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A Grey Wolf Optimization-Based Clustering Approach for Energy Efficiency in Wireless Sensor Networks

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Abstract

In the realm of Wireless Sensor Networks, the longevity of a sensor node's battery is pivotal, especially since these nodes are often deployed in locations where battery replacement is not feasible. Heterogeneous networks introduce additional challenges due to varying buffer capacities among nodes, necessitating timely data transmission to prevent loss from buffer overflows. Despite numerous attempts to address these issues, previous solutions have been deficient in significant respects. Our innovative strategy employs Grey Wolf Optimization for Cluster Head selection within heterogeneous networks, aiming to concurrently optimise energy efficiency and buffer capacity. We conducted comprehensive simulations using Network Simulator 2, with results analysed in MATLAB, focusing on metrics such as energy depletion rates, remaining energy, node-to-node distance, node count, packet delivery, and average energy in the cluster head selection process. Our approach was benchmarked against leading protocols like LEACH and PEGASIS, considering five key performance indicators: energy usage, network lifespan, the survival rate of nodes over time, data throughput, and remaining network energy. The simulations demonstrate that our Grey Wolf Optimisation

	method outperforms conventional protocols, showing a 9% reduction in energy usage, a 12% increase in node longevity, a 9.8% improvement in data packet delivery, and a 12.2% boost in data throughput. ***Keywords: Grey Wolf Optimization, Wireless Sensor Networks, Cluster Head, Data aggregation, Energy Consumption Rate, LEACH, PEGASIS.***

1. Introduction

The Internet of Things (IoT) is a system of collecting from wireless devices and interrelated smart objects, and people can interact with the data over a network. Various studies assumed a global market in which IoT will enhance from \$157B-\$457B in 2016 to the 2022 year [1]. Smart retail, smart industries, logistics, transportation, smart supply chains, smart homes, and cars are applications that will profit from IoT technology. Wireless Sensor Networks (WSN) play an important role in implementing the IoT vision. WSNs-based spatially distributed sensors can gather the environment data. These sensors can produce larger data volumes, and they have heterogeneous features such as computational power, memory, and communication capabilities. It is referred to as homogenous when all of the nodes are similar. For instance, they have similar transmission rates and hardware. These devices are battery-based powered and collect data through WSN. Clustering is a technique which is adopted for energy-efficient solutions that have been shown by the research community to collect the data from WSN, and this also provides the cluster- et. Each cluster has a set of Member nodes (member nodes) and the Cluster Head (CH). This data is also collected from its member-like communication of the intra-cluster. CHs also join to report the data to centralised BS (base station).

There are various other clustering protocols are present, which are scalable in nature and provide the energy perspective savings method to improvise the network lifetime and reduce energy consumption [2]. WSN is a network where that can disperse as the Sensor Nodes(SN) also measures different parameters such as voice activity, pressure, water pollutants, and motion-based application scenario. WSN has a small embedded processor device with interfaced sensors, and it has 3 major functionalities: sensing, signal processing, and wireless communication. These nodes are battery-driven that limits an operative life. Among the above functionalities, the node uses more the energy during wireless communication than with other functionalities [3]. Below, Figure 1 shows the architecture of the WSN-based cluster model.

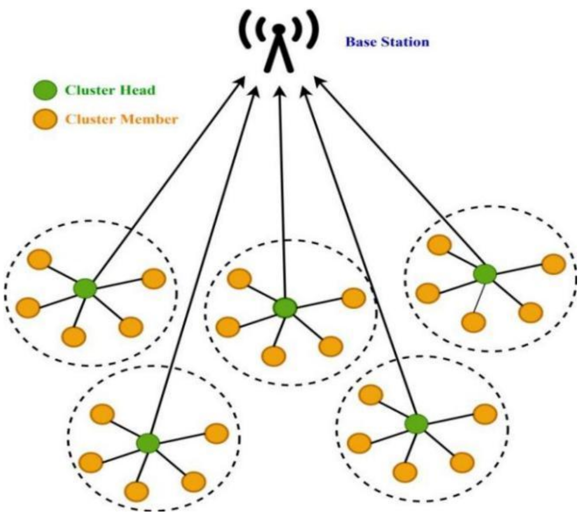

Figure 1. Clustering Procedure in WSN

Thus, several kinds of research focus on evaluating the energy consumption because of radio communication by designing a different model of communication. Communication models contain a receiver and transmitter, which are placed at a distance. Every circuit operation consumes some amount of energy, whether it's operating in active mode or idle mode. These are known as energy factors, and it has to be considered to evaluate the energy spent by the device. The main challenge of WSN is to maximise network lifetime to eliminate the nodes depleting their batteries when accomplished tasks are not needed. The useful methods are clustering, whereas traditional routing carries better for the higher network.

In networks comprising multiple nodes, select nodes are designated as Cluster Heads (CHs). These CHs are responsible for collecting data from associated nodes, a process that reflects the nodes' contributions. Nodes transmit their measurements to their nearest CH. Each CH then aggregates the data from its cluster and forwards it to the Base Station (BS). This method is designed to prevent nodes from having to communicate with the BS over long distances, which would rapidly deplete their batteries due to the non-linear increase in power loss with distance. The configuration of CHs is predetermined; however, different nodes are rotated into the CH role to evenly distribute the energy consumption among them. As a result, the CH hierarchy within the network is dynamic, changing as different nodes assume the CH function [4].

Clustering in networks involves various methods where the Cluster Head (CH) directly transmits data to the Base Station (BS). These techniques are categorized based on the specific activities conducted through the BS. This categorization includes different clustering approaches, each distinguished by its unique operational characteristics:

- In centralized clustering, the Base Station (BS) exercises complete control over the clustering process. It is responsible for selecting nodes to be transformed into Cluster Heads (CHs). In this scenario, the BS relies on data from nodes to choose suitable CHs. Key factors influencing this decision typically include the geographical location of each node, its remaining energy, and its position within the sensing area.
- In distributed clustering, nodes operate autonomously, deciding independently whether to become Cluster Heads (CHs) or not. This decision is based on attributes that the nodes can assess on their own. Subsequently, data are evaluated using specific methods to determine if a node should assume the CH role. Finally, the selected nodes announce their CH status to the network, allowing other nodes to join their clusters.

Cluster formation and CH selection are the two main operations in the clustering algorithm. Energy wastage due to the direct transmission between sensors and BS that can be removed in WSN clustering. Clustering enhances the scalability of WSNs in the application of the real world. Selecting cluster maintenance, CHs reselection, and the optimum size of the cluster is an eminent issue that is addressed in designing the algorithms of clustering in order to select and isolate the CHs for selection criteria that should be maximising energy usage.

The main contribution of this article is as follows:

- In this research work, we have developed a new clustering algorithm for use in heterogeneous wireless sensor networks (WSN), with the goal of resolving the issue of buffer overflow along with improving the network throughput and lifetime of the nodes in the WSN.
- For the proper selection and formation of cluster heads in the heterogeneous WSN, we utilised the Grey wolf optimisation (GWO) technique, which takes care of the size of the sensor's buffer level and effectively reduces the data packet overflow from the sensor.
- Our proposed protocol has the potential to be an effective solution, as the sensor nodes are heterogeneity in nature as opposed to a traditional WSN; these sensors may have highly restricted power availability and processing capabilities; as a result, preserving the energy of the nodes is of utmost significance. In addition, an extremely low transmit power per node is required so that there will be as little interference as possible.

Section 2 provides an examination of the existing scholarly works. Section 3 elaborates on the presuppositions made within the context of the WSN network, detailing the energy and network models. Section 4 offers an in-depth explanation of the Grey Wolf Optimization (GWO) algorithm and elucidates the integration of solutions for buffer overflow issues in standard nodes. The construction of the fitness function is explicated in Section 5. Section 6 showcases the proposed model, delineating the experimental outcomes across various test cases. Finally, the paper concludes by accentuating the enhancements observed in the experimental results.

2. Related Concepts

In wireless geographical ranges, sensor hubs more often work inattentively. Hubs might be performing in artificially or naturally oriented areas, in large structures, at the depth of seas, or in battle zone beyond foe lines. To deal with communication between BS and sink, special remote routing conventions are essential. In WSNs, hundreds and thousands of hubs are managed through bunching approaches. Clustered hub systems are broadly classified as homogeneous and heterogeneous various levelled hub systems. All hubs in homogeneous systems are indistinguishable in case of functionality and vitality. Whereas two or many distinctive types of hubs are considered in heterogeneous systems as far as battery vitality and usefulness are concerned. In homogeneous and heterogeneous locations, we consider that both homogeneous and heterogeneous hubs are sent individually in our project. Here, we exhibit a literature review of different published works in this segment [5].

The directing (routing) conventions, in general, are of two sorts in nature, one relaying upon system configuration and alternative relays upon working procedure included in the convention. Plain directing system that is various levelled routing system and geographical-based conventions are recognised as further classifications involved in system configurations. Relying upon negotiation, multiple links, cohesion, inquiries and Quality of Service (QoS) directing, the division of processing of conventions are accomplished. By considering the system framework and the hierarchical directing algorithms, most particularly, the steering conventions are shortly elaborated in the upcoming segment. Making the best system resources in use in heterogeneous sensor systems incorporates bunching convention understanding. WSN optimising in the sense, which requires system establishment in an appropriate way such that the system's throughput and system life span achieve incrimination. Vitality efficiency, data accumulation, and directing and maintaining load are several parameters utilised in optimising the system. Energy proficiency and load management of heterogeneous remote systems are extreme focusing points [6].

With several connections, various bunching algorithms were inherently brought up before, but not even one of those algorithms, according to our concern, is aiming at energy deduction that is spent in a system. These algorithms hugely contain heuristic characteristics, which are looking forward to creating bunches with minimal quantity so that in any bunch, a hub is high 'd' hops far from the bunch head. The minimal quantity of bunches established may not guarantee the utilisation of energy minimally in our setup. To check for strategies that support vitality proficient conventions improvement in remote sensor systems, significant studies were advanced [7].

[4] developed a method combining differential evolution and particle swarm optimization for mobile robot path planning, aimed at enhancing convergence accuracy and overcoming simplicity in maturity. The approach involves refining particle swarm optimization through corporate governance principles, which include adaptive adjustment of weights and acceleration coefficients to speed up algorithm convergence. Additionally, the performance of the differential evolution algorithm is enhanced by adaptively controlling the mutation size. This modified differential evolution technique is applied in an intensive training mode to robustly refine the particle swarm optimization's global optimal position, thereby increasing search precision. The method also incorporates a dual-objective optimization, focusing on both the length of the route and the level of danger, to optimize robot path planning. Simulations of path planning demonstrate the effectiveness and practicality of this approach in guiding mobile robots.

Alzaqeba et al. [5] have discussed the Grey Wolf Optimization algorithm (GWO), a modified bio-inspired method that improves the Intruder detection system's ability to detect regular and anomalous network traffic. The smart initialisation step combines the filter and wrapper approaches to ensure that informative characteristics are incorporated in early iterations. The Extreme Learning Machine (ELM), a fast classification system, was tuned using the modified GWO. This paper's main objective was to detect generic attacks in network traffic, the dataset's most common attack type. In reducing crossover error and false positive rates to less than 30%, the suggested model beat conventional techniques [6].

Hou Y, Gao H et al. [6] introduced a refined Grey Wolf Optimizer (GWO) that enhances the equilibrium between exploratory and exploitative search by incorporating a nonlinear convergence factor derived from the Gaussian distribution curve. This factor, coupled with an initial wolf pack arrangement via chaotic tent mapping, sets a robust foundation for the algorithm. To accelerate convergence, they introduced an advanced dynamic weighting method to update the position of the wolves. The performance of this modified GWO was benchmarked against eight other algorithms through a series of standard function tests and pathfinding trials. The results underscore the modified GWO's superiority in precision and convergence velocity over the original [8].

Othman et al. [10] have delved into virtualisation within wireless sensor networks (WSNs), acknowledging its complexity due to issues like node failure, communication delays, and node identification. While previous research has addressed resource optimisation and node failure resilience in virtual WSNs, the challenge of communication latency remained unexplored. This latency is particularly pertinent to IoT virtual networks. To address these challenges, the researchers developed the Evolutionary Multi-Objective Crowding Algorithm (EMOCA). This algorithm is designed to enhance fault tolerance and minimize communication delays in virtual network embedding, particularly for service-oriented applications in diverse IoT environments. EMOCA differs from existing wireless virtualization solutions, such as those based on the Non-dominated Sorting Genetic Algorithm-II (NSGA-II), by utilizing both dominance and diversity principles within an expanding population to solve optimization issues. The results from their study suggest that EMOCA effectively improves fault tolerance and reduces communication delays in the virtualization of Wireless Sensor Networks (WSNs).

Zhao et al. [9] introduced the Multi-Strategy Ensemble Firefly Algorithm (MEFA-CD) to address certain limitations. Initially, they employ an advanced linear congruence method to generate a uniformly distributed initial population, ensuring a robust global search capability and a solid foundation for population evolution. Next, a hybrid learning strategy is used to identify the optimal elite solution based on the highest fitness value. This involves the firefly algorithm learning from the current best solution and a compensation factor. This approach not only accelerates convergence towards the Pareto optimal solution set but also expands the population's search scope, enhancing the diversity and precision of the Pareto optimal set. Lastly, the crowding distance mechanism is utilized to eliminate clustered solutions, preserving the diversity of external archives. This ensures the potential for local development within the population and enhances the algorithm's convergence. The MEFA-CD demonstrates superior performance in terms of convergence, diversity, and optimization efficiency, showing a 61% improvement over the standard Multi-Objective Firefly Algorithm (MOFA).

Jing Xiao et al. [1] have proposed an enhanced adaptive elite ant colony optimisation (AEACO) to lower Heterogeneous WSN routing energy consumption and a QoS routing energy consumption model. This algorithm accelerates convergence with adaptive and elite operators. AEACO is compared to PSO and GA to prove its efficiency. AEACO converges faster than PSO and GA in simulations. AEACO HDWSNs use 30.7% less energy than GA and 22.5% less than PSO. AEACO reduces HDWSN energy consumption.

Deep Kumar et al. [10] introduced an algorithm focused on enhancing both energy efficiency and security in Wireless Sensor Networks (WSN). In their research, they compare two opportunistic routing algorithms against their newly developed algorithm to analyze performance in WSNs. The evaluation involves running these algorithms in MATLAB and benchmarking their results against routing algorithms based on Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO). Key performance metrics include energy efficiency, network longevity, packet delivery ratio, end-to-end delay, and average risk level. The algorithms are tested under scenarios with up to 50% malicious nodes in networks of 25, 50, and 100 nodes to assess their effectiveness.

Cao et al. [11] suggested an algorithm to optimise Heterogeneous WSN(HWSN) coverage and reduce energy usage. First, a difficult combinatorial optimisation problem is used to model HWSN coverage. A chaotic initialisation method generates the initial population to speed up the global convergence of the suggested algorithm. The neighbourhood search, global search, and matching radius improve the SSO algorithm's convergence speed and search ability. In the iterative optimisation process, the spider colony's movement law—female and male spiders' cooperation, mutual attraction, and mating—is simulated to find the best solution [12]. The CSSO chaos-based SSO algorithm is suggested for HWSN sensory node deployment optimisation. Optimising network coverage and affordability is the goal. The CSSO algorithm finds the best node deployment plan to avoid network coverage blind spots and redundancy [11].

Zhao et al. [13] have devised an energy-efficient coverage enhancement strategy, drawing inspiration from the behaviors of vampire bats. This strategy utilizes the Vampire Bat Optimizer (VBO) to address specific challenges in this domain. Simulation tests reveal that their approach significantly enhances the uniformity of node residual energy, showing improvements of 30.53%, 43.44%, and 32.03% when compared to the Virtual Force-Directed Particle Swarm Optimization (VFPSO), the 3-D Virtual Force Algorithm (3DVFA), and the Hungarian Algorithm (HA), respectively. Additionally, this technique effectively reduces overall node energy consumption and demonstrates strong performance in terms of the maximum energy consumption of nodes, final coverage rate, and time efficiency.

Qu et al. [14] have crafted a method combining reinforcement learning with the grey wolf optimizer, tailored for managing individual operations based on performance metrics. This innovative algorithm is specifically designed for Unmanned Aerial Vehicle (UAV) route planning. It encompasses four key operations for each individual: exploration, exploitation, geometric adjustment, and optimal adjustment. Additionally, the algorithm employs a cubic B-spline curve to refine the calculated flight route, ensuring that the path is suitable and smooth for UAV navigation. According to simulation results, the Reinforcement Learning-based Grey Wolf Optimizer (RLGWO) algorithm demonstrates its capability to identify feasible and efficient paths in complex environments.

A. Saxena, R. Kumar Power network harmonic estimation design is difficult. Estimating network inter, power, and sub-harmonics can help develop ways to eliminate them. The harmonic estimation design problem has been optimised using the least square technique. This study introduces an Evolutionary Operators Equipped Grey Wolf Optimizer (E-GWO). This proposal includes a sinusoidal function-enabled bridge, tournament selection operator, crossover, and mutation operations at position updation. After benchmarking on current CEC-2017 functionalities, this design issue is fixed. We conclude that proposed adjustments improve GWO performance after a meaningful comparison with existing techniques. Under varied operational situations, proposed harmonic designs are robust [15].

In this paper, we can take a look at protocols involved in the communication process, which show significance impact by taking an account of dissipated energy for those systems. During their discoveries, they found that previous conventions of direct deliverance, least transmission energy, multi-hopping router schemes and fixed cluster may not be ideal for sensor systems [16]. He proposed LEACH, which is based on clustering conventions that require rotation randomly of CHs in order to create even dissemination of vitality load amongst all sensor hubs in the system. To empower scalability, to have robustness in dynamic systems and to incorporate information fusion into routing convention for reducing the overall data that should be communicated to the BS, limited coordination is utilised by the LEACH protocol [8].

Since the drain is completely shared, there is no need for worldwide awareness of the system. Reduction of vitality utilisation takes place by optimising correspondence cost amongst hubs and respective CHs and reasonably killing expected non-head possible hubs. LEACH is not relevant for systems incorporated in substantial regions since in LEACH, single bounce directing takes place, where every hub specifically transmits information to CH and sink [9]. The further possibility of element clustering brings traffic additionally, for example, CH changes, promotions and so on, which eliminates the increase in vitality utilisation. LEACH supports the hubs inside their group to disperse their energy gradually; when CHs are located far away from the sink then, they devour a large measure of energy. LEACH grouping, like wisely, gets ended at a limited number of iterations; however, it does not ensures better CH dispersion and accepts uniform vitality utilisation for CHs respectively [1], [10].

In remote sensor systems, one of the real primarily enhancement in bunching conventional technique was from adaptive less vitality grouping hierarchy or LEACH. Break down of system to a numerous sensor bunches also steering and huge versatile dissemination of information is given by LEACH. Scattered generation of bunches is incorporated in LEACH [11]. For vitality dissemination deduction within bunch and for sensor's even vitality stack appropriation in the system, CH's randomised circulation part is considered. In the setup stage, generation of the bunch is held, and in the steady state stage, mobility of information is held in this convention. At the start of round r+1, every hub self turns as a bunch head with Pi(t) probability, and the quantity of hubs is indicated by 'k' [17].

Regard extends the basic plan of LEACH, which chooses a bunch by contaminated energy usage and degree or thickness of hub as metric parameters to accomplish adjustment of power. Uses versatile sending power since it works as multiple hopping systems in bunching in-between communication. Residual vitality of every sensor hub, which is for the ascertaining the probability of turning as CH is an essential parameter, and intra-group communication rate as bunch thickness or hub degree, i.e. neighbour numbers function is the auxiliary parameter. Initial arrangements of CHs are probabilistically chosen by essential parameters, whereas breaking up as ties are accomplished through auxiliary parameters. Since LEACH chooses CHs haphazardly, i.e. bu,nch size, which brings about faster demise of a few hubs ta,king this fact into consideration, the system lifetime is expanded more when compared to the LEACH bunching scheme. CHs chosen last are well circulated in HEED all over the network, where the correspondence expenses are also minimised. Bunch determination, anyhow deals just with parameters subset that imposes limitations possibly on the network. Just for delaying the lifetime of the system, these approaches are appropriate and not applicable to the complete requirements of WSN [18], [13], [14].

The author of [15] has developed a novel algorithm Energy Efficient Clustering strategy (EECS) for remote sensor systems, which is better suited for periodic information-gathering applications. The summary of EECS benefits is as follows: EECS structures adjusting point among intra-group vitality perception is based on vitality and separation; dynamic measuring relies on bunch separation from BS while performing bunching. Clusters with more separation to BS address the issue that they acquire higher energy to forward than those with shorter separation; this brings less message traffic and even dispersion of CHs over LEACH convention. The existence of few benefits nonetheless in EECS, as takes, is: extended area transmissions straightforward to BS from CHs may cause much vitality consumption when taking account of single jump correspondence in EECS, it is consequently not applicable to vast reach systems; there is a requirement of worldwide intelligence for EECS regarding separations involved among BS and CHs, and also errand of global information accumulation includes overheads for all sensor hubs; control overhead becomes much high intricacy due to EECS production since to become CHs there should be an involvement of all hubs is required.

[10] demonstrated a bunching algorithm that is homogeneous for remote hub organisation for sparing power and drawing out a lifetime of the system. Ensuring the homogeneous dissemination of hubs in the bunching range of life for the network is being incremented. Based of the lingering energy of current CHs, esteem holdback and closest hop separation of the hub, another CH is being chosen. The surety given by the homogeneous algorithm is that each hub can either be a CH or an individual from any one of the bunches in WSN. Bunch individuals are evenly appropriated and permits for more development of system life in grouping algorithm which is proposed. Later, anyone CH telecasts a bunch of creation messages but not each hub in the convention proposed, which consequently drags out hub network life. This methodology emphasises on extending the system's life span by guaranteeing homogeneous dissemination of hubs in bunches such that there is not too much overhead in forwarding and replaying on CH.

The GWO method was initially suggested by [15] in the year 2014. This technique is designed to simulate the hunting and social order that occurs naturally among grey wolves. A GWO was suggested by Kalpana as a way to reduce the amount of energy that is lost between nodes. However, at this time, rather than employing GWO for clustering, authors developed a Multi-Level Hybrid energy-efficient clustering routing Protocol known as MLHP. Because of its straightforwardness, ease of implementation, and reduced number of control parameters—there are only two primary parameters, a and C, that need to be modified [19], GWO has garnered a lot of interest. It is also possible to generalise it to apply to difficulties on a larger scale [20]. However, the accomplishment of this meta-heuristic algorithm is contingent on maintaining a balance between exploratory and exploitative activities. It has the unique capacity to establish the correct balance between them as the search is being done, which ultimately results in favourable convergence. Because GWO only uses one position vector, it requires significantly less storage space. The GWO algorithm, in contrast to other population-based heuristics, will only keep the top three answers [21], [22]. Below Table 2.1 shows the Comparative analysis of GWO methods.

Table 2.1. GWO- Comparative Analysis Based on Clustering Approach

Authors	Protocol	Cluster Scheme	Hetro-genous	Cluster Balance	Cove rage	Latency	Energy Efficiency	Throu ghput	Benchmark
Al-Aboody	MLHP	Centralised	Yes	-	-	-	Yes	Yes	LEACH/SEP/ DEEC
Rajarajeshwari & Kalpana	GO	Distributed	No	-	-	-	Yes	Yes	AODV/ BeeSensor
Emary	GO	Distributed	No	-	Yes	-	Yes	Yes	LEACH
Jabinian	PGWO	Distributed	No	Yes	-	-	Yes	-	GA
Khan & Diwan	Fuzzy-GWO	Distributed	Yes	-	-	-	Yes	-	LEACH
Zhao	FIGWO	Distributed	No	Yes	-	-	Yes	Yes	SEP/LEACH

3. System Model and Assumptions

This system model is evaluated as the model for free space. It consists of a receiver and transmitter having a separation distance of d. Amplifier circuits are represented at Rx and Tx. The situation of WSN is considered for recreation that has all the accompanying constraints and properties to form a framework model; all SNs are scattered by using the Poisson homogenous distribution.

- Nodes are heterogeneous, and it has restricted support sizes.
- BS is fixed and is located within the detecting area.
- DF (Data fusion) is used to decrease the aggregate sum of the forwarded information.
- The sent nodes are static in nature which implies no way can change their area once the distribution procedure is finished.
- Each node has its fixed communication range.
- Node with max number of neighbours, max energy, and max size of the cradle that is set around the gravity focus of the cluster is one of the reasonable possibilities for the CH job.
- Another node isn't fulfilling the rules that have a lower likelihood, or there is zero chance to turn into the CH.
- On the off chance that two nodes have the same chances in the area, one of them will be bound by then to assist with the network lifetime.
- On the off chance that the separation between the node and it is relation to CH is higher than its separation to BS, this node will transmit it is detected as data to the BS legitimately.
- The number of boundaries is boosted, energy utilisation, calculations,, and time are additionally increments.

A.Energy Model

Here, the energy model is utilised where the consumed energy is to send an l-bit message over distance d, which is as described in equation (1):

$$E_{T_x}(l,d) = \begin{cases} l \times E_{elec} + l \times \epsilon_{fs} \times d^2 & \text{if } d \leq d_0 \\ l \times E_{elec} + l \times \epsilon_{mp} \times d^4 & \text{if } d > d_0 \end{cases} \quad (1)$$

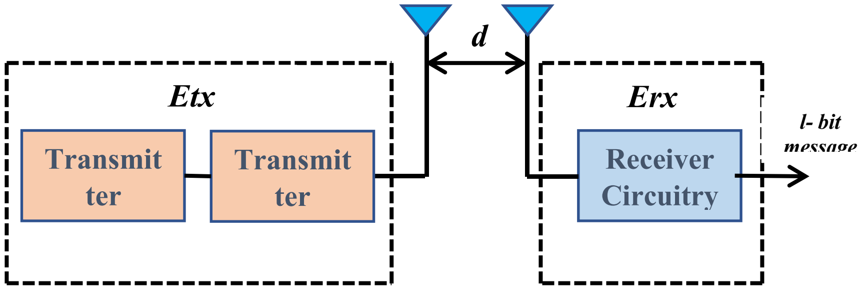

Figure 2. Energy Dispersion Model

Where, E_{T_x} is transmitted energy, E_{elec} is defined as energy that dissipated per bit in the receiver and transmitter unit. ϵ_{fs}andϵ_{mp} is based on the model of the transmitter amplifier as shown in Figure 2. The transmitter and receiver are lesser than d_0 threshold among the distance; the model of free space is also used to model the used multipath. $d_0$is computed as seen in equation (2):

$$d_0 = \sqrt{\frac{\epsilon_{fs}}{\epsilon_{mp}}} \tag{2}$$

Another other, the consumption of energy for the receiver-to-receiver 1-bit-long packet is defined as given in equation (3):

$$E_{Rx} = l \times E_{elec} \tag{3}$$

B.Network Model

In this network model, many scenarios of WSN are utilised. A various number of heterogeneous SNs can be dispersed in the network area. The nodes like ($m_1$and m_2) can be equipped with β and α times of buffer size and more energy acts as super nodes and advanced nodes. N is the total number of the nodes, which is computed as below equation (4):

$$N = \big(1 - (m_1 + m_2)\big) \times N + m_1 \times N + m_2 \times N \tag{4}$$

In this network model, chosen nodes are selected through advanced nodes based on introduced WA and GW based on the algorithms of CH-selection. In SN, the remaining nodes have the properties of a normal node. It is noted, that introduced algorithms are the advanced nodes in CH, but the advanced node cannot be assigned as the CH.

4. Methodology

In the last few decades, many researchers have been introduced as an outcome of evolutionary algorithms. This result shows that a few methods of hybridisation meta-heuristics are outstanding. Nonetheless, a large portion of the papers have been concentrated on every heuristic that is executed without combination with the heuristic algorithms. This computation can be hybridised with a portion of the algorithms, for example, Grey Wolf. This hybridisation can be actualised in various manners; for example, GA can be used as a beginning stage so as to make better starting arrangements, and the remainder of the search ICA care. Now and again, this can be utilised as a beginning stage to create introductory arrangements, and others can be utilised to look. Moreover, GA might be hybridised into a reciprocal instrument to help misuse ability and produce a high caliber of the arrangements. The GA can be used to choose CHs and structures as the clusters.

4.1 GWO Model

The leadership hierarchy is utilised for GW colonies that use the sorts of 4 wolves such as beta, omega, alpha, and delta. The alpha is known as the leader who is responsible for making the decisions. It is known as the prevailing wolf since it is essential to be observed by the pack. Alpha is the best part of dealing with the pack. Naturally, it's not the most grounded wolf. This speaks to the quality that isn't more significant than the order and association of a pack. In the subsequent level, beta is a chain of command. This beta backings alpha to produce choices. Beta orders have a lower level of wolves. Alpha passes away, betas are the proper contender to supplant alpha in this situation. Omega has a lower positioning than GW. This wolf category must be applied to all dominant decision wolves. If the wolf has no beta, omega and alpha, then it is known as delta. The level of wolf dominates omegas bit, and it has to submit alphas and betas. The most important phases of this technique are encircling prey, attacking prey, and searching for the prey. In this study, CH selection was inspired by the help of the GW structure in a heterogeneity of the cluster network.

4.2 Proposed Cluster Head Selection Algorithm Using GW

The below sub-section describes the various process involved in the cluster head selection.

A. Search for prey, also known as exploration:

Here, we explain how to choose CHs by utilising GW. In this prey, the positions of the delta, alpha, and beta positions are to search the prey in GWs. For prey, they also converged from each other to attack the diverged prey, as shown in Figure 3.

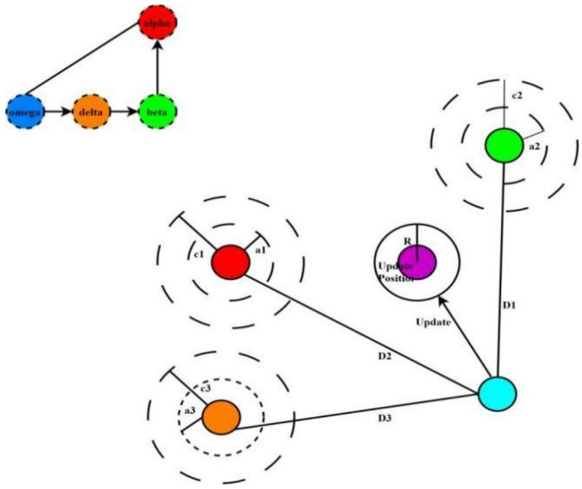

Figure 3. Position of the Grey Wolf for Catching Prey

For the mathematical divergence model, we use A with random values which are less than -1 and greater than 1 to oblige the divergence and also discover the agent from the prey. In order to control the parameter value by a, which is reduced from 2 to 0, another parameter is C in GW, which favors exploration. It consists of random values in the range of [0;2]. This contribution is strong when $C < 1$, also this solution gravitates more towards to prey, the avoidance of local optima, and favouring the exploration.

B. Encircling prey:

As mentioned earlier, prey can be encircled during hunting through grey wolves. In this behaviour, the mathematical model is introduced as shown in equation (5) below:

$$X(t+1) = X_p(t) - A \times D \qquad (5)$$

Where the next location of a wolf is $X(t+1)$, the current location is $X(t)$, the coefficient matrix is A and a vector is defined as D that depends on Xp prey-location and it is computed as in equation (6):

$$D = |C \times X_p(t) - X(t)| \qquad (6)$$

Where the constant C is calculated by the equation (7):

$$C = 2 \times r_2 \qquad (7)$$

Note that a randomly generated vector is r_2, which ranges from [0,1] interval. These two equations, 6 & &, are the given equations; the solution can relocate to another solution. The equations utilise vectors as the position and velocity are used. In the above condition, the arbitrary parts are mimicked at different advance sizes and the development velocities of the dim wolves. These given conditions are characterised by their qualities as given below in equation (8):

$$A = 2 \times a \times r_1 - a \qquad (8)$$

Where random vector is defined as a where its values are reduced from 2 to 0 during the run time. The generated vector is r_1 from the [0,1] interval. Then, parameter a is updated as equation (9):

$$a = 2 - t \times \left(\frac{2}{T}\right) \tag{9}$$

Where t represents the current iteration, and T is defined as the max number of iterations.

The modified version of GW is introduced to achieve exploration. Instead of reducing linear value, it is used as the function of exponential and is described in the equation (10):

$$a = 2 \times \left(1 - \frac{2^2}{T^2}\right) \tag{10}$$

C. Optimisation process, also known as hunting:

In the GW, delta, alpha, and beta are the best solutions that have been gained so far. The optimisation problem of the global optimum has a better idea of the location that is responsible to all population. Other wolves should be satisfied to update positions. The given positions are updated in the first round, which is followed as given by equation (11):

$$\begin{aligned} X_1 &= X_{alpha}(t) - A_1 \times D_{alpha} \\ X_2 &= X_{beta}(t) - A_2 \times D_{beta} \\ X_3 &= X_{delta}(t) - A_3 \times D_{delta} \end{aligned} \tag{11}$$

Where X_{delta}, X_{alpha} and X_{beta} are computed by utilising the below equation (12):

$$\begin{aligned} X_1 &= |C_1 \times X_{alpha} - X| \\ X_2 &= |C_2 \times X_{beta} - X| \\ X_3 &= |C_3 \times X_{delta} - X| \end{aligned} \tag{12}$$

$X(t+1)$is achieved by utilising equation (13):

$$X(t+1) = \frac{1}{3}X_1 + \frac{1}{3}X_2 + \frac{1}{3}X_3 \tag{13}$$

For other rounds, these positions are updated by utilising one case as given in the equation (14), (15), (16) & (17) respectively:

For Case-1*:*

$$\begin{aligned} D_{alpha} &= |C_1 \times Fit_{alpha} - Fit_X| \\ D_{beta} &= |C_2 \times Fit_{beta} - Fit_X| \\ D_{delta} &= |C_3 \times Fit_{delta} - Fit_X| \\ X_1 &- Fit_{alpha} - A_1 \times D_{apha} \\ X_2 &- Fit_{beta} - A_2 \times D_{beta} \\ X_3 &- Fit_{delta} - A_3 \times D_{delta} \\ X(t+1) &= \frac{1}{3}X_1 + \frac{1}{3}X_2 + \frac{1}{3}X_3 \end{aligned} \tag{14}$$

For Case-2*:*

$$\begin{aligned} X_1 &- Fit_{alpha} - A_1 \times D_{apha} \\ X_2 &- Fit_{beta} - A_2 \times D_{beta} \\ X_3 &- Fit_{delta} - A_3 \times D_{delta} \\ X(t+1) &= \frac{1}{3}X_1 + \frac{1}{3}X_2 + \frac{1}{3}X_3 \end{aligned} \tag{15}$$

For Case-3*:*

The modified version of WA and GW is introduced. This aims to have a faster convergence by updating the position of wolves' based on including the size that is proportional to the individual fitness in search space, which is given in the current generation.

$$X(t+1) = \frac{1}{\text{iteration}}^{\frac{Fit_{alpha} - Fit_X}{Fit_{alpha} - Fit_{worst}}} \quad (16)$$

For Case-4*:*

$$X(t+1) = \left| \frac{Fit_{alpha} - Fit_X}{Fit_{alpha} - Fit_{worst}} \right| \quad (17)$$

D. Attacking Prey (Exploitation):

The exploitation is advanced when $-1 < A < 1$. The balance between investigation and exploitation is expected to find the exact estimation worldwide using stochastic algorithms. This balance is done in GWA with lessening behaviour of parameter in the condition for boundary A. With limiting, a half search is given to the investigation ($A \geq 1$), as shown in Figure 4.

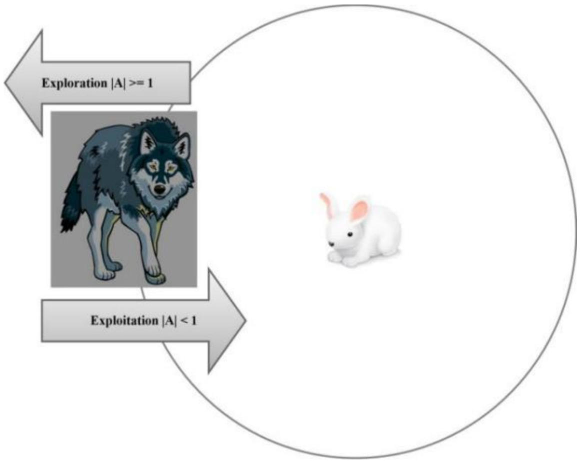

Figure 4. Explore/Exploit Estimation by Grey Wolf for Boundary Condition |A|

E. Termination-condition:

In this condition, there are three models: if the number of the cycles is perceived, the union to an ideal when it does not know about an ideal worth at that point, no progressions are required after the specific number of reiterations. In this, the end condition has been finished by a given number of iterations. Our main goal is to reduce the function of fitness, selecting the node with more neighbourhoods, more energy, and more memory space. This function of fitness is defined in equation (18):

$$\begin{aligned} &\text{fitness}(i) = coe_{f1} \times \text{NumberofNeighbors} \\ &+ coe_{f1} \times \text{CurrentBatteryPower}(i) \\ &+ coe_{f3} \times \text{Capacity}(i) + \text{Suitability}(i) \end{aligned} \quad (18)$$

Where:

$$coe_{f1} = 0.2$$
$$coe_{f2} = 0.3$$
$$coe_{f3} = 0.5$$

These coefficients are selected based on the priority. That means we have more memory space node (coe_{f3}), remaining energy (coe_{f2}), and neighbourhood (coe_{f1}). This can solve the problem of buffer overflow and reduce data loss as much.

Here, we described the parameters of the fitness function in detail. The node location is computed in equation (19). Where DistMaxToBS and DistMinToBS can be formulated through equation(20) and (21). The coordinates $(X_{min}, Y_{min}) = (100,100)$ and $(X_{max}, Y_{max}) = (0,0)$ show the closest and utmost points from the BS.

$$\text{Location}(i) = \begin{cases} \text{if } i! = \text{farthest and closest node from BS} \\ \dfrac{\text{DistMaxToBS} - \text{Dist}(i)\text{ToBS}}{\text{DistMaxToBS} - \text{DistMinToBS}} \\ \text{other situations} \end{cases} \tag{19}$$

$$\text{DistMaxToBS} = \max\left(\sqrt{(X_{min} - X_{BS})^2 + ((Y_{min} - Y_{BS})^2)}\right) \tag{20}$$

$$\text{DistMinToBS} = \min\left(\sqrt{(X_{max} - X_{BS})^2 + ((Y_{max} - Y_{BS})^2)}\right) \tag{21}$$

In order to compute the neighbourhood node, we assume the radius. Utilising the uniform clustering method in the randomly arranged network can generate the structure of an unbalanced network. The radius utilised to discover the neighbour nodes which is computed as equation (22):

$$R = \sqrt{\frac{A}{\pi \times k}} \tag{22}$$

Where $A = M \times M$ is a network area and an optimum number of the clusters is k. We utilise k as the following:

The nodes are placed in an area S with $(d < d_0)$. Furthermore, the dissipation of energy is transmitted 1-bit of a message in CH is given in equation (23):

$$E_{CH} = E_{Tx} + E_{Rx} + E_{DA} \tag{23}$$

$$= \left(l \times E_{elec} + l \times \epsilon_{fs} \times d^2_{ToBS}\right) + \left(\left(\frac{N}{k} - 1\right) \times l \times E_{elec}\right)\left(\frac{N}{k} \times E_{DA}\right)$$

Where, d^2_{ToBS} is defined as the distance from BS to CH. The dissipated energy from another-nodes is calculated as given in equation (24):

$$E_{nonCH} = T_{Tx} = l \times E_{elec} + l \times \epsilon_{fs} \times d^2_{ToCH} \tag{24}$$

The sensing area is formulated by several clusters that have the CHs as a center. It is computed as below equation (25):

$$S = \left(2 \times \pi \times d^2_{ToCH}\right) \times k \simeq A \tag{25}$$

From equation (26), we minimise the separation m distance as a node from CH:

$$d^2_{ToCH} = \frac{A}{2 \times \pi \times k} \tag{26}$$

So:

$$d^2_{nonCH} = l \times E_{elec} + l \times \epsilon_{fs} \times \frac{A}{2 \times \pi \times k} \tag{27}$$

Now, the energy-dissipated cluster is defined in 1-frame is calculated as below equation (28) respectively:

$$E_{cluster} = l \times \left(E_{CH} + \frac{N}{k} \times E_{nonCH}\right) \tag{28}$$

The total energy is calculated as below equation (29):

$$E_{Total} = k \times E_{cluster} = k \times l \times \left(E_{CH} + \frac{N}{k} \times E_{nonCH}\right) \tag{29}$$

To discover k, several formed clusters in the round, we compare equation (30) to 0 and differentiate with k:

$$k = \left(\frac{\sqrt{N \times A}}{\sqrt{2 \times \pi}} \times \frac{1}{d_{toBS}}\right) \times 100 \tag{30}$$
$$= \frac{\sqrt{(1-(m_1+m_2)\times N + m_1 \times N + m_2 \times N \times A)}}{\sqrt{2 \times \pi}} \times \frac{100}{d_{toBS}}$$

Where the number of SNs is N computed from equation (4) and d_{toBS} is defined as an average distance through the node to the BS, which is simplified by equation (31):

$$d_{toBS} = 0.765 \times \frac{A}{2} \tag{31}$$

The maximising number of the clusters leads to the smaller size of the cluster distribution in terms of energy consumption. A fixed cluster count maximises the SN stability. Since our goal is to maximise the fitness function in order to compute the capacity of the memory node, we use the fractions among the remaining space. The fitness function is being calculated as in equations (32), (33) & (34) respectively:

$$\text{Capacity}(i) = \frac{BS(i)}{BS(i) - \text{CurrentBufferSize}(i)} \tag{32}$$

Node energy is computed by using the fraction among initial node energy; an IBP remaining energy is given in equation (33):

$$\text{Energy}(i) = \frac{BP(i)}{BP(i) - \text{CurrentBatteryPower}(i)} \tag{33}$$

One of the last fitness-function parameters is computed in the below equation:

$$\text{Suitability} = \frac{\text{CurrentBatteryPower}(i)}{\text{Energy}(i) - \text{Location}(i)} \tag{34}$$

Algorithm: Pseudocode of Cluster head selection using Grey Wolf Optimizer

Requirement: Wireless Sensor Network consisting of N nodes

Ensure: CH nodes

- Initialize grey wolf population Xi (i = 1, 2, . . . , n)
- Initialise a, A and C
- Calculate the fitness of each agent
- Choose the three best solutions: Xalpha, Xbeta and Xdelta

While Iteration< max number of Iteration do

For each search agent, do

Update the position of the current search agent

If round =0 then

Use Formulas 11,12 &13.

else

Use cases 1,2,3 & 4

end if

end for

Update a, A and C

Calculate fitness of all search agents

Update Xalpha, Xbeta and Xdelta

iteration = iteration + 1

end while

return CHs

F.Data Transmission:

Once the clustering process is complete, the nodes will transmit their data to the relevant CH. In this example, the cluster is separated into different areas. There is an established protocol whereby each member learns to wait for the data from the previous level and then pass it on to the next higher level. Once the CH has collected all of the necessary information from its constituents, he will forward that information to the BS.

5. Results and Discussion

To implement the proposed GWO algorithm, we have used MATLAB 2017 version, which requires a desktop of 1TB hard disk, 4GB RAM, Intel i3 Processor. To simulate the results in MATLAB we considered 100 nodes which are deployed randomly, and Base station BS position (50,150),(100,100),(50,50). For better understanding, we have deployed only 10 nodes; its positions, occupied memory, and current power and fitness values have been tabulated in Table I, as shown below. Node deployment and cluster head selection are shown in Figure 5 and Figure 6. These nodes have been deployed randomly, and cluster head selection is done based on fitness value. We notice by the figure that the CH is positioned in a strategic place to receive the maximum of data. According to the below table, node 9 (121,304446822) max fitness value is having; hence, node 9 is selected as cluster head using the Gray Wolf Optimization Algorithm. The selection of cluster head is not always a unique node when we run iteration by iterations; cluster head selection is dynamic based on the fitness values.

Table 5.1. Different Parameters the Nodes

Nodes	X	Y	Occupied Memory	Current battery Power	Fitness Values
1	78	59	32	0.266297	113,293041842
2	7	96	16	0.265841	120,391234588
3	95	22	32	0.266285	113,142636991
4	74	77	8	0.26583	24,870323651
5	77	89	1	0.266274	64,851620409
6	67	37	64	0.265818	97,37376436
7	57	25	32	0.266263	113,473284611
8	72	18	16	0.265816	121,23507957
9	78	53	16	0.266252	121,304446822
10	8	8	16	0.265806	120,251344027

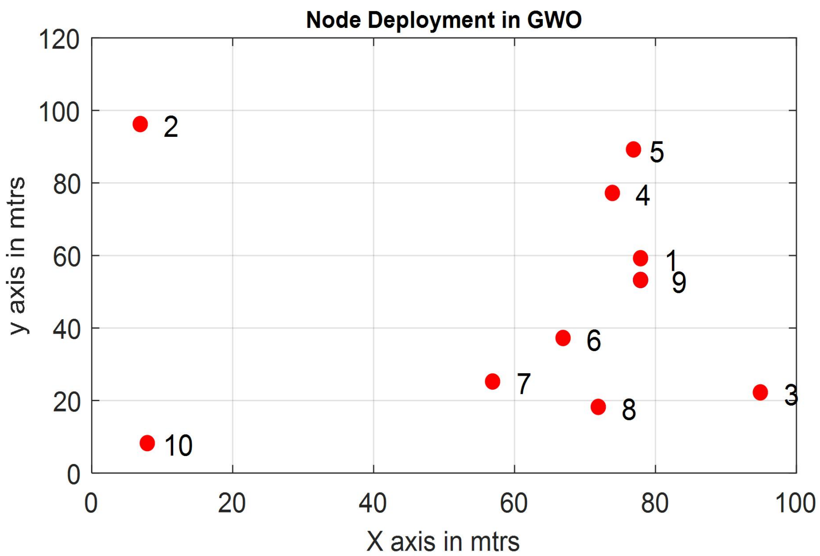

Figure 5. Node Deployment Using GWO

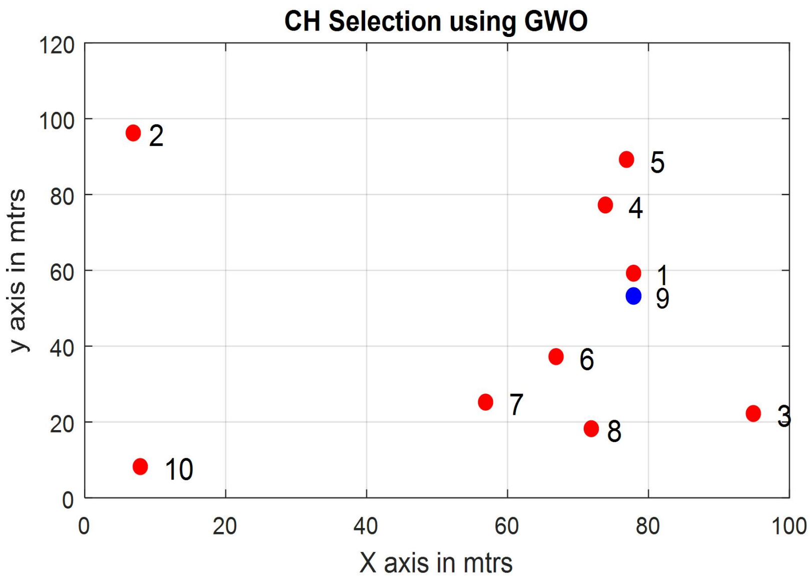

Figure 6. CH Selection using GWO

5.1.Experimental Setup

To Implement the GWO algorithm, we have considered a network area of 100x100 m2. Simulations are done in three different scenarios; in the first network, we have used 50 nodes; in the second network we have used 100 nodes; and in the third network, we have used 250 nodes. The base station is also varied with the different positions, as shown in Table 5.2. BS position (50,50); (100,100); (50,150). Initially, BS is placed within the sensing network area (50x50); in the second simulation, BS is deployed in the edges of the sensing area (100x100); in the third simulation, BS is placed in the out-of-sensing area (50x150); for every simulation with respect to BS, we have recorded and tabulated simulation results. The various parameters considered for simulations are given in Table 5.2.

Table 5.2. Network Parameters

Sl no	Parameter	Value
1	Target Area	100x100 m2
2	BS position	(50,50); (100,100); (50,150)
3	Number of nodes	50 -100 - 250
4	Initial energy of node	2J or 4J
5	Buffer size	2^24bits
6	Transmitter/Receiver electronics	50nJ/bit
7	Transmitter amplifier (free space) -εfs	100pj=bit=m2
8	Transmitter amplifier (multipath) - εmp	0:013pJ=bit=m4
9	Data aggregation energy cost - EDA	50nJ=bit
10	Packet size	4000bits
11	Number of iterations	Variable

By considering Different BS location (50,50), (100,100) and (50,150) we have simulate and tabulated the results in the below Table 5.3. and we could see when BS is at the center of the sensing area, at the end of simulation time we could see only 21% of the alive nodes, and in case BS location at the edge is also more or less equal number of alive nodes but if the BS location is situated outside the network area have only 8% alive nodes which states the more power is required outside the network area. Energy consumption is higher if BS is placed outside the sensing area, and nodes will die very fast. The same is displayed in the Figure 7 below.

Table 5.3. Number of Alive Nodes

Time	BS position		
	(50,150)	(100,100)	(50,50)
0	100	100	100
200	60	85	86
400	40	65	70
600	25	50	60
800	28	40	50
1000	25	40	43
1200	22	35	38
1400	18	30	32
1600	15	25	27
1800	11	21	23
2000	8	20	21

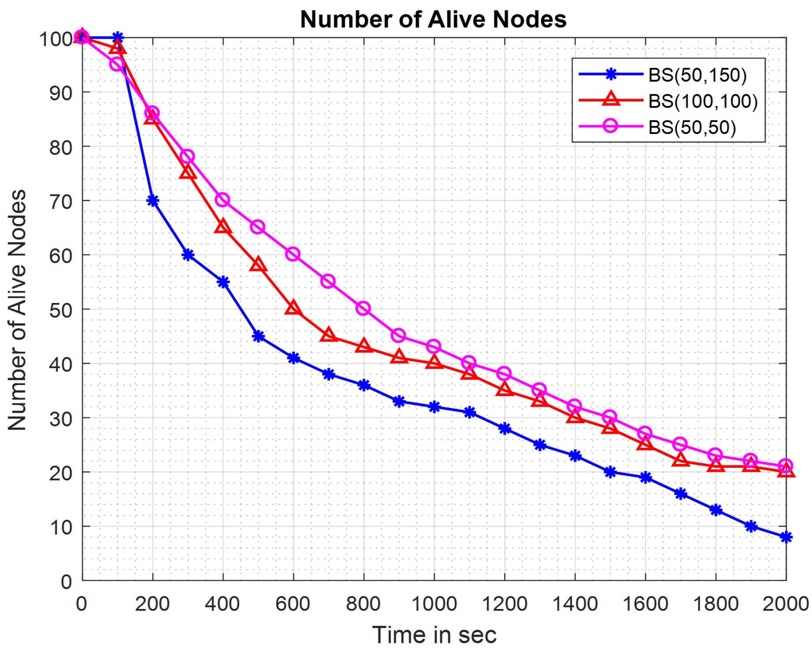

Figure 7. Number of Alive Nodes with Different BS Positions

Figure 8 illustrates the outcomes from varying Base Station (BS) locations at coordinates (50, 50), (100, 100), and (50, 150), with the results derived using the Grey Wolf Optimizer (GWO) algorithm. The data indicates a clear trend: as the BS moves further from the monitored area, the lifespan of the sensors decreases. Notably, when the BS is positioned at the network's center, the volume of data collected is significantly higher.We run the simulation and tabulated the results for BS location (50, 50), (100,100) (50,150) with respect to Data packets received and one can observe the data packets received when BS at centre & the edge is almost same and particularly 15.6% increase as compared to the outside the BS (50,150) and the same is plotted as shown in below Figure 8 & Table 5.4.

Table 5.4. Data Packets Received

Time (s)	BS position		
	(50,150)	(100,100)	(50,50)
0	0	0	0
200	12000	12000	12000
400	18000	18000	18500

600	20200	20500	21500
800	21000	22500	23500
1000	21800	23500	24500
1200	22000	24500	25500
1400	22500	25800	26500
1600	22800	27500	28000
1800	23000	29500	29000
2000	23200	30800	31000

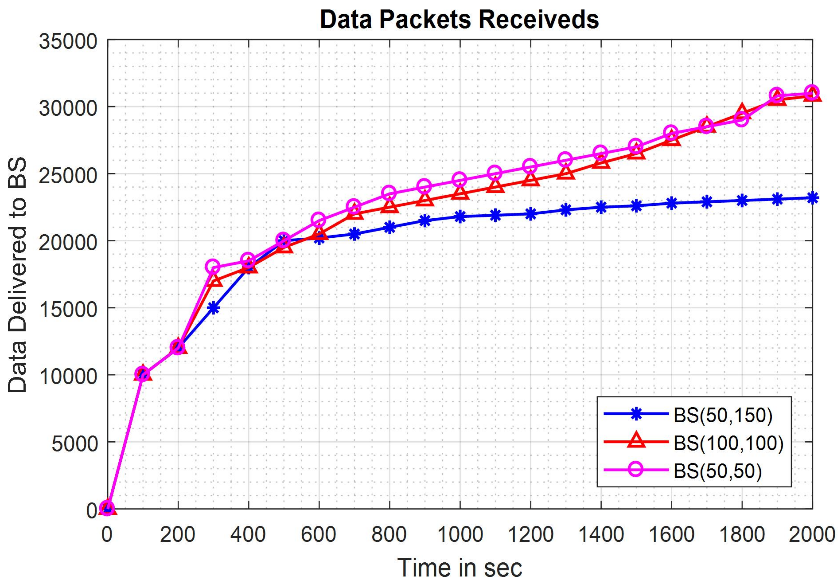

Figure 8. Data packets Received with Different BS Position

It can clearly say that by seeing graph BS location (50, 50) shows better packet deliver ratio than BS location (100,100) (50,150). We implemented and simulated GWO algorithm with different BS location (50, 50), (100,100) (50,150). We have simulated and tabulated the results for BS location (50, 50), (100,100) (50,150) with respect Energy consumed by nodes and also we plotted the graph as shown in Figure 9 & Table 5.5, respectively. We can clearly conclude that by seeing the graph BS located at BS (50, 50) consumes less Energy compared to BS located at the outside (50,150). Almost 15-17% of energy consumption is less when BS is situated at the centre.

Table 5.5. Energy Consumed By Nodes

Time(s)	**BS position**		
	50,150	**100,100**	**50,50**
0	0	0	0
200	140	130	125
400	155	145	143
600	170	155	150
800	180	165	161
1000	188	173	168
1200	193	180	173
1400	196	188	180
1600	200	192	185
1800	210	195	195
2000	230	200	200

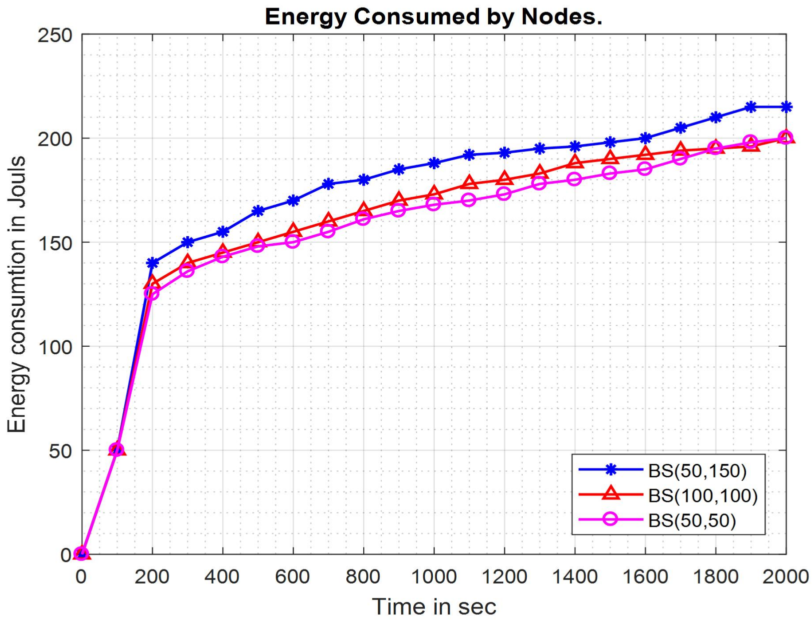

Figure 9. Energy consumed by Nodes with Different BS Positions

5.2.Comparison of GWO Algorithm with Standard Protocols

Results that we obtained from the Grey Wolf Optimization (GWO) algorithm have been compared with some of the standard Protocols such as LEACH and PEGASIS. When the number of clusters equals k, k + 5, k + 10 and k + 15, (k=50), the number of alive nodes is more in GWO than LEACH and PEGASIS, which is tabulated in below Table 5.6 and also depicted in Figure 10. Hence, we can say that the GWO algorithm gives 10%-12% better performance in terms of the alive nodes as compared to standard protocols, as shown in Table 5.6.

Table 5.6. Number of Alive Nodes

Iterations / **Protocols**	**k**	**k+5**	**k+10**	**k+15**
GO	94	95	96	98
LEACH	85	87	90	92
PEGASUS	85	86	88	90

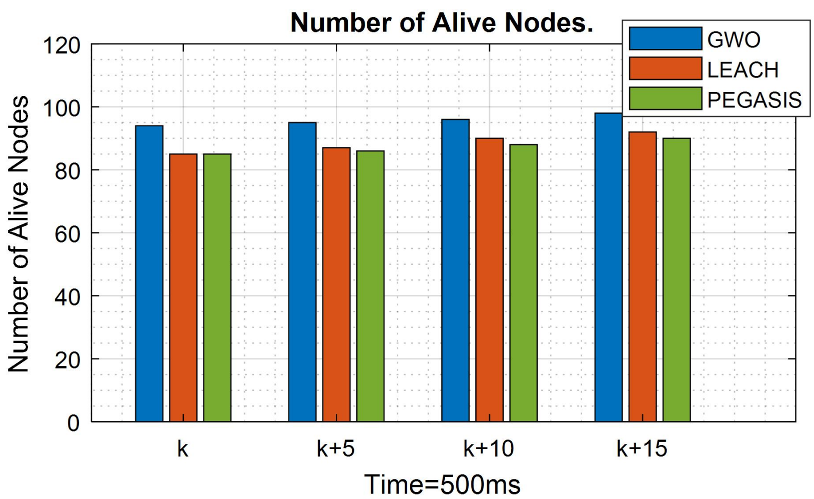

Figure 10. Number of Alive Nodes Comparison

When the number of clusters equals k, k + 5, k + 10 and k + 15, (k=50) Data packets received are more in GWO than LEACH and PEGASIS, which is tabulated in the below Table 5.7 and also depicted in Figure 10, as the number of alive nodes is more hence data packets received is also more. Hence, we can show that the GWO algorithm shows better performance than existing protocols, as displayed in Table 5.7. Nearly 9- 14 % there is an increase in the received data packets as compared to other protocols.

Table 5.7. Data Packets Received Comparison

CH / Protocol	k	k+5	k+10	k+15
GO	8474	8872	10303	10600
LEACH	7800	8050	9500	9950
PEGASUS	7500	7950	9250	8580

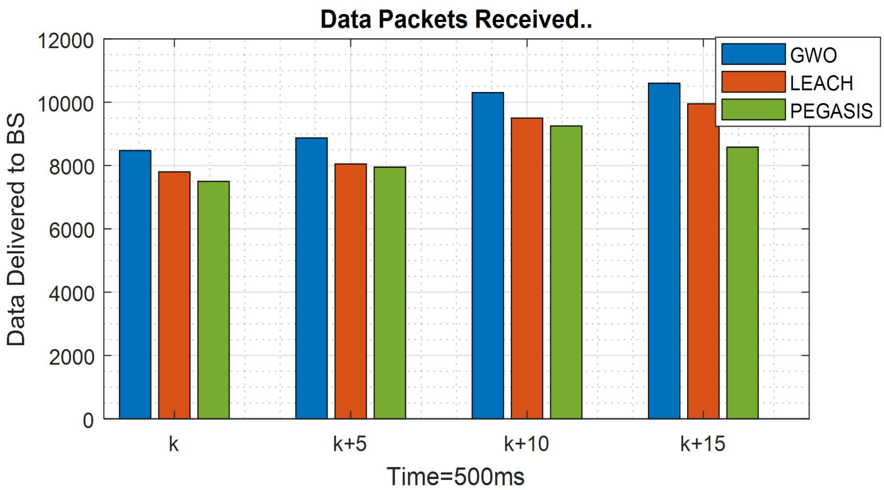

Figure 11. Data Packets Received Comparison

As the number of cluster heads (k=50) is varied to k, k + 5, k + 10 and k + 15, Energy consumed by nodes is less in GWO than LEACH and PEGASIS, which is tabulated in below Table 5.8 and also depicted in Figure 12. Hence we can conclude that GWO algorithm efficiently selects the cluster heads which gives better performance in terms of less energy consumption than with other existing protocols. Almost about 11-12% of the energy is consumed less in the proposed approach as you vary the number of clusters compared to the standard protocol, displayed in Table 5.8.

Table 5.8. Energy Consumed by Nodes

CH / Protocol	k	k+5	k+10	k+15
GO	44	45	64	51
LEACH	52	50	76	60
PEGASUS	56	52	80	65

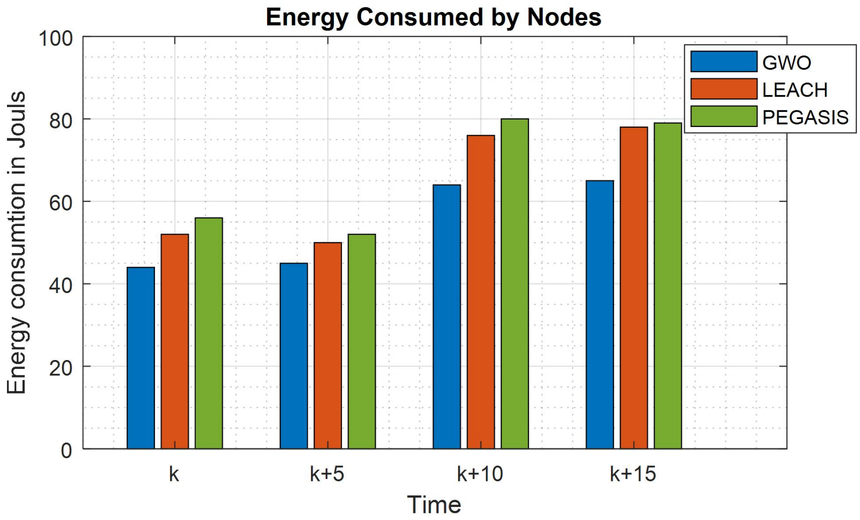

Figure 12. Energy Consumed by Nodes Comparison

The performance of the GWO algorithm is also compared by its simulation time with some of the standard Protocols such as LEACH and PEGASIS. Table 5.9 shows the recorded simulation time where we recorded from 0 ms to 2000 ms. We noted a number of alive nodes of each standard protocol, and we plotted the graph as shown in Figure 13. When we run simulation time up to 2000 ms, the GWO algorithm shows better results compared to standard protocols, as we can see in the graphs clearly and Tabulation in Table 5.9.

Table 5.9. Number of Alive Nodes

Protocols / **Time(s)**	**GO**	**LEACH**	**PEGASUS**
0	100	100	100
200	85	80	80
400	65	63	61
600	45	40	38
800	35	30	28
1000	25	20	18
1200	20	16	15
1400	19	14	12
1600	16	12	8
1800	12	8	6
2000	8	5	5

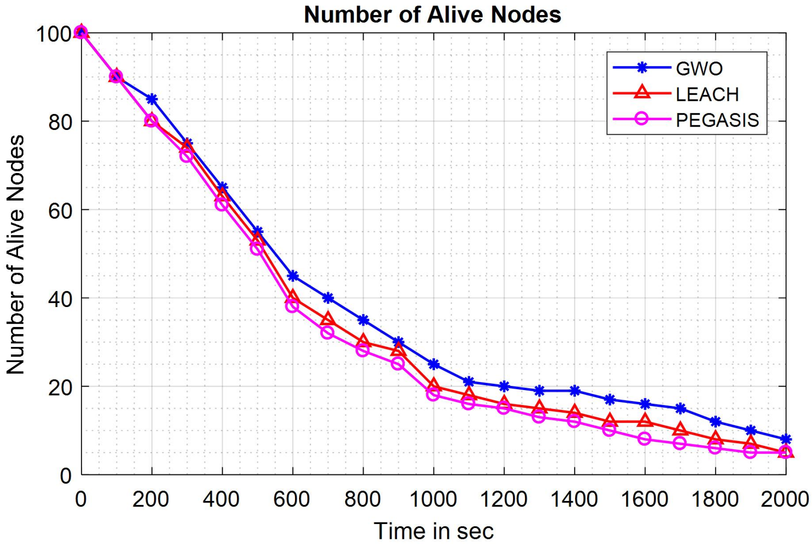

Figure 13. Number of Alive Nodes Comparison with Simulation Time

The performance of the GWO algorithm is also compared by its simulation time with some of the standard Protocols such as LEACH and PEGASIS. Table 5.10 shows the recorded simulation time where we recorded from 0 ms to 2000 ms. We noted the number of Data Packets Received by each standard protocol, and we plotted the graph as shown in Figure 14. When we run simulation time up to 2000 ms. At the end of simulation time, our GWO algorithm has more number of alive nodes compared to Leach & Pegasis.

Table 5.10. Data Packets Received

Protocol Time(s)	GO	LEACH	PEGASUS
0	0	0	0
200	10000	8000	6000
400	15200	14000	8000
600	15400	14800	11000
800	15500	15100	12500
1000	15650	15300	13500
1200	15800	15500	13900
1400	16500	15800	14200
1600	17000	16000	14800
1800	17000	16500	15200
2000	17000	16500	15800

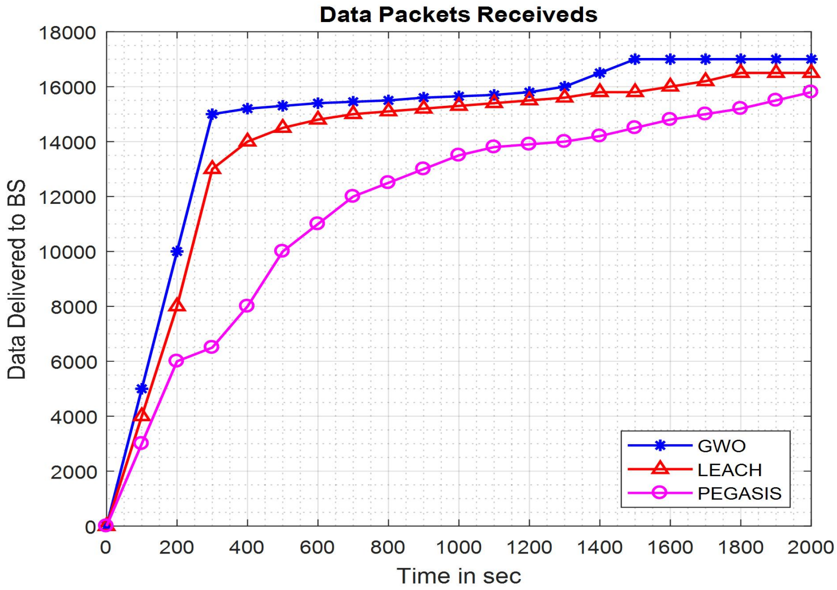

Figure 14. Data Packets Received Comparison with Simulation Time

The performance of the GWO algorithm is also compared by its simulation time with some of the standard Protocols such as LEACH and PEGASIS. Table 5.11 shows the recorded simulation time, where we recorded from 0 s to 2000s, when we run simulation time up to 2000s GWO algorithm shows better results compared to standard protocols as we can observe in Table 5.11 & Figure 15 respectively. About 8-12% of energy consumption is less by the proposed method.

Table 5.11. Energy Consumed by Nodes

Protocol / Time (s)	GO	LEACH	PEGASUS
0	0	0	0
200	150	160	160
400	170	175	185
600	180	190	200
800	190	200	215
1000	198	210	225
1200	200	230	235
1400	200	240	245
1600	200	250	250
1800	200	250	265
2000	200	250	270

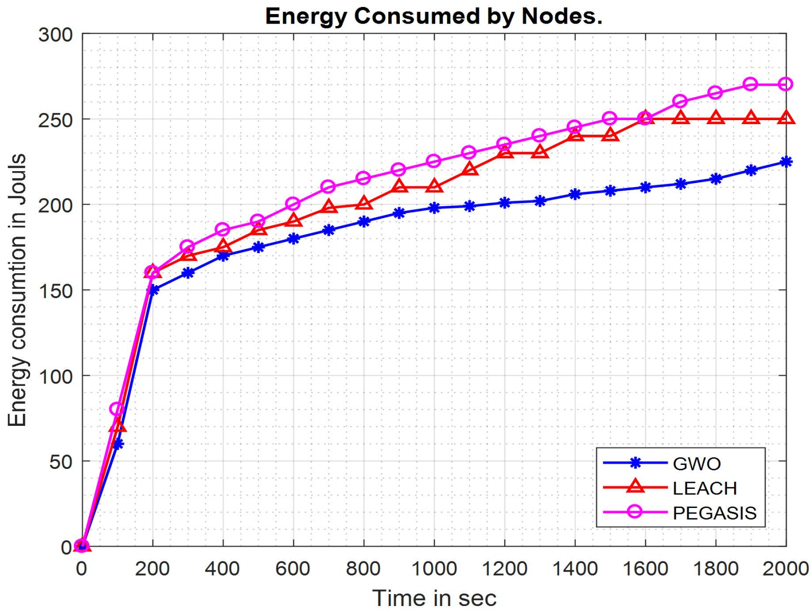

Figure 15. Energy Consumed by Nodes Comparison with Simulation Time

6. Conclusion

The exploration of swarm intelligence, inspired by the collective behaviour of social creatures like grey wolves, has become a focal point in research. This study introduces a Grey Wolf Algorithm (GWA) tailored to address data congestion issues within diverse network environments. The algorithm's performance was assessed against established protocols such as LEACH and PEGASIS, using various metrics for comparison. The findings indicate that GWA consistently surpasses its counterparts, particularly in expansive networks with fewer than 100 nodes. The analysis took into account different placements of the base station—central, peripheral, and external to the network grid. To mitigate buffer overflow at the Cluster Head (CH), our approach integrates nodes with lower sampling rates and higher storage capacities to serve as auxiliary data repositories for the CH. Additionally, secondary CH roles, beta and delta, are designated to support the alpha CH by temporarily caching data, thereby extending buffer capacity and minimising data loss. This strategic CH selection contributes to a 5-7% extension in node longevity and an 8% improvement in network throughput, thereby enhancing overall network durability and efficiency.

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