of the solutions. This phase will tune the best solution X_{best}:

$$X_i^{g+1} = X_{\text{best}} + E \times \left(e \times X_{\text{best}} - h \times X_i^g\right) \tag{19}$$

Where E is the decomposition factor, and e and h are weight parameters.

WOAAEO is not merely a juxtaposition of WOA and AEO but introduces an interleaved operator-switching strategy that selects the best-suited mechanism, spiral exploitation, agent-based consumption, or decomposition, based on the evolving fitness landscape. Additionally, it uses a fitness-driven role assignment (herbivore, carnivore, omnivore) to regulate population behavior dynamically, fostering novel solution-generation pathways. This formulation offers a substantial departure from existing hybrids by orchestrating an ecosystem-driven feedback loop within the swarm-intelligence framework, ensuring improved convergence stability and robustness in dynamic WSN environments.

The main contribution of the WOAAEO is to extend WOA by incorporating AEO operators to enhance diversity and convergence speed. The algorithm switches periodically between consumption and decomposition operators via AEO, whereas the spiral updating mechanism of WOA applies. When $|\vec{A}| > 1$, the consumption operator of AEO operates on the agents and divides all agents into herbivores, carnivores, and omnivores according to their fitness. This operator adopts several equations to improve the solutions by consuming information from weaker agents or exploring the search space.

The decomposition operator of AEO refines the best solutions by composing and rebuilding around the optimal candidate when $|\vec{A}| \le 1$. The WOA, for $p \le 0.5$, uses the spiral updating mechanism to model the bubble-net hunting strategy for its exploitation. The transition between AEO and WOA mechanisms is controlled by probability, as shown in Fig. 5.

Input:
n: Number of population search agents (nodes).
Max_Iter: Maximum number of iterations for optimization.
Output:
Optimal CH positions in the network.
Initialize:
Generate an initial population of n nodes randomly distributed in the search space.
Compute the fitness value of each node based on residual energy and distance to the sink node.
Identify the best search agent X_{best} with the highest fitness value.
Sort population:
Rank nodes by their fitness values.
While (iteration $t <$ *Max_Iter*) **do**
    For each search agent (node) in the population:
        Update control parameters a, A, C, p, and l.
        If $p \le 0.5$ **then**
            If $|\vec{A}| \le 1$ **then**
                Apply AEO decomposition operator (Eq. 19) to refine cluster head selection.
            Else $|\vec{A}| \ge 1$ **then**
                Perform AEO consumption operator to improve exploration:
                    For each node:
                        If *rand<1/3* **then**
                            Update position using Eq. (16) (Herbivore mechanism).
                        Else if *1/3≤rand<2/3* **then**
                            Update position using Eq. (17) (Carnivore mechanism).
                        Else
                            Update position using Eq. (18) (Omnivore mechanism).
        Else $p \ge 0.5$ **then**
            Update position using Eq. 9 (WOA spiral updating mechanism).
Boundary check:
    Verify if any node exceeds the search space boundaries and adjust its position if necessary.
Fitness update:
    Recalculate the fitness value for each node.
    Update X_{best} if a better solution is found.

Fig. 5. Pseudocode for WOAAEO algorithm in clustering for WSNs.

The computational complexity of WOAAEO is derived from the combined processes of AEO and WOA. It can be expressed as:

$$O(WOAAEO) = O(WOA) + O(AEO) \tag{20}$$

Initialization, evaluation, and updating are coordinated in WOAAEO to ensure optimization effectiveness. Initialization generates a set of random solutions within defined bounds in a *D*-dimensional space, with *N* solutions (agents) assuming diverse initial positions to explore. Further, each solution will be evaluated with a fitness function that measures the quality of any solution to guide further updates.

Updates in WOAAEO explore further the phases of exploration and exploitation. AEO uses its consumption and decomposition operators for exploration, where the agents can refine solutions by consuming weaker candidates- herbivores, carnivores, or omnivores decomposing around the most optimal solution.

On the other hand, regarding exploitation, WOA models a spiral updating mechanism that represents the bubble-net hunting patterns of humpback whales to intensify the search effort focused on the most promising solutions. The combination thus ensures that WOAAEO strikes an equilibrium between global exploration throughout the early iterations and local exploitation during the later steps. This provides rapid convergence to optimal solutions. The proposed processes have very efficient computational complexity since the computational complexity evolves with the order of *O(DNT)*, where *D* is the problem dimension, *N* is the population size, and *T* is the iteration count. The total complexity is represented as:

$$\begin{aligned} O(WOAAEO) &= \big(O(DN) + O(N)\big) \times T + O(ND) \\ &= O(DNT) \end{aligned} \tag{21}$$

D. Fitness Function

In the proposed WOAAEO algorithm, the fitness function is essential for selecting an optimal CH node. It contains two key parameters to evaluate: residual energy, which signifies the energy efficiency of any node, and distance, which represents the proximity of any node to the sink or BS. These parameters are included in the hybrid WOAAEO framework to ensure effective CH selection. Residual energy quantifies the remaining energy in a node relative to its initial energy, ensuring that nodes with sufficient energy are prioritized, calculated as follows:

$$R_i = \frac{E_{avail}}{E_{init}} \tag{22}$$

Where E_{init} refers to the initial energy of node *i* and E_{avail} stands for its current energy level. The distance parameter evaluates the proximity of a node *i* to the sink node. Nodes closer to the sink are preferred to minimize communication costs. The distance is computed using the Euclidean formula:

$$dis_{i,sink} = \sqrt{\sum_{i=1}^{n} (sink - i)^2} \tag{23}$$

The fitness of a node *i* is calculated by combining the residual energy and distance, with equal weight assigned to each parameter:

$$fitt_i = 0.5 \times \big(1 - dis(i)\big) + 0.5 \times \big(1 - R(i)\big) \tag{24}$$

This equation ensures a balance between energy efficiency and distance optimization. In WOAAEO, the fitness function is computed iteratively for each candidate node. Each round selects the node with the best fitness value as the CH. This iterative selection process integrates the exploration capabilities of AEO and the exploitation features of WOA, ensuring an optimal balance between energy conservation and communication efficiency.

E. Cluster Formation

In this network, n sensor nodes are deployed and organized into clusters based on CH selection. Once CHs have been selected, developing energy efficiency to increase network lifetime becomes essential. The Euclidean distance metric is used for clustering and is also one of the major factors in creating good clustering.

Each sensor node calculates its distance concerning all possible CHs in the network and relies on proximity information, which becomes necessary to select the best CH. The intelligent choice ensures that optimal clusters will be achieved, energy consumption will be minimal, and communication efficiency will be promoted. The Euclidean distance between two nodes, *i* and *j*, is calculated as follows:

$$dis_{i,j} = \sqrt{\sum_{i=1}^{n} (j - i)^2} \tag{25}$$

i and *j* are the coordinates of two nodes within the network area. This clustering approach is well-suited for scenarios where energy efficiency and communication optimization are critical.

IV. Simulation and Performance Evaluation

A simulation environment of MATLAB 2020a is used within a *500m × 500m* network area to evaluate the performance of the proposed WOAAEO along with other approaches. In the simulation, a flat network model was used. The nodes are randomly distributed in the network region of 400 nodes. As such, the sink node was put at the network's center position with coordinates of (250 m and 250 m), and any sensor node randomly generated would have a neighbor node in its communication range.

Each node was initialized with 1 Joule battery energy and allowed to transact a data packet to the sink node with just one hop. Different aspects of energy were selected, namely, E_{elec} (electronic energy) 50 nJ/bit, ε_{fs} (free-space model energy) 10 pJ/bit/m² and ε_{mp} (multipath fading energy) 0.0013 pJ/bit/m⁴. Receive signal energy $E_{receive}$ = 0.055 µJ/bit, transmit energy $E_{transmit}$ = 0.039 µJ/bit, aggregation energy $E_{aggregate}$ = 0.00012 µJ/bit, and amplifier energy E_{amp} = 10 pJ/bit/m².

WOAAEO efficiency was tested by simulation against EECHIGWO, HSWO, and CEDAR benchmarks. Performance indicators like communication overhead, the number of alive nodes, energy consumption, and packet delivery ratio were some of the critical parameters for evaluation. The simulation was run for 3000 rounds, and the size of the packet used for data transmission was kept at 4000 bits to investigate performance for heterogeneity and uniform communication range conditions. This was done to have identical input parameters for all benchmark techniques so that a valid and workable comparison can be done.

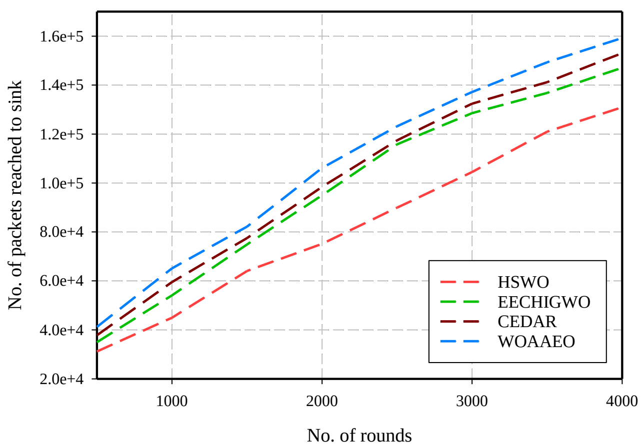

Fig. 6. Packet delivery ratio comparison

Fig. 6 illustrates the packet delivery performance of WOAAEO to the sink node, with an average of 159,300 packets at the end of 4000 rounds. This is an improvement of 4%, 8.2%, and 21.5% versus CEDAR, EECHIGWO, and HSWO, respectively. The exceptional performance attained by WOAAEO is principally due to the underlying hybrid optimization based on AEO's exploration capability and WOA's exploitation ability. This synergy provides the most effective CH selection by considering the node's optimal energy and proximity metrics while minimizing packet loss during transmission. Additionally, due to adaptive mechanisms, WOAAEO balances energy consumption so that data collision is minimized and packet delivery becomes highly reliable.

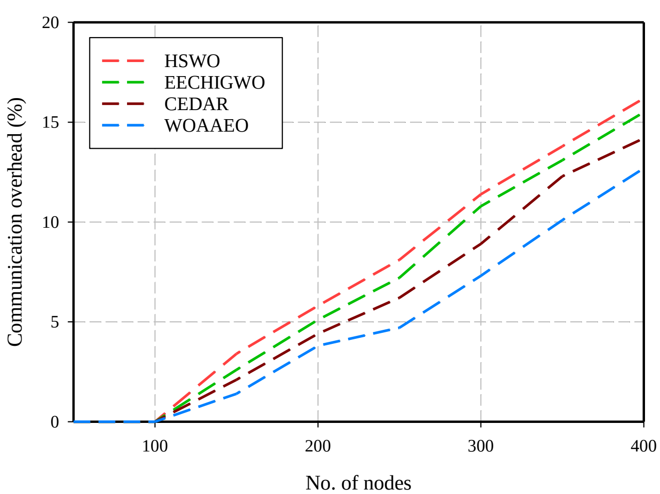

Fig. 7. Communication overhead comparison.

According to Fig. 7, for a network of 300 nodes, WOAAEO has the least communication overhead compared to other algorithms. Such a significant reduction in overhead is achievable due to the hybrid optimization approach through which WOAAEO intelligently handles CH rotation due to an appropriate balance of exploration and exploitation phases. The dynamic exploration capability of AEO and the correct exploitation mechanism of WOA are useful for WOAAEO for the optimum selection of CHs with minimum redundant communications. The adaptive streamlining of communication paths reduces superfluous data transmissions, better-utilizing energy and reducing the overall communications overhead.

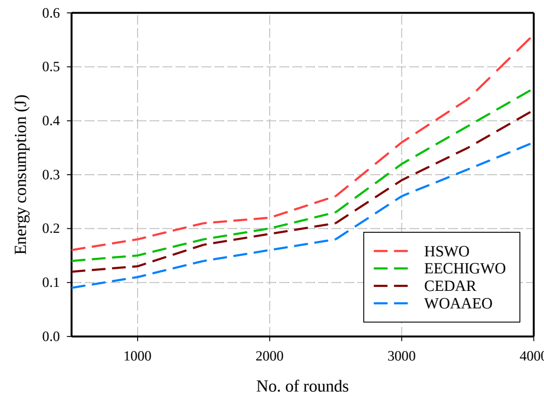

Fig. 8. Energy consumption comparison.

As shown in Fig. 8, WOAAEO reduces energy consumption to 0.36 J within 4000 rounds, which accounts for the energy consumption reduction, compared with CEDAR, HSWO, and EECHIGWO, respectively, by 14%, 35.7%, and 21.7%. This is driven by the remarkable energy efficiency induced within the network by the hybrid optimization approach of WOAAEO, which integrates the remaining energy and distance parameters within the CH selection process. By employing the exploration factor of AOE in identifying energy-efficient nodes and the exploitation factor of WOA in further refining CH placement, WOAAEO ensures that energy is utilized in a balanced manner throughout the network. Additionally, its adaptive mechanisms minimize redundant data transmissions and optimize clustering for reduced energy utilization, thus prolonging the network's lifespan.

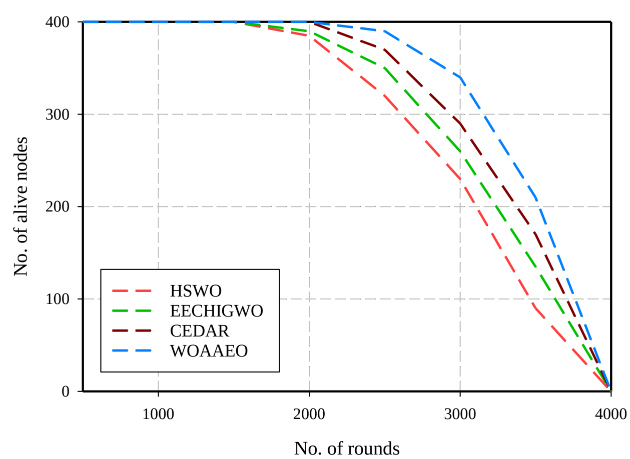

Fig. 9. No. of alive nodes comparison.

Fig. 9 illustrates that WOAAEO has kept 300 live nodes for up to 3000 rounds, which is considerably higher than other algorithms. This extended lifetime of the WOAAEO network has been achieved because its hybrid optimization model leverages the strengths of AEO exploration and WOA exploitation capabilities. The energy-efficient WOAAEO selects CHs dynamically based on residual energy and distance from the BS to avoid overutilizing particular nodes. Moreover, its adaptive CH rotation mechanism spreads out the network's energy consumption evenly so that no early node depletion occurs and more nodes remain active for more rounds. This balance in energy usage directly contributes to the network's operational life.

While the current evaluation focuses on a mid-range static WSN with 400 nodes, the extension of WOAAEO to very large or dynamic IoT deployments is a critical area that necessitates further investigation. For applications involving thousands of heterogeneous mobile devices, distributed re-clustering and CH selection schemes must be explored. Future research avenues for WOAAEO include distributed agent-based techniques to overcome bottlenecks in the centralized approach and mobility-aware schemes that adapt and reformulate cluster topologies based on dynamic updates to node movements. This will make WOAAEO scalable and efficient in supporting very dense IoT systems in real-world setups.

Although the presented work focuses on energy consumption, packet delivery ratio, and network lifetime as key performance metrics, other critical QoS factors, such as latency, network reliability, and network throughput, are also relevant to actual IoT applications. These were not explicitly modeled in the current version of WOAAEO, as energy efficiency was the key optimization area. Preliminary latency profiling indicated that the algorithm has an acceptable average latency due to the reduced CH switching rate and dynamic clustering. A more detailed evaluation of these additional QoS factors will be incorporated in subsequent works to validate WOAAEO under various operating conditions.

Even if WOAAEO efficiently optimizes CH selection, its current implementation considers direct single-hop communication between CHs and the BS. Massive deployments can cause substantial energy consumption by distant CHs. A better improvement would be to include a relay node optimizing strategy that supports multi-hop data transmission, minimizes the burden on distant CHs, and maximizes energy efficiency.

The WOAAEO framework supports technical performance in achieving overall goals, such as cost-effectiveness and environmental sustainability, which are crucial to successfully deploying IoT-based WSNs. WOAAEO reduces the battery replacement rate and e-waste by conserving energy consumption and extending the lifespan of the operating sensor node, thereby lowering the overall environmental cost of large-scale sensor deployments.

In applications such as remote farms, woodland surveillance, and urban infrastructures, where manual maintenance is expensive and logistically cumbersome, WOAAEO can alleviate operational budgets by increasing node lifespan and reducing manual intervention. Adaptive rotation and clustering of CH ensure energy is spent effectively without inducing early node death and avoidable replacements.

Additionally, the algorithm's efficiency in utilizing limited hardware resources makes it suitable for use in a lower-cost microcontroller-based platform, which aligns with the economic limitations common in developing areas or large-scale public projects. Such traits are the foundation of WOAAEO as a cost-effective and sustainable solution in energy-sensitive IoT applications.

V. Conclusion

This paper introduced WOAAEO, a novel hybrid optimization algorithm incorporating AEO into WOA to promote energy efficiency in WSNs. The full utilization of AEO's strong exploration ability and WOA's high exploitation precision enabled WOAAEO to reach an excellent trade-off between residual energy and communication overhead. These modifications significantly improved CH selection, packet delivery, and network lifespan. Simulation results suggested that WOAAEO outperforms the existing CEDAR, EECHIGWO, and HSWO algorithms on every key performance metric of energy consumption, communication overhead, and network lifetime. These results emphasize the potential capability of WOAAEO to prolong WSN operational life and reduce resource wastage, thereby giving promise in IoT-enabled environments that demand scalable and energy-efficient operations.

Future research avenues for WOAAEO include experimentation with its applicability through actual deployment within dynamic and heterogeneous IoT environments. Research that integrates WOAAEO with other IoT protocols, such as data combining and securing, is expected to further enhance its utility in advanced systems. Additionally, to realize its full potential in actual applications, WOAAEO will be enhanced to operate with massive-scale, mobile, and diverse IoT networks. This entails the development of decentralized variants, the inclusion of mobility prediction schemes, and the deployment of real-time feedback schemes to provide adaptive cluster control. Such enhancements in the future will be crucial to realizing the algorithm’s practicality in various emerging IoT applications, such as smart cities, industrialization, and agriculture.

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