JOURNAL OF INFORMATION AND COMMUNICATION TECHNOLOGY
https://e-journal.uum.edu.my/index.php/jict

How to cite this article:
Bahl, V., & Kumar, A. (2022). Probabilistic multi-tiered grey wolf optimizer-based routing for sustainable sensor networks. *Journal of Information and Communication Technology, 21*(4), 627-663. https://doi.org/10.32890/jict2022.21.4.7

Probabilistic Multi-Tiered Grey Wolf Optimizer-Based Routing for Sustainable Sensor Networks

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Received: 14/3/2022 Revised: 21/7/2022 Accepted: 9/8/2022 Published: 20/10/2022

ABSTRACT

Wireless sensor networks (WSN) have a wide range of applications. Therefore, developing an energy-efficient methodology for estimating cluster heads (CHs) to ensure efficient data transmission has become highly relevant. Meta-heuristic strategies for optimal CHs are the current investigation inclination. As the network grows, the conventional optimization strategies emerge unsuccessful, and the outcomes of hybridizing bring performance enhancement in WSN. A Probabilistic Multi-Tiered Grey Wolf Optimizer (GWO) was implemented in this study on an upgraded Grey Wolf Optimizer for optimum CH selection. It used fitness value to strengthen GWO's search for the best solution, resulting in even dispersal of CHs. Communication routes were updated based on routes to the CHs and base station to lessen energy consumption by a layered-based routing scheme. GWO's governance enhanced the network's ability. The distributed nodes' geographical territory was categorized into four tiers. CH was chosen grounded on the objective value that required fewer difficult control factors than existing techniques. Simulations showed that the suggested technique could extend the network's stability time by (31.5 %) compared to hetDEEC-3, L-DDRI, Novel-LEACH-POS, DBSCDS-GWO, and P-SEP.

Keywords: Cluster head, energy optimization, grey wolf optimization, cluster head selection, wireless sensor network lifespan.

INTRODUCTION

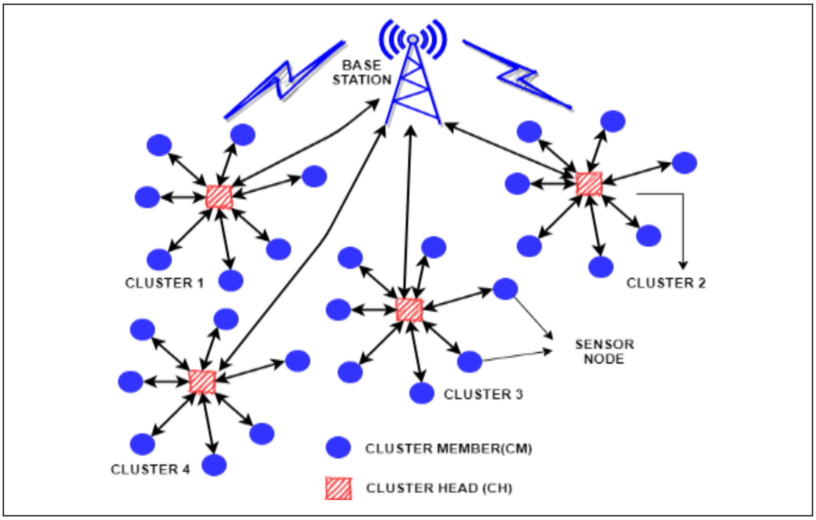
Sensor nodes are dispersed in a wireless sensor network (WSN) to evaluate humidity, temperature, pressure, and other variables. On the other hand, their computational power, battery capacity, and transmission range are incredibly restricted. Furthermore, many WSNs operate sensors in hostile settings, making restoration and refill of malfunctioning nodes problematic and costly. Consequently, energy-proficient nodes will assist in prolonging the lifetime of the network. Nodes placed in the target zone continue to operate till the energy lasts. As a result, one of the most difficult tasks in extending the life of a WSN is figuring out how to create an energy-efficient routing scheme. According to Wang et al. (2016), by decreasing the overall transmission range and regulating energy utilization across nodes during the network lifespan, a clustering-based tiered routing scheme helps enhance energy efficiency and boost network sustainability.

In the clustering approach, the sensing region is divided into many clusters. A specific node in every cluster will take on the role of cluster head (CH) or leader node. CH is the cluster's nerve centre; it aims to connect with cluster members (CM), gather statistics from CMs, and deliver them to the base station (BS), as shown in Figure 1. The most challenging difficulty in clustering-dependent routing algorithms is to optimize the choice of CHs and create a more robust dispersed cluster. Haque et al. (2020) and Gao et al. (2019) argued that WSNs ought to be reliable, self-configurable, modular, and resource-efficient. Every sensor node in a network comprises a sensing component, processing module, and communication component. Thakkar et al. (2020) stated that the sensor detects a circumstance and transforms it into the suitable processing category, while the sensed signal is processed as per the criteria in the processing unit. Then, data are sent to the communication module for distribution to the adjacent nodes. Das et al. (2020) and Elshrkawey et al. (2018) compared the overall energy ratio of the communicator (about 51%), which is greater than that of other activities. Wang et al. (2018) suggested traffic congestions from CM and other CHs sending data to BS, whereby the spots around BS are stronger than other sites. This condition can be addressed by integrating Particle Swarm Optimization (PSO) with a Genetic Algorithm (GA) that takes a sequence of shifting routes as its sink node. As a result, Janarthanan and Kumar (2019) proposed various heuristic strategies based on enhanced routing to reduce the proportion of energy consumed by WSNs and increase overall efficiency. It can ensure the quality of the connectivity, battery exhaustion as a consequence of the high transmission, and node mobility.

Conventional routing strategies prioritize finding the quickest path to the destination, minimizing latency, and optimizing throughput by efficiently utilizing available resources. As a result, despite traditional routing that minimizes latency, most WSN routing methods aim to make the most of the network node's limited resources. This research will address the CH's decision difficulty using a tier routing technique by partitioning the network communication zone into numerous tiers. Each manifold has been assigned unique responsibilities based on the Grey Wolf Optimizer (GWO) concept.

Figure 1

Wireless Sensor Network



Contribution of Research

This study presents a novel energy-competent optimized protocol, built on the meta-heuristic GWO algorithm, to equalize network energy usage and lengthen the life cycle of cluster-based WSNs. In creating an energy-efficient and robust sensor network, a Probabilistic Multi-Tiered Grey Wolf Optimizer-Based Routing (PMR-GWO) is proposed to optimize the network throughput and balance the network load. The formation of clusters, transmission within clusters, communication between clusters, and auxiliary transmission are all improved in this article by taking into account residual energy, transmission angle, and distance. The threshold function of the CH is updated to change the size of the clusters, and the network region partition technique is optimized by considering residual energy and node distance. Bahl and Kumar (2021) recommended LEACH-Distance Degree Residual Index (DDRI-L) for a more comprehensive search (exploration), in which changing the stage process factor leads to a global refinement search, improving exploration performance. For a confined search (exploitation), Bahl and Bhola (2022) suggested Multi-Tiered Grey Wolf Optimization (MGWO), with the factor coefficient vectors being necessary to emphasize exploitation. Further, the integrated proposed PMR-GWO maintains the exploration-exploitation trade-off, extends the network's lifetime, improves energy efficiency, and improves the network's total throughput performance. By contrasting the results of the designed PMR-GWO to that of other current cluster head selection algorithms, the superiority of the proposed PMR-GWO is demonstrated.

The content of this paper is organized as follows: the use and underlying work of various heuristic strategies that can be applied to routing algorithms in WSNs is discussed in Section 2. Section 3 examines the existing GWO method for the current situation, while Section 4 introduces the formulation of the planned method PMR-GWO. Section 5 deals with simulations and their investigation. Finally, Section 6 concludes the paper and gives the future scope of PMR-GWO.

RELATED WORKS

Several routing conventions of WSNs have caught the interest of many experts due to the exponential growth and expansion of sensors. Gherbi et al. (2017) and Mazumdar et al. (2018) compared other common routing protocols and found that clustering routing was a far more optimal approach to minimize sensor energy utilization and extend the lifespan of networks. Low-Energy Adaptive Clustering Hierarchy (LEACH) is the most well-known clustered routing protocol amongst homogeneous WSNs. The CHs are chosen randomly in LEACH, and the sensors are swapped into CHs on a regular basis. Energy utilization is distributed evenly among the sensor nodes to lengthen the network's service life expectancy and boost effectiveness. Rohit and Deepti (2017) presented a Vice-CH Empowered Centralized Cluster-Based Routing technique (VCH-ECCR). By combining Vice-CH, VCH-ECCR minimized the probability of clustering; thus, cluster analysis would incur overhead. Within every loop of the network, the count of CHs was modified depending on the percentage of alive nodes.

Hamzah et al. (2019) proposed a Fuzzy Logic-based Energy-Efficient Clustering for WSN based on minimum separation Distance enforcement between CHs FL-EEC/D as a fuzzy logic-dependent energy effectual clustering for WSNs estimating separation range monitoring among CHs. In FL-EEC/D, a fuzzy inference framework for CH choice was presented. The remaining energy, density, density, position appropriateness, and interspace from BS were employed as the major characteristics to designate a suitable node as CH when utilizing this paradigm. Compared to LEACH, FL-EEC/D had a longer life cycle for homogeneous WSNs.

Purkar and Deshpande (2018) suggested an Energy Efficient Clustering Protocol to Enhance Performance of Heterogeneous Wireless Sensor Network (EECPEP-HWSN) as an energy-efficient clustering technique for improving HWSN's functionality. The approach was built as a three-level HWSN, comprising ordinary, advanced, and super nodes. The initial power of the sensors, hops, and leftover vitality of the sensors in service were all taken into account through the CH shortlisting. HWSN's energy competence and steadiness were improved using this protocol.

Wang et al. (2019) analysed the Energy Centres Screening via Particle Swarm Optimization algorithm (EC-PSO) as a new clustering method. Initially, the procedure divided node locations using spatial approaches to pick CHs. The PSO procedure was then used to discover the network's energy centre, and the CH was elected as the node adjoining the energy centre. Furthermore, the strategy presented a low-energy safety technique to prevent vulnerable nodes from being relay nodes. The protocol could efficiently extend the network lifespan by integrating the above methods. Zhao et al. (2018) suggested Fitness-value-based Improved GWO (FIGWO) that incorporated a modified GWO to optimize the access to information of the GWO's global optimal to ensure an improved dispersal and additional symmetrical clustering architecture of CHs for energy-efficient routing technique for WSNs. Chithaluru et al. (2020) proposed Node Ranked-LEACH (NR-LEACH) as a position-based energy-efficient approach. Each relay node in this technique had data from the source node. Additionally, each node could send data to BS. NR-LEACH admitted all nodes for packet transmission to BS and used the same energy level. The link could be assembled successfully using a pessimistic process since each node was robust and had global awareness.

Al-Baz and El-Sayed (2018) presented a Genetic Algorithm-based LEACH (LEACH-GA) that incorporated node energy and range as selection criteria, including main and auxiliary factors for CH election, to ensure equal energy utilization. It solved overhead costs, similar clusters in terms of region, and limited life.

Research has indicated several bio-inspired meta-heuristic methods as WSN routing grows increasingly difficult and sophisticated. The residual energy of nodes and the knowledge of their surroundings are provided to every node in this technique. Coverage and interactive nodes are allotted to all networks; subsequently, clustering and active nodes are assigned to some nodes. The approach has a high performance in relation to energy depletion. A Multi-Level Hybrid Clustering Routing Protocol (MLHP) relying on GWO was proposed by Al-Aboody and Al-Raweshidy (2016). The GWO method was applied at level two with no changes to the existing method. This method was capable of achieving improved network energy efficiency, longevity, and stabilization phase efficacy. However, this technique lengthened the instability phase, which caused data transfer to be unpredictable.

Ullah (2020) offered a Hybrid Energy-Efficient Distributed Algorithm (HEED) and proposed the concept of categorizing CHs based on the amount of node leftover energy and discontinuous overhead. The method struck a compromise between dispersing network energy among all nodes for longer network durability and not reducing the minimal node at any stage for faster time convergence. It did not function better in the presence of heterogeneous external factors.

Naranjo et al. (2017) presented a Prolonged Stable Election Protocol (P-SEP) that took into account the heterogeneities of two levels of nodes: advanced and normal nodes. Both had the same chance to become a CH. This method outperformed the competition regarding network longevity. Priya et al. (2020) suggested the PSO method by employing an energy-efficient CH selection technique for both particle encoding and fitness value design. The intra-cluster range, sink node range, and leftover energy were all regarded for achieving energy efficiency. Cluster creation was based on the computed weighted range, with member nodes joining their corresponding CHs. In this instance, the sink range and residual energy of sensors were considered. GWO is a collection of Swarm Intelligence (SI) approaches influenced by the grey wolf behaviour through their leadership and hunting strategy. Because of its accessibility and simplicity, this technique has been used by several domain investigators to tackle their domain-related difficulties. Mirjalili et al. (2016), Faris et al. (2018), Gupta et al. (2020), Lipare et al. (2020), and Bansal and Singh (2021) presented GWO as a new meta-heuristic encouraged by grey wolves. It depicts the governing structure and the searching activity of grey wolves. The dominance organization is postulated in a pack of 5–12 wolves on an estimate, founded on four categories of wolves' alpha(α), beta(β), delta(δ), and omega(ω). The α is at the highest of the formal organization. It is in charge of making judgments, leading all the other wolves, and leading the pack in hunts or other activities. The β's duty in the second level of the work is to counsel the commander and promote group dominance amongst the other wolves. The ω, at the base of the pyramid, can only seek prey and procreate before a leader. δ are wolves that do not fit into any of these three groups. It is the third wolf in the organization, above the ω but below the β. δ keeps an eye on the region's borders and warns the pack if anything goes wrong. The primary phases are: (i) detecting, chasing, and encircling, (ii) harassing the target until it reaches a steady state, and (iii) striking.

Kaushik et al. (2019) developed a Distance-Based Stable Clustering algorithm using GWO (DBSCDS-GWO) for establishing a stable, symmetric, and energy-efficient connected dominating set-based WSN. The meta-heuristic method GWO specified a set of dominator nodes computationally and identified the best arrangement of the dominator nodes concerning the sink and dominate nodes. The fundamental criterion for achieving a stable network was to balance the load and delay the fatality of the foremost dominator by comparing the comparative energy of sensor nodes with the suggested parameter Dominator Lifetime Index (DLI).

Nigam and Dabas (2021) presented an advanced technique termed Enhanced Structural Optimization using LEACH (ESO-LEACH). The PSO-driven energy-efficient clustering was proposed, and a meta-heuristic particle swarm enhancement was used for essentially clustering the sensor nodes. Improved nodes and an enhanced set of rules for CH election were applied to reduce the randomness of the standard approach. Kumar and Kumar (2021) suggested Inertia Motivated GWO (IMGWO) to achieve a better balance between exploration and exploitation. The convergence of an Artificial Neural Network (ANN) with Back Propagation (BP) was poor since it depended on initial values. Rather than BP, the meta-heuristic technique was a superior option. IMGWO was utilized to train ANN (IMGWO-ANN) to demonstrate its proficiency regarding medical diagnostics prognosis.

The above-discussed benchmarks were selected due to their similarity in parameters such as distance, residual energy for CH selection, and cluster formation. Researchers and practitioners emphasize meta-heuristic algorithms that can quickly and effectively solve clustering problems. For its advantages of fast exploring speed, high search resolution, and ease of application, GWO outperforms PSO, Gravitational Search Algorithm (GSA), Differential Evolution (DE), and Free Energy Perturbation (FEP) algorithms in terms of optimization. However, because GWO is a novel biological intelligence algorithm, the theory's evolution and investigation are still in their early stages. Further study and analysis are required to make the technique work at a higher level.

GWO has a small set of variables that allow it to address non-deterministic polynomial (NP)-hard challenges in a few repetitions. This approach handles various domain challenges, including WSN geolocation, load frequency control dispatch, feature extraction, technical difficulties, and single objective challenges, among others. Clustering is an NP-hard task in WSN, but it can be handled with an appropriate optimization approach. This study suggests PMR-GWO, an optimum cluster head scheme technique relying on the GWO algorithm. This approach considers residual energy, intra-cluster distance, sink distance, and node dormancy ratio to choose the best collection of CHs. Further, the present study establishes an objective function that incorporates crucial factors for determining the best option. This study used the accurate detection agent modelling approach in PMR-GWO to characterize the energy-efficient CHS. From either perspective, a cluster-based routing weight metric is presented. This attribute guides the sensors to join their corresponding CH groups. The sensor nodes with the highest weight will be transferred to the clusters that correlate to them. As a result, the sensors will function as CM under the CHs, transmitting data to the BS via the CHs.

The suggested approach is evaluated in several sensor node conditions by altering the nodes and CHs. The proposed architecture is contrasted to various algorithms such as 3-level heterogeneous Distributed Energy-Efficient Clustering (hetDEEC-3), L-DDRI, Novel-LEACH-POS, DBSCDS-GWO, and P-SEP to assess its efficacy. The PMR-GWO algorithm was used to achieve the best energy efficacy and navigation performance in WSNs by out-spreading its lifespan.

METHODOLOGY

The route optimization strategy for WSN predicated on the GWO is detailed in this subsection. A centralized clustering route discovery system was presented to minimize the unpredictability of CH selection. The phase of CH choice was focused on by BS using the redesigned GWO, and the decision of CH election was subsequently propagated to all devices connected to the network. The CM entered the cluster and reached a steady phase in the equivalent stages in the LEACH methodology. The sensors relayed the position and starting charge to the BS, which gathered and preserved the knowledge in the first phase of the CH set-up. The starting strength of the nodes was supplied to the BS, and the location of each node was preset. By clustering knowledge from each iteration, the energy usage of the node could be approximated, and the energy statistics of the node every iteration might be acquired. As a result, the nodes did not have to report the location and energy data to the BS for iterations.

The PMR-GWO algorithm employed an energy-efficient CHS method, including adequate particle encoding and fitness function. The intra-cluster coverage, sink node interval, node dormancy, and leftover energy for the sensor node were all taken into account for achieving energy efficiency. Cluster development was carried out based on the analytical weight distance, and member nodes re-joined their associated CHs. In this setup, the sink distance and leftover energy of sensors were considered.

The populace-based meta-heuristic algorithm was founded on golf's social conduct and lifespan enhancement of a GWO technique for wireless networks. As a rectilinear obstacle, it optimized the network to pick the optimum CH nodes over numerous groups. The strategy was to divide the network into multiple levels using a tiered design, with each layer having its own set of duties. The cluster head in manifold 1 and near the BS was chosen using a cluster-based technique. If there were multiple nodes in the manifold, the residual energy of each node was used to make a decision. If there were additional two nodes in manifold 1, the CH was determined by a game theory model. Game theory is the process of modelling the strategic interaction between two or more players in a situation containing set rules and outcomes. In this study, only one node was chosen as CH. The foremost aims of the planned research are to extend the network lifespan sequence, reduce vitality utilization, and raise network performance.

Its grey wolf pyramid was based on the GWO paradigm. Grey wolves are categorized as alpha(α), beta(β), delta (δ), and omega(ω), each with its own set of roles. The rules below should be adhered to in putting this guidance pecking order in place in the WSN. Across both tiers and clusters, the holistic method was applied. Among these levels, sensors were dispersed as per their distance from the BS, with each tier containing many sensors. Thus, every level was R range from the preceding layer, i.e., R radius from the BS in layer 1 and 2×R range from the BS in layer 2. As a result, the network was separated into tiers, with layer 1 being the first, layer 2 being the second, layer 3 being the third, and layer 4 being the fourth. The length of extent R would be chosen in a stable/augmented manner based on the sensing system's design. If a low R value was used, the node would cluster near the BS, triggering an energy pit (hot-spot problem). If a high R value was utilized, the signal intensity would be insufficient on either side. Nodes in layer 1 were chosen as leader nodes or CH, and nodes in a layer designated as a linked layer (layer 2) were stated as co-leaders. As indicated in Figure 2, the nodes in layer 3 were referred to as standby co-leaders, while the member nodes in layer 4 were addressed as CMs.

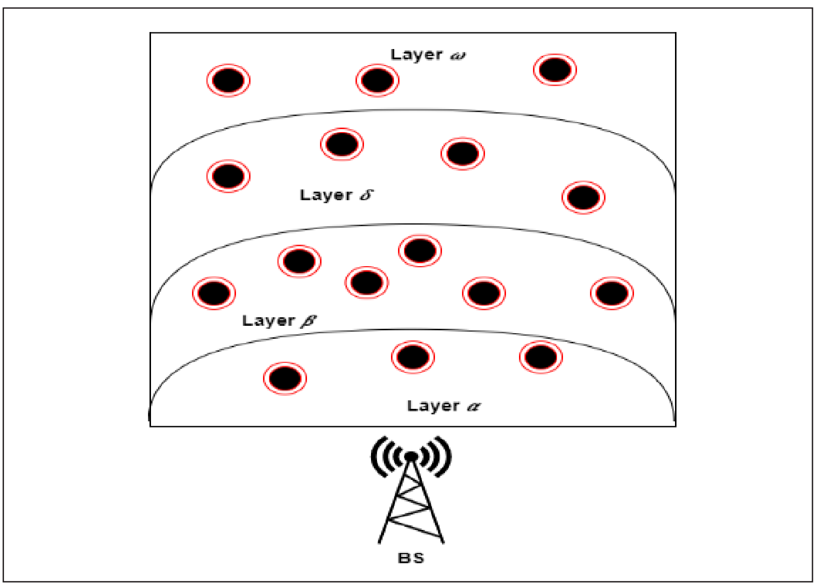
To improve the energy efficiency of WSNs, choosing the right CHs in hierarchical clustering approaches is critical. The first key consideration when choosing CHs was its dispersal, as CHs focusing on one side resulted in significant distances between sensors and CHs. As a result, each node's benefit from the propagation location near

CH was lowered. To lessen transmission energy usage at the nodes, the CHs must be deployed appropriately. A quantitative formalization was essential in characterizing the optimum combination of CHs. The conveying, reception, leftover, and data-gathering energy were separated from the node energy, which were mixed back into the buffered energy (energy used and left once a node acted as a CH). If a node with low standby energy was chosen as a CH, it might be drained before acquiring all of the information from its neighbours, affecting network steadiness.

The CHs were chosen using an optimization technique. The suggested conceptualization's optimization model took into account the location proportion among BS and CH, coverage area, residual energy, CH balancing factor, and node dormancy ratio. This fitness function guaranteed that the node with the highest energy and closest to the BS had a better probability of being chosen as CH. When a newer CH was identified, the range to transfer signals was also adjusted. For the evaluation of CH, the suggested technique in this work employed GWO due to its fast convergence rate compared to other meta-heuristic strategies.

Figure 2

Systematic Layering of Grey Wolf's Hierarchy for PMR-GWO



This study proposed a new computational framework, PMR-GWO's optimization capability, to certify the choice of the optimum CHs for WSN. It included two steps. In the primary step, LEACH-Distance Degree Residual Index (L-DDRI) by Bahl and Kumar (2021) was used to filter out the cluster members as candidate cluster heads (CCHs) by adaptively probing for the finest parameter balance using the novel threshold of LEACH to generate the initial population of CCHs. In the second stage, the efficacious MGWO was applied to tackle the localization challenge in WSN, which limited the localization error. Consequently, strategies were incorporated to eliminate the communication overhead and reduce the energy costs of WSN, based on the optimum dataset acquired in the first level. A two-level hybrid clustering algorithm (i.e., PMR-GWO) based on GWO for WSN was projected in this research. A centralized choice was suggested for the primary level, in which the CCHs list played a significant part in the decision-making process of CHs. In level 2, a modified GWO was proposed for the selection of optimal CHs for WSN to save more energy. The PMR-GWO methodology is presented in Figure 3.

The proposed PMR-GWO's operation was on the arbitrarily positioned immobile nodes in the sensor network. It is presumed that n nodes signify the CH search mediators (wolves) as $(CH = CH1, CH2, \ldots, CH\text{n})$. For emulating the locations of the search mediators (wolves) in WSN while the nodes were fixed, the location of the search mediator (candidate CH) was denoted by CHi in the two-dimensional (2D) space demonstrating the node's sites $[Posi\ (t) = xi\ (t), yi\ (t)]$. The finest search mediator's site was then adopted to decide the finest solution for the optimal CHs. The foremost intent of the PMR-GWO was to designate the CHs for prolonged life expectancy. A fitness function was built on numerous constraints to proficiently designate the CHs, like remaining energy, sink distance, intra-cluster distance, node dormancy ratio, and degree.

The criteria involved in the suitability method's formulation were as follows:

- Network Coverage (f1)

The network coverage of each CH, where a suitable allocation of CHs shall return both identical network coverage among CHs and availability for each node, is as shown in Equation 1:

$$\mathrm{N}_{\mathrm{Cover}} = (\mathrm{d}_{\mathrm{far}}^{2} \times \pi)/n \tag{1}$$

Here, N_{Cover} denotes the network coverage and d_{far}^2 signifies the squared distance between the distant node and the node's midway. As a result, all nodes were within $(d_{far}^2 \times \pi)$, the rounded zone was amid the node's midpoints and d_{far}^2, and the node's interior loop enclosed by a CH had a radius more concise than the CH's extent.

Figure 3

PMR-GWO Methodology

1- Level

CCHs Selection Step - L-DDRI

- Calculate Energy, Distance, Density, and $T(n_i)$ Node Placement

$$T(n_i) = \frac{P_i}{1 - P_i \times \left(r \times \mathrm{mod}\left(\frac{1}{P_i}\right)\right)} \times \alpha \frac{E_{res}^n}{E_{in}[n]} + \rho\left(1 - \left(\frac{\mathrm{Degree}[n]}{N_{alv}}\right)\right) + \varphi\left(1 - \frac{d_{toBS}[n]}{d_{toBSrmax}[n]}\right), \text{if } n_i \in N$$

- Analyse Optimal Clusters Count
- Resolve WSN Cluster Set Using Localization Techniques
- The CH selection parameters are implicitly related to the probabilistic strategy to the threshold and find $CCH1$, $CCH2$, $CCH3$, $CCH4$, $CCH5$, …….

↓

2- Level

Optimal CHs Selection - MGWO

- Call_Procedure MGWO ($CCH1$, $CCH2$, $CCH3$, $CCH4$, $CCH5$, …….)
- Analyse Objective Function Estimate of Novel Cluster

$$\mathrm{fi} = \sigma * \left|\bigcup_{k=1}^{N} \mathrm{cover}_K\right| + \mu * \sum_{j=1}^{N}\left(\frac{n_{alv}}{N} - l_j\right) + \vartheta * \sum_{j=1}^{m}\left(\frac{1}{l_j} * (d_{toBS})\right) + € * \sum_{j=1}^{N}\sum_{R=1}^{M}(E_0 - E_d) * E_R \pm \varphi * \mathrm{P}$$

Furthermore, assessing distances was less time-consuming than determining if a node was in a loop, as shown in Equation 2:

$$R_{Cover} = \sqrt{\frac{N_{Cover}}{\pi}} = \sqrt{\frac{(d_{far}^2 \times \pi)/n}{\pi}} = = \frac{d_{far}^2}{\sqrt{n}} \tag{2}$$

The R_{Cover} distance (radius) was used to evaluate if a node was in the service area N_{Cover}. The subset of the node that the k-th CH covered (range) is written as in Equation 3:

$$cover_K = \{Node_{ID} | Distance(Node_{ID}, CH_k) < R_{Cover}\}, k = (1,2,3 \dots N) \forall ID \tag{3}$$

Here, $Distance(Node_{ID}, CH_k)$ is the radius between the ID-unique node and the k-th CH. It is worth noting that R_{Cover} divided the overall service area proportionally. As a result, the further the nodes connected by the CHs, the stronger the dispersal. A fitness value may be written as in Equation 4:

$$f1 = |\cup_{k=1}^{n} cover_K| \tag{4}$$

Here, $|\cup_{k=1}^{n} cover_K|$ signifies the cardinality set (i.e., element count) and the unification averts enumeration overlying nodes enclosed by an additional CH.

- Balancing Element (f2)

There is a requirement for the cluster to be balanced. There is a risk that certain giant clusters, as well as some small clusters, will form due to the arbitrary grouping of sensors. As a result, this statistic was factored in for balancing energy use, as in Equation 5.

$$f2 = \sum_{j=1}^{N} \left(\frac{n_{alv}}{N} - l_j\right) \tag{5}$$

Where n_{alv} is the number of alive sensor nodes in each round.

- Interspace Proportion among BS and CH (f3)

The proportion of the separation amid the BS and CH to the maximum number of nodes in the relevant CH was used to determine the average sink radius. Since distance has a significant effect on energy usage, this characteristic was considered. As a result, to reduce energy usage, this distance must be reduced. It is written in the form of Equation 6:

$$f3 = \sum_{j=1}^{m} \left(\frac{1}{l_j} * (d_{toBS})\right) \tag{6}$$

- Residual Energy (f4)

The communication, reception, leftover, and data gathering energy were separated from the node energy, which were mixed into the backup energy (vitality expended and leftover as the node turned into a CH). If a node with a low standby vitality was chosen as a CH, it might be drained before acquiring all of the content from its neighbours, affecting robustness and reliability. Because the network's lifespan is determined by how much energy is used, it is critical to reduce energy usage. As a result, this statistic was taken into consideration. It was determined as the sum of all the nominated CHs' current energy. Therefore, CH nodes with large backup energy were prioritized in Equation 7:

$$\mathrm{f4} = \sum_{\mathrm{j}=1}^{\mathrm{N}} \sum_{\mathrm{R}=1}^{\mathrm{M}} (\mathrm{E_0} \text{ -} \mathrm{E_d})^{*}\mathrm{E_R} \tag{7}$$

- Node Dormancy Ratio (f5)

The node dormancy strategy is divided into two parts: (a) choosing nodes in diverse locations to be inactive on an arbitrary base, and (b) identifying nodes in diverse locations to be dormant founded on extending to CHs. An optimal set of nodes is recognized and defined as the weighted ranking of remaining energy, range, degree difference, and equivalent diameter. The node dormancy procedure on this collection of nodes causes CMs with the least energy and elongated maximum range to turn out to be defunct, ultimately picking CH for the cluster, which diminishes the energy utilization on CH and thus improves bandwidth utilization. Configure S_{dor} dormancy criteria for all CMs as studied by Mengjia et al. (2019) given as Equation 8:

$$S_{dor}\ (s(x) * E\ d_{BS}^{x} = \left(\ s(x).\frac{E}{d_{BS}^{x}}\right) \tag{8}$$

Here, S(x) is the node and $E\ d_{BS}^{x}$ is the energy at distance from BS. The S_{dor} and mortality ratio of the node were inversely proportionate. The higher the S_{dor}, the higher the likelihood of dormancy. As a result, Equation 9 calculates the node dormancy proportion, P (Zhidong et al., 2018).

$$\mathrm{P} = \frac{c(y)*n-\frac{n}{k}}{c(y)} * n \tag{9}$$

$c(y)$ is a collection of clusters. If BS was within the radio range of the CCH list, nodes would evaluate it as the best collection of CHs in the WSN, indicating node (i). The fitness function (fi) was then computed via node(i) $d_{toBS} < R$, as in Equation 10:

$$\mathrm{fi} = \sigma \times \mathrm{f1} + \mu \times \mathrm{f2} + \vartheta \times \mathrm{f3} + \tau \times \mathrm{f4} + \varphi \times \mathrm{f5} \tag{10}$$

Here, σ, μ, ϑ,τ and φ signify persistent value and $\sigma + \mu + \vartheta + \tau + \varphi = 1$.

If (node(i). $d_{toBS} < Radius$)

Rather than minimizing each fitness function independently, it is preferable to minimize the sum of all, as stated in Equation. The fitness functions listed above were in perfect sync with one another, and thus, Equation 11 is computed as follows:

$$\text{fi} = \sigma * |\cup_{k=1}^{N} \text{cover}_K| + \mu * \sum_{j=1}^{N}\left(\frac{n_{alv}}{N} - l_j\right) + \vartheta * \sum_{j=1}^{m}\left(\frac{1}{l_j} * (d_{toBS})\right) + € * \sum_{j=1}^{N}\sum_{R=1}^{M}(E_0 - E_d) * E_R \pm \varphi * \text{P} \quad (11)$$

An effective CH nominee would have a low transmission cost and remaining energy of more than 1/2 E_a.

ENERGY MODEL

The energy model was similar to the model given in Elshrkawey et al. (2018) that considered the required energy to convey a k-bit signal across a radius of d, as formulated in Equation 12:

$$E_{TX}(k,d) = \begin{cases} k\,E_{elec} + k\,E_{fs}\,d^2, & d < d_0 \\ k\,E_{elec} + k\,E_{mp}d^4, & d > d_0 \end{cases} \quad (12)$$

The cluster creation in LEACH was designed to guarantee that the predicted batch size was k- bit signal and threshold distance value (d_0). On the other hand, the CH's decision was based on arbitrary numbers produced by the sensors. Furthermore, its unpredictability contributed to the set of initial nodes' unpredictability. The ideal cluster count (k_{opt}) was calculated, and the estimate differed substantially from the quantity in the actual WSN. By computing the actual k_{opt}, the suggested technique derived an appropriate cluster that ensured a CH in every round for Tier 1 nodes, and nodes in Tier 2 could transfer data if no CH was identified in Tier 2.

Cluster Number Calculation

For Tier 1, the optimal value of CHs (K1) was: all Phase One nodes (m) in the network model were in the region$(\mathrm{A} = \mathrm{M}/3), (\mathrm{d} < \mathrm{d0})$, which was close to BS. As a result, the energy required to send a l-bit word in the CH is as given in Equation 13:

$$E_{ch} = l\,E_{elec}\left(\frac{m}{K1} - 1\right) + lE_{DA}\,\frac{m}{K1} + l\,E_{elec} + l\,\epsilon_{fs}\,d_{toBS}^2 \quad (13)$$

Where d_{toBS} is the interspace in CH to BS, and the data accumulation is as expected in Equation 14:

$$E_{non-CH} = lE_{elec} + l\epsilon_{fs}\, d_{toCH}^2 \tag{14}$$

Subsequently, nodes were likewise dispersed, whereby d_{toCH}^2 was set to $E\,[d_{toCH}^2] = \frac{A}{2\pi K1}$, as in Equation 15:

$$E_{non-CH} = lE_{elec} + l\epsilon_{fs}\, \frac{A}{2\pi K1} \tag{15}$$

Now, energy degenerate in a cluster in one edge is as given in Equation 16:

$$E_{cluster} = l\,(E_{elec} + \frac{m}{K1} E_{non-CH}) \tag{16}$$

and the over-all energy is given in Equation 17:

$$\begin{aligned} E_{total} &= K1 E_{cluster} \\ &= l(E_{elec}m + E_{DA}m + E_{elec}m + \ K1\epsilon_{fs}\, d_{toBS}^2 + \epsilon_{fs}\, \frac{A}{2\pi K1})m \end{aligned} \tag{17}$$

To calculate $K1$, associate Equation 18 to zero and discriminate wrt $K1$:

$$K1 = \sqrt{\frac{mA}{2\pi}}\ \frac{1}{d_{toBS}} \tag{18}$$

Here, m is the node count in Tier 1 and regular span from CH to BS is assumed by

$$\mathrm{E}[d_{toBS}\,] = 0.765\,\frac{A}{2}$$

The ideal proportion of CHs ($K2$) is formulated in Equation 19 for the current network. The remaining network (Tier 2 and Tier 3) had been calculated using the same formulation as in LEACH-C:

$$K2 = \sqrt{\frac{n}{2\pi}}\ \sqrt{\frac{\epsilon_{fs}}{\epsilon_{mp}}}\ \frac{M}{d_{toBS}} \tag{19}$$

Here, $n = N - m$ and $d_{toBS} = 0.765\,\frac{M}{2}$. Subsequently, in this research phase, a multi-tiered CHS procedure was prompted.

Candidate Cluster Heads (CCHs) Selection

The CH selection variables were directly linked to the modelling approach of the probabilistic threshold strategy. The best-suited node for CH could indeed be obtained by modifying the categorization strategy. Furthermore, combining any technique with the unified arbitrary numeral-generating system could improve the statistical procedure's clustering process. This adjusted arbitrary numeral was compared to the T(n) threshold to decide whether a node should behave as a CH. The purpose of the L-DDRI method was to see how random numbers affected the CH electoral system. The Gaussian Arbitrary Numeral Generator, which generated haphazard statistics from a normal dispersal, produced such random values. At the onset of each round, a node generated a random number (R_d) ranging from 0 to 1. This (R_d) was calculated using a regular dispersal with a mean of 0 and a variation of 1.The (R_d) must be $0 < (R_d) < 1$; else, the node would choose a fresh R_d.This process was repeated until an arbitrary numeral in the series of 0 to 1 was found. R_d was compared to the $T(n_i)$ level after it formed. If a node appointed itself as a CH in $R_d \leq T(n_i)$,it must participate in the present round as a non-CH node. The CH notified other nodes in the network about its current condition. The non-CH node selected one of the CH nodes with the least amount of communication assets and sent a joint announcement to the elected CH. In essence, changing the designated CH threshold was required to maximize the network's longevity and vitality output. In other words, three key criteria would be examined when determining the level of threshold: the distance between node and BS, residual energy, node dormancy, and neighbour's node density inside the cluster zone. The CH selection was enhanced by the node's additional residual energy and the number of alive neighbours. Furthermore, nodes with the same remaining energy, a shorter distance to sink, and compatible alive neighbours counted as CCH. The newly designed node index variable (N_i) was determined from presently offered energy, baseline energy, living node counter, and node density from BS, which was crucial to CCH's electoral mechanism. The threshold value was rebuilt as a decisive criterion for a node to be picked as a CH. The node index (N_i) was integrated with threshold equation, which was derived from Equation 20 by embracing the above metrics:

$$T(n_i) = \frac{P_i}{1\text{-}P_i \times \left(r \times \mathrm{mod}\left(\frac{1}{P_i}\right)\right)} \times \alpha \frac{E_{res}^{n}}{E_{in}[n]} + \rho \left(1\text{-} \left(\frac{\mathrm{Degree}[n]}{N_{alv}} \right) \right) + \varphi \left(1\text{-} \frac{d_{toBS}[n]}{d_{toBSrmax}[n]} \right) \quad \text{, if } n_i \in N \tag{20}$$

Where E_{res}^{n} is the leftover vitality of node n, E_{in} is the preliminary vitality, N_{alv} is the alive node enumeration, $d_{toBS}[n]$ is the interspace node n to BS, and $d_{toBSrmax}[n]$ is the node span restrained to BS. The BS picked $K1$ nodes as in Equation 18 and designated them as CHs for Tier 1 through a centralized process.

The node's eligibility for CH was decided by its distance from the BS, remaining energy, and energy utilization ratio. The most appropriate nodes were designated as CCHs according to Equation 21:

$$\text{Suitability(m)} = \frac{E_r}{ECR \times net_{dtoBS}} \qquad \text{ECR} = \frac{E_0}{E_0 - E_r} \tag{21}$$

Here, E_r is the node's remaining vitality and E_0 is the node's opening vitality.

Probabilistic GWO - Predicated preference of CHs in Two Levels

In Tier 2, the suggested GWO design was aimed at the randomly dispersed stationary nodes. The CH exploration investigators (wolf) were represented by m nodes (CH = $CCH1$, $CCH2$, …, $CCHm$).Because altering the location of a static sensor was impossible in GWO, the screening mediator's location (contender CH) was denoted by CHi in a 2D space that depicted the nodes' coordinates($Posi$ (t) = xi (t), yi (t)). The closest node to the leading search coordinator role (position) was used to arrive at the final answer. The two-tiered GWO-based CH selection is as described in the MGWO Algorithm.

- The number of CCH in each layer shall be determined by the BS based on the adaptation function of L-DDRI. The adaptation function includes the residual energy and relative centrality of the node its distance from the BS, degree of node, and node dormancy.
- Simulate MGWO to divide the network into several layers based on the relationship between signal reception, transmission, and distance. Each node determines which layer it belongs to depending on its position and distance from BS.
- Probabilistic multi-tiered GWO-based selection of CHs dependent on suitable fitness function based on coverage area and CH balancing factor is implemented to identify the most dominating member among the group as CH and subordinates to CH as backup CH.
- After the CH is determined, all member nodes select the nearest CH to form the cluster.
- The node in the cluster communicates with the CH in a single-hop network, and the MGWO communication route is established between CHs to avoid a long-distance transmission.

- The CH is reselected based on its residual energy and round-robin time to establish and maintain the new route.

A fitness function determined the CH choice; the fitness function played a critical role in the MGWO algorithm's probing-for-prey process. The node's attributes, comprising remaining energy (Er) and the population of neighbours, were fed into this formula. The outcome was a value indicating how well the node was suited to becoming a leader.

A structure could be separated into several clusters using the clustering technique, and a cluster subset was made up of manifold groups in the network. The original cluster population, defined as the best feasible cluster set in this study, was referenced as the initial cluster set, and the objective role estimate of the present optimum cluster set was determined. MGWO generated a new cluster set by changing each cluster in the existing optimum set at arbitrary, and a multiplicity of the new clusters created a novel cluster set. The objective role estimate of the novel cluster set was then determined as in Equation 22.

$$f(CH_i) = V_1|N(CCH_i)| + \sigma * \left|\bigcup_{K=1}^{N} cover_K\right| + \mu * \sum_{j=1}^{N}\left(\frac{n_{alv}}{N} - l_j\right) + \vartheta * \sum_{j=1}^{m}\left(\frac{1}{l_j} * (d_{toBS})\right) + € * \sum_{j=1}^{N}\sum_{R=1}^{M}(E_0 - E_d) * E_R \pm \varphi * P \tag{22}$$

Where V_1, σ, μ, ϑ and φ are the arbitrary statistics in [0,1], $N(CCHi)$ is the checklist of sensors adjacent to a specific CHi, and d_{toBS} is the overall communication distance from CH to BS. The efficacious contender was the one with the maximum f; the node with the uppermost remaining energy and adequate adjacent nodes would announce itself as a CH. Subsequently, the choice was finalized; CHs would send a $HELLO\_Msg$ with CH _ID and CH range from BS. The PMR-GWO pseudo-code was defined as Algorithm 1.

Algorithm 1 PMR-GWO

Input:

N = alive nodes count

K = desired clusters count

$(CCHi)$ = list of sensor neighbours

d_{toBS} = total distance from CH to BS

Output:

Set of K clusters

CH, Vice CH, Backup CH

1. Initialization
2. Initial CHs selection, Call_Procedure L-DDRI($CCH_$Sel (Random_Number *Rd*, Novel_Threshold $T(n_i)$))
3. Outstanding nodes agree to link their adjoining CH rendering to Euclidean distance
4. Arrange preliminary clusters
5. Existing optimum cluster = preliminary cluster
6. Analyse the impartial role estimates of the existing optimum cluster (Fopt)
7. While t ≤ tmax do
8. ∀ existing optimum clusters
9. If (quantity of cluster associates ≥ 3)
10. Initialize packs Pi, $(CCH1, CCH2, CCH3, CCH4, CCH5, \ldots\ldots.)$ indicate 10% nodes as CHs in a pack from $(CCHi)$ list whose (residual energy > average remaining energy).
11. Initialize the population size Pi $(CCHi)$ (i = 1, 2, ..., n).
12. Initialize the max numbers of iteration T_{max}.
13. Call_Procedure MGWO$(CCH1, CCH2, CCH3, CCH4, CCH5, \ldots\ldots.)$
14. ConFignovel clusters
15. Analyse objective function estimate of novel cluster (Fnew)
16. If (Fnew < Fopt)
17. Existing optimum cluster = novel cluster
18. Fopt = Fnew
19. Else If (rand() > probability)
20. Existing optimum cluster = novel cluster
21. Fopt = Fnew
22. End if
23. End while

The technique combined GWO and the probability-based strategy. By dynamically investigating for the best parametric equilibrium via innovative threshold T (n) of reactive clustering to construct the approximate solution of CCHs, the fundamental step was employed to sort out the cluster members as potential CHs. Threshold T (n) was used to select the reserve and active CHs. The node's energy, proximity from the BS, and population were all considered while calculating the CH, and the threshold T was calculated using the energy, distance aspect, and density effect. Focusing on the ideal dataset obtained in the first level, stage two employed the effective Revised GWO to address the geolocation issue in WSN, which limited the path loss and incorporated measures to eliminate the transmission delay and decrease the WSN's energy. In determining the most dominant teammate as CH and subordinates to CH as reserve CH, a probabilistic multi-tiered GWO-based choice of CHs linked to specific fitness functions relying on network coverage, leftover energy, node dormancy proportion, distance, and CH balancer factor was developed.

SIMULATION RESULTS

The PMR-GWO algorithm was simulated in MATLAB to validate its efficacy, as illustrated in Sensor Network in Figure 4. The PMR-GWO method was compared to the P-SEP, L-DDRI, Novel-LEACH-POS, hetDEEC-3, and DBSCDS-GWO algorithms under similar investigational environments. Table 1 lists the key simulation constraints. The BS identified CHs at the start of every round via the mechanism in this article, and each round lasted 1 s. The network lifetime, CH count, and data packet count processed by BS were implemented as estimation indications for the algorithm's performance. Table 2 presents the comparative analysis of protocols in terms of significant parameters considered for implementation, location of node, whether protocol was multi-hop or single-hop, level of hierarchy, load balancing, type of node either mobile or static, type of nodes, and CH rotation in each iteration.

A. Network lifetime: The time interval between the start of the network and the demise of the foremost node, also referred to as network steadiness duration.

B. Throughput: The number of data packets acknowledged by BS.
C. CH sums up per round: A total node that conveys accumulated data to BS from its associates is preferred in accordance with the $T(n_i)$ threshold function. It is decided in numerous network representations, as in Equation 23.

$$k_{op} = (\sqrt{(n * \varepsilon_f}\ )/\sqrt{2\pi}) * (1/\varepsilon_m) * (\frac{M^2}{d_{toBS}^2}) \tag{23}$$

D. Energy consumption: This metric evaluates how much energy each node expends when transmitting packets to sink nodes.

Figure 4

Sensor Network (200 m × 200 m)

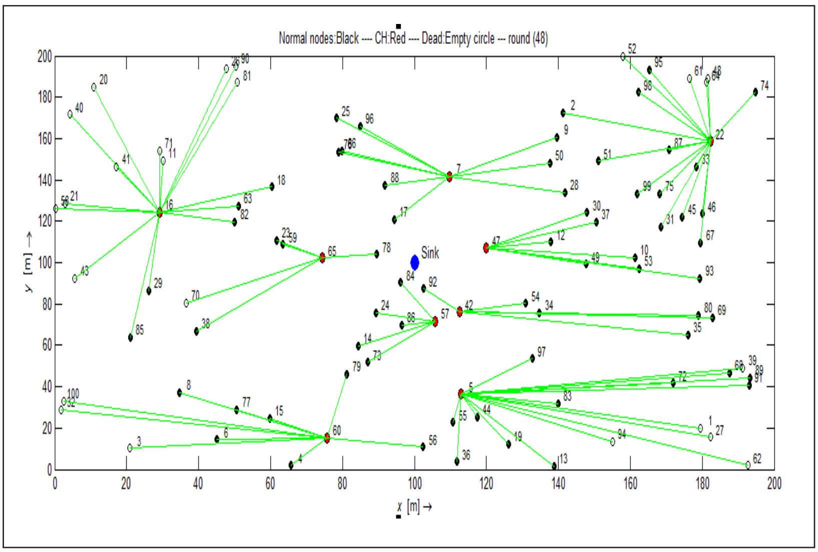


Table 1

Simulation Framework

Constraints	Value
Range of sensing zone, node count	200x200 m^2, N = 100
Portion of cluster heads	p = 0.1
Packet size	l = 4000 bits
Preliminary energy of ordinary node	0.5 J
Data aggregation energy cost	EDA = 5 nJ/bit
Energy cost of transmitter/receiver	Eelec = 50 nJ/bit
Transmission coefficient of amplifier (free space)	ϵ_{fs} = 10 pJ/bit/m2
Transmission coefficient of amplifier (multi-path space)	ϵ_{mp} = 0.0013 pJ/bit/m4

Table 2

Comparative Analysis of Protocols

Protocol	Parameters	Location	Multi-hop	Hierar chical level	Load balancing	Mobility type (static or mobile)	Nodes types (Homogeneous (H)/ heterogeneous (h))	Rotation of CH
P-SEP	Residual energy, energy efficiency, distance			Two		S	h	Y
L-DDRI	Residual energy, energy efficiency, distance, network coverage			Two		S	H	Y
Novel-LEACH-POS	Communication range, velocity, position			Two		S	H	Y
hetDEEC-3	residual energy, initial energy			Three		S	H/h	Y
DBSCDS-GWO	Dominator Lifetime Index (DLI), CH Lifetime Index (CLI), distance			Two		S	H	Y
PMR-GWO	Residual energy, initial energy, node dormancy, distance network coverage, density factor			Multi		M	H/h	Less random due to advanced nodes

Network Lifetime

The entire activation duration of a WSN is controlled by the network initiation time and node mortality period. Figure 5 demonstrates the contrasts in the quantity of survived nodes and network lifespan in rounds for P-SEP, L-DDRI, Novel-LEACH-POS, hetDEEC-3, DBSCDS-GWO, and PMR-GWO. Figure 6 shows the mean alive node count for P-SEP, L-DDRI, Novel-LEACH-POS, hetDEEC-3, DBSCDS-GWO, and PMR-GWO as 17.27, 16.24, 25.87, 23.94, 25.27, and 39.5, respectively. Meanwhile, the alive node count for P-SEP, L-DDRI, Novel-LEACH-POS, hetDEEC-3, DBSCDS-GWO, and PMR-GWO was 32.25, 34.66, 37.95, 38.52, 36.92, and 33.41, sequentially. In Figure 5, the lifespan of the projected PMR-GWO was improved by 51.2 percent, 52.0 percent, 33.2 percent, 24.6 percent, and 32.8 percent, correspondingly, comparative to P-SEP, L-DDRI, Novel-LEACH-POS, hetDEEC-3, and DBSCDS-GWO. The above statistics were due to the fact that nodes with little remaining energies had a slight possibility of being the CH, which prevented the occurrence of the quick demise of the node with little remaining vitality, thereby outstretching the network's lifespan sequence.

Figure 5

Performance Comparison of Network Lifetime

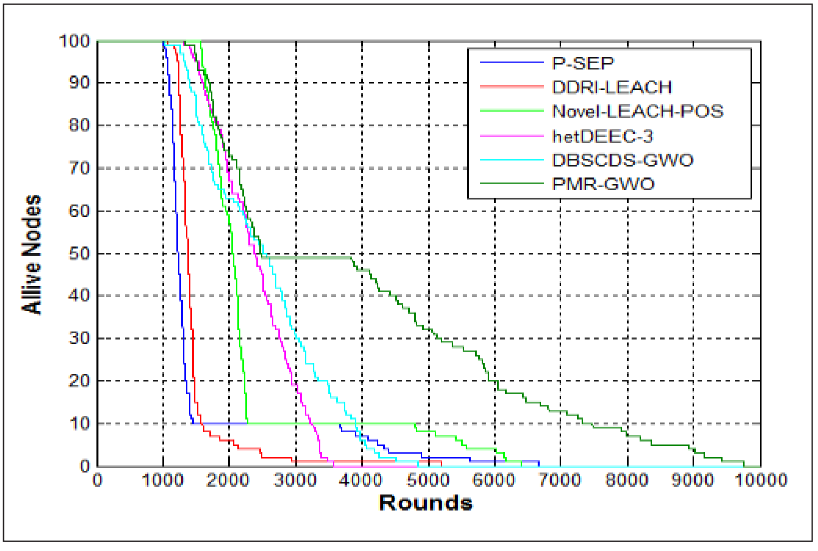
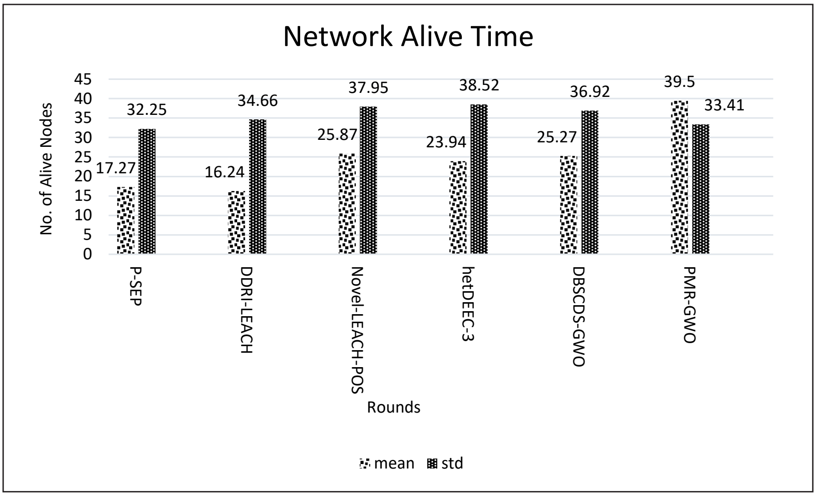


Figure 6

Alive Node Count

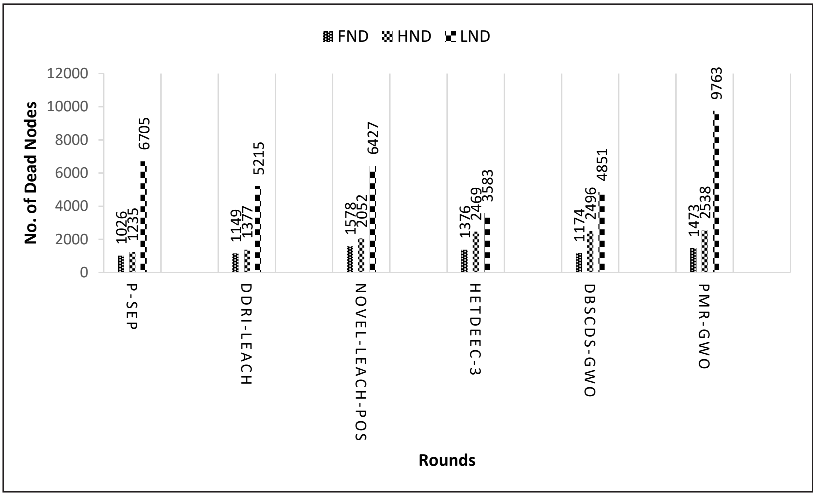


Figures 7 proved the effectiveness of related strategies with different primary vitalities using the first node dead (FND), half node dead (HND), and last node dead (LND) parameters. It indicated that the nodes for P-SEP, L-DDRI, Novel-LEACH-POS, hetDEEC-3, DBSCDS-GWO, and PMR-GWO started vanishing (FND) subsequently at 1,026, 1,149, 1,578, 1,376, 1,174, and 1,473 rounds. Moreover, nodes did not perish before 1,473 rounds with said PMR-GWO. The network lifetime of PMR-GWO was lengthened when the death node count approached 50 percent, relative to P-SEP, L-DDRI, Novel-LEACH-POS, hetDEEC-3, and DBSCDS-GWO. Consequently, as seen in Figure 7, all nodes perished at the same time. Likewise, imitation consequences amid HND and the sum of rounds for numerous conventions for P-SEP, L-DDRI, Novel-LEACH-POS, hetDEEC-3, DBSCDS-GWO, and the proposed PMR-GWO method with fluctuating preliminary energies are revealed in Figure 7. The total round for HND of P-SEP, L-DDRI, Novel-LEACH-POS, hetDEEC-3, DBSCDS-GWO, and PMR-GWO was 1,235, 1,377, 2,052, 2,469, 2,496, and 2,538 separately. In comparison to prior methods, PMR-GWO required additional rounds for HND.

The total round for LND of P-SEP, L-DDRI, Novel-LEACH-POS, hetDEEC-3, DBSCDS-GWO, and PMR-GWO was 6,705, 5,215, 6,427, 3,583, 4,851, and 9,763, respectively. The PMR-GWO algorithm necessitated extra rounds for the LND compared to the other methods. PMR-GWO adopted a clustering approach that was unique among conventions. It also had a predetermined time mount communication, which reduced the number of participating nodes in genuine data transmission and enhanced the life cycle.

Figure 7

First Node Dead Count, Half Node Dead Count, and Full Node Dead Count

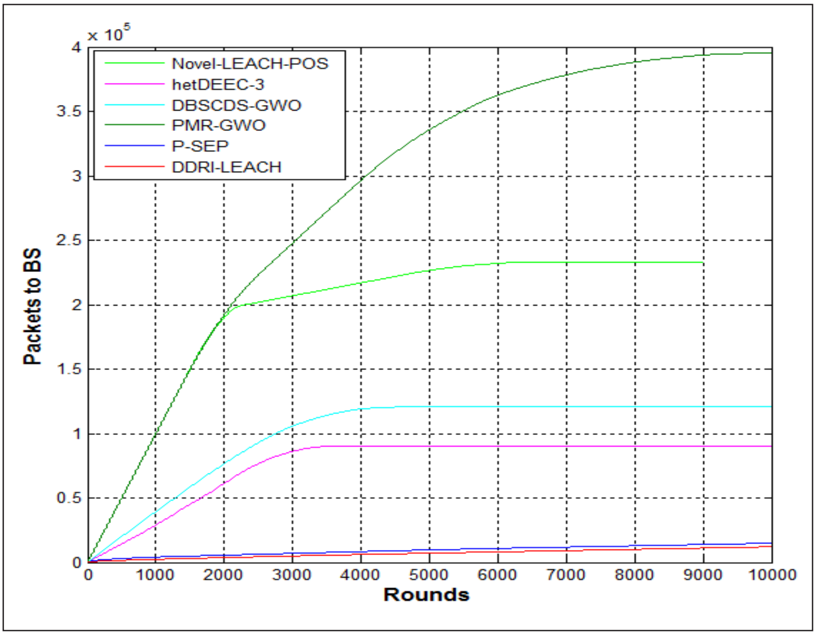


Packets Received By BS

Figure 8 illustrates the amount of data packets acknowledged by the BS as the network throughput of PMR-GWO improved by 150.4 percent, 175.6 percent, 70.5 percent, 142.5 percent, and 137.6 percent proportional to P-SEP, L-DDRI, Novel-LEACH-POS, hetDEEC-3, and DBSCDS-GWO. The PMR-GWO method used an appropriate CH choice process, and nodes had a prolonged life duration. When the number of iterations remained constant, the proportion of sustaining nodes in the network was greater than in other techniques, causing more packets to be transmitted by the BS.

Figure 8

Performance Comparison of Data Transmission



Comparison of CH Count

The number of CH stabilizing had a substantial influence on the procedure's energy efficiency. If the population of CHs was reduced, the data transmission period from nodes to CH would be prolonged, leading to greater energy consumption, and the CH would be able to spend more energy by transmitting unneeded data. When the total number of CHs was large, the entire system load and the mean energy demand of each network round increased, and the efficiency of network data fusion decreased, reducing the network's longevity. Figures 9–10 exhibit the P-SEP, L-DDRI, Novel-LEACH-POS, hetDEEC-3, DBSCDS-GWO, and PMR-GWO protocols' headcount per round for each cluster. Compared to existing techniques, the CH variance in the suggested PMR-GWO delivered better results, as seen in the graph. In the domain of PMR-GWO, the CH count ranged from 15 to 21. The PMR-GWO technique required determining the optimal CH number based on the WSN's energy consumption per transmission, which reduced cluster headcount unpredictability. The importance of stabilizing the CH count in PMR-GWO in relation to node demise could not be overstated. The aggregate cluster frequency band would indeed be reduced if WSN included a considerable number of dead nodes to accommodate the network's energy consumption. Maximum counts of CHs for P-SEP, L-DDRI, Novel-LEACH-POS, hetDEEC-3, DBSCDS-GWO, and PMR-GWO are shown in Table 3.

Figure 9

Performance Assessment of CH Count as r=100

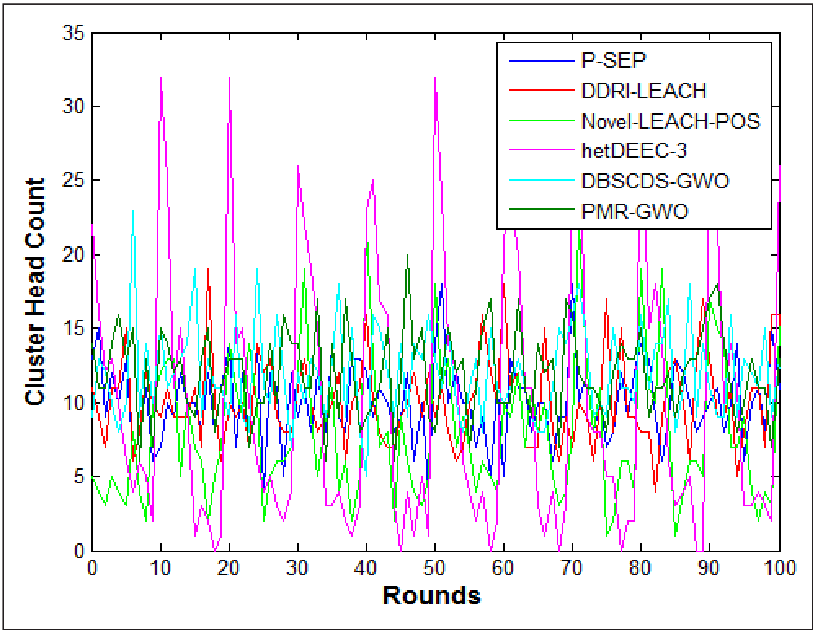


Figure 10

CHs Count at r=500

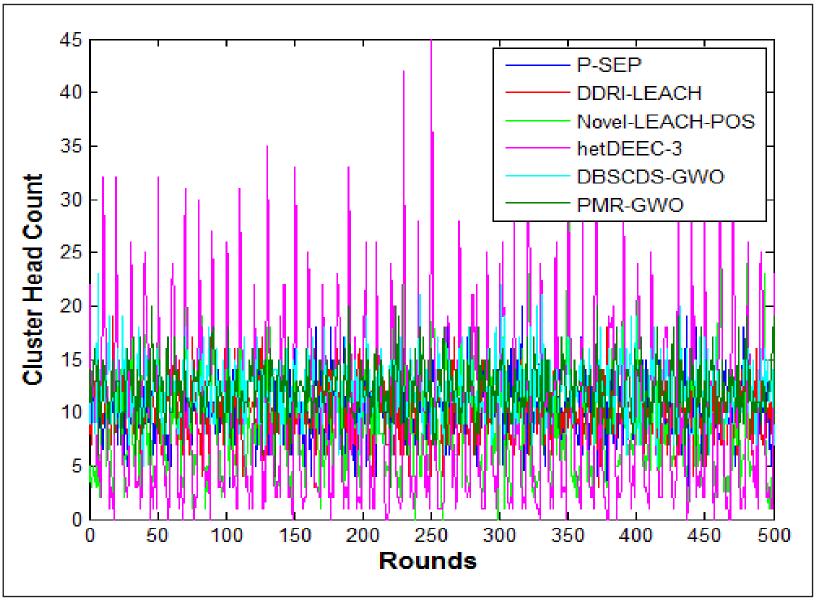


Table 3

Maximum Count of CHs

Protocol	Max Count of CHs (No.)
P-SEP	22
L-DDRI	20
Novel-LEACH-POS	71
hetDEEC-3	45
DBSCDS-GWO	23
PMR-GWO	21

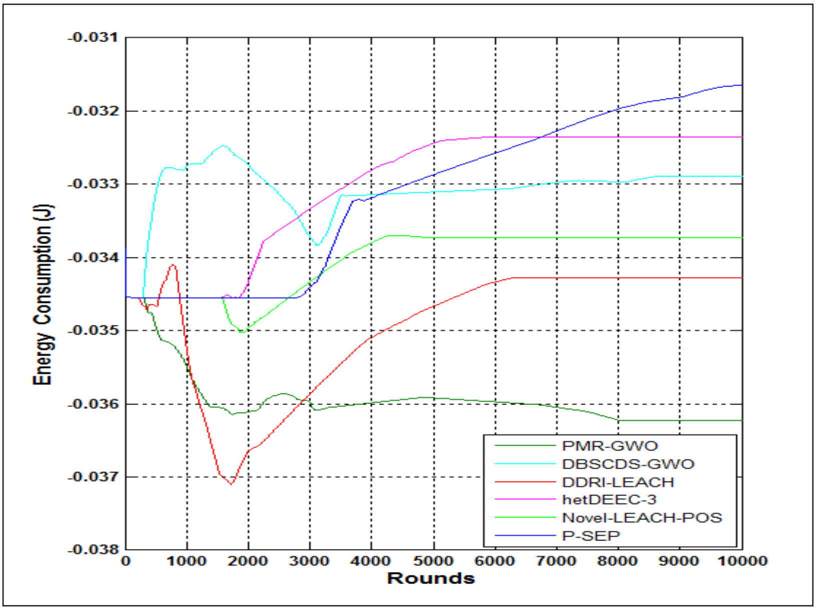
Energy Consumption

The comparative assessment of energy consumption for PMR-GWO and other routing protocols is shown in Figure 11. The aggregate resource used by the network for communication, receipt, and interpretation of results was referred to as energy usage.

The energy usage of both CH and cluster members was used to create contrasts amid various techniques. The PMR-GWO approach, as shown in Figure 11, utilized the least amount of energy possible. According to the simulation results, the PMR-GWO network lifetime was increased while energy consumption was reduced. In PMR-GWO, the network survived up to 9,763 rounds. It clearly surpassed other protocols in relation to network lifetime, number of active and dead nodes, and energy consumption, as evidenced by the analytical outcomes. The energy consumption of P-SEP, L-DDRI, Novel-LEACH-POS, hetDEEC-3, DBSCDS-GWO, and PMR-GWO was -0.03165 J, -0.03387 J, -0.03503 J, -0.03235 J, - 0.03456 J, and -0.03623 J, correspondingly, which specified the lowest energy consumption.

Figure 11

Performance Evaluation of Energy Consumption



CONCLUSIONS AND FUTURE RESEARCH

As revealed in the simulation outcomes, the suggested PMR-GWO method was computationally competent in stabilizing energy expenditure, preserving a substantial quantity of energy, and prolonging the network's lifetime for a layered-established design that focused on WSN compared to further recognized algorithms. This investigation projected a routing convention for WSNs founded on an improved GWO. This approach ensured that sophisticated nodes in the cluster were further prospective to qualify as CHs by providing unique fitness functions for enhanced and regular nodes and altering GWO. As a result, the accountability of choosing lower energy nodes as CHs could be decreased, and the network lifetime could be enlarged.

The simulation outcomes demonstrate that concerning P-SEP, L-DDRI, Novel-LEACH-POS, hetDEEC-3, and DBSCDS-GWO, the energy consumption, lifetime, and throughput of the network were meaningfully enhanced. The suggested PMR-GWO was expanded to bigger sensor networks to consider multi-hop connectivity across CHs, resulting in lower energy usage of both distant BS and CHs. Furthermore, after the CHs were chosen, non-essential energy dissipation was decreased to rationally lessen the additional energy exhausted by overall sensors to communicate their locations and energy to the BS. PMR-GWO assured deterministic CH allocation, reduced the effective communication range of sensed data to the sink, and equalized network load. The energy consumption of P-SEP, L-DDRI, Novel-LEACH-POS, hetDEEC-3, DBSCDS-GWO, and PMR-GWO was -0.03165 J, -0.03387 J, -0.03503 J, -0.03235 J, -0.03456 J and -0.03623 J. On the other hand, the network lifespan of the suggested PMR-GWO was amplified by 51.2 percent, 52.0 percent, 33.2 percent, 24.6 percent, and 32.8 percent, respectively, relative to P-SEP, L-DDRI, Novel-LEACH-POS, hetDEEC-3, and DBSCDS-GWO. The number of data packets acknowledged by the BS as network throughput of PMR-GWO was improved by 150.4 percent, 175.6 percent, 70.5 percent, 142.5 percent, and 137.6 percent in relation to P-SEP, L-DDRI, Novel-LEACH-POS, hetDEEC-3, and DBSCDS-GWO. The suggested viewpoint can be elongated to new developing futuristic technologies such as the Internet of Things (IoT) and the Internet of Everything (IoE), where network scopes are large, and energy usage by sensor networks must be optimized. As a result, the suggested technique may reduce a sensor network's energy usage, making it suitable for IoT and IoE deployments.

ACKNOWLEDGMENT

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

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