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An energy-efficient cluster head selection in wireless sensor network using grey wolf optimization algorithm

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ABSTRACT

Clustering is considered as one of the most prominent solutions to preserve the energy in the wireless sensor networks. However, for optimal clustering, an energy efficient cluster head selection is quite important. Improper selection of cluster heads (CHs) consumes high energy compared to other sensor nodes due to the transmission of data packets between the cluster members and the sink node. Thereby, it reduces the network lifetime and performance of the network. In order to overcome the issues, we propose a novel cluster head selection approach using grey wolf optimization algorithm (GWO) namely GWO-CH which considers the residual energy, intra-cluster and sink distance. In addition to that, we formulated an objective function and weight parameters for an efficient cluster head selection and cluster formation. The proposed algorithm is tested in different wireless sensor network scenarios by varying the number of sensor nodes and cluster heads. The observed results convey that the proposed algorithm outperforms in terms of achieving better network performance compare to other algorithms.

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1. INTRODUCTION

Wireless sensor networks can be expounded as a collation of crammed dissipation of ad-hoc sensor nodes that acts as a watchdog which provides contiguous information about its surroundings which are coagulated in a central processing node called sink. Due to its compactness and low value, it has been predominantly used across different kinds of monopoly such as military, health, education, design and engineering sectors. It has grabbed its attention because of the applications that cater to diverse variants have been discovered. In a packed environment of nodes, routing poses a hefty concern. It is obvious since nodes are optimal in size, energy is also an argument where lots of research has been concerted. Since the nodes are battery-powered devices which are deployed in a downtrodden area, it is not possible to reconstitute back which poses a limitation in case of a vast set up of wireless sensor networks [1-3]. One of the most poignant stipulations in the deployment of nodes in wireless sensor network (WSN) is to exercise the energy that is stored in the nodes. Countering to this need, many protocols and schemes have been evolved. Since routing mainly confides on battery power, clustering captures its attention among the researches due to its efficiency during information exchange. Clustering can be defined as a grouping of nodes based on parameters such as proximity, range, power, and location, [4-6]. Cluster-based sensors aids to utilize the resources efficiently in wireless sensor networks. Clustering facilitates the cluster members to transmit data only to cluster heads (CHs) and then the CHs transmits the collected data to the base station and thereby reducing the energy consumption and minimizing the routing overhead as shown in Figure 1. However, the communication cost of data is higher than the processing; therefore, clustering the sensors will be beneficial. The central processing unit is mainly responsible for the intimating the common mob about the happenings that have been captured from the down-trodden environment. Clustering provides many leverages which include; a) ease of deployment; b) wide area coverage; c) fault tolerance; and d) energy conservation. During the dissipation of information from one node to the other, several nodes may contain the same redundant information resulting in huge energy consumption. However, the selection of cluster heads poses a problem against the lifetime of the network [7, 8].

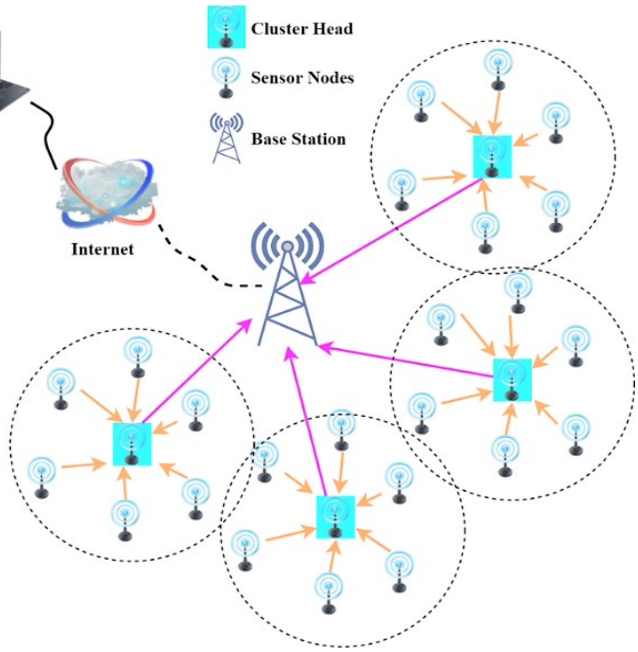

Figure 1. Working flow of cluster head and base station (BS) in wireless sensor network (WSN)

Grey wolf optimization algorithm is family of the swarm intelligence techniques which is inspired by the behaviour of grey wolf (i.e. leadership and hunting strategies). This algorithm has been utilized by different domains researchers to solve their domain related problems due to its simplicity and ease of implementations. Grey wolf optimization (GWO) algorithm has few parameters to solve the non-deterministic polynomial (NP)-hard problems within the course of iterations. This algorithm is used to solve different domain problems such as Localization in WSN [9], economic load dispatch problem [10], feature selection [11], engineering problems [12], unit commitment problems [13] and so on. Clustering in WSN is considered an NP-hard problem which can be solved using an efficient optimization algorithm. In this paper, we proposed an optimal cluster head selection mechanism based on grey wolf optimization algorithm namely GWO-CH. This algorithm considers the residual energy, intra-cluster and Sink distance to select the optimal cluster heads. In addition to that, we introduced an objective function which includes the essential parameters to select the optimum. In GWO algorithm, we incorporated the efficient search agent representation scheme to represent the energy efficient cluster head selection. On the other hand, we proposed a weight parameter for cluster formation. This parameter guides the sensor nodes to join their respective cluster head groups. The sensor node with high weight will be moved to the corresponding clusters. Thereby, that sensor will act as cluster members under the CHs and transmits their information to the base station through the CHs. The experimentation of the proposed algorithm is tested in the different scenarios of sensor nodes by varying the number of sensor nodes and the CHs. To analyze the efficacy of the proposed work is compared with the other algorithms namely end-to-end secure low energy adaptive clustering hierarchy (E-LEACH) [14], genetic algorithms (GA) [15, 16], cuckoo search (CS) [17], particle swarm

optimization-C (PSO-C) [18], and fruit fly optimization algorithm (FFOA) [19]. Our contributions in this paper are described as follows:
- Proposed cluster head selection using grey wolf optimization with energy efficient parameters.
- Proposed an objective function and weight parameters to select the optimal CHs and efficient cluster formation.
- Tested proposed work with various WSN scenarios and efficacy compared with other algorithms.

The rest of the paper formulated as follows. Section 2 deals with the literature study of the existing mechanism to select the cluster heads. Section 3 discussed the preliminaries of GWO algorithm and energy consumption models. The proposed methodologies with its formulated objective function and weight parameter for cluster formation presented in section 4. The experimentation results are discussed in section 5 and finally, conclusion and future works are provided in section 6.

2. LITTERATURE REVIEW

Vast research has been plunged in the area of wireless sensor networks in order to perpetuate the lifetime of the network. Since the selection of cluster heads is an NP-hard problem each algorithm has its own flaws as well. Algorithms devised for increasing the longevity of the network can be broadly categorized into 1) heuristic and 2) meta-heuristic approaches. Elaborations of these approaches are as follows:

2.1. Heuristic-based clustering algorithm

Since diverse algorithms catering to different needs are there, low-energy adaptive clustering (LEACH) [20] is of the predominant clustering algorithm which elects the cluster head with some feasibility. It provides aggregation of the crammed data thus reducing the unwanted traffic and energy consumption of the network [21], thereby increasing the longevity of the network. However, it does not provide any adequate information about the number of cluster heads in a network. Sometimes it may opt a node with low energy as a cluster head thereby shortening the lifetime of the network. Other most popular algorithms include power-efficient gathering in sensor information systems (PEGASIS) and hybrid energy-efficient distributed (HEED). PEGASIS [22] is an addendum to that of LEACH protocol. It is more advantageous in the sense because it aggregates all the data and sends it to the central processing unit. However, it introduces an additional lag if nodes are distant. It is unsuitable for large scale WSNs which involves multi-hop communication. HEED [23] is also an extension of the LEACH; it suffers from serious communication overhead between a cluster head and a base station. In the case of E-LEACH [14], the cluster head communication between different clusters is highly efficient, but in the case of larger networks, it fails to select the nodes with low energy. TL-LEACH [24] increases the lifetime of the network, but it wastes the energy while performing communication between cluster heads and the other nodes. M-LEACH carries an advantage by considering mobility in a routing protocol. It assumes that all the nodes are congruent, and it does not care about the formation of the cluster while clustering. B-LEACH [25] is another extension where the communication is entirely depending upon the position of the cluster heads which needs no information about all the other nodes inside the cluster. Therefore, the residual energy of the CHs gets drained which further reduces the lifetime of the network. LEACH-C [26, 27] outperforms LEACH-A, LEACH-B, and MTE because the central processing unit takes care of the location and the energy of all the nodes in the network, hence cluster formation and cluster maintenance will not get affected. The only disadvantage is that it is not vigorous. E-LEACH is much energy efficient in case of multi-hop communication. It enhances the cluster head selection process by considering the higher residual energy available at a particular time within a cluster. Though V-LEACH [28] has been proposed as an alternative to LEACH, it elects additional CHs to that of main CHs in order to mitigate the failure of the main CHs. Hence whenever the main CHs, fails the additional CHs selected takes care of its position and perform the flooding. The algorithm suffers from deprivation that it does not bother about the cluster formation process.

2.2. Meta-heuristic approaches

Meta-Heuristic algorithms act as the most promising approach for NP-hard combinatorial problems. Since they mimic from nature, it concentrates mainly on the aspirant which has a high survival rate. Meta-heuristic algorithms are broadly categorized into two types namely evolutionary and swarm intelligence approaches [29]. Genetic algorithm [15, 30] and simulated annealing are the most popular evolutionary algorithms. Some of the swarm intelligence approaches are ant colony optimization (ACO), fish colony optimization (FCO), bird flocking behaviour, particle swarm optimization (PSO), firefly algorithm (FA) [31], bat algorithm (BA), cuckoo search (CS), artificial bee colony optimization (ABC), fish swarm optimization (FSO), glow-worm swarm optimization (GSO), grey wolf optimizer (GWO), fruit fly optimization algorithm (FFOA). Sweta Potthuri *et al.* [32] proposed a hybrid differential evolution and simulated annealing (DESA) algorithm which aims to increase the liveliness of the network by selecting the cluster heads which has optimal energy, thereby preventing the energy loss. The author in [15] proposed an energy efficient clustering algorithm in order to extend the lifetime of the network. It uses a genetic algorithm (GA), where the cluster heads are elected by using appropriate fitness function until the information is propagated through to the central processing unit i.e. base station. Osama Helmy *et al.* proposed an algorithm that provides energy consumption thereby increasing the longevity of the network. The different approaches such as preying, and swarming are employed in order to achieve the selection of the optimal cluster head. The method offers a wide range of coverage leveraging a better lifetime for the nodes as well as the network and it proves its efficiency even after increasing the number of clusters compared with LEACH and PSO approach [8].

Sariga *et al.* [33] proposed a meta-heuristic ACO based unequal clustering (MHACO-UC) algorithm that concentrates mainly on preserving the lifetime of the CHs, by using a distance estimation function. It also keeps knowledge about the nearness of the nodes present in the clusters and in the entire network thereby propagating the information to the central processing unit and this increases the longevity of the lifetime of the network. Tauseef Ahmad *et al.* [34] proposed an algorithm that concentrates mainly on selecting the cluster head that has the optimum energy using bee colony optimization algorithm. The author provides a significant contribution in identifying the proximities of the nodes inside the cluster and between the cluster heads using an optimized fitness function. Amit Sarkar *et al.* [35] utilized the firefly algorithm for increasing the lifetime of the network and the liveliness of the nodes by electing optimal cluster heads. Cyclic randomization is employed which outperforms the traditional cluster head selection algorithms respectively. Srinivasa Rao *et al.* [8] came up with a solution based on particle swarm optimization approach to address the issues such as energy and clustering. It employs a geometric method to elect a cluster head and as flooding occurs, the higher energy nodes are only used and the nodes with lower energy are preserved from propagating the information to the central processing unit thereby preserving the lifetime of the network. Kia *et al.* [26] a new hybrid protocol based on cuckoo search optimization have been proposed in order to conserve energy while flooding the information inside the clusters by selecting the optimal cluster heads. It employs an energy conservator in order to increase the longevity of the network. Dattatraya *et al.* [19] proposed a hybrid algorithm by combining glom worm swarm optimization (GSO) and fruit fly optimization (FFOA). GSO suffers from low computational speed and low searching capacity. Fruit fly optimization algorithm (FFOA) has its own merging rate. Hence hybridizing both yields perfect results thereby outperforming the traditional cluster head selection algorithms.

3. METHODS

3.1. Grey wolf optimization

Grey wolf optimization [28] is a recently proposed swarm intelligence algorithm which mimics the intelligent behavior of grey wolves which includes leadership and hunting characteristics of the grey wolf. Grey wolf works in a pack of 5-12 members which follows a very strict social hierarchy. Grey wolf pack consists of four level hierarchy namely alpha, beta, delta, and omega. Alpha is the first level in the hierarchy which is considered as the first leader of the pack. It is responsible for all the decision making a process like hunting the prey, approaching the prey and instructing the wolves in the entire pack. The second level in the hierarchy is beta, which guides the alpha in decision making and also acts as alpha whenever the alpha is passed away. In most cases, beta is also called as subordinate wolves. Delta is the third level in the hierarchy which also known as caretaker and finally. Omega is the last level in the hierarchy which obeys the decision of the three above leaders and also maintains the safety and integrity in the wolf pack. GWO working process is mathematically modelled as follows:

3.1.1. Encircling process

All the grey wolves in the pack start encircling the prey before it starts the hunting process. The encircling process is mathematically formulated and it is given in the (1) and (2).

$$\vec{D} = \left|\vec{C}.\overrightarrow{X_p}(k) - \vec{X}(k)\right| \tag{1}$$

$$\vec{X}(k+1) = \left|\overrightarrow{X_p}(k) - \vec{A}.\vec{D}\right| \tag{2}$$

where, $\vec{D}$ represents the distance between the prey and wolf, $\vec{X}$ determines the current position of the wolf in k iterations and $\overrightarrow{X_p}$ is the position of the prey. The constant parameters $\vec{A}$ and $\vec{C}$ are measured using the (3) and (4).

$$\vec{A} = 2\vec{a}.\overrightarrow{rand_1} - \vec{a} \tag{3}$$

$$\vec{C} = 2.\overrightarrow{rand_2} \tag{4}$$

where, $\overrightarrow{rand_1}$ and $\overrightarrow{rand_1}$ determines the arbitrary vectors generated between the range of [0,1]. These values aids to adjust the position of the grey wolf randomly at any position towards the prey. Parameter $\vec{a}$ is aids to control the movement of the algorithm which linearly reduces from 2 to 0 over certain generations.

3.1.2. Hunting process

In the hunting process, all the dominant wolves ω adjust their positions using non-dominant wolves $\alpha, \beta,$ and δ. The position update using these non-dominant wolves have mathematically modelled and it is given in (5-7).

$$\overrightarrow{D_\alpha} = |\overrightarrow{C_1}.\overrightarrow{X_\alpha} - \vec{X}|, \overrightarrow{D_\beta} = |\overrightarrow{C_2}.\overrightarrow{X_\beta} - \vec{X}|, \overrightarrow{D_\delta} = |\overrightarrow{C_3}.\overrightarrow{X_\delta} - \vec{X}| \quad (5)$$

$$\overrightarrow{X_1} = |\overrightarrow{X_\alpha} - \overrightarrow{A_1}.\overrightarrow{D_\alpha}|, \overrightarrow{X_2} = |\overrightarrow{X_\beta} - \overrightarrow{A_2}.\overrightarrow{D_\beta}|, \overrightarrow{X_3} = |\overrightarrow{X_\beta} - \overrightarrow{A_3}.\overrightarrow{D_\beta}| \quad (6)$$

Using in (5) and (6) are used to update the position of the grey wolf and it is shown in (7).

$$\vec{X}(k+1) = 0.33 * \sum_{i=1}^{3} \overrightarrow{X_i} \quad (7)$$

The position update using alpha, beta and delta are graphically represented in Figure 2.

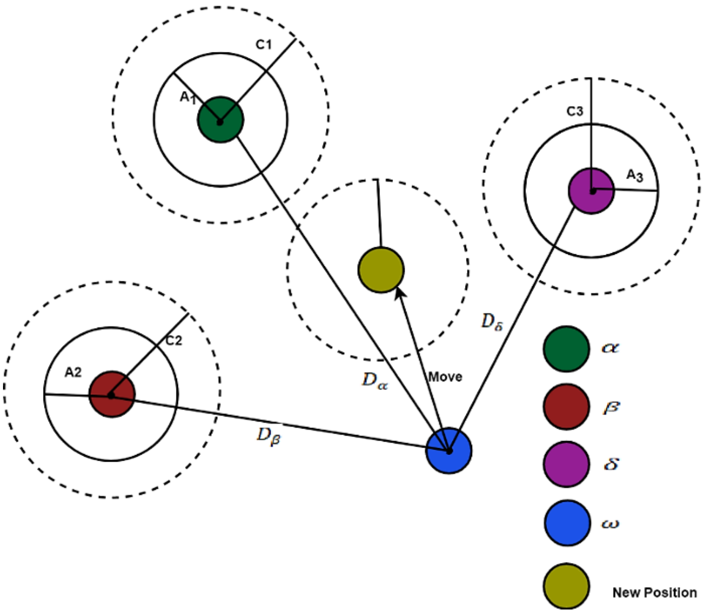

Figure 2. Position update in GWO

3.1.3. Seeking and attacking the prey

The parameter $\vec{A}$ is a random vector which is used to explore and exploit the search position of the grey wolves. Every course of iterations, this parameter has been adjusted in the range of$[-\vec{a}, \vec{a}]$, where the value $\vec{a}$ linearly decreases from 2 to 0. GWO algorithm exploits the prey if $|\vec{A}| < 1$ otherwise it seeks for new prey if $|\vec{A}| > 1$. In addition to that, parameter $\vec{C}$ lies in the range of [0, 2] which aids the algorithm to avoid the local optima stagnation by providing some random weight to the position update. However, tuning the parameter $\vec{a}$ provides better results compare to the generic GWO algorithm. In this proposed work, we tuned the parameter $\vec{a}$ for better results. The working flow of the GWO algorithm is mathematically modelled and it is shown in algorithm 1.

Algorithm 1: Grey wolf optimization algorithm

Input – Initialize the population size of the wolves $X_i = (1,2,3, \ldots n)$ and parameters A, C
Step 1: Randomly generate solutions X_i within the boundary regions
Step 2: Evaluate the fitness of the wolves f_i
Step 3: Select the first best solution as Alpha, second best as beta, third best as Delta and rest as Omega.
Step 4: Update the position of the grey wolves and its parameters

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Step 5: Evaluate the new fitness of all wolves
Step 6: Update the alpha, beta, and delta
Step 7: Repeat step 5 to 7 until condition satisfies
Output – visualize the Alpha wolf
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3.2. Energy consumption model

In this paper, the energy consumption model is used based on the suggestions of the author in [36]. In this model, the energy has been utilized by the transmitter and receiver for transmitting and receiving their signals and to operate the radio amplifiers. The energy consumption of a sensor for transmitting (E_{TX}) n-bit of information is mathematically represented in (8).

$$E_{TX}(n,\theta) = \begin{cases} n \times E_{elec} + n \times \varepsilon_{fs} \times \theta^2 & if\ \theta < \varphi \\ n \times E_{elec} + n \times \varepsilon_{mp} \times \theta^4 & if\ \theta \geq \varphi \end{cases} \tag{8}$$

where, E_{elec} represented as energy utilized per bit to operate the transmitter or receiver. ε_{fs} and ε_{mp}determined as the free space model and multipath of amplification power. φ and θ denoted as the threshold and distance for transmitting the information from one sensor location to other sensors.

At the same time, energy consumed by the receiver for receiving n-bit of information ($E_{RX}(n)$) is computed as follows;

$$E_{RX}(n) = n \times E_{elec} \tag{9}$$

The total energy consumption (E_{total}) of a sensor node for transmitting and receiving the n-bit information is mathematically calculated as follows;

$$E_{Total} = E_{TX}(n,\theta) + E_{RX}(n) \tag{10}$$

A sensor node lifetime is computed based on the initial energy of the node and the remaining energy of the node after transmitting and receiving the n-bit information. It is expressed as follows;

$$L = \frac{E_{intial}}{E_{total}} \tag{11}$$

where, E_{intial} represents initial energy of the sensor node (i.e. 2J in our work) and E_{total} represented as the total consumed the energy of the sensor node. In our work, the network lifetime considered based on the number of iterations until the last node of death.

4. PROPOSED ALGORITHM

The proposed algorithm mainly contributes to selecting the cluster heads by considering the residual energy and distance measurement of the sensor nodes. Initially, all the sensor nodes send their information (node_id, residual energy, location) to the base station. Our proposed GWO algorithm executed at the base station to select the optimal CH (i.e. by sensor node information) and to form the optimal clusters. In order to process the cluster formation, we have formulated the weight function which involves the intra-cluster distance information, residual energy, and neighborhood ratio of CHs respectively.

4.1. The objective function for CH selection

In this work, we derived the objective function which utilizes the intra-cluster distance among the sensors and the distance from the target node. Let us assume f_1 be a function of mean intra-cluster and the target distance of the CHs. In order to select the optimal CHs, the f_1 to be minimized. Let us assume f_2 be the function which is inverse of total current energy of all the selected CHs. In order to provide better results both the objective function is to be minimized and it to be within $(f_1,\ f_2) \in [0,1]$.

The objective function f_1 is represented as;

$$\min f_1 = \sum_{i=1}^{m} \frac{1}{n_i} \left(\sum_{i=1}^{n_i} \theta\left(T_j, CH_i\right) + \theta(CH_i, BS) \right) \tag{12}$$

where, $\theta\left(T_j, CH_i\right)$ represented as the distance between the target node j to the cluster head i. $\theta(CH_i, BS)$ denoted as the distance between the cluster head i to the base station. n and m denoted as the number of target sensor nodes and cluster heads.

The objective function f_2 is mathematically represented as;

$$\min f_2 = \frac{1}{\sum_{i=1}^{m} E_{CH_i}} \quad (13)$$

where, E_{CH_i} denoted as the residual energy of the cluster head i. In order to minimize both the objective function, we use GWO algorithm to select the optimal CH to linearly decrease the function. The combined objective function is mathematically represented in (14).

$$F = \mu \times f_1 + (1-\mu) f_2, \quad 0 < \mu < 1 \quad (14)$$

where μ is the weight parameter in the range of [0,1]. The search agent with minimal objective value is considered as the CH.

4.2. Cluster formation

In WSN, selecting the optimal CHs will lead to a proper cluster formation and it aids to prolong the network lifetime. In this work, we select the CHs using the residual energy, neighborhood ratio and distance from BS. To create an optimal cluster formation, we formulate weight function which guides the sensor node to join in their respective CHs. The derived weight function is mathematically represented in the (15).

$$CH_w(T_i, CH_j) = K * \frac{E_R(CH_j)}{\theta(T_i, CH_j) \times \theta(CH_j, BS) \times DN(CH_j)} \quad (15)$$

where K is the constant parameter value (i.e. $K = 1$). $E_R(CH_j)$ represented as the residual energy of the j^{th} cluster head. $\theta(T_i, CH_j)$ denoted as the distance between the ith target sensor node (i.e. normal sensor node) and jth cluster head. $\theta(CH_j, BS)$ represented as the distance between j^{th} cluster head and the base station. $DN(CH_j)$ denoted as the neighborhood ratio of the j^{th} CH. The i^{th} sensor node with high weight value can able to join in a j^{th} cluster head.

4.3. GWO algorithm for CH selection

In the proposed GWO algorithm, the search agent represented as m dimensional cluster heads with its position (x-axis, y-axis) and sensor id as shown in Figure 3. Initially, the algorithm selects the random cluster head with their appropriate locations and it computes the objective value for those cluster heads. Next, it selects the first best search agent α, second best search agent β and third best search agent δ and rest of the search agent as ω. With the aid of three best solutions, the remaining search agents update its position and the new position represented as the new cluster heads which satisfies the objective function. Later, identify the weight function to determine the appropriate cluster members to join in their respective CHs. The working flow of the proposed GWO is presented in Algorithm 2.

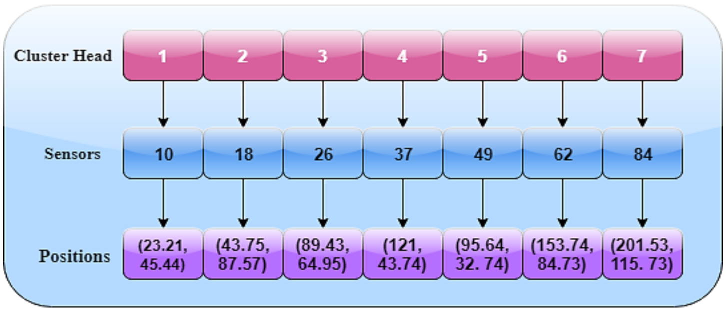


Figure 3. Representation of search agent in GWO

Algorithm 2: GWO algorithm for CH selection

Input: Number of sensors $S = \{S_1, S_2, \ldots, S_n\}$, Population size = N_P

Step 1: Randomly initialize the search agent $X_i \; \forall_{i,j}$, $1 \le i \le N_P$, $1 \le j \le D$

$$P_{ij}(0) = \left(PX_{ij}(0), PY_{ij}(0)\right)$$

Step 2: Calculate the fitness $f(X_i)$

Step 3: Select $\alpha = \min f(X_i)$, $\beta = \min f(X_{i-1})$, $\delta = \min f(X_{i-2})$

/* α- first best solution, β second best search agent, δ - third best search agent */

Step 4: *while* $(t < t_{max})$ /* t_{max} - the maximum number of iterations */

```
for i = 1:N_p
        Update the position of search agent X_i^t
        Calculate the fitness f(X_i^t)
        Update α, β and δ
end for
for i = 1:n
        calculate θ(P_ij(t+1), S_k)

        P_ij(t+1) → {S_k | min(θ(P_ij(t+1), S_k)), ∀_i, 1 ≤ j ≤ N_P

end for
        end while
Step 5: Repeat Step 4 until it reaches the maximum number of iterations
Output: Visualize the best cluster heads CH = {CH_1, CH_2, ..., CH_m}
```

5. EXPERIMENTAL SETUP

5.1. Simulation setup

In this paper, the algorithms were implemented in MATLAB (version 8.5) with configurations of Intel Core i5 Processor with 8GB RAM in a Windows 10 platform. The parameter settings of the proposed system are given in Table 1. To analyze the performance of the proposed system, the state-of-art other algorithms such as E-LEACH, GA, CS, PSO-C, and FFOA algorithms are used respectively. In our work, we considered the network region as 300x300 m^2, with a varying number of sensors from 400 to 700 and the number of clusters from 20 to 40. The detailed information about the network considerations is given in Table 1.

Table 1. Network configurations

Parameter	Value
Network Field	(300, 300) m^2
Base Station Position	(150-400, 150-400)
Sensor Nodes	400-700
Initial Energy	2J
Number of Cluster Heads	20-40
E_{elec}, ε_{fs}, ε_{mp}	50 nJ/bit, 10 pJ/bit/m^2, 0.0013 pJ/bit/m^4
d_{max}, φ	100 m, 30 m
Packet Size, Message Size	4000 bits, 500 bits

To measure the performance of the algorithms, we considered three different cases in WSN with the varying number of sensors and CHs. Firstly, case#1 deals with the 400 sensor nodes with 20 CHs. Next, case#2 deals with 500 sensor nodes with 30 CHs, case#3 consists of 600 sensor nodes with 30 CHs and finally, case#4 holds 700 sensor nodes with 40 CHs. In addition to that, we have placed the Base station in three different locations namely mid of the network region (150, 150), corner of the network region (300, 300) and outside of the network region (400, 400). Owing to the Placement of BS in different locations are used to analyze the performance of packet delivery information and the network lifetime. Every algorithm has been executed repeatedly for 30 times and average values of that execution are measured and plotted in the figures. The proposed algorithm has been tested with different population size and based on the experimentation analysis we fixed the population size as 50. At the same time, the weighted sum of μ value is fixed as 0.27 based on the experimentation analysis. This value provides better performance compared to values from 0 to 1. The detailed parameters information of the GWO algorithm is given in Table 2.

Table 2. GWO parameters

Parameters	Value
No. of Search agents	50
C	(2 – 0)
a	(0 – 1.5)
μ	0.27
Dimension of search agents	20-40 (CHs)
Number of Iterations	100

5.2. Performance analysis

The performance of the proposed algorithm has been measured using three metrics namely total energy consumption (TEC), network lifetime (NL) and packet received by BS (PR-BS). These three-performance metrics are used to analyze the performance of the proposed algorithm with other algorithms.

5.2.1. Performance analysis of TEC

In order to measure the performance of energy consumption, firstly we executed the algorithms by varying the number of sensor nodes from 400 to 700 and the number of cluster heads from 20 to 50. The performance measures of E-LEACH, GA, CS, PSO-C, FFOA, and GWO-CH are shown in Tables 3 and 4 and Figures 4-8 in terms of total energy utilization in all the different cases. In the first case, the BS location was considered as mid of the network region (150, 150). The observed results notify that the proposed GWO-CH algorithm outperforms better than E-LEACH, GA, CS, PSO-C, FFOA in terms of total energy consumption respectively. In addition to that, we have noticed that if the sensors are nearest to the CHs, the energy consumption for transferring packets from one sensor to other is decreased. Because of the proposed fitness function which concentrates on the energy consumption of the normal nodes by minimizing the distance between the sensor and CHs.

Table 3. Total energy consumption for 20CHs in case#1 (5000 iterations)

Sensors Nodes = 400	BS (150,150)	BS (300,300)	BS (400,400)
E-LEACH	800.00	800.00	800.00
GA	786.54	794.74	800.00
CS	782.92	784.96	788.82
PSO-C	764.64	774.82	784.68
FFOA	710.28	724.65	746.87
GWO	646.54	680.38	702.49

Table 4. Total energy consumption for 30CHs in case#2 (5000 iterations)

Sensors Nodes = 500	BS (150,150)	BS (300,300)	BS (400,400)
E-LEACH	1000.00	1000.00	1000.00
GA	954.87	968.75	986.78
CS	914.15	932.87	954.54
PSO-C	880.54	917.54	942.87
FFOA	864.54	886.40	902.14
GWO	804.51	835.21	856.12

On the other hand, we have noticed that when the network size increases then the performance of the existing algorithm decreases, which was in Figures 4-8. Initially, the performance of the proposed algorithm is not that much satisfactory compared to PSO-C and FFOA. As the number of iterations increases, the residual energy of the sensors is decreasing due to the improper cluster head selections. In this case, our proposed algorithms provide a better solution in case of selecting the proper cluster heads by our derived fitness function. In order to measure the energy consumption performance, we executed our algorithm by varying the number of sensors from 400 to 700 and the cluster heads from 20 to 50. For efficient performance analysis, the algorithms are executed for 5000 iterations. The overall energy consumption was measured at the final iterations 5000. Figures 4-8 displays that the proposed algorithm provides better performance compared to other state-of-art algorithms. The efficacy of the proposed algorithm has been achieved by the novel derived fitness function which handles in selecting the appropriate cluster heads by minimizing the distance between the sensors and CHs. Finally, the performance of the algorithm in terms of energy consumption with varying number of sensors from 400 to 700 and cluster heads from 20 to 50 with 5000 iterations shown in Tables 3 and 4.

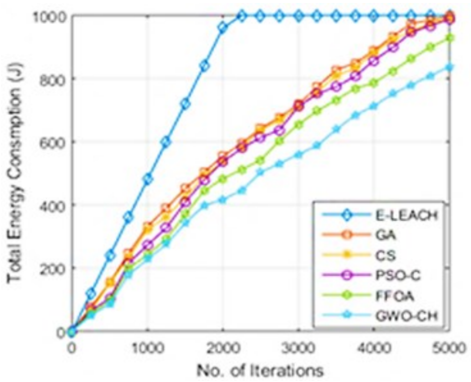


Figure 4. Total energy consumption in case 2 with 30 CHs

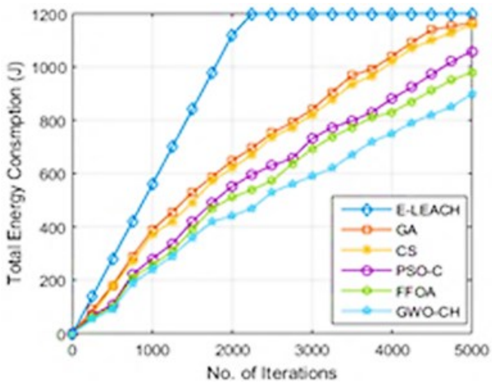
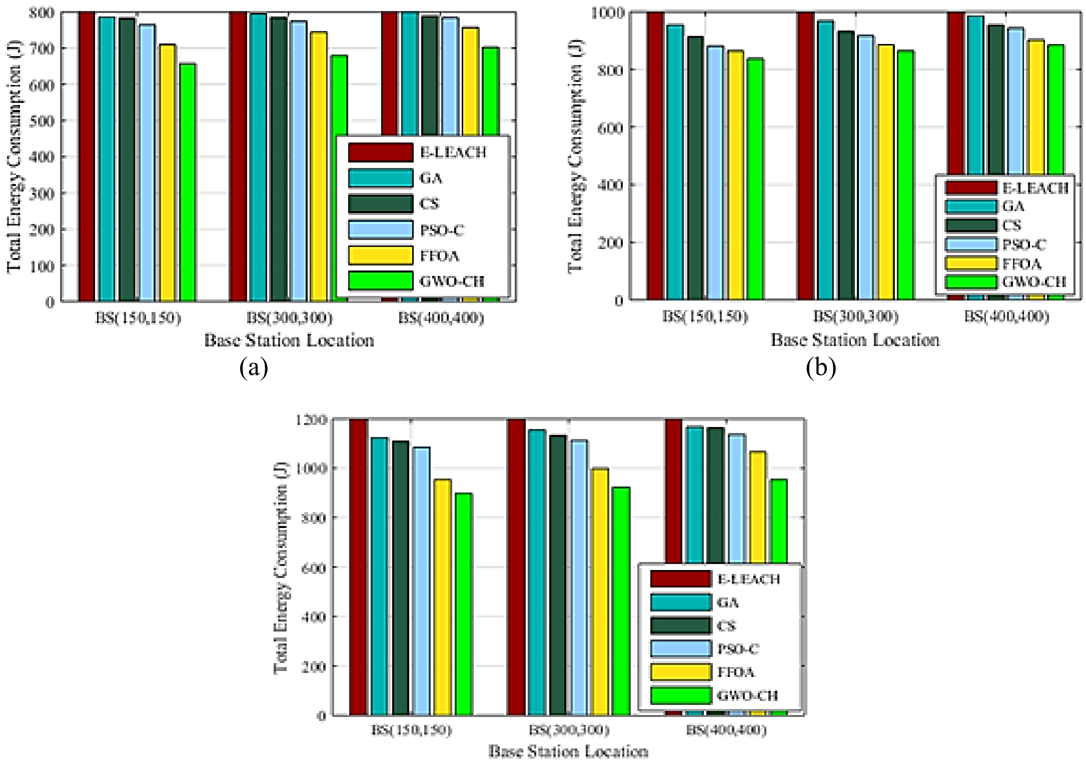
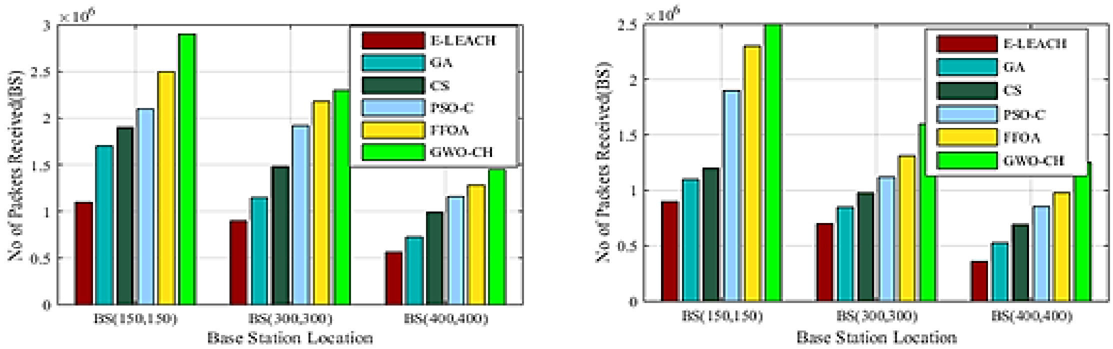


Figure 5. Total energy consumption in case 3 with 40 CHs



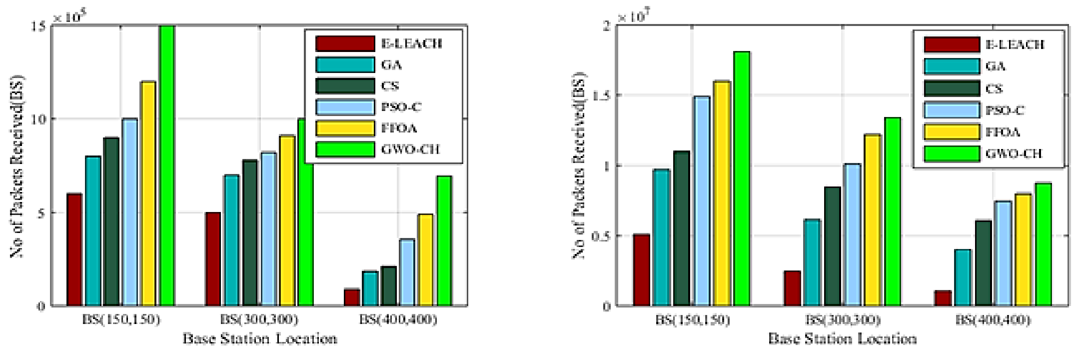
(a) (b) (c)

Figure 6. Total energy consumption by placing BS in different locations; (a) case 1 (b) case 2 (c) case 3



(a) (b)

Figure 7. Comparison of packet received by BS by placing the BS in different locations; (a) case 1 (b) case 2



(a) (b)

Figure 8. Comparison of packet received by BS by placing the BS in different locations; (a) case 3 (b) case 4

Finally, we specify that the proposed algorithm utilizes the minimum energy consumption and maximizes the network lifetime achieves better performance in delivering the maximum number of packets. It is also observed that the proposed algorithm achieves the maximum number of packets received when compared to other algorithms E-LEACH, GA, CS, PSO-C, and FFOA. In the existing algorithm, when the BS location is at out of the network region then the number of packets received is less but the proposed algorithm maximizes the number of packets received in terms of selecting the efficient cluster head using the derived fitness function.

6. CONCLUSION

In this paper, we introduced a novel cluster head selection algorithm based on GWO using efficient search agent representation and novel objective function. For the energy efficacy, we have considered intra-cluster distance, sink distance and the residual energy of sensors respectively. In addition to that, we have formulated the weighted function for the efficient cluster formation. The experimental results with its comparison of existing algorithms E-LEACH, GA, CS, PSO-C, and FFOA has been presented. The algorithm has been executed in the different test cases with a varying number of sensors and CHs. The observed results convey that the proposed algorithm outperforms better compared to other algorithms in terms of energy consumption, network lifetime and packet received by the BS. Further, this work can be extended by formulating novel routing algorithm in the proposed algorithm. Still, we can consider the various issues viz., load balancing and fault tolerance in WSN. In this work, we have tested the proposed algorithm in the homogeneous network. In the future, the same can be tested on heterogeneous networks.

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