Wireless Sensor Networks: Network Life Time Enhancement using an improved Grey Wolf Optimization Algorithm

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Abstract

Clustering is an effective technique in a wireless sensor network (WSN) to minimize energy consumption and low-energy adaptive clustering hierarchy (LEACH) is the most popular clustering protocol in WSNs. However, a random selection of cluster head (CH) in LEACH protocol results in poor performance in real network deployments. Dynamic formation of CHs and energy-aware clustering schemes helps in enhancing the lifetime of WSNs. In this paper, we have proposed an improved version of the grey wolf optimization (IGWO) algorithm to overcome the premature convergence of the basic GWO algorithm and it has been applied in optimizing the CH selection in WSNs to maximize the network lifetime. The improvements of IGWO algorithm are based on sink distance, CH balancing factor, residual energy, and average intra-cluster distance. The proposed algorithm has been tested in terms of the number of rounds, number of operating nodes, number of transmissions, and energy levels used for communications. Using the proposed algorithm is compared with a conventional LEACH protocol and it is observed that the total number of operational rounds has been increased by 441.4% and 869.6% for a network size of 50 and 699.8% and 990.8% for a network size of 100 when CH selection probability is 5% and 10% respectively. The simulation results show that the proposed IGWO based LEACH protocol outperforms the existing state-of-the-art algorithms based on GWO for enhancing the WSNs lifetime.

Keywords: Wireless sensor network; low-energy adaptive clustering; grey wolf optimization; sensor network lifetime; cluster head selection; improved grey wolf optimization algorithm.

1. Introduction

A wireless sensor network (WSN) is a combination of several sensors installed on physical devices that are geographically distributed in a network field to collect the data based on the application. The scattered nodes can be grouped into clusters to deliver the information to the base station (BS). The sensor nodes are self-organized, having the ability to sense, process, and communicate. In most WSN applications, it is not feasible to recharge or replace the batteries of sensor nodes. The main challenges in WSNs are the optimal number of CHs, energy efficiency, optimal network coverage, network lifetime, stability, reliability. Designing an energy-efficient protocol for optimum selection of CHs is essential for maximizing network lifetime in WSNs. Low energy adaptive clustering (LEACH) is a hierarchical protocol at MAC sublayer used to form clusters in WSNs. [1] The node which has maximum residual energy becomes CH to improve energy efficiency and network lifetime. The functioning of LEACH protocol has two phases: the “setup phase” in which cluster formation is performed and in the next phase called the “steady phase”, information is transferred to the sink node.

Setup phase: In this phase, every sensor node chooses a random number in the range 0 to 1 and if this number is lower than the threshold of n^{th} node ‘T(n)’, then the sensor node becomes CH for that specific cluster and the remaining nodes will act as cluster members. The CH selection phase and clustering phase are the key parts of the LEACH protocol. Each sensor node is having threshold energy as per (1).

$$T(n) = \begin{cases} \dfrac{p}{1 - p\left(r \bmod \left(\frac{1}{p}\right)\right)} & \forall\ n \in G \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

Initially, CHs are chosen based on a threshold value T(n) and BS transmits the message to every CH of the first round. This strategy ensures that all the sensor nodes uniformly spend equal energy. Once CH selection is completed, the CHs advertise their selection to all sensor nodes in the network. After receiving the advertisements, the sensor nodes choose their nearest CH based on the received signal strength, and then CHs assign a TDMA schedule for the nodes in their respective clusters.

Steady phase: In this phase, cluster members join their CHs and transmit data based on the TDMA schedule. To achieve energy conservation, CHs perform data aggregation (or fusion) through local computation and the resultant data is further transmitted to BS. A longer steady phase minimizes overhead of cluster formation. After a certain amount of time in the steady phase, the selection of CHs is repeated through the setup phase. Adaptive CH selection based on event occurrence instead of periodic selection significantly minimizes message overheads and computations without compromising for network throughput and end-to-end delay. [2]

1.1 Grey Wolf Optimization (GWO) algorithm

GWO is a meta-heuristic algorithm inspired by the food searching behavior of grey wolves and it mimics the hunting mechanism and leadership hierarchy of grey wolves present in nature. The wolves do attacks in a group and the best position of any wolf can be provided with the best solution. They follow a strict social dominance hierarchy as alphas (α), beta (β), delta (δ), and omega (ω) which is shown in Fig. 1 and the implementation of hunting, searching, encircling, and attacking the prey. The dominance\ decreases from top to bottom of the hierarchy. This algorithm is applied to WSNs in which the position of wolves represents the position of CH in each cluster and the position of the grey wolves updates the position of CH in LEACH protocol.

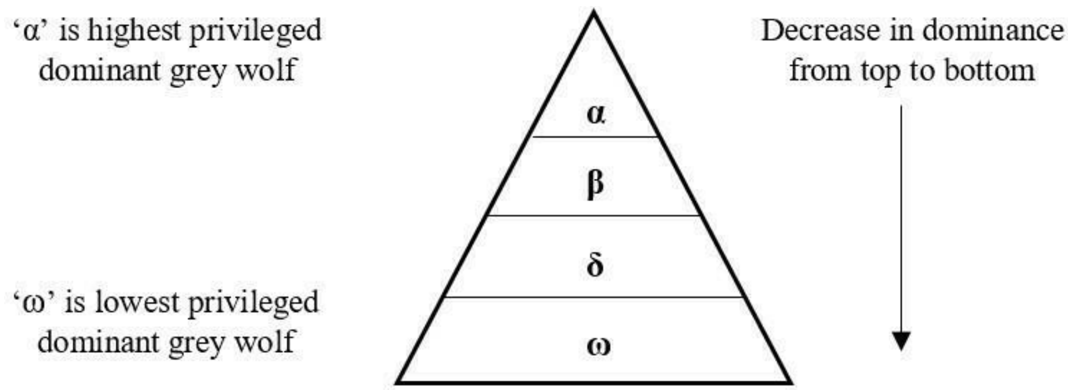

Fig. 1 Hierarchy of Grey Wolves.

A schematic illustration of the synthesis process of The α wolves (both male and female) are most responsible in the decision making, organization, the discipline of the group and the other category of wolves in a group follows α wolf's decisions. In the second level, β wolves (either male or female) help, advice the α wolf in decision-making, feedback and pass commands to lower level wolves in the hierarchy. δ category wolf is subordinate of α, β and dominant of ω wolves. δ wolves play a role of scouts, sentinels (guarantee the safety and protection of group), elders (experienced wolves who are used by α and β wolves, hunters (help the α, β wolves in hunting for providing food for the group), caretakers (take care of weak, ill and wounded wolves in the group). Grey wolf, ω is the lowest level animal in a group that follows orders of all other dominant wolves. ω wolf assists the entire group and if ω wolf is absent in a group, there are chances of the internal fight due to frustration of all other wolves. The main steps of group hunting by grey wolves are: 1) Tracing, chasing, and approaching the prey 2) pursuing, encircling, and harassing the prey till it stops movement 3) attack towards prey. The social hierarchy and hunting techniques of grey wolves are modeled to design the GWO algorithm and its performance optimization. The GWO algorithm is used in solving real time engineering problems across various fields. [3-4]

2. Performance optimization in WSNs

Optimization of CH selection in WSN greatly improves the network lifetime. As energy is a major constraint in WSNs, optimum energy utilization is an important aspect in WSNs to enhance the lifetime of the network and this feature is essential for IoT and IIoT applications. As a part of energy harvesting in WSNs, there are many algorithms and techniques proposed in the literature for CHs selection based on residual energy, centrality, the position of nodes, etc., to minimize the energy consumption and improve network lifetime without compromising the reliability of the network. Cluster formation and CH selection as well as re-formation and re-selections based on residual energy further improve network efficiency over LEACH protocol. However, the reformation of clusters occurs only if there exists a large separation between CHs and sensor nodes. This approach improves the efficiency of the network in terms of lifetime and decreases complexity over the LEACH protocol.[5] In a normal operation of LEACH protocol, the energy consumption of WSN is equalized by randomly selecting CHs in an iterative fashion and it leads to network instability. Therefore, it is essential to optimize the routing protocol and number of CHs in order to minimize the energy consumption for data transmissions. Decentralized clustering protocols that differentiate intra-cluster and inter-cluster communications reduce the number of transmissions and routing control packets thereby longer lifetime for the network.[6] CDMA-based LEACH protocol uses a different set of codes in each cluster to reduce inter-cluster interference.[7] Rank-based algorithms consider a number of links between nodes and path cost while electing CHs, LEACH protocol based on node rank enhances the lifetime of WSN.[8] Using Voronoi diagrams to form clusters and ant colony algorithms to optimize multi-hop routing can improve the first node death time by 14.5% and 127% compared to SEP and LEACH protocols respectively.

[9] A Combination of ARSH-FATI-based CH selection algorithm and rank-based clustering minimizes the consumption of communication energy at sensor nodes and this algorithm switches dynamically between exploration and exploitation of search process during the run-time to have a 25% higher network lifetime over PSO.[10] Fuzzy based clustering provides an efficient data aggregation and enhances the life span of WSNs.[11-12] In heterogeneous WSNs, adaptive clustering routing techniques consider residual energy at a given node and its location for efficient CHs selection. The nodes which are close to BS and have more residual energy become CH with higher probability. The CHs which are far away from BS uses multi-hop routing and the other nodes use single-hop routing. These features balance energy consumption and enhances the network lifetime, network throughput over SEP and DEEC protocols.[13] A hybrid meta-heuristic algorithm with a combination of cuckoo search and Krill herd for homogeneous and heterogeneous WSNs environments enhance their lifetime. Krill herd algorithm is used to compute the optimal cluster centroid positions and a cuckoo search algorithm is applied to select optimal CHs.[14]

2.1 Performance optimization of WSN based on GWO algorithm

The selection of CH is not optimal in conventional LEACH schemes, therefore usage of GWO improves the optimal selection of CH in LEACH protocol.[15] GWO is a unique metaheuristic algorithm that mimics the social behavior of grey wolves with respect to their leadership hierarchy and, attacking strategy. Localization problems (search for the geographical position of unknown nodes using anchor nodes) in WSNs can be resolved using the GWO algorithm. CHs selection using GWO considers the distance between clusters and sink, current residual energy of each node and predicted energy consumption. This technique considers the same clustering in consecutive rounds to enhance energy efficiency and the saved energy can be utilized for cluster reformation. For CHs that are far away from BS can use dual-hop routing and it ensures optimum energy consumption.[16] GWO is applied in defining objective functions and weights for efficient cluster formation and CH selection.[17] Appropriate fitness function ensures the coverage of WSN and it is fed to the GWO algorithm to determine its optimum. This procedure outperforms the LEACH clustering and routing algorithm in terms of network throughput, lifetime and, residual energy.[18] Energy efficiency and network stability are two typical trade-off parameters in WSNs. Distance-based stable CDS method and clustering algorithms using GWO in WSN minimizes effective transmission distance with deterministic CH selection and achieves a load-balanced, energy efficient and stable network. These algorithms perform much better than GA and LEACH by 70.5% and 74.7% respectively in terms of network stability and energy efficiency.[19] To improve the energy-efficiency of the clustering mechanism, a combination of two meta-heuristic algorithms named whale and GWO can be used to define the objective function for the formation of an optimal number of clusters, dynamic CH selection, and relay nodes selection on a priority basis.[20-21] MLHP with three levels based on the GWO for WSNs shows better performance in terms of maximum residual energy, network lifetime, stability period compared to other algorithms named LEACH, DEEC, and SEP. At level 1, BS selects CHs, at level 2, GWO routing gives the best route to BS for data transfer, and at level 3, distributed clustering is performed based on cost function.[22] In the cluster-based architecture of WSNs, gateways which are far from BS communicate with BS through the gateways that are close to BS. This causes faster energy depletion at gateways closer to BS because of heavy traffic load and causes energy hole problems around BS. GWO can resolve the energy hole issue by distributing traffic load with minimum traversal distance and number of hops. GWO based algorithm performs better than GA, PSO and multi-objective fuzzy clustering.[23] The percentage of localized nodes, quick convergence rate and success rate of GWO algorithm is higher with less computation time and, localization error compared to PSO, and MBA metaheuristic algorithms.[24] Random deployment of sensor nodes causes a high degree of aggregation and a low coverage rate. The simulated annealing method embedded into GWO avoids falling into local optimum, improves convergence rate, accelerates the convergence speed, coverage optimization and this leads to higher network stability and network life cycle in WSNs.[25] GWO is used to compute the threshold for sensor decision rules from the fusion center that is independent on initial values and with lesser complexity. The results of this algorithm demonstrate the reduced buyer's risk by 15%-20% of fusion system.[26] The Virtual Force-Levy technique embedded with the GWO algorithm effectively enhances the coverage optimization in WSNs in terms of uniformity in nodes distribution, node's average moving distance, changes in the number of nodes, and coverage rate.[27] The robust deployment of WSNs for industrial applications introduces redundant nodes and causes overhead. Quantum clone GWO algorithm is proposed to design and optimize the sensor duty cycle, also avoid falling into a local optimum. The convergence speed of this algorithm is much faster than GA, SA, and enhances the network lifetime.[28] The combination of crow search optimization with the GWO algorithm for optimal CH selection enhances the network lifetime by reducing delay, energy stabilization, and distance between nodes.[29] Providing energy efficiency in heterogeneous WSNs is much more challenging due to the irrational utilization of energy at nodes. For this kind of network, GWO provides a solution based on the node's fitness values. The fitness values are treated as weights and they are dynamically updated based on the distance between wolves and their prey. This algorithm ensures the optimal CHs selection and enhances the network lifetime by 55.7%, 46.3%, 27.0%, and 31.9% over SEP, modified SEP, fitness value based-GWO, and DEEC respectively.[30] The combination of GWO and GOA algorithms improves the convergence levels of meta-heuristic algorithms.[31]

GWO can be used in the implementation of server-less systems to improve task allocation and minimize runtimes.[32] The performance of intrusion detection systems in WSNs can be enhanced using binary GWO with a support vector machine. These techniques can minimize false alarm rates in the WSN environment thereby detection rate and accuracy of the intrusion detection system are increased with minimum processing and execution times.[33] Energy aware clustering in WSNs based on fuzzy logic improves the formation of clusters and CH selection. This technique uses a neural network to have an optimum training set of energy and density values at all sensor nodes to compute the expected energy for uncertain CHs.[34] "Optimal Clustering in Circular Networks" is proposed where a single-hop communication between the sink and CHs is replaced with optimal multi-hops to enhance the WSNs lifetime by reducing the energy consumption.[35] The precision of the node positions is a very significant parameter for effective data transmission and to enhance the network lifetime in WSNs. Geographic routing based on weighted centroid localization improves the precision of node positions which uses fuzzy logic to compute the position of unknown nodes. This technique helps in the efficient selection of next-hop CH for minimizing the energy dissipation and enhances network lifetime.[36] An improved version of GWO which is based on the fitness value, ensures optimal distribution of CHs and enhances the chances of finding the optimal solution in GWO. To decrease the energy consumption, each sensor node's communication distance is recomputed based on the distance between BS and CHs. This feature improves the WSN in terms of throughput, energy consumption and, stability by 57.8% compared to the LEACH protocol. The optimum method for selecting CHs and their distribution with balanced cluster structures can be achieved using fitness value based GWO. This optimal solution ensures that the node in a cluster located near to BS and having maximum energy becomes CH.

To decrease the energy consumption, the communication range of sensor nodes is recalculated as per the distances between BS and CHs, it means that when a new CH is elected. This approach minimizes the average communication distance, reduces the energy consumption and improves WSN stability by 31.5% and 57.8% compared to SEP, LEACH protocols respectively.[37] IGWO algorithm benefits from DLH search strategy which is inherited from individual wolf's hunting behavior. DLH uses dimension learning to collect neighbor's information at every wolf and this information is shared among other wolves. This DLH search strategy maintains diversity as well as improves balancing between global and local search to improve convergence speed. The results of the engineering experiments and statistical reports prove that the applicability, optimal performance, effectiveness, solution stability, convergence speed, robustness, convergence precision, and efficiency of the IGWO algorithm outperforms the other existing metaheuristic algorithms.[38-39] Dynamic mutation strategy improves the diversity of wolves and effectively increases the search range. This improved version of GWO gives faster convergence, high coverage and, search precision in WSNs even in the presence of obstacles of various shapes (rectangular, trapezoidal, and triangular). The convergence and coverage performance of the improved version of GWO is better than GA, PSO, conventional GWO algorithms thereby minimizing the deployment cost of WSN.[40] The introduction of biological evolution and elimination mechanisms using the "survival of the fittest" principle in the GWO algorithm gives a balance between exploitation and exploration to accelerate its optimization accuracy and convergence.[41]

3. Proposed Method

The energy model as shown in Fig.2 is followed by LEACH protocol with the two-channel model as: free space (d^2) for single-hop path and multipath fading (d^4) for the multi-hop path.

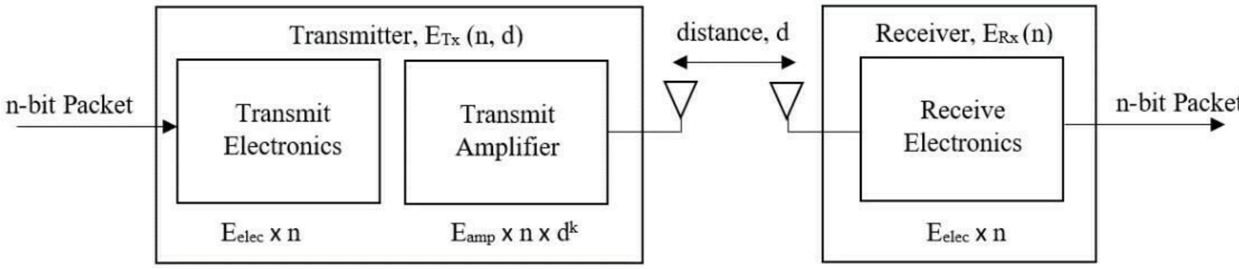

Fig. 2 Radio energy model of a sensor node.

So the energy consumption of m-bit packets over distance 'd' is computed as

$$E_{TX}(m,d) = \begin{cases} mE_{elec} + m\ \ e_{fs}\ \ d^2 & d < d_0 \\ mE_{elec} + m\ \ e_{mp}\ \ d^4 & d \geq\ \ d_0 \end{cases} \quad (2)$$

Where e_{fs} → free space energy loss m → packet length e_{mp} → multipath fading loss

d → distance between sender and receiving node, $d_0 = \sqrt{e_{fs}\ /e_{mp}}$ → threshold distance

E_{elec} → circuit energy consumption

The energy variable depends on the node distance, so via optimizing node distance, we can minimize the energy consumption at every sensor node in WSN. IGWO algorithm is designed to avoid the impact of premature convergence in conventional GWO algorithms. Some of the features are modified to provide a cost-effective solution to a WSN. The IGWO is a kind of swarm intelligence optimization as the objective function does not include strong mathematical formulations and does not demand specific requirements for the objective function. The benefits of the proposed algorithm include higher robustness, conversion precision, and higher speed of convergence. The mathematic model of the GWO algorithm which is influenced by the hunting strategy of the grey wolves is as follows:

The hunting process can be formulated as follows:

$$\overrightarrow{D} = |\vec{C}.\overrightarrow{X_p}(k) - \vec{X}(k)|, \quad \vec{X}(k+1) = |\ \overrightarrow{X_p}(k) - \vec{A}.\vec{D}| \qquad (3)$$

$\overrightarrow{D}$ is the distance between prey and wolf, in WSN, $\overrightarrow{D}$ is the distance between CH and sensor node. $\vec{X}$ is position of wolf and in WSN, it is the position of sensor node. $\overrightarrow{X_p}$ is position of prey and in WSN, it is the position of CH. $\vec{A}$ and $\vec{C}$ are constant parameters that are measured using:

$$\vec{A} = 2\vec{a}.\overrightarrow{r_1} - \vec{a} \quad , \vec{C} = 2\ \overrightarrow{r_2} \qquad (4)$$

$\overrightarrow{r_1}$ and $\overrightarrow{r_2}$ are arbitrary vectors between [0 1]. The parameter $\vec{a}$ is equal to 2*(1-t/maximum iterations) and it reduces linearly from 2 to 0 and helps to control the flow of the algorithm. The changes that were inculcated in WSN clustering protocol for the selection of CH include “Gaussian perturbation” and “Cosine control factor”.

3.1 Gaussian perturbation

The value of $|\vec{C}|$ in equation 3 is used to avoid falling of algorithm into local optima as it showcases random behavior. The initial selection of sensor node was random due to which there are chances of the CH falling into premature convergence. To avoid this convergence, the co-efficient $|\vec{C}|$ in equation 3 is replaced with Gaussian perturbation value. This helps to maintain the diversity of sensor nodes that in turn helps to keep away the local optima.

3.2 Cosine control factor

Another factor that is added in the IGWO algorithm is cosine control factor. The vector $\vec{A}$ in equation 4 is used to balance the search capability. It comprises factor $\vec{a}$ that decreases from 2 to 0 in a linear fashion and hence acts as an attenuation factor. The cosine control factor helps to enhance the search range and improvises the ability to search globally. In addition to the change in attenuation factor, IGWO also includes weight cosine control factor W(t). This value changes in compliance with the factor $\vec{a}$ to elevate the global search capability.

3.3 Weight functions for CH selection using GWO

The proposed algorithm selects the initial CH using LEACH protocol and later it optimizes the selection using GWO algorithm. Implementation of the algorithm is performed at BS to select optimum CHs and further form optimum clusters using the weight functions. The objective function considers intra-cluster distance, residual energy of the sensor nodes, and neighborhood ratio. Further modification of GWO i.e. IGWO is carried out to select the CH. The IGWO is a combination of two modifications that include Gaussian perturbation and Cosine control factor.

The weight function combines two objective functions. The first objective function is based on the distance between sensor nodes and distance from BS, it is mathematically modelled as follows:

$$\overrightarrow{X_1} = \left|\vec{X}\alpha - W(t).\vec{A}.\vec{D}\alpha\right|$$

$$F_1 = \sum_{j=1}^{m} D(SN, SNj) + D(SN, BS) \tag{5}$$

D (SN, SNj) → distance between a given sensor node and all other sensor nodes

D (SN, BS) → distance between a given sensor node and BS.

This objective function is calculated for all the nodes and a sensor node with minimum value is given preference. The second objective function is based on residual energy of nodes and it is mathematically modelled as

$$F_2 = 1/(\textstyle\sum_{j=1}^{m} E\text{resi}\,(j)) \tag{6}$$

*E*resi(j) is the remaining energy at a sensor node ‘j’ and the purpose is to minimize both objective functions.

The combined weight function is given as

$$F = m \times F_1 + (1 - m)\ F_2 \qquad \text{where } 0 < m < 1 \tag{7}$$

‘m’ is the weight parameter. Sensor node with the least objective value is chosen as CH of the cluster. The cluster members belong to a cluster sends data to the selected CH and further CH delivers the aggregated data to BS.

3.4 Formation of clusters

CHs are picked using three criteria that are neighborhood ratio, residual energy, and distance between intra-cluster and BS. There is a definite function that will help in the formation of clusters and that is mathematically formulated as follows:

$$CHw(SNi, CHj) = K \times \frac{Eresi(CHj)}{D(SNi,CHj) \times D(CHj,BS) \times Rn(CHj)} \tag{8}$$

$CHw(SNi, CHj)$ will define which sensor node will join the j^{th} CH.

K → a constant parameter. Eresi → residual energy at j^{th} CH

$D(SNi, CHj)$→distance between i^{th} sensor node and j^{th} CH.

$D(CHj, BS)$→distance between j^{th} CH and BS.

$Rn(CHj)$ →neighborhood ratio of the j^{th} CH.

The i^{th} sensor node with a higher value will join the respective CH.

3.5 Inclusion of gaussian perturbation and cosine control factor

These two factors are inculcated in GWO to improvise the algorithm. The Gaussian value is described with the help of variance(σ^2), mean(μ), upper limit(ul) and lower limit(ll). The steps to find a Gaussian perturbation value are:

x = μ + rand (200,1) * σ; This generates sufficient random value to choose from.

idx = (ll <= x) & (x <= ul); This helps to extract the value in the given range [ll ul].

x = x(idx); This is used to select the values within the range.

The Gaussian value generated by the above expression replaces the constant $|\vec{C}|$ in equation 3. The new expression for distance between wolf and prey in the grey wolf pack and analogously the distances between the alpha, beta, and delta sensor nodes with all other nodes take a vector form which is given as:

$$\vec{D} = |Gaussian(\delta).\overrightarrow{X_p}(k) - \vec{X}(k)| \tag{9}$$

Due to the change in distance formula, the equations providing the location of sensor nodes also get necessary changes and give optimized locations. The addition of cosine control factor changes the value of $\vec{a}$ given in equation 4. It is modified to provide better results during the searching process of optimization. The new value of $\vec{a}$ after the inclusion of cosine factor is given as follows:

$$\vec{a} = 2 \times \cos(\left(\frac{\pi}{2}\right) \times \left(\frac{t}{maximum\ \ iterations}\right)) \tag{10}$$

Another factor included in defining the position of nodes i.e. the weight cosine control factor is given as:

$$W(t) = \cos(\left(\frac{\pi}{2}\right) \times \left(\frac{t}{maximum\ \ iterations}\right)) \tag{11}$$

The CHs are changed depending on their fitness value and the mathematical model is given as follows:

$$\overrightarrow{D_\alpha} = |\overrightarrow{C_1}\ .\ \ \overrightarrow{X_\alpha}(k) - \vec{X}|,\quad \overrightarrow{D_\beta} = |\overrightarrow{C_2}\ .\ \ \overrightarrow{X_\beta}(k) - \vec{X}|,\quad \overrightarrow{D_\delta} = |\overrightarrow{C_2}\ .\ \ \overrightarrow{X_\delta}(k) - \vec{X}| \tag{12}$$

$$\overrightarrow{X_1} = |\overrightarrow{X_\alpha} - \ W(t).\overrightarrow{A_1}.\overrightarrow{D_\alpha}|,\ \overrightarrow{X_2} = |\overrightarrow{X_\beta} - \ W(t).\overrightarrow{A_2}.\overrightarrow{D_\beta}|,\ \overrightarrow{X_3} = |\overrightarrow{X_\delta} - \ W(t).\overrightarrow{A_3}.\overrightarrow{D_\delta}| \tag{13}$$

$$\vec{X}(k+1) = |\overrightarrow{X_1} + \ \overrightarrow{X_2} + \ \overrightarrow{X_3}|/3 \tag{14}$$

3.6 Steps to integrate IGWO algorithm with LEACH protocol

Input: Define network parameters.

Step 1: Place sensor nodes at required positions.

Step 2: Select CHs based on threshold function

Step 3: While (operating nodes > 0)

Step 4: Compute objective function

Define node's fitness, $F(SN_i)$, ∀ sensor nodes.

Step 5: Select $\alpha = \min F(SN_i)$

$\beta = \min F(SN_{i-1})$

$\delta = \min F(SN_{i-2})$.

Step 6: while ($i < i_{max}$)

For j = 1: Np

Update sensor nodes position as per equations 12, 13, 14.

Calculate the fitness value using objective function

Update α, β, and δ.

End for;

Step 7: Select α node as CH.

Step 8: Compute the energy dissipation at each round as per equations 3, 4.

i=i+1;

End While loop;

Step 9: operating nodes < = 0

End While loop;

Step 10: Note the outputs and plot the graphs;

4. Results and discussions

This section covers the performance of LEACH protocol integrated with a meta-heuristic algorithm named IGWO as shown in section 3 and the results are compared with the state-of-the-art energy-efficient algorithms [16-17] in WSNs including conventional LEACH algorithm and LEACH integrated with GWO algorithm. The simulations are conducted using MATLAB 2021b tool and result analysis is performed by creating a geographical area of 100m x 100m with random placement of sensor nodes as shown in Fig.3 and the sets of simulated results (where each set of results are averaged for fifteen simulations) are considered for comparison. The simulation parameters that were set while experimenting with LEACH protocol by placing BS at different locations of the network and the probability of CH selection values are given in Table 1. The sensor node locations are predefined to ease the process of comparison and to provide accurate results when compared with existing GWO based algorithm.

Table 1: Initial Parameters of LEACH Protocol for Simulations

Parameter	Value
Network Field Dimensions	100 m $\times$ 100 m
Total Number of Sensor Nodes (N_P)	50, 100
Initial Energy (E_0)	2J, 0.5J
Probability to become CH (P)	0.05, 0.1
Number of CHs	P $\times$ 100
E_{fs}, E_{elec}, E_{amp}	10pj/bit/m^2, 50nj/bit, 0.0013pj/bit/m^4
D_{max}, $D_{critical}$	100m, 30m
Data Packet size	4000 bits
Position of BS	(0, 0), (50, 50), (100, 100)

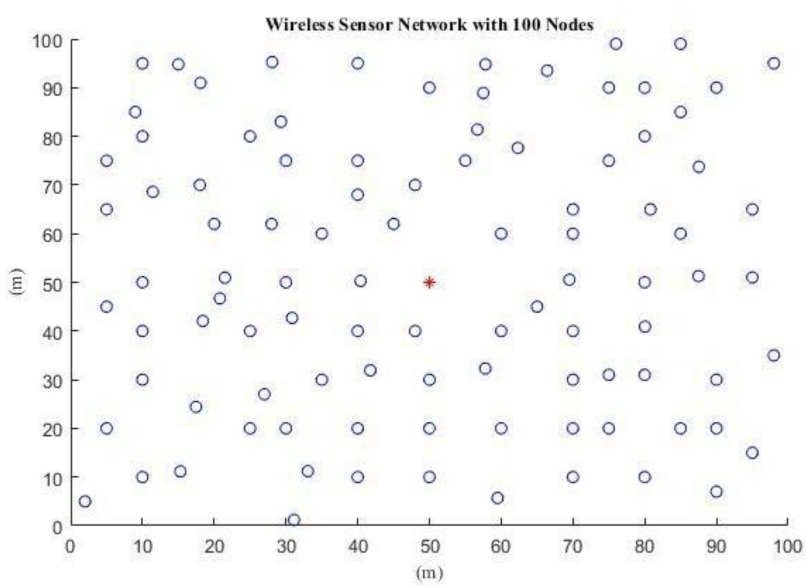

Fig. 3 Node distribution in WSN network generated for 100 nodes and placed randomly.

The parameters considered to analyze the performance matrix of WSN concerning the energy efficiency and life span of the network are the total number of operating rounds, number of transmissions, and energy consumed per transmission. The average of simulated values is calculated to estimate the approximate value of network life when similar parameters are given as input to the WSN.

The simulated results of WSN for 50 nodes using conventional LEACH protocol and its integrated versions with GWO, IGWO algorithms are illustrated in Table 2. The total number of operational rounds has been increased in the integrated versions of LEACH protocol i.e. LEACH with GWO and IGWO algorithms by 544.8% and 869.6% respectively compared to conventional LEACH protocol when the CH selection probability is 10% as shown in Fig. 4a. Similarly, the total number of operational rounds using LEACH integrated with GWO, and IGWO algorithms have been increased by 367.4% and 441.4% respectively compared to the conventional LEACH algorithm with the CH selection probability of 5% as shown in Fig. 4b.

Table 2: Number of operating rounds in the WSN of size 50 nodes with BS located at (50, 50)

Parameters	Set Number	Conventional LEACH		LEACH with GWO		LEACH with IGWO	
CH selection Probability		p=0.1	P=0.05	p=0.1	p=0.05	p=0.1	P=0.05
Total number of operating rounds	1	1724	2746	10000	11209	16279	13240
	2	1838	3167	10239	11909	16473	13543
	3	1893	3492	10614	12538	16522	14929
	4	2181	3725	10751	12588	17123	16243

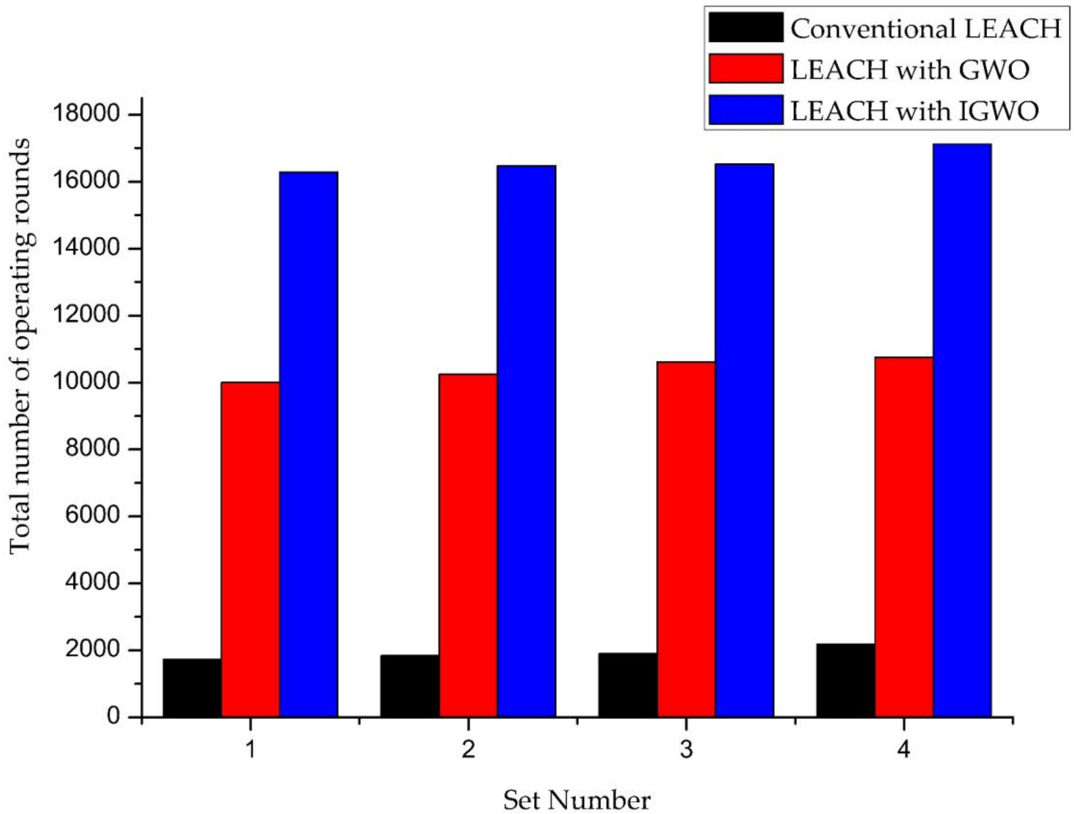

Fig. 4 (a) Total number of operational nodes per round in a WSN of 50 nodes with CH probability of 10%.

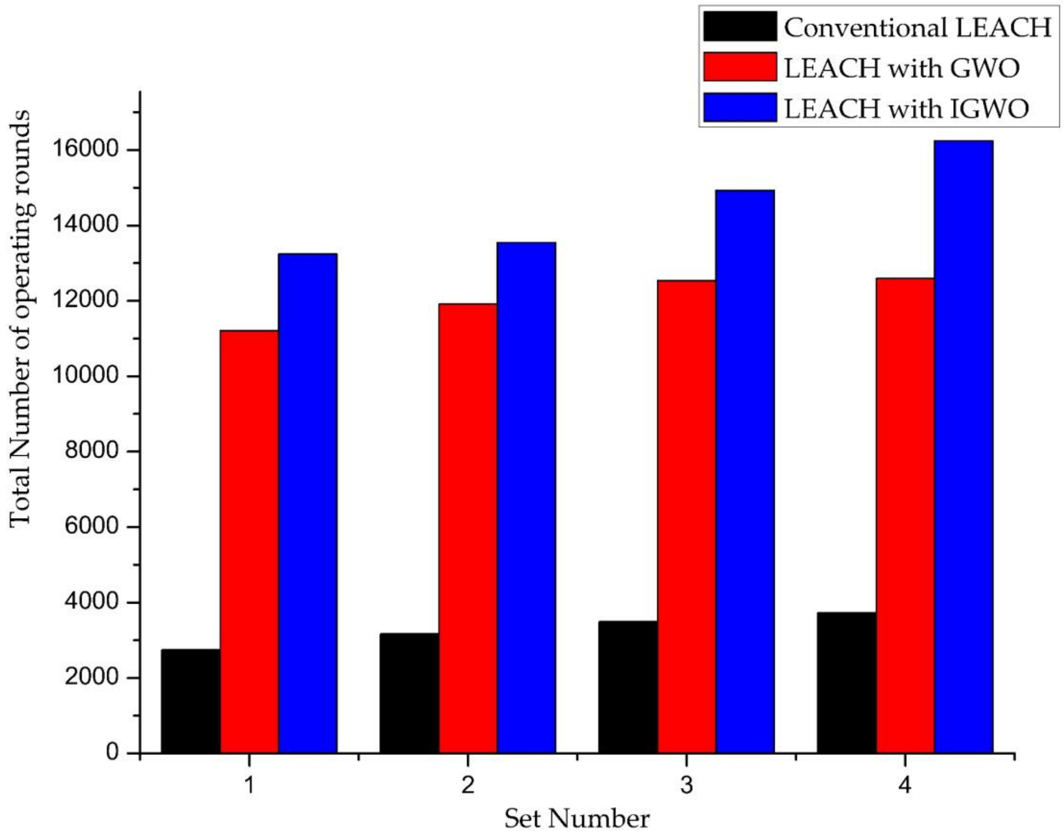

Fig. 4 (b) Total number of operational nodes per round in a WSN of 50 nodes with CH probability of 5%.

Table 3: Number of operating rounds in the WSN of size 100 nodes with BS located at (50, 50)

Parameters	Set Number	Conventional LEACH		LEACH with GWO		LEACH with IGWO	
CH selection Probability		p=0.1	P=0.05	p=0.1	p=0.05	p=0.1	P=0.05
Total number of operating rounds	1	2017	3215	23776	36240	17421	20491
	2	2082	3469	25424	38819	18240	21107
	3	2122	3626	29284	41267	24141	29796
	4	2400	4193	32587	43350	25618	30109

The simulated results of WSN with 100 nodes using conventional LEACH protocol and its integrated (with GWO and IGWO algorithms) versions are illustrated in Table 3. The total number of operational rounds has been increased in the LEACH protocol integrated with GWO and IGWO algorithms by 1288.5% and 990.8% respectively compared to conventional LEACH protocol with a CH selection probability of 10% as shown in Fig. 5a.

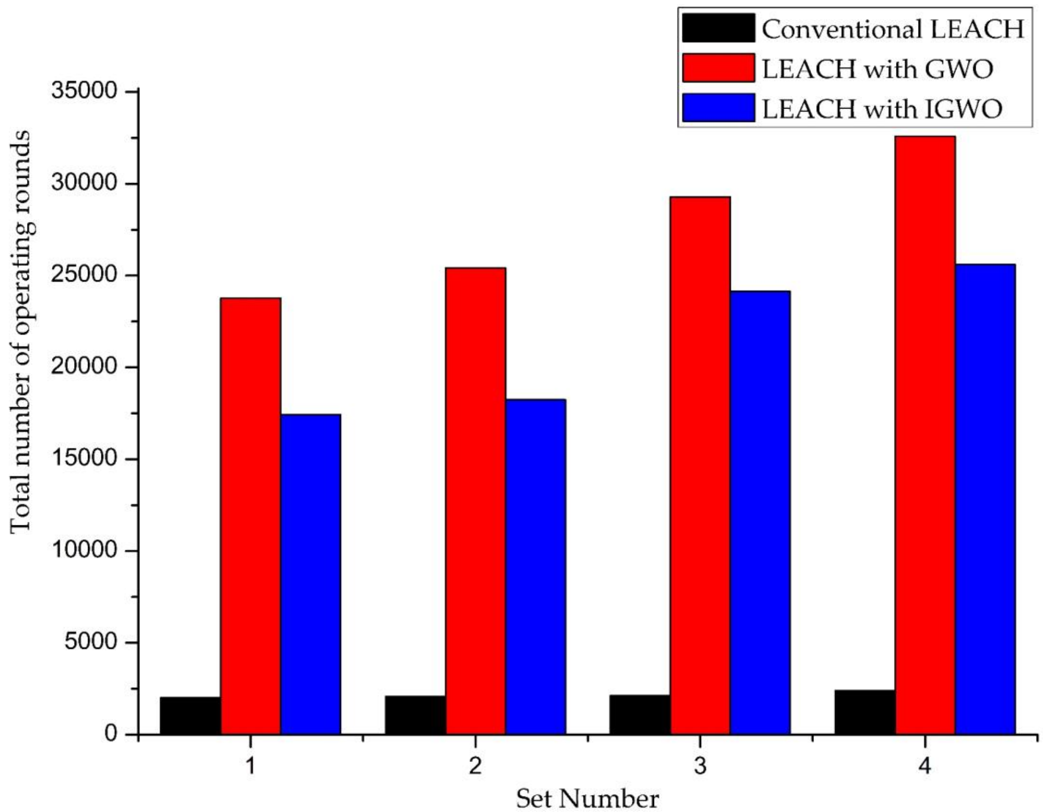

Fig. 5 (a) Total number of operational nodes per round in a WSN of 100 nodes with CH probability of 10%.

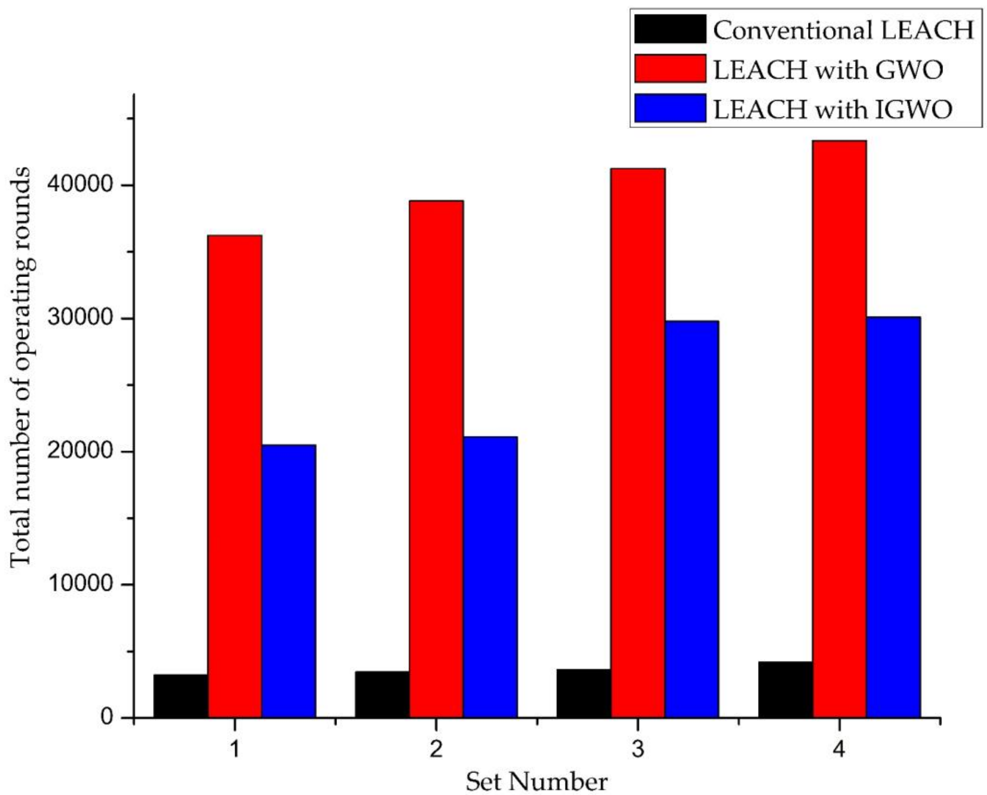

Fig. 5 (b) Total number of operational nodes per round in a WSN of 100 nodes with CH probability of 5%.

Similarly, the total number of operational rounds has been increased in the LEACH protocol integrated with GWO and IGWO algorithms by 1101% and 699.8% respectively compared to conventional LEACH protocol with CH selection probability of 5% as shown in Fig. 5b. Surprisingly, for a WSN with 100 nodes, the total number of operational rounds is higher in LEACH protocol integrated with GWO algorithm compared to LEACH protocol integrated with IGWO algorithm for both cases where CH selection probability is 10% and 5%.

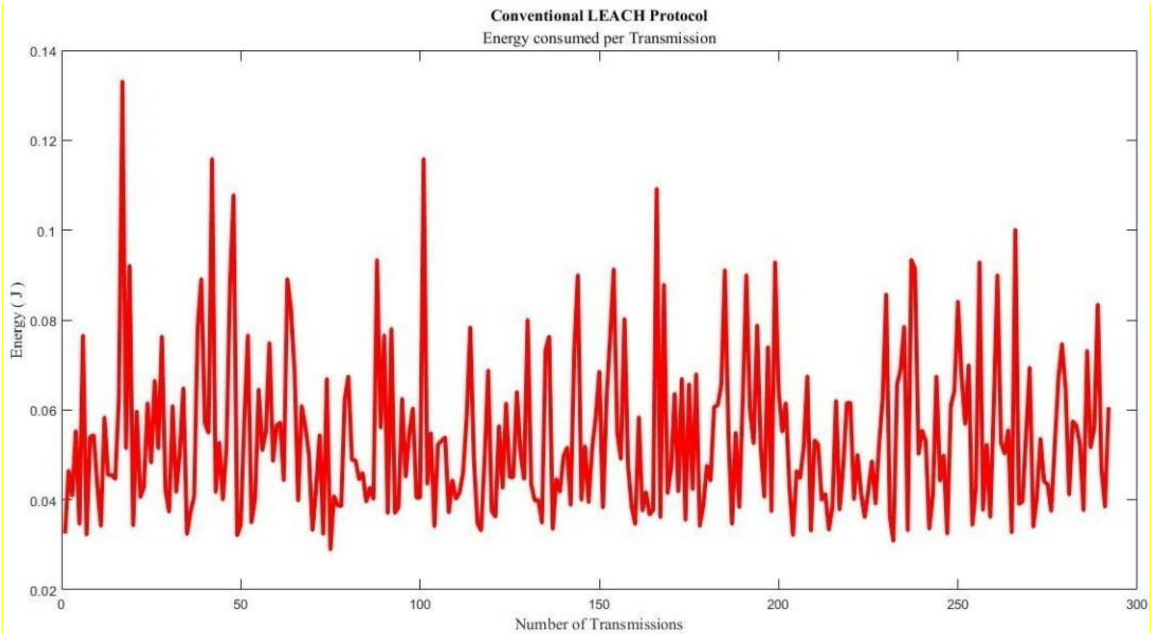

Fig. 6 (a) Energy consumption per transmission in a conventional LEACH protocol

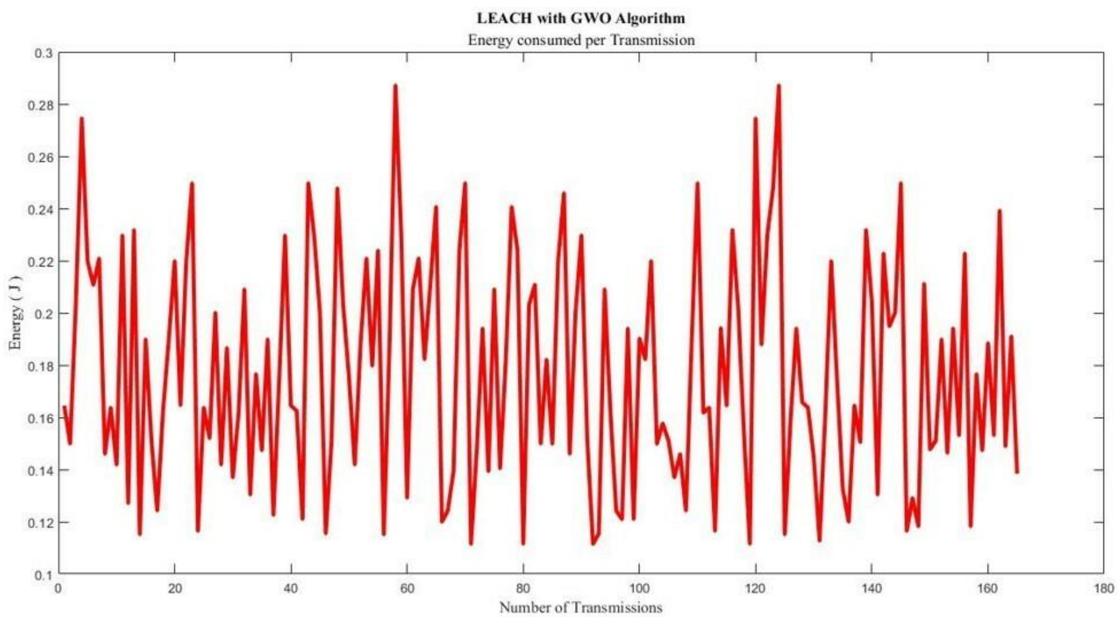

Fig. 6 (b) Energy consumption per transmission in a LEACH protocol integrated with GWO algorithm

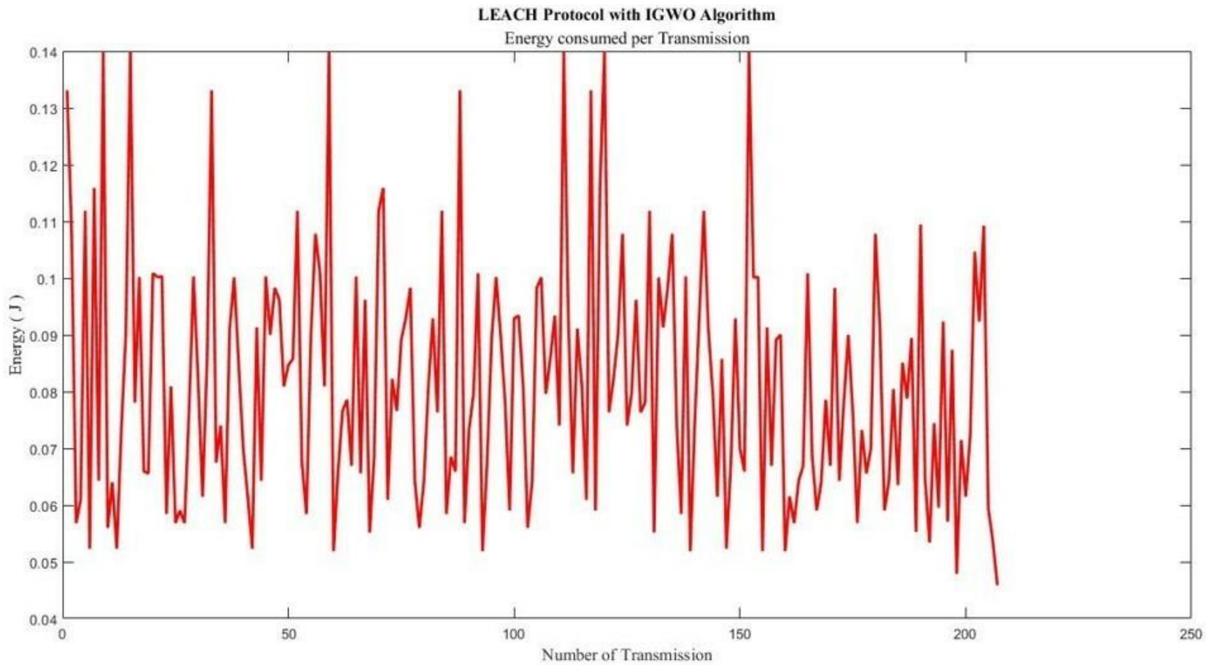

Fig. 6 (c) Energy consumption per transmission in a LEACH protocol integrated with IGWO algorithm

Fig. 6 Energy consumption performance comparison of conventional LEACH protocol and LEACH integrated with GWO, IGWO algorithms in a WSN of size 100 nodes

Fig.s 6a, 6b, and 6c show the energy consumption per transmission in LEACH protocol and its integrated versions with GWO, and IGWO algorithms. There are two main observations, firstly the variance in energy consumptions and the number of transmissions are reduced in GWO, IGWO based LEACH protocol. Secondly, the maximum energy consumption levels per transmission are greatly reduced in IGWO based LEACH protocol compared to conventional LEACH and GWO algorithm-based LEACH protocol. We have observed that the number of transmissions is reduced by 165.71% in IGWO based LEACH protocol compared with the conventional LEACH protocol. Fig.s 7a, 7b, and 7c shows the comparison of number of operational nodes per round in the IGWO based LEACH protocol, GWO based LEACH, and the conventional LEACH. The number of operational nodes indicate the activities in the network using alive nodes. From the graphs mentioned in Fig. 7, it is very clear that IGWO based LEACH has outperform the existing GWO algorithms.

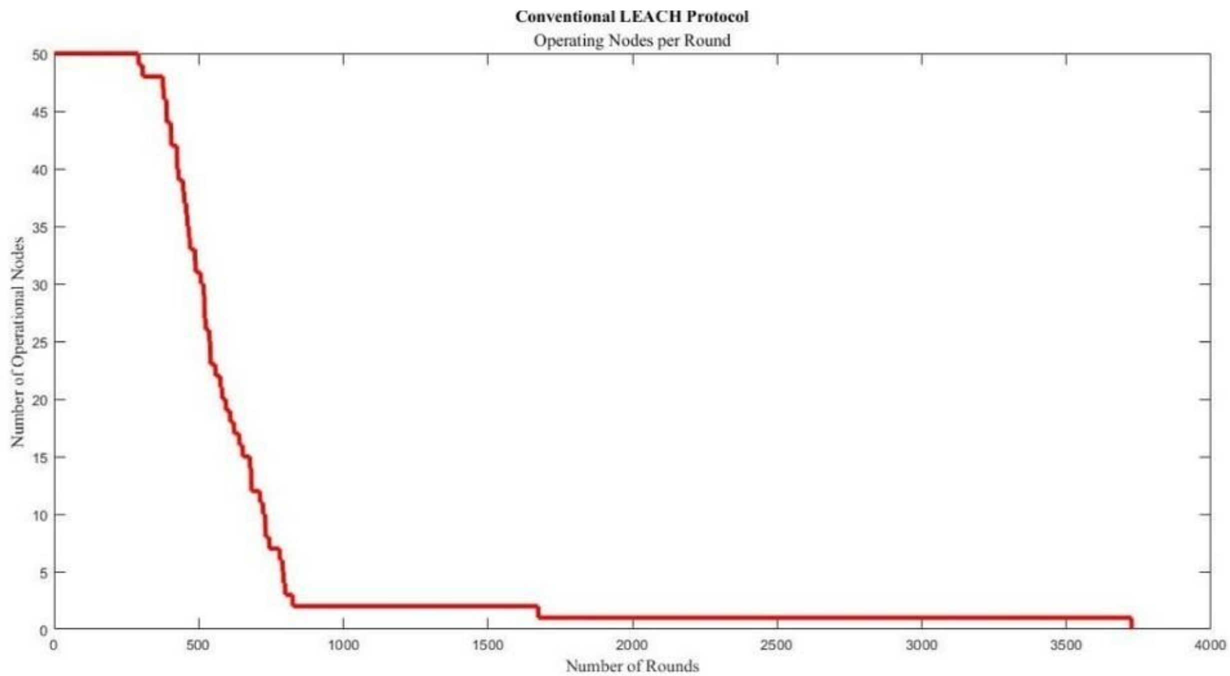

Fig. 7 (a) Number of operational nodes per round in a conventional LEACH Protocol

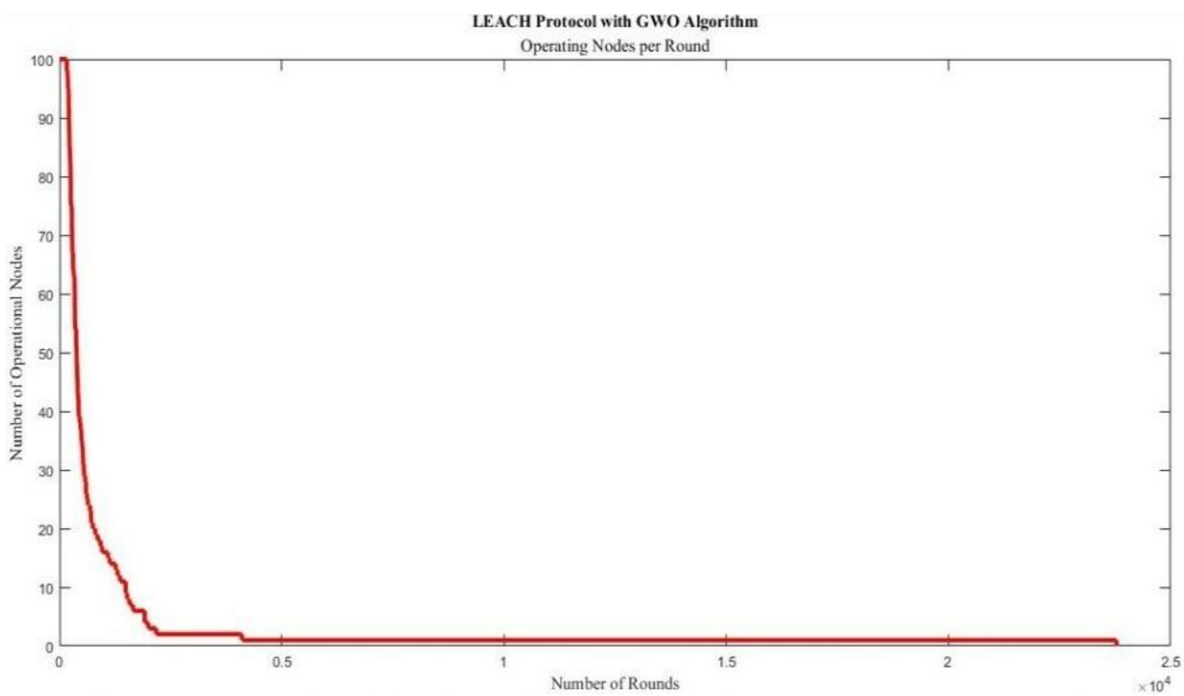

Fig. 7 (b) Number of operational nodes per round in a LEACH Protocol integrated with GWO Algorithm

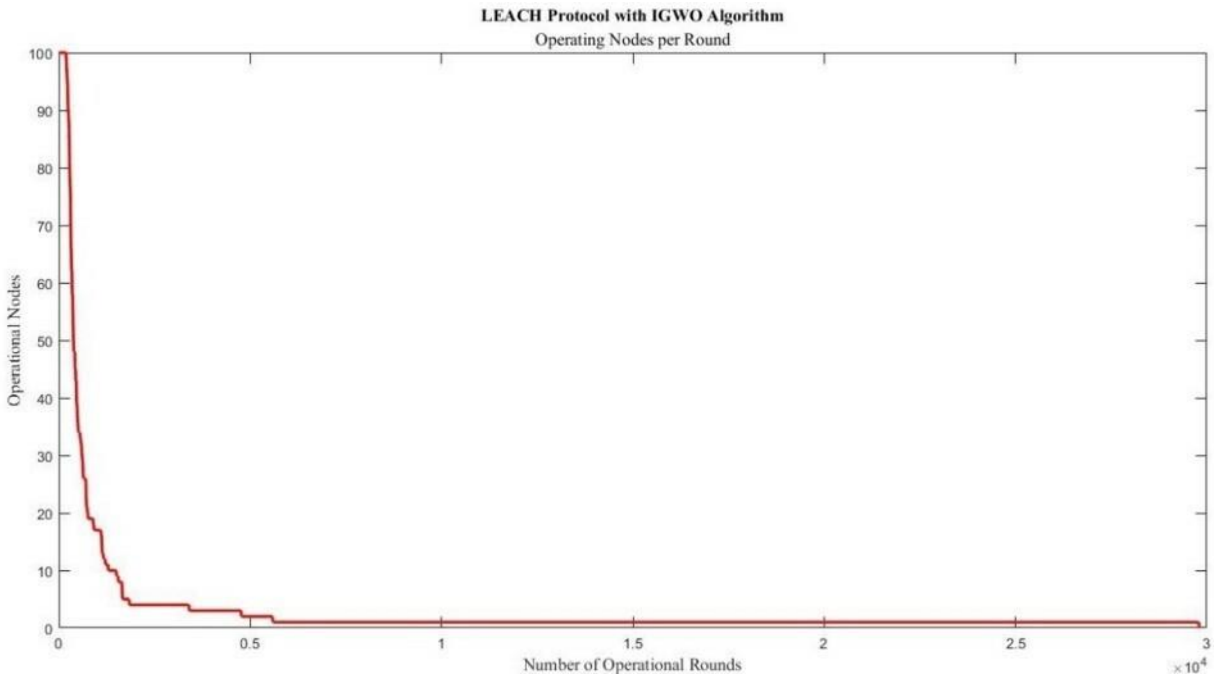

Fig. 7 (c) Number of operational nodes per round in a LEACH Protocol integrated with IGWO Algorithm

Fig. 7 Comparison of Number of operational nodes per round

5. Conclusions and future scope

In this research article, we have attempted to enhance the lifetime of the sensor networks in terms of the number of operational rounds and reduce the number of transmissions using a novel meta-heuristic approach. The prominent clustering protocol known as LEACH for WSNs is considered and it is integrated with an improved version of the GWO algorithm called IGWO. The results were noted for different CH selection probabilities and node densities by locating BS at the center of the network terrain. By reducing the CH selection probability from 0.1 to 0.05, the network lifetime is higher as the number of rounds is higher in WSN that uses the proposed IGWO algorithm-based LEACH protocol. From the overall results, it is strongly recommended to use meta-heuristic algorithms in enhancing the energy-efficiency of WSNs as the LEACH protocol integrated with the IGWO algorithm gives more network lifetime with optimum results than conventional and GWO based LEACH protocols which are recently proposed. As future work, we can test the proposed algorithm in the IoT and IoE networks that deal with large sensor networks in terms of network terrain, node density. The proposed algorithm can also be extended for heterogeneous sensor networks with added efforts to reduce energy consumption by computing optimum probabilities in selecting CHs.

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Nomenclature

p: percentage of desired CHs among all the network nodes

r: current round number

G: set of non-selected CH nodes in the last 1/p rounds

e_{fs}: free space energy loss

m: packet length

e_{mp}: multipath fading loss

d: distance between sender and receiving node

d_0: threshold distance

E_{elec}: energy consumption by the electronic circuitry

E_{amp}: energy consumed by the amplifier for bit transmissions

T(n): threshold energy

$\vec{a}$: attenuation factor

$\overrightarrow{D}$: distance between prey and wolf

$\vec{X}$: position of the wolf

$\overrightarrow{X_p}$: position of prey

$\vec{A}$, $\vec{C}$: constant parameters

$\overrightarrow{r_1}$, $\overrightarrow{r_2}$: arbitrary vectors between [0 1]

$D\ (SN, SN_j)$: distance between a given sensor node 'j' and all other sensor nodes

$D\ (SN, BS)$: distance between a given sensor node and BS

E_{resi}(j): remaining energy at a sensor node 'j'

m: weight parameter

F_1, F_2: combined weight functions

F: combined weight function

m: weight parameter

$CH_w(SN_i, CH_j)$: defines the sensor node that joins the j^{th} CH

K: constant parameter

E_{resi}: residual energy at j^{th} CH

$D(SN_i, CH_j)$: distance between i^{th} sensor node and j^{th} CH

$D(CH_j, BS)$: distance between j^{th} CH and BS

$R_n(CH_j)$: neighborhood ratio of the j^{th} CH

W(t): weight cosine control factor

σ^2: variance

μ: mean,

ul: upper limit

ll: lower limit

Glossary

ACO ant colony optimization
BS base station
CDMA code division multiple access
CDS connected dominating set
CH cluster head
DE differential evolution
DEEC distributed energy efficient clustering
DLH dimension learning-based hunting
EP evolutionary programming
ES evolution strategy
GA genetic algorithm
GOA grasshopper optimization algorithm
GSA gravitational search algorithm
GWO grey wolf optimization
IGWO improved grey wolf optimization
IIoT industrial IoT
IoE internet of everything
IoT internet of things
LEACH low energy aware clustering hierarchy
MAC medium access control
MBA modified bat algorithm
MLHP multilayer hierarchical routing protocol
PSO particle swarm optimization
SA simulated annealing
SEP stable election protocol
TDMA time division multiple access
WSN wireless sensor network

Conflict of interest

There are no conflicts to declare.

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