A Co-evolutionary Algorithm-based Enhanced Grey Wolf Optimizer for the Routing of Wireless Sensor Networks

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***Abstract*—Wireless networks are frequently installed in arduous environments, heightening the importance of their consistent operation. To achieve this, effective strategies must be implemented to extend the lifespan of nodes. Energy-conserving routing protocols have emerged as the most prevalent methodology, as they strive to elongate the network's lifetime while guaranteeing reliable data routing with minimal latency. In this paper, a plethora of studies have been done with the purpose of improving network routing, such as the integration of clustering techniques, heterogeneity, and swarm intelligence-inspired approaches. A comparative investigation was conducted on a variety of swarm-based protocols, including a new coevolutionary binary grey wolf optimizer (Co-BGWO), a BGWO, a binary whale optimization, and a binary Salp swarm algorithm. The objective was to optimize cluster heads (CHs) positions and their number during the initial stage of both two-level and three-level heterogeneous networks. The study concluded that these newly developed protocols are more reliable, stable, and energy-efficient than the standard SEP and EDEEC heterogeneous protocols. Specifically, in 150 m^2 area of interest, the Co-BGWO and BGWO protocols of two levels were found the most efficient, with over than 33% increase in remaining energy percentage compared to SEP, and over 24% more than EDEEC in three-level networks.**

***Index terms*—Gray wolf optimizer, Co-evolution, swarm optimization, wireless sensor networks.**

I. INTRODUCTION

Over the past few years, wireless sensor networks have rapidly emerged as a growing technology. These networks rely on sensors to monitor and gather data on environmental events. Their adaptability in tackling various problems across diverse fields has led to their widespread adoption in various application domains, including detecting air pollution, forest fires, and greenhouse monitoring, as well as identifying landslides, structural monitoring, industrial, and agricultural processes. Additionally, WSNs have the potential to innovate daily life in various ways, such as healthcare, transportation, smart-houses, and military applications [1].

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The progress of WSNs is impeded by a number of challenges, including scalability, power limitations, fault tolerance, and reliability. To ensure optimal network performance when its size expands, scalability is a critical factor. Moreover, since WSNs rely on batteries with limited lifespans, it is vital that they function for as long as possible. Several protocols and schemes have been proposed to manage WSNs' power consumption, such as energy-efficient MAC protocols, data aggregation, topology management, data compression, intelligent battery usage, and utilizing low-power electronic devices [2].

Designing self-organizing wireless sensor networks (WSNs) is essential to account for potential node failures and ensure fault tolerance, particularly in hostile environments. Reliability issues such as packet loss due to their wireless nature also pose a challenge. In critical areas such as chemical attack detection, WSNs' usage can lead to devastating consequences. Additionally, security concerns arise due to the susceptibility of wireless channels to unauthorized access. Therefore, exploring multiple approaches, including traffic encryption, is crucial to prevent such access [3].

The longevity of a network and reliable data transmission are often achieved through the use of energy-efficient routing protocols. Despite extensive research, there is no optimal routing protocol that balances energy efficiency with computational speed. In order to tackle network latency in large networks, hierarchical routing protocols have been developed. By aggregating data at the cluster head (CH) level, these protocols save energy and ensure balanced energy consumption by alternating the CH role between nodes. Hierarchical networks offer several benefits, such as speedy data delivery through data aggregation, fault tolerance through CH role rotation, and scalability via multi-hop routing strategies [4].

In Wireless Sensor Networks (WSNs), the majority of clustering-based protocols prioritize extending the network's lifespan without considering its stability or the time frame until the first node dies. This is a significant concern in real-world WSN applications. To address this issue, Heterogeneous networks have emerged to improve both network lifespan and its stability. These protocols equip certain nodes, often serving as cluster heads, with higher energy capacity. There exist several heterogeneous protocols, such as SEP, EDEEC, EDFCM, BEENISH, and ZREECR [5].

Despite these numerous potential solutions, their effectiveness is limited by the initial selection of Cluster Heads (CHs) based on probability. The process of determining the ideal set of cluster heads falls under the category of Non-deterministic Polynomial (NP)-hard problems, requiring extensive exploration to identify potential solutions. The use of Swarm-based techniques has proven successful in discovering optimal solutions within vast research spaces.

The aim of this research is to enhance the conventional routing protocols SEP and EDEEC by utilizing swarm optimization techniques to select the most efficient cluster heads (CHs). The research employs an improved co-evolutionary binary grey wolf optimizer (Co-BGWO), a binary grey wolf optimizer (BGWO), a binary whale optimizer (BWHALE), and a binary Salp swarm algorithm (BSSA) to identify the most suitable CHs based on three distinct objective functions. The primary goal is to prevent node failure and prolong the network's lifespan while improving data reliability. Compared to standard protocols, the proposed methods resulted in better stability, packet delivery, and energy conservation.

The focal point of this study (Fig.1) is the dynamic and centralized selection of Cluster Heads (CHs) in the base station. The nodes within the network regularly transmit information about their remaining energy levels to the base station. This data is then utilized by the Co-BGWO (BGWO, BWHALE, or BSSA) algorithm to determine the optimal set of CHs. The identification numbers (IDS) of the CHs that best meet the optimized criteria are subsequently shared with the nodes. Each node then joins the CH node that has the strongest received radio signal (RSSI), by sending a request message (Join-REQ) using the CSMA (carrier-sense multiple access) protocol. To prevent data overlap between nodes, each CH establishes a scheduling plan based on the TDMA protocol (Time-division multiple access) for communication with its associated nodes. If necessary, the CHs aggregates the received data before transmitting it to the base station via the CSMA protocol to check the channel's accessibility [6].

The entire process is composed of two key sections: setup and communication phases. During the setup stage, cluster heads and clusters are determined, while communication phase entails the transport of sensed data from nodes to CHs using TDMA and then from CHs to BS using CSMA.

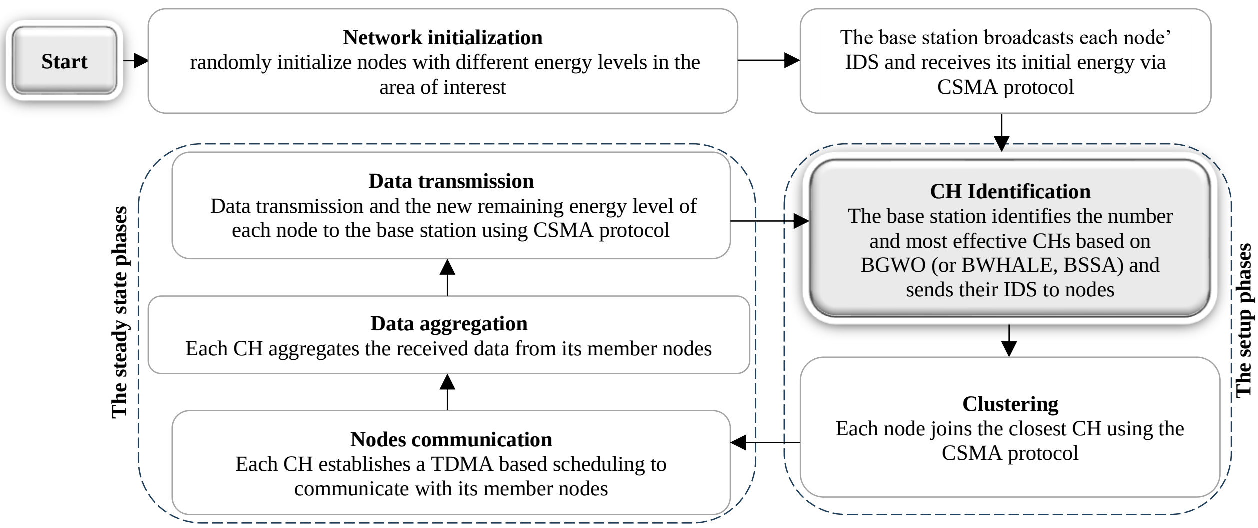

Fig. 1. A diagram illustrating the data flow within the system

If the channel is deemed available, the cluster head proceeds to transmit the accumulated data to the base station. However, if the channel is found to be unavailable, the cluster head enters a waiting state [6].

This document is organized into four sections. The second section provides a brief overview of relevant research, whereas the third section delves into the swarm optimization techniques that were utilized to select cluster heads (CHs). The algorithms used for this purpose were BGWO, co-evolutionary BGWO, BWHALE, and BSSA. The subsequent section lays out the results achieved, and the article concludes with a conclusion and a glance into future prospects.

II. Literature Review

In the field of wireless sensor networks, swarm intelligence holds great promise. This decentralized and distributed problem-solving method mimics the collective behaviour of animal groups and is especially useful for tackling complex problems with multiple potential solutions. As the demand for energy-efficient and reliable data transmission continues to rise, swarm intelligence could be the key to optimizing network performance.

By refining routing protocols, swarm intelligence has the capacity to reduce energy usage, boost network coverage, and enhance fault tolerance. Its potential effectiveness is derived from the prioritization of robust cluster heads, the creation of optimal node paths, and the enhancement of both latency and reliability. In the next section, there will be an examination of different swarm optimization protocols that have achieved some of these objectives.

The aim of the work presented in [7], is to propose an energy-efficient method for selecting CHs in WSNs. This method utilizes an improved version of the Grey Wolf Optimization (GWO), taking into account the distance from the sink, the nodes' remaining energy, and a balancing factor that assigns 80% weightage to residual energy and 20% weightage to the distance between nodes and the BS. The proposed protocol, named EECHIGWO, incorporates multi-hop capabilities and yields optimal values for the fitness function, thereby enhancing the lifetime of the WSN. The fitness function for CH selection is designed to consider both the residual energy of the Sensor Nodes (SNs) and their Euclidean distance to the BS. Simulation results have demonstrated that the network's throughput, stability, and lifetime are significantly improved when compared to existing energy-efficient routing protocols for WSNs.

In [8], a novel routing protocol is introduced that combines the grey wolf optimizer (GWO) and the Tabu search algorithm (TSA) to achieve energy efficiency. The protocol proposes a routing system with a primary focus on clustering and the selection of cluster heads (CH) using GWO. This selection process is conducted by a fitness function that evaluates the residual energy of sensor nodes and the average distance between CH and sink nodes. The experimental findings demonstrate that the proposed GWO-TSA algorithm offers significant benefits compared to other algorithms the genetic algorithm with Tabu search algorithm (GA-TSA) and the grey wolf optimizer with crow search algorithm (GWO-CSA).

The research paper [9] introduces a GWO-based strategy to enhance energy conservation in WSNs. The study proposes and examines a fuzzy-GWO technique. This approach takes into account various factors, including residual energy, node centrality (NC), neighbourhood overlap (NOVER), and link quality assessment. These factors are used as a fuzzy rule set to identify the most suitable node to act as a CH. Based on the experimental results, the proposed F-GWO algorithm outperforms the LEACH, HEED, MBC, and FRLDG protocols in terms of network lifetime, packet delivery ratio, throughput, bit error rate (BER), buffer occupancy, time analysis, and end-to-end delay. The fitness function employed ensures that nodes with the highest energy levels and those in close proximity to the base station have a higher probability of being selected as CHs [9].

In the research paper [9], a strategy based on GWO is introduced to improve energy conservation in WSNs. The paper presents and evaluates a technique called fuzzy-GWO, which takes into consideration multiple factors including node centrality, residual energy, the intra-cluster distance, and the link quality assessment. These factors are used as a set of fuzzy rules to determine the optimal node to act as a Cluster Head. The fitness function employed in the algorithm ensures that nodes with the highest energy levels and those in close proximity to the base station have a higher likelihood of being selected as CHs. According to the experimental results, the proposed F-GWO algorithm outperforms the LEACH, HEED, FRLDG, and MBC protocols in terms of network lifetime, packet delivery ratio, throughput, and end-to-end delay [9].

The GWO-DFO is an innovative approach to multipath routing which strives to enhance the life expectancy of the WSN and reduce energy consumption. This method is a hybrid of Grey Wolf Optimization (GWO) and Dragonfly Optimization (DFO) and is used to locate the optimal route between the target node and the base station. GWO is employed to detect the best route for data transfer and DFO helps find a local optimal solution and pick the correct node. With the help of the cluster head, the nodes that require data transfer can be easily pinpointed for subsequent processing. This system was found to be superior to other strategies such as k-means, LEACH-C, CHIRON, and Optimal-CBR when taking into consideration aspects such as energy saving, stability, reliability, rate of packets delivery, and delay [10].

In a proposal to prolong the lifespan of wireless networks, a cluster-based routing strategy is proposed [11]. The technique involves two phases. During the first phase, a novel algorithm dubbed the Moth Levy-adopted Artificial Electric Field Algorithm (ML-AEFA), is used to select the best cluster heads (CHs). While the second phase involves transmitting data via a Customized Grey Wolf Optimization (CGWO). The CH selection process is based on a range of factors including energy, distance between nodes, node degree, first death node, and distance between CH and the base station. The findings of the study revealed that the proposed technique was able to prolong network lifetime by an impressive percentage of 34% outperforming thus other algorithms such as ACO, MSA, GWO, BOA+ACO, and AEFA.

Another multi-hop routing based on Whale Optimization to select cluster heads is presented in [12]. The fitness function aimed to balance energy consumption evenly across the network by taking into account the remaining energy of sensor nodes and their neighbour nodes. This resulted in a longer network lifespan and reduced energy usage. Compared to other protocols like MobiCluster, MASP, and EEDCRP, the proposed approach outperformed EEDCRP, MASP, and MobiCluster, by achieving an average increase of 20% in network lifetime and a 25% reduction in energy consumption.

A Whale-based routing called WOA-Clustering (WOA-C) is proposed in [13]. This approach uses a fitness function that takes into account the remaining energy of node and energy of its neighbouring nodes. Results demonstrated that the proposed algorithm outperforms LEACH in terms of residual energy, network lifespan, and stability period.

In [14], an energy-saving routing protocol was proposed which utilizes the Brainstorm algorithm to decide on the optimal CHs. To this purpose, the BrainStorm Optimization (BSO) algorithm was improved by the integration of the Modified Teacher-Learner Optimized (MTLBO) algorithm. This modified BSO-MTLBO algorithm was then employed to increase the network's lifetime and to raise the throughput. The selection of the CHs through the BSO-TLBO algorithm was based on metrics, such as Residual energy, Node degree, the average intra-cluster distance, the total distance between CHs and BS, and Node centrality, for the efficient transmission of data from the sensor nodes to the BS. The performance of the proposed work was compared with other existing approaches, and proved to be more effective.

The Hybrid Cuckoo Search (AHCS) algorithm, outlined in [15], applied the position update of GWO, and incorporated the inertia weight w in the Lévy flight method of CS algorithm, as well as the dynamic adjustment methods of parameters α and β. This approach involves mobile node selection and data routing. First, an algorithm is designed to identify the near-optimal set of CHs. Then, the non-CH nodes are assigned to the cluster heads based on a derived function. Furthermore, a routing algorithm is designed to identify the optimal route from each mobile node to the event location. The performance of AHCS-GWO has been assessed in terms of end-to-end delay, energy saving, packet drop ratio, and dead time. The AHCS-GWO based protocol was found superior to other methods such as EMEER and YSGA [15].

In [16], the Salp Swarm Algorithm (SSA) is presented to determine the optimal placement of a sink node. After that, pathways between the sink node and the rest of nodes are established and the shortest one is determined with the help of Prim's minimum spanning tree. For the fitness function that is intended to reduce the network energy consumption, it is based on the number of active nodes, energy of the sink node's neighbours, and the total distance between the sink and nodes. Results showed that the proposed algorithm delivers the best outcomes in terms of extending the network lifetime when compared to Cat Swarm Optimization (CSA) and Particle Swarm Optimization (PSO).

Table I outlines the characteristics of the presented swarm-based protocols, which were designed to extend the network duration, and improve the throughput, latency, and reliability.

TABLE I
EXAMINATION OF ANALOGOUS ALGORITHMS AND THEIR CHARACTERISTICS

Reference	Heuristic approach	Objective function	Heterogeneity	Topology	Goal
EECHIGWO[6]	Improved GWO	A weighted function with a balancing factor of 80% given to residual energy and 20% given to the distance between nodes and BS.	Homogeneous	Multi-hop	Extending the network lifetime
GWO-TSA [7]	grey wolf optimizer (GWO) and the Tabu search algorithm (TSA)	A weighted function based on the total distance from nodes to BS, the total distance from each CH and its member nodes and the total initial energy and remaining energy.	Heterogeneous	Multi-hop	Maximizing network lifetime, and boosting network throughput.
F-GWO [8]	fuzzy-GWO	A weighted function based on the average Intra-cluster Distance, the average Distance between Sink and the cluster heads, the total energy of cluster heads, and clusters sizes.	Homogeneous	Single- hop	Maximizing network lifetime, the network throughput, delay and reliability.
GWO-DFO [9]	Grey Wolf Optimization and Dragonfly Optimization	the maximum of remaining energy	Homogeneous	Single- hop	Energy efficiency and reliability
ML-AEFA & CGWO [10]	Moth Levy-adopted Artificial Electric Field Algorithm (ML-AEFA), & Customized Grey Wolf Optimization (CGWO).	Fitness based on energy, distance between nodes, node degree, first death node, and distance between CHs and BS.	Homogeneous	Multi-hop	Extending the network lifetime
WOA-based [11]	Whale Optimization	A weighted function based on number of each CH neighbours and the remaining energy of each CH members	Homogeneous	Multi-hop	Energy efficiency & extending the network lifetime
WOA-C [12]		A weighted function based on number of each CH neighbours and the remaining energy of each CH members	Homogeneous	Single-hop	Stability and network lifetime
BSO-TLBO [13]	An improved BrainStorm Optimization (BSO) with the Modified Teacher-Learner Optimization (MTLBO)	A weighted function based on the CHs' residual energy, the CH node degree, the average intra-cluster distance, the total distance between CHs and BS, and Node centrality.	Homogeneous	Single-hop	Energy efficiency, network lifetime, and throughput.
AHCS [14]	an Adaptive Hybrid Cuckoo Search (AHCS)	Fitness based on intra-cluster distance, residual energy, distance from mobile node to the event location and node degree.	Homogeneous	Multi-hop	maximizing network lifetime, throughput, delay and reliability.
SSA [15]	Salp Swarm Algorithm	is based on the number of active nodes, energy of the sink neighbouring node, and the total distance between the sink node and all sensor nodes.	Homogeneous	Multi-hop	Prolonging the network's lifetime

The present research stands out for its comprehensive examination concerning the application of swarm intelligence techniques to prolong the lifetime of heterogeneous networks and maintain their stability and reliability. In this investigation, the most advanced swarm intelligence optimization strategies have been employed to address the routing problem through the analysis of different objective functions with an exhaustive comparison based on numerous performance metrics.

III. RESEARCH METHODS

In this work, a proposal to enhance network reliability using swarm-based protocols for choosing the best cluster heads

(CHs) in heterogeneous networks. The efficiency of these swarm-based techniques is measured against conventional heterogeneous procedures, such as SEP and EDEEC.

Both SEP and EDEEC protocols use probabilistic equations to assign the role of Cluster Head (CH) among nodes. For SEP, the probabilistic equation considers two energy levels (advanced and normal), the desired percentage of CHs, the unelected nodes as CHs, and the number of rounds completed. Similarly, EDEEC selects CHs based on residual energy, network average energy for a given number of rounds, and three initial energy levels (super, advanced, or normal) as well as the set of nodes that have not been elected as CHs.

Cluster heads identification is crucial to ensure longevity and network reliability. In this investigation, the selection process employs a method of optimization guided by Co-BGWO, BGWO, BWHALE or BSSA. The objective is to assess the initial and residual energy of nodes, the node degree, the intra-cluster distance and nodes' distances from the base station to identify the best candidates for the CH role.

The suggested techniques utilize clustering to enhance speed and diminish redundancy. Each cluster head collects messages from its respective members, merges similar packets, and serves as a gateway for other cluster heads. The process entails two critical stages: setup and communication. The setup phase identifies cluster heads and clusters, whereas the communication phase transports sensed data from nodes to cluster heads via TDMA protocol and from cluster heads to the base station via CSMA protocol. Further details regarding these steps are elaborated in the subsequent subsections.

In the initial stage, the BS bears the responsibility of choosing the cluster heads centrally through the mentioned swarm intelligence-based techniques. Once the CHs are determined, the found list is disseminated to all nodes, which then join to the nearest CH based on the strength of radio signals. After nodes clustering, each CH initiates a transmission plan among its member nodes using the TDMA protocol.

In order to determine the best network configuration, the CHs selection issue can be resolved by utilizing Co-BGWO, BGWO, BWHALE, or BSSA. Each solution is represented by a structure that consists of a binary vector indicating whether a specific node is chosen as a cluster head or not. These structures correspond to wolves, whales, or Salps.

A solution	0	1	0	1	1	0	1
Nodes IDs	1	2	3	4	5	6	7

Fig. 2. Solution representation for a network comprising 7 nodes

The process of optimization is directed by an objective function that prioritizes the cluster heads (CHs) with the highest ratio of residual energies to initial energies, or the CH degree and its remaining energy or an objective function based on the CH intra-cluster distance and the CHs' distances from the base station. This is expressed in the following equations.

$$Fitness1 = \frac{\sum_{i=1}^{N} Er_i}{\sum_{i=1}^{N} Ei_i} \quad (1)$$

$\mathrm{Er_i}$ represents the remaining energy of node i

$\mathrm{Ei_i}$ represents its initial energy level

N is the number of CH nodes.

In order to compare our work with prior studies, two other objective functions were considered. the first one is related to the number of cluster nodes for each CH as well as the energy available in the CHs while the second is focused on the intra-cluster distance and the distances from CHs to base station.

$$Fitness2 = w \times \left(d(C_i)\right) + (1-w) \times \sum E(C_i) \quad (2)$$

$\mathbf{d(C_i)}$ is the CH degree i.e., number of each CH neighbours

$\mathbf{E(C_i)}$ is the remaining energy of each CH $(\mathbf{C_i})$.

In order to identify the suitable CH, using Fitness2, the node degree is employed to select a CH with the least number of neighbouring nodes. Moreover, the CH requires more energy to transmit data from its nodes to the Base Station, making nodes with a higher energy level more probable to be chosen as CH.

$$Fitness3 = w \times \left(T - D_{c_i}\right) + (1-w) \times (n - n_{c_i}) \quad (3)$$

w=0.3;

T is the total distance between nodes and BS

$\mathrm{D_{c_i}}$ is the intra cluster distance

n is the Number of nodes

$\mathrm{n_{c_i}}$ is the number of CHs

T $=\sum_{i=1}^{N} dis(SN_i - BS)$

$\mathrm{D_{c_i}} = \sum_{i=1}^{l}\sum_{j=1}^{K} dis(SN_i - CH_j)$

The first part of formula (3) seeks to raise the size of cluster heads, whereas the second part attempts to regulate their number.

The subsections below outline the process by which the swarm optimization techniques were tailored to address the issue of routing in wireless networks.

A. The BGWO based Routing

Inspired by the chasing strategies of gray wolves, the GWO categorizes the population into four distinct groups of wolves: alpha, beta, delta, and omega. The alpha wolf is the primary leader, with the beta wolf aiding in prey detection. The delta wolf serves as the third leader and maintains authority over the omega wolves [17].

The mathematical model's hunting mechanism is overseen by three superior solutions designated as alpha (α), beta (β), and delta (δ). Omega (ω) wolves, on the other hand, follow these alphas, betas, and deltas leaders. This implies that the omega wolves are directed towards the optimal prey location by the alpha, beta, and delta solutions [17].

$$X(t+1) = \frac{X_1 + X_2 + X_1}{3} \quad (4)$$

The omega wolf's position at iteration t+1 is denoted as X, while X1, X2, and X3 are the positions of the three leading wolves.

The prey encirclement behaviour by wolves can be expressed using the prey positions (the three leading wolves at iteration t) denoted as $\mathrm{X_\alpha}$, $\mathrm{X_\beta}$ and $\mathrm{X_\delta}$, and the three leader positions at a future iteration t+1 denoted as X_1, X_2, and X_3[18].

$$X_1 = |X_\alpha - A_1.D_\alpha|$$
$$X_2 = |X_\beta - A_2.D_\beta| \quad (5)$$
$$X_3 = |X_\delta - A_3.D_\delta|$$

A_1, A_2 and A_3 are calculated as follows [18]:

$$A = 2 \times a \times r - a \quad (6)$$

"r" is a real number randomly chosen from the uniform distribution between 0 and 1. " a " is a weight that decreases from 2 to 0, and it helps to balance the trade-off between exploration and exploitation [17],[18]:

$$a = 2 \times \left(1 - \frac{I}{I_{max}}\right) \quad (7)$$

with I the current iteration number and I_{max} is the maximum number of iterations

Dα, Dβ and Dδ are defined as follows [17],[18]:

$$D_\alpha = |C_1.X_\alpha - X|$$
$$D_\beta = |C_2.X_\beta - X| \quad (8)$$
$$D_\delta = |C_3.X_\delta - X|$$

C_1, C_2 and C_3 are calculated by the equation below [17]:

$$C = 2 \times r \quad (9)$$

r is a random value from the uniform interval]0,1[.

In order to address the CHs selection issue, we utilized the version BGWO1 proposed by Too et al [19]. In this algorithm, the wolf's positions are converted to binary by applying the sigmoid function on the parameters $D_\alpha, D_\beta, D_\delta$, and A_1, A_2, A_3 as per the equation below [19]:

$$V_i^d = \begin{cases} 0, & if\ sig\left(-A_i^d.D_i^d, [10{,}0.5]\right) < r \\ 1, & otherwise \end{cases} \quad (10)$$

d is the search space dimension, i=α, β or δ. r a random number from the uniformly distributed interval]0,1[.

$$sig(-A_i^d.D_i^d, [10{,}0.5]) = \frac{1}{1 + exp^{(-10(-A_i^d.D_i^d - 0.5))}} \quad (11)$$

Then the positions of the three leader wolfs are obtained as follows:

$$Y_i^d = \begin{cases} 1, & if X_i^d + V_i^d \geq 1 \\ 0, & otherwise \end{cases} \quad (12)$$

The new position of each grey wolf is obtained using the crossover operator on $Y_\alpha, Y_\beta, Y_\delta$ as follows [19]:

$$X^d(t+1) = \begin{cases} Y_\alpha^d, if\ r < 0.33 \\ Y_\beta^d, if\ r < 0.66 \\ Y_\delta^d, otherwise \end{cases} \quad (13)$$

The routing problem using the BGWO algorithm can be summarized in the subsequent steps:

The BGWO-based routing protocol

Input: A sink and several nodes dispersed over the area of interest

Output: Cluster heads determination and routing data to sink node.

Step 1: Network Initialization

1. Initialize a fraction of nodes as advanced, intermediate, or super nodes, each with different initial energy capacities depending on the number of heterogeneity levels.
2. Initialize the remaining normal nodes with a standard energy capacity
3. Initialize the sink with unlimited energy power

Step 2: grey wolves' initialization

4. Randomly initialize gray wolf population with binary values as illustrated in figure (Fig.2)
5. Randomly initialize the three best wolfs (X_α ,X_β, X_δ)

Step 3: CHs optimization

6. *For each round do*
   7. Calculate the coefficient a using equation (7)
   8. *For each wolf do*
      9. Nodes clustering around the nodes associated with value 1 in the current wolf position
      10. Evaluate the wolf fitness using equation (1, 2 or 3)
      11. Identify the three best wolfs based on their fitness
      12. Calculate A_i and C_i using equations (6) and (9) with $i = \alpha, \beta$ or δ
      13. Calculate D_i based on the current three leaders positions and the current wolf position using equation (8)
      14. Calculate the binary three leaders using equations: (10), (11) and (12)
      15. Update the current wolf position by applying the crossover operator on the new found three leaders' positions using equation (13)
   16. *End* for each wolf

Step 4: CHs identification

17. The current round's cluster heads are nodes that have been linked with a value of 1 in the alpha wolf position.
18. Every remaining node connects to the cluster head that is closest to them.

Step 5: Communication

19. The transfer of data from nodes to CHs operates using TDMA protocol, while from CHs to BS, it operates through CSMA protocol.

20. *Until* a maximum number of rounds

B. The Co-evolutionary BGWO based routing

Co-evolutionary algorithms represent a category of optimization methods that draw inspiration from the mutual advantages shared among species in the natural world. This study introduces a co-evolutionary algorithm aimed at enhancing the efficacy of the grey wolf optimizer in the context of sensor network routing. The fundamental concept revolves around the notion that the aforementioned parameters: A_1, A_2, A_3 as well as C_1, C_2, and C_3 significantly impact the GWO search strategy. Consequently, these parameters and cluster heads, along with their number, have been treated as distinct species coexisting in an environment where they can derive mutual benefits from each other.

In order to optimize the parameters of the grey wolf, a particle swarm optimizer (PSO) is utilized in this research. The process of co-evolution is accomplished by retaining the optimal CHs and parameters that have contributed significantly to the enhancement of network energy efficiency while searching for the best CHs using the grey wolf optimizer.

In this article, we present a symbiotic co-evolutionary algorithm that combines the strengths of PSO and GWO. Our inspiration draws from the work [20], however our representation relies on binary GWO concepts.

The first species, comprises a swarm of particles, is utilized for optimizing the grey wolf parameters A_1, A_2, and A_3, along with C_1, C_2, and C_3 using PSO optimization. Each particle in the swarm is represented by a vector of grey wolf parameters. The second species is employed to preserve the top-performing network configuration that resulted in the least energy consumption. A grey wolf is a collection of cluster heads IDs with variant size as illustrated below:

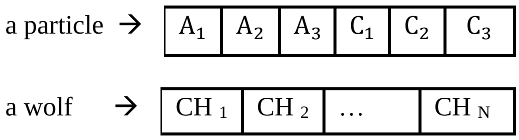

Fig. 3. Structure of each species

The purpose of co-evolution is the adaptation of parameters with their companion cluster heads via a co-evolutionary algorithm as explained in [20]. In this study, each configuration is linked with a particle that encodes the grey wolf parameters. Co-evolution occurs when the network configuration obtains its fitness from their companion parameters, allowing the parameters to adapt to the network structure using the particle swarm optimizer.

The network configuration changes consistently by considering the new related parameters. Consequently, the network's fitness is ascertained through its interaction with these associated parameters. This fitness signifies the enhancement brought by the parameters to the network, which equates to the subsequent sum:

Improvement (parameters) = (*old fitness - new fitness*) of related network configuration

The parameters with the highest improvement are considered the best. The fitness assignment for these parameters is done for each 30 iterations, unless they are kept unchanged during the process of the network optimization.

In order to establish a network for data routing, a sink and multiple nodes are positioned across the designated area to detect cluster heads and transmit data. To begin configuring the network, a percentage of n nodes are designated as advanced nodes, with an initial energy level of E_0 multiplied by (1+a) in two-level protocols. In three-level protocols, a portion of n nodes are initialized as intermediate nodes, while a fraction of m_O nodes are initialized as super nodes with initial energy levels of $(E_0 * a)$ and $(E_0 * b)$ respectively. The remaining normal nodes are initialized with an energy capacity of E_0, while the sink node has an infinite energy power.

This Co-evolutionary-BGWO based protocol can be illustrated in the diagram below:

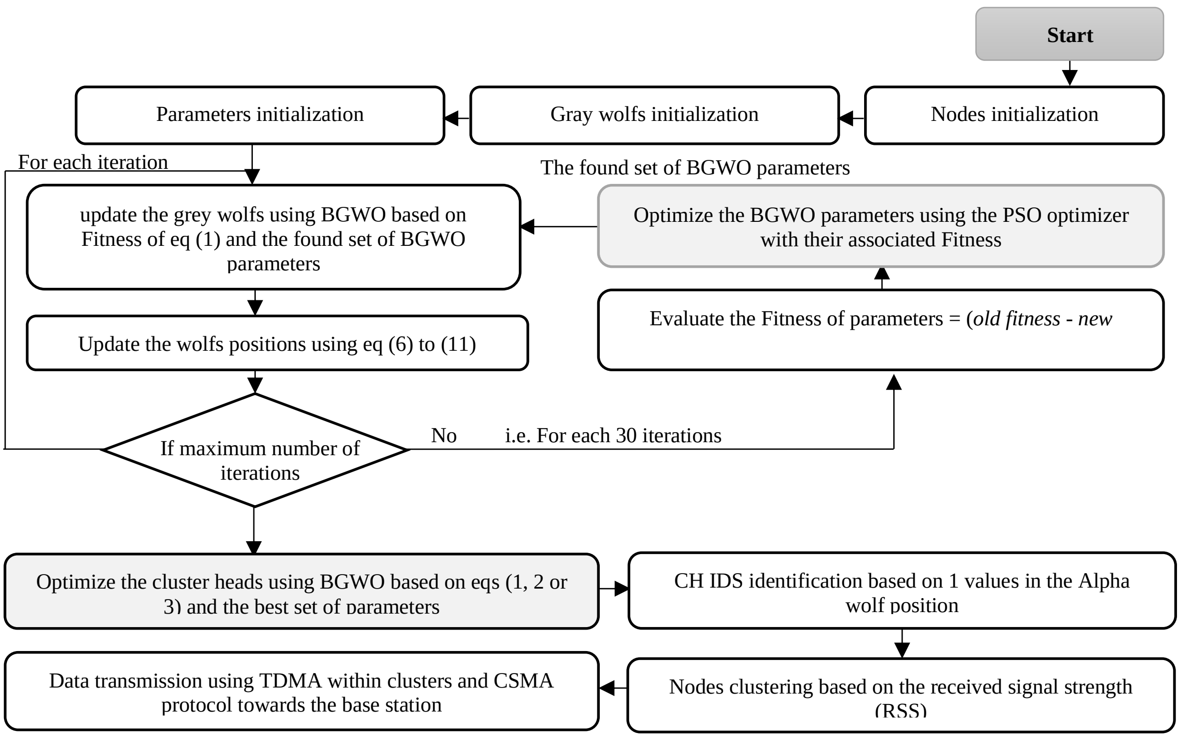

Fig. 4. Illustration of the CO-BGWO based routing steps

The process of routing using Co-BGWO can be detailed through the following steps:

The Co-BGWO-based routing protocol
Step1: Network initialization
Step2: Parameters initialization
1. Initialize a number of particles with random values between 2 and -2
Repeat
2. Calculate the coefficient a using equation (7)
For each wolf *do* (number of wolfs = number of particles)
3. Determine the current set of cluster heads according to the position of ones in the current wolf (p)
4. Nodes clustering around the current cluster heads
5. Utilize Equation (1,2 or 3) to assess the current fitness of wolves.
6. Select the best three wolves
7. Identify the current parameters $A_1, A_2, A_3, C_1, C_2, C_3$
8. Adjust the current wolf position using equations (8) to (13) while taking into account the current set of parameters
9. Set Old_fitness (p)= the wolf fitness before the next 30 iterations
10. Set Current_fitness (p) = the current wolf fitness after 30 iterations
11. Set Current_fitness_parameter(p) = Current_fitness (p) – Old_fitness (p)
12. Adjust the parameters positions using PSO algorithm
13. *end* for each wolf
14. *end* for iterations
15. Set bestparameters = the best-found parameters by PSO
16. *For* each round *do*
17. optimize cluster heads positions based on BGWO using the best-found parameters
Step 6: cluster heads determination
18. The nodes rated with a value of 1in the position occupying the alpha wolf' role, are selected as cluster heads of the current round.
19. Each of the remaining nodes connects to the cluster heads that are nearest to them.
Step 7: The communication phase
20. The transmission of data from nodes to CHs follows the TDMA protocol, while the transmission from CHs to BS follows the CSMA protocol.
21. *Until* the maximum number of rounds

C. Whale Optimization based routing

The Whale Optimization Algorithm (WOA), mimics the hunting behavior of whales. The algorithm has three steps: searching for prey, encircling prey and bubble net attacking [21].

The Search Stage: This stage is inspired by how whales detect and locate other whales before beginning their hunt. In this step, the whales adjust their positions towards a solution that has been randomly selected to prevent becoming trapped in a local optimum as formulated below [21]:

$$X(t+1) = X_{rand} - A.D \tag{14}$$

The position of a whale is denoted as " X ". The variable "t" signifies the current number of iterations. Meanwhile, "X_{rand}" represents a position vector that is generated randomly [21].

$$A = 2 \times a \times r - a \tag{15}$$

$$D = |C.X_{rand} - X| \tag{16}$$

"r" is randomly chosen from the uniform interval]0,1[

"a" is a decreasing weight from 2 to 0 to balance exploration and exploitation [21], [22]:

$$a = 2 \times \left(1 - \frac{I}{I_{max}}\right) \tag{17}$$

$$C = 2.r \tag{18}$$

The optimum Prey encirclement is modelled by decreasing the value of "a" in the equations below [21], [22]:

$$X(t+1) = X_p(t+1) - A.D \tag{19}$$

$$D = |C.X_p - X| \tag{20}$$

X_p is the position of the best solution (the prey). C and A are calculated as before.

Therefore, reducing the "a" value shortens the distance between a whale X and the best solution X_p, leading to the prey encirclement.

The "bubble net" attacking strategy employs two-pronged approach. Firstly, the coefficient "a" is reduced in order to encircle the prey. Secondly, the position of the spiral whale is adjusted based on the distance between it and the prey. Both of these techniques are applied with a probability of 50%, as expressed below [23].

$$X(t+1) = \begin{cases} X_p(t) - A.D, & if\ px < 0.5 \\ Dis.e^{b\,l}.cos(2\pi l) + X_p(t), & if\ px \geq 0.5 \end{cases} \tag{21}$$

$$Dis = |X_p - X| \tag{22}$$

"l", is randomly chosen from [-1, 1]. The logarithmic spiral's shape is defined by the constant, "b", which is set to 1[21].

In the proposed binary version, the positions are transformed into binary values using the sigmoid function, as follows:

$$X^d = \begin{cases} 0, & if\ sig(X^d) < 0.5 \\ 1, & otherwise \end{cases} \tag{23}$$

d: dimension of the search space:

$$sig(X^d) = \frac{1}{1 + exp^{(-X^d)}} \tag{24}$$

The process of routing using binary whale optimization can be succinctly explained through the following steps:

The BWhale -based routing protocol
Step1: Network initialization
Step2: Whales initialization
1. Randomly initialize a number of whales with binary values
2. Use equation (1) to assess the value of whales.
3. Select the superior whale.
Step 3: CHs optimization

4. *For* every round, perform the following steps:
 5. Calculate a using equation (17)
 6. *For* each whale *do*
  7. Compute values for A and C by utilizing equations (15) and (18) respectively
  8. Randomly initialize px between 0 and 1
  9. *If* px<0.5
   10. *If* abs (A) >=1
    11. Update the whale position by utilizing formula (14).
   12. *Else* if abs(A)<1
    13. Update the whale position by applying equation (19)
   14. *End* if abs(A)
  15. *Else* (if px >= 0.5)
   16. Adjust the whale position using the second part of equation (21)
  17. *End* if
 18. *End* for each whale
 19. Restriction of whale positions between upper & lower bounds
 20. Convert whale positions to binary by utilizing equation (23)
 21. Whale fitness calculation and best Whale update

Step 6: CHs identification
 22. The nodes associated with value 1 in the best whale position are the cluster heads of the current round.
 23. The nearest cluster heads are connected to each of the remaining nodes.

Step 7: Communication
 24 The transmission of data from nodes to CHs adheres to the TDMA protocol, whereas the transmission of data from CHs to BS is based on the CSMA protocol.

25. *End* for each round

D. BSSA based Routing

The optimization technique known as SSA (Salp Swarm Algorithm) emulates the behaviour of salps as they swarm the ocean searching for food. These diaphanous sea creatures navigate the seawater in spirals. with the leader Salp guiding its followers towards the most favorable food source. The leader Salp repositions itself nearer to the best food source, while the first follower tracks the leader. Subsequent followers then adjust their positions closer to the preceding follower, thereby emulating the Newtonian mechanism. During the next iteration, the superior food source replaces the previous one. This process continues until a maximum number of iterations is reached. The proposed binary version of SSA, transforms Salps positions into binary using the sigmoid function, similar to BWHALE optimization [24].

IV. Results & Discussion

A. Simulation Model

To correctly measure the energy utilized by sensors' electronic circuits, the first-order radio energy model is used. This latter is widely accepted in clustering-based protocols.

The purpose is to guarantee that every energy expenditure is accurately recorded [25]. The first-order energy model aims to assess the energy used by electronic components and disregards the energy lost by the microprocessor and microsensors. The first-order radio energy model involves the source node expending energy through its transmitter and amplifier circuits, while the destination node consumes energy through its receiver electronic circuit. Additionally, the model takes into account two channel types: the free-space channel model and the multipath fading channel model. The former is employed when the distance between the source and destination nodes is below a predetermined threshold [26]. While, the second serves to boost the signal in order to prevent any deterioration in its quality when the distance exceeds the predefined limit [27].

The $E_{TS}(S, D)$ energy used by electronic devices when transmitting a S-bit packet to a node that is D meters away in free-space can be described by the following equation:

$$E_{TS}(S,D) = S \times E_{elec} + S \times E_{fs} \times D^2 \ , \ if \ D < d_{th} \quad (25)$$

E_{elec} is the energy consumed by the transmitter's electronic circuit.

E_{fs} is the energy consumed by the amplifier circuit in free space.

$d_{th} = \sqrt{E_{fs}/E_{amp}}$, is a distance limit.

In a multipath fading space, the required energy for transmitting a S-bit packet is modelled as:

$$E_{TS}(S,D) = S \times E_{elec} + S \times E_{amp} \times D^4 \ , if \ D > d_{th} \quad (26)$$

"E_{amp}" refers to the energy necessary for the amplifier circuit to operate in an environment with multipath fading. While the energy consumed by a CH node when receiving a S-bit packet is expressed by the following model [27].

$$E_c(S) = S(E_{elec} + EDA) \quad (27)$$

EDA is the energy needed for data compression.

B. Parameters Initialization

In conducting the experiments, Matlab 2018 was utilized on a Windows 10 operating system with the specifications of an Intel (R) Core (TM) i5-5300U, 2.30 GHz, and 4GB RAM. The sensors initially had 0.5 joules of energy, while the sink had an unlimited supply of energy.

Heterogeneity is incorporated in accordance with specific percentages. The percentages of advanced or intermediate nodes and super nodes are mo = 0.2-and m = 0.1, respectively. The energy factors of these nodes' types vary accordingly a = 1, and b = 1.25.

TABLE II
Parameters Setting

The network parameters	
The size of the detection area	500m2, 300m2 and 150m2
Number of nodes	100
Initial Energy of each Node	0.5 Joules
Eelec	50 nano joules
Emp (the amplifier energy)	100 Pico joules
EDA (Data Aggregation Energy)	5 nano joules
K (Size of a data packet)	4000 bits

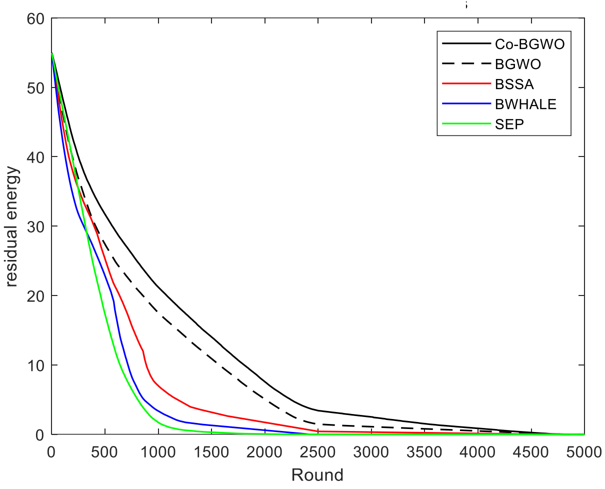

Fig. 5. Energy consumption in case of medium network (300 m^2) & two-level of heterogeneity

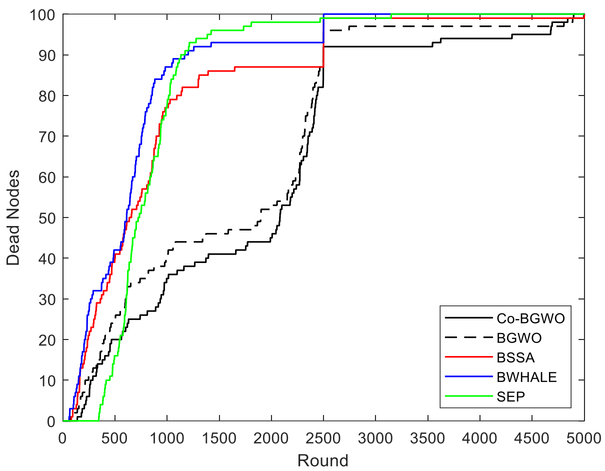

Fig. 6. Dead nodes in case of medium network & two-level of heterogeneity

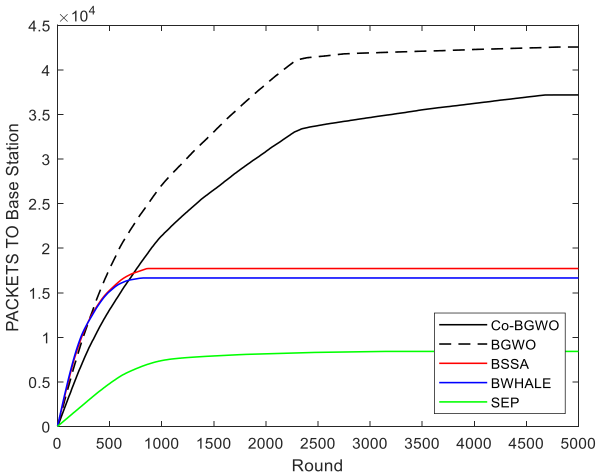

Fig. 7. Delivered packets to BS in case of medium network & two-level of heterogeneity

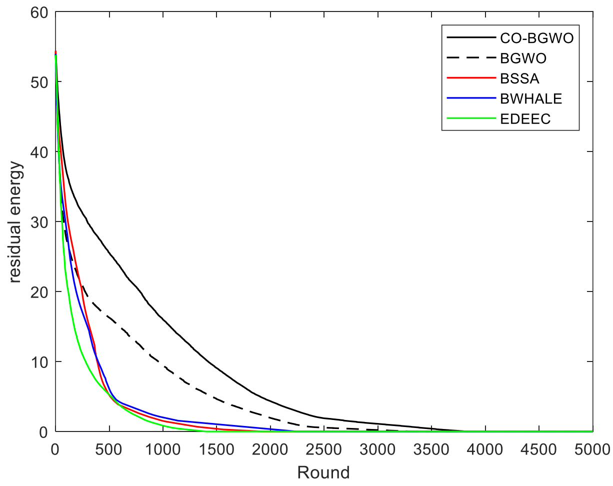

Fig. 8. Energy consumption in case of large network (500 m^2) & three-level of heterogeneity

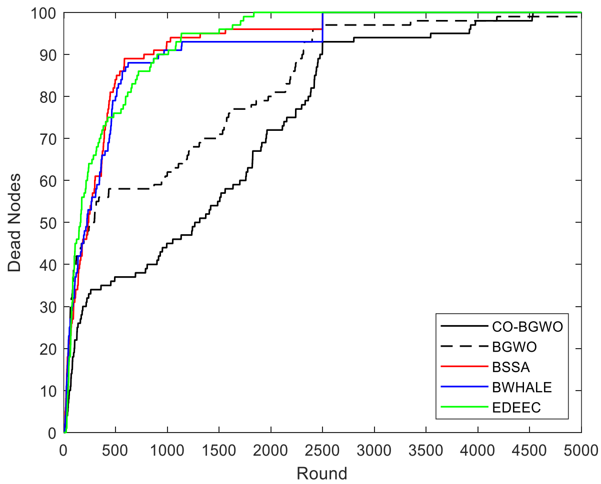

Fig. 9. Dead nodes in case of large network & three-level of heterogeneity

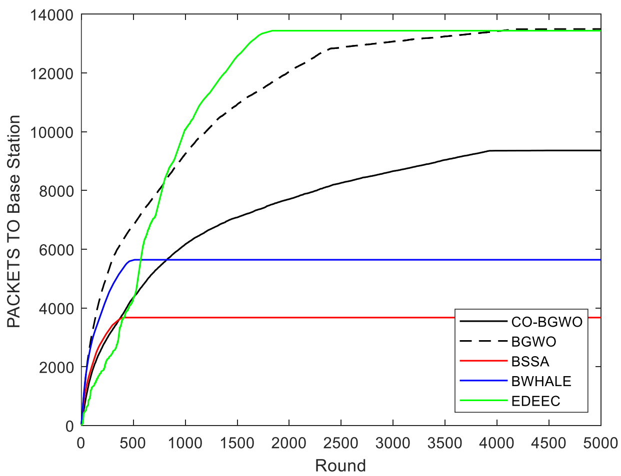

Fig. 10. Delivered packets to BS in case of large network & three-level of heterogeneity

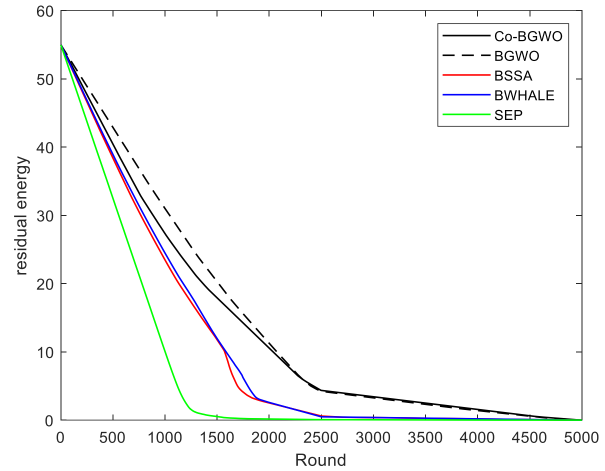

Fig.11. Energy consumption in case of small network (150 m^2) & two-level of heterogeneity

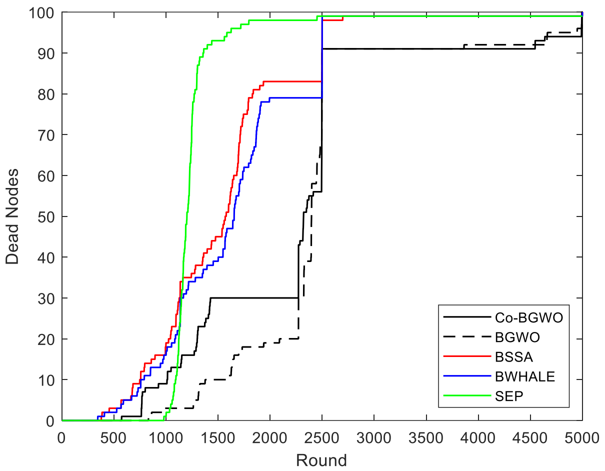

Fig. 12. Dead nodes in case of small network & two-level of heterogeneity

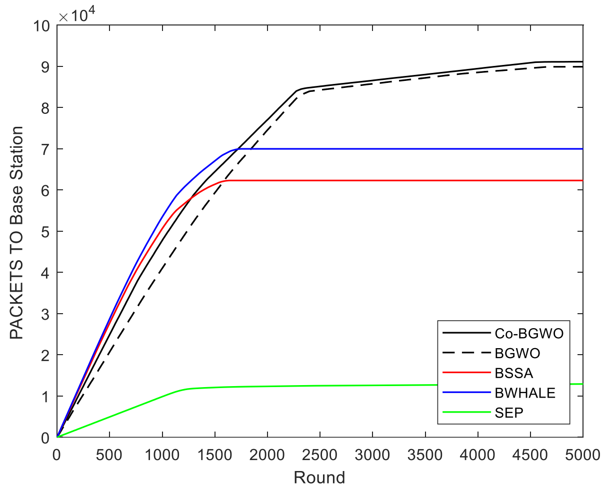

Fig. 13. Delivered packets to BS in case of small network & two-level of heterogeneity

The data and graphics presented above illustrate the energy savings of the suggested protocols, measured in Joules, number of dead nodes, and packets conveyed to the base station (each packet is 4000 bits in size).

Tables III, IV, and V present data on (FND, HND, and LND), that is, the round of First Node Dies, the round of Half Node Dies, and the round of Last Node Dies, respectively. Additionally, the tables include the percentage of residual energy (RES%) and the time per round for the curves depicted in figures 5 to 13.

The percentage of residual energy is determined by using the equation referenced in [28], which is the ratio between the remaining and initial energy of the network in a particular round (in our experiment, the round 1500).

TABLE III

COMPARISON IN CASE OF SMALL NETWORK– CASE OF FITNESS1

	FND	HND	LND	RES %	Time
THREE LEVEL OF HETEROGENEITY					
Co-BGWO	530	2422	5000	31,97	0,059
BGWO	763	2397	5000	36,13	0,063
BWHALE	455	1264	5000	15,12	0,015
BSSA	325	1234	4824	12,14	0,031
EDEEC	949	1238	3491	7,95	0
TWO LEVEL OF HETEROGENEITY					
Co-BGWO	961	2415	5000	35,30	0,047
BGWO	890	2392	4950	33,40	0,063
BWHALE	455	1433	4959	14,45	0,016
BSSA	332	1141	4887	10,61	0,047
SEP	1011	1194	1967	1,41	0,032

TABLE IV

COMPARISON IN CASE OF MEDIUM SIZED NETWORK–CASE OF FITNESS1

	FND	HND	LND	RES %	Time
THREE-LEVEL OF HETEROGENEITY					
Co-BGWO	75	2280	5000	23,39	0,063
BGWO	128	1052	4591	16,88	0,078
BWHALE	51	743	2450	6,5	0,016
BSSA	55	666	4553	10,08	0,015
EDEEC	170	742	4129	5,46	0
	FND	HND	LND	RES %	Time
TWO-LEVEL OF HETEROGENEITY					
Co-BGWO	139	2081	4815	25.49	0.156
BGWO	76	1493	4639	19,58	0,054
BWHALE	81	637	4581	5.77	0.024
BSSA	60	612	2418	2.34	0.024
SEP	345	722	2186	0.55	0.008

TABLE V

COMPARISON IN CASE OF LARGE NETWORK –CASE OF FITNESS1

	FND	HND	LND	RES %	Time
THREE-LEVEL OF HETEROGENEITY					
Co-BGWO	19	652	3955	17,48	0,047
BGWO	16	184	3364	11,58	0,047
BWHALE	9	276	2641	3,34	0,015
BSSA	10	206	948	0	0,031
EDEEC	20	111	1537	0,77	0
TWO-LEVEL OF HETEROGENEITY					
Co-BGWO	15	795	3519	24.99	0.093
BGWO	15	151	2902	14.32	0.063
BWHALE	11	176	1691	3.88	0.065
BSSA	11	166	1435	5.51	0.062
SEP	37	258	1096	0.59	0

By examining tables III to V and figures 5 to 13, it becomes evident that the protocols based on Co-BGWO and BGWO exhibit superior performance as compared to BWHALE, BSSA, EDEEC, and SEP protocols with respect to FND, HND, LND, and the percentage of energy saved.

From table IV, in a medium-sized area (300 m^2), the EDEEC protocol experienced its first node failure during round 170, followed by gradual sensor failures leading to the complete failure of the network in 4129 rounds. The BSSA algorithm optimized the selection process of CHs, resulting in a slower sensor death rate than EDEEC from round 55 until round 4553. The Co-BGWO-based protocol allowed nodes to survive longer, with the first death occurring at round 75 until round 5000.

In comparison to the SEP and EDEEC protocols, the BWHALE and BSSA-based protocols have demonstrated better performance in terms of LND and percentage improvement in power conservation. Specifically, in two-level heterogeneous networks, the LND has been demonstrated to be more effective by a margin of over 300 and has managed to save over 0.5% more energy compared to SEP and EDEEC.

According to Table IV, it appears that the Co-BGWO and BGWO-based protocols are the most effective methods for prolonging the life of sensors in medium-sized networks. Specifically, the three-level Co-BGWO protocol experienced its midpoint of nodes' deaths at 2280, extending the network lifetime up to 5000 rounds. The Co-BGWO protocol outperforms BSSA, BWHALE, SEP, and EDEEC with more than 1500 rounds of HND, more than 1200 rounds of LND, and more than 13 % energy savings.

Table IV revealed similar findings to those mentioned previously for networks of a larger size. The Co-BGWO and BGWO-based protocols were found to be the most effective, followed by BWHALE and then BSSA, in regards to HND, FND, and energy conservation percentage. Regarding FND, the SEP protocol remained the top performer, with EDEEC and BGWO coming in after, followed by CO-BGWO. On the other hand, BSSA and BWHALE had the lowest stability period (FND).

Table III reveals that in a small area of interest, BGWO outperforms CO-BGWO in regards to FND and HND. Despite this, Co-BGWO remains the most effective method for conserving energy.

After conducting extensive experiments on packet delivery rates in large networks, it was found that in three-level networks, the most competitive protocols in terms of packet delivery were BGWO and EDEEC, followed by CO-BGWO, then BWHALE, and finally BSSA. On the other hand, in two-level networks, the BGWO protocol proved to be the most effective, followed by CO-BGWO, BWHALE, and then BSSA. The lowest packet delivery rate to the base station was observed in the SEP protocol, as evidenced by the curves in figures (8 to 10).

In medium-sized networks (Figures 5- 8), it has been found that in two-level networks, the BGWO and Co-BGWO are competitive, followed by BSSA and BWHALE-based protocols, and finally the SEP protocol. In three-level networks, the BGWO and EDEEC are competitive, followed by the CO-BGWO. In small-sized networks (Figures 11- 13), it has been found that in two-level networks, the BGWO and Co-BGWO are competitive, followed by BWHALE then BSSA, and finally the SEP protocol.

In terms of delay (tables III to V), SEP and EDEEC protocols are the fastest, followed by BSSA and BWHALE, and finally BGWO and Co-BGWO but they still rapid as they take less than 1 milli second for data delivery.

The data in the tables below compares the efficiency of Co-BGWO and BGWO, using the three distinct objective functions outlined in equations (1, 2 & 3).

TABLE VI
COMPARISON IN CASE OF SMALL TWO-LEVEL NETWORK

	FND	HND	LND	RES %	Time
FITNESS1					
Co-BGWO	961	2415	5000	35,30	0,047
BGWO	890	2392	4950	33,40	0,063
FITNESS2					
Co-BGWO	1015	2421	4987	35,71	0,062
BGWO	1092	2452	4958	38,92	0,062
FITNESS3					
Co-BGWO	892	2381	4975	33,62	0,063
BGWO	590	2396	4984	34,03	0,062

TABLE VII
COMPARISON IN CASE OF MEDIUM TWO-LEVEL NETWORK

	FND	HND	LND	RES %	Time
FITNESS1					
Co-BGWO	139	2081	4815	25.49	0.156
BGWO	76	1493	4639	19,58	0,054
FITNESS2					
Co-BGWO	222	2331	4602	24,45	0,063
BGWO	112	2262	4835	27,72	0,078
FITNESS3					
Co-BGWO	171	1313	4622	20,19	0,063
BGWO	84	1006	4645	12,98	0,078

TABLE VIII
COMPARISON IN CASE OF SMALL THREE-LEVEL NETWORK

	FND	HND	LND	RES %	Time
Fitness1					
Co-BGWO	530	2422	5000	32,97	0,059
BGWO	763	2397	5000	36,13	0,063
Fitness2					
Co-BGWO	993	2498	4980	34,99	0,047
BGWO	857	2446	5000	38,16	0,063
Fitness3					
Co-BGWO	527	2383	5000	32,04	0,066
BGWO	921	2395	5000	33,78	0,062

TABLE IX
COMPARISON IN CASE OF MEDIUM THREE LEVEL NETWORK

	FND	HND	LND	RES %	Time
THREE LEVEL OF HETEROGENEITY (Fitness1)					
Co-BGWO	75	2280	5000	23,39	0,063
BGWO	128	1052	4591	16,88	0,078
THREE LEVEL OF HETEROGENEITY (Fitness2)					
Co-BGWO	189	2257	4891	24,60	0,062
BGWO	161	2220	5000	26,74	0,062
THREE LEVEL OF HETEROGENEITY (Fitness3)					
Co-BGWO	120	1197	4812	16,49	0,063
BGWO	78	952	4824	14,67	0,063

Analysing Tables VI to IX, Co-BGWO and BGWO revealed superior results when Fitness2 is the objective function, followed by Fitness1 and then Fitness3 in order.

In conclusion, the most effective protocols are those based on Co-BGWO and BGWO, which outperform their counterparts in terms of metrics such as HND, LND, energy preservation percentage, and packet delivery rate. Meanwhile, the SEP protocol stands out for its extended stability duration (FND), followed by EDEEC and BGWO. SEP and EDEEC protocols also demonstrate the highest speeds in data delivery. Overall, the Co-BGWO and BGWO algorithms contribute significantly to the lifespan of heterogeneous networks, thanks to their strategic identification of powerful cluster heads and their optimal positions and numbers.

V. Conclusion

By harnessing swarm intelligence, wireless sensor networks can achieve optimal performance, energy efficiency, and reliability. Swarm optimization yields faster and more reliable connections, while simultaneously reducing the time and energy needed to manage and maintain wireless networks. Furthermore, it automatically detects and adjusts routes to ensure secure and reliable connections.

The central aim of this research was to improve both the longevity and energy efficiency of heterogeneous WSNs. To achieve this, swarm intelligence-based techniques were employed to implement many communication protocols with the goal of improving the performance of conventional heterogeneous protocols (SEP and EDEEC). Four distinct protocols were implemented, each using a different optimization algorithm: the co-evolutionary binary GWO for the first, the binary GWO for the second, the binary whale optimization for the third, and binary SSA for the fourth.

The suggested protocols proved to be highly efficient in conserving energy and extension of sensor durability, Specifically the protocols relying on coevolutionary binary grey wolf optimization and the based once on BGWO. They achieved an impressive energy-saving rate of over 30% in small area of interest, surpassing thus the basic SEP and EDEEC protocols, as well as other protocols analysed. Their success in data routing can be attributed to their effective strategy of load balancing among network nodes.

This research explored three distinct objective functions for a reliable comparison. The first focused on the proportion between the CHs' residual energy and their initial energy. The second was based on the number of member nodes each CH had and the CHs' remaining energy. The third involved both the internal cluster distance and the distance of the CHs to the base station.

Results showed that the second objective function, which is based on the residual energy of CHs and their degree, yielded the best performance in terms of FND, HND, LND, and energy savings. It was followed by the first objective function, and then the third.

The reason for this is that the distance between nodes and the base station does not accurately reflect the strength of the chosen CH in terms of power. Moreover, the second function is more effective than the first one, as it motivates CHs with fewer nodes in their neighbourhood, enabling them to send the data from their nodes with no failure and thus more reliability.

In future endeavours, it would be beneficial to examine additional factors. For instance, implementing these algorithms in practical scenarios like monitoring the environment and agriculture systems. Additionally, refining the quality of results can be achieved by considering various factors like packet loss rate, link quality, delay, reliability and security through multi-objective optimization. Moreover, exploring alternative swarm intelligence techniques such as the Rao algorithm, dragonfly algorithm …etc., can also lead to better outcomes

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