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Leveraging Gradient based Optimization based Unequal Clustering Algorithm for Hotspot Problem in Wireless Sensor Networks

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ABSTRACT

Wireless sensor networks (WSNs) serve as the basic unit of the Internet of Things (IoT). Because of their low prices and potential use, in recent years, wireless sensor networks (WSNs) have garnered attention for various uses. Then sensor nodes (SN) can prepared with limited battery is critical energy utilization be monitored closely. Hence, reducing the node energy utilization is obviously vital to extending the network lifespan. Clustering is an effectual manner for diminishing energy utilization in WSNs. In a multi-hop clustered network condition, every SN transfers data to its individual cluster head (CH), and the CH gathers the information from its member nodes and relays it to base station (BS) using other CHs. Conversely, the "hotspot" issue is inclined to take place in clustered WSNs while CHs near the BS are heavier intercluster forwarding tasks. In this article, we leverage Gradient based Optimization based Unequal Clustering Algorithm for Hotspot Problem (GBOUCA-HP) technique in the WSN. The GBOUCA-HP technique is applied to get rid of the unequal clustering process in the WSN using metaheuristic algorithms. The GBOUCA-HP technique focuses on the optimization of energy usage, resolving hot spots, and extending the network lifespan. In the GBOUCA-HP technique, the GBO algorithm is based on two concepts such as diversification and intensification search and the gradient-based Newton's phenomena. Moreover, the GBOUCA-HP technique adaptive selects the CHs with varying cluster sizes for diverse energy levels and computation abilities of the nodes. The widespread set of simulations and evaluations shows the effective performance of the GBOUCA-HP technique. The GBOUCA-HP technique is found to be a significant approach to tackling the hotspot issue in the WSN with the intention of decreasing energy consumption optimization and enhancing network efficiency.

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1. INTRODUCTION

Wireless Sensor Networks (WSNs) are designed to monitor and identify the crucial indications of the surroundings and field by employing interconnected and distributed sensor nodes (SNs) [1]. The SNs are categorized into Gateway Nodes (GN), sink nodes, and normal nodes. The SNs have smaller dimensions and insufficient resources with respect to storage space, processing, and energy [2]. In many states, the SNs are utilized in highly robust and hostile surroundings. The major goal of this utilization is to remotely detect the data and it is transmitted to the system or end-user for decision-making. In data transmission, there is a requirement for highly effectual techniques for controlling the energy system of nodes and increasing the lifespan of network [3]. The SNs identify and observe the data in the ambient environment and it processes and transfers to the nearby node until the data is received in the base station (BS). In WSN, there is an important necessity for an effectual and balanced data combination method and energy-efficient routing protocols because of the restricted energy resources of SNs [4]. The energy parameter is persistently the most significant factor for developing some solutions for WSNs. Various types of routing protocols are offered to preserve the energy of SNs. The clustering method is an effectual topological control mechanism that will excellently increase the lifetime and scalability time of WSNs. The applications of WSNs have gained popularity comprising health monitoring, disaster response, target monitoring, ecological monitoring, and security [5].

The majority of optimum methods for enhancing energy becomes clustering. In clustering, some clustering techniques could be utilized to choose cluster heads (CHs) from the normal nodes. Afterwards, the CH selection (CHS), the residual nodes at a cluster with the adjacent CH [6]. Unequal clustering (UC) decreases the dimensions of the clusters that are nearer to BS, and if the distance to BS is increased, the size of clusters improves [7]. The dimension of the cluster is closely compared to the distance between CHs and BS. This method of clustering specifies to decrease of cluster members in the clusters near BS, which minimizes the intra-cluster overhead [8]. Accordingly, clusters with tiny sizes take less energy in intra-cluster links than large cluster sizes and more consideration on the inter-cluster traffic [9]. The improvement of UC is to permit the CHs to utilize the same quantity of energy, wherein the CHs that are near to BS consume around similar quantity of energy such as CHs not adjacent to BS [10]. Therefore, UC method prevents hot-spot problems by producing a balance in energy consumption.

This article presented a Gradient based Optimization based Unequal Clustering Algorithm for Hotspot Problem (GBOUCA-HP) technique in the WSN. The GBOUCA-HP technique is applied to get rid of the UC process in the WSN using metaheuristic algorithms. The GBOUCA-HP technique focuses on the optimization of energy usage, resolving hot spots, and extending the network lifespan. In the GBOUCA-HP technique, the GBO methodology, is based on two concepts such as diversification and intensification search and the gradient-based Newton's phenomena. Moreover, the GBOUCA-HP technique adaptive selects the CHs with varying cluster sizes for diverse energy levels and computation abilities of the nodes. The widespread set of simulations and evaluations shows the effective performance of the GBOUCA-HP technique.

2. LITERATURE SURVEY

Wireless Sensor Networks (WSNs) have emerged as a pivotal technology in various applications, including environmental monitoring, healthcare, and smart city initiatives. As these networks become increasingly prevalent, the challenge of optimizing energy consumption has gained paramount importance. Energy efficiency is critical for prolonging the operational lifetime of sensor nodes, which are often deployed in remote or resource-constrained environments. This literature survey explores recent advancements in energy-efficient routing and clustering techniques within WSNs, highlighting innovative methodologies aimed at addressing this challenge.

In [11], an innovative technique for IoT-enabled WSNs named the Fire Hawk Optimizer-based UC method for Hotspot Mitigation (FHOUCS-HSM) model was presented. This method employed a 1st order radio energy system. The FHOUCS-HSM algorithm tracks the foraging features of black kites, brown falcons, and whistling kites. Besides, the method estimates a fitness function (FF) for the usage of UC dimension and the CHS. In [12], a Grey wolf optimization (GWO) algorithm based CHS method was developed for WSN with different parameters like priority factor, node degree, node energy level, intra-cluster distance, and distance of sink. In [13], a Hybrid Optimizer based UC with Mobile Sink (HOUCMS) methodology has been projected. Primarily, butterfly optimization (BO) has been utilized for CHS, later the nodes should be allocated to the CHs dependent upon the opposition radius standard at UC system. The HOUCMS was analyzed by employing different SNs and sequences.

Alsolai et al. [14] designed an improved tuna-swarm-algorithm-based UC for hotspot elimination (ITSAUC-HSE) method. Besides, the ITSAUC-HSE method calculates a fitness value dependent upon distance and energy metrics. In [15], a hybrid of FL method and harmony search (HS) method was developed. UC was a method developed by the research workers to deal with the hot-spot complexity; therefore, it should be also considered. The developed technique makes UCs. To demonstrate the effectiveness of the developed method, a few popular UC methods and HS-based techniques have been employed for comparison with the developed technique under diverse network settings. In [16], a new enhanced routing method was developed for mitigating hot-spot complexity (NORTH) for WSN-assisted IoT. The proposed model utilizes the TSA algorithm for optimizing the cluster-based routing, particularly the CHS of every cluster by employing a few innovative factors, which comprises load balancing, node distance from the sink and alternative nodes, energy conditions, network's average energy storage, and node proximity.

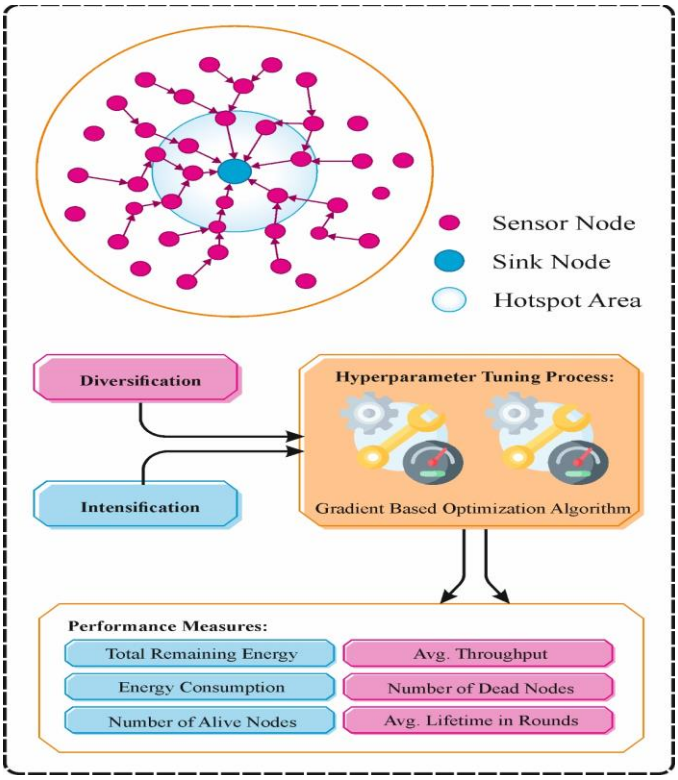

Figure 1. Overall process of GBOUCA-HP technique

Jain et al. [17] proposed a hybrid gradient field-based routing protocol that addresses both energy efficiency and congestion in WSNs. Their approach leverages gradient fields to dynamically adjust routing paths based on energy levels and traffic conditions, thereby prolonging network lifespan and improving data delivery rates. This work highlights the importance of considering both energy and congestion in routing strategies to enhance overall network performance. Zhou and Liu [18] introduced a genetic algorithm (GA)-based clustering approach for WSNs. Their method focuses on optimizing cluster head selection and formation, which is crucial for minimizing energy consumption during data transmission. By utilizing GA, the authors effectively balance the load among sensor nodes, ensuring that energy is utilized efficiently and extending the network's operational lifetime. Sharma et al. [19] explored the use of reinforcement learning (RL) for adaptive clustering in WSNs. Their proposed algorithm dynamically adjusts the clustering process based on real-time network conditions and energy availability. The RL-based approach enhances the adaptability of the network, allowing it to respond to varying environmental factors and ensuring efficient energy utilization. Kumar and Singh [20] presented a routing protocol based on Grey Wolf Optimization (GWO) that targets energy efficiency in WSNs. Their protocol selects optimal paths for data transmission by mimicking the hunting behavior of grey wolves, thereby reducing energy consumption and improving data transmission reliability. This bio-inspired approach demonstrates the potential of natural algorithms in solving complex optimization problems in WSNs. Yadav et al. [21] proposed a hybrid clustering approach that combines Particle Swarm Optimization (PSO) and Simulated Annealing (SA) to enhance energy efficiency in WSNs. Their method optimizes cluster formation and head selection, leading to reduced energy consumption and improved network performance. The integration of PSO and SA provides a robust framework for tackling the challenges associated with energy management in WSNs. Mirjalili [22] introduced the Ant Lion Optimizer (ALO), a novel metaheuristic algorithm inspired by the hunting mechanism of ant lions. Although not specifically focused on WSNs, ALO has potential applications in optimizing various parameters within WSNs, such as routing and clustering. The algorithm's efficiency in exploring the solution space makes it a valuable tool for addressing energy-related challenges in WSNs. Devika and Shaby [23] proposed a deep reinforcement learning-assisted Butterfly Optimization Algorithm applied to the MOD-LEACH routing protocol. This innovative approach enhances energy efficiency by optimizing the selection of cluster heads and the routing paths based on the dynamic learning of network conditions. The integration of deep learning techniques with traditional optimization algorithms represents a significant advancement in the field of WSNs. Wireless Sensor Networks (WSNs) have emerged as a pivotal technology in various applications, including environmental monitoring, healthcare, and smart city initiatives. As these networks become increasingly prevalent, the challenge of optimizing energy consumption has gained paramount importance. Energy efficiency is critical for prolonging the operational lifetime of sensor nodes, which are often deployed in remote or resource-constrained environments. This literature survey explores recent advancements in energy-efficient routing and clustering techniques within WSNs, highlighting innovative methodologies aimed at addressing this challenge.

The reviewed works encompass a range of approaches, from bio-inspired algorithms to machine learning techniques, each contributing to the enhancement of energy management in WSNs. For instance, Jain et al. (2021) introduced a hybrid gradient field-based routing protocol that considers both energy levels and traffic conditions, while Zhou and Liu (2021) employed a genetic algorithm to optimize cluster head selection. Furthermore, the integration of reinforcement learning, as demonstrated by Sharma et al. (2021), showcases the adaptability of clustering processes to real-time network conditions.

Other notable contributions include Kumar and Singh's (2020) Grey Wolf Optimization-based routing protocol and Yadav et al.'s (2020) hybrid PSO-SA clustering approach, both of which emphasize the importance of energy efficiency. Additionally, the exploration of deep reinforcement learning-assisted methods, as presented by Devika and Shaby (2024), exemplifies the potential of combining traditional optimization algorithms with modern machine learning techniques to tackle energy-related challenges. This literature survey not only summarizes these significant contributions but also addresses the practical challenges associated with deploying these methods in real-world scenarios. By examining the current state of research, this survey aims to provide insights into the ongoing efforts to optimize energy consumption in WSNs and to identify future research directions that could lead to more robust and scalable solutions in the evolving landscape of wireless sensor networks.

Despite the developments in wireless sensor networks (WSNs) and the application of different clustering algorithms, there remains a substantial gap in handling the hotspot issue efficiently while reducing energy consumption and boosting network lifetime. Most present techniques largely concentrate on either energy efficiency or hotspot avoidance, sometimes disregarding the relationship between these two crucial elements. Furthermore, many clustering algorithms do not adaptively pick cluster heads (CHs) based on the various energy levels and processing capabilities of sensor nodes, resulting to poor energy consumption and probable network failures. Moreover, although the Gradient based Optimization based Unequal Clustering Algorithm for Hotspot Problem (GBOUCA-HP) exhibits promising results, there is little comparison study with other state-of-the-art algorithms in real-world settings. The efficiency of GBOUCA-HP under varied network circumstances, node density, and dynamic settings remains underexplored. Additionally, the scalability of the GBOUCA-HP approach in larger networks and its performance in the presence of mobility among sensor nodes need additional exploration. To address these gaps, future research should concentrate on creating hybrid systems that incorporate energy optimization with strong hotspot mitigation mechanisms, coupled with full assessments of these techniques in varied operating scenarios. This will not only improve the comprehension of energy dynamics in WSNs but also aid in the construction of more robust and efficient IoT ecosystems.

3. THE PROPOSED MODEL

The Gradient-Based Optimization with Uncertainty Compensation and Hybrid Optimization (GBOUCA-HP) method is introduced as a solution for reducing energy consumption, alleviating hotspot problems, and improving the overall longevity of Wireless Sensor Networks (WSNs). The suggested model integrates metaheuristic optimization techniques emphasizing energy conservation and the reduction of hotspots, which are significant difficulties in large-scale wireless sensor networks (WSNs). In Wireless Sensor Networks, energy saving and efficient communication are the two important objectives. Sensor nodes, often powered by batteries, possess constrained energy resources. The core of the GBOUCA-HP model focuses on three main objectives: optimizing energy usage, mitigating hotspots, and enhancing network longevity. It begins with an initial network setup, where sensor nodes are randomly distributed, and energy levels are assigned. The model then compensates for uncertainties such as environmental factors and node mobility by dynamically adjusting energy consumption estimates. A hybrid metaheuristic optimization algorithm is applied to iteratively adjust the routing paths and transmission schedules, ensuring energy-efficient communication. As the optimization process progresses, the model actively detects and mitigates hotspot formation by redistributing traffic from overburdened nodes, thus balancing the energy load across the network. The technique ensures a more uniform energy consumption profile, which directly contributes to the extension of the network's lifetime. The GBOUCA-HP technique also adapts to environmental changes and node failures, ensuring reliable and continuous operation in dynamic WSNs. Through these combined strategies, the technique offers significant advantages over traditional methods, including energy conservation, hotspot avoidance, scalability, and adaptability, making it a promising solution for large-scale, long-term WSN applications. Inefficient routing, excessive energy consumption, and the formation of hotspots—where some nodes use more energy than others—can result in the early breakdown of the network. The GBOUCA-HP approach employs metaheuristic algorithms to address these issues by:

- Enhancing communication pathways to minimize energy use.
- Mitigating hotspots by traffic redistribution to achieve equitable load distribution across nodes.
- Prolonging the network's lifespan via effective energy management.

A. **Design of GBO model**

Iman Ahmadianfar et al., in 2020 introduced GBO the new metaheuristic optimization algorithm depends on two theories: diversification and intensification search and the gradient-based Newton's phenomena [24-25]. The Gradient Search Rule (GSR) assists in exploration and enhances the convergence rate to obtain the optimum fitness value within searching range. In a different way, the Local Escaping Operator (LEO) trajectory allows the GBO to escape from local optimum. The steps of GBO methodology are given below.

Initialization

The GBO is used to generate an initial population from a standard distribution. The population has N count of agents within D-dimension search space where the population agent is called a trajectory". The following mathematical expression represents the initialization process.

$$X_n = X_{\min} + rand(0,1) \times (X_{max} - X_{\min}) \tag{1}$$

In Eq. (1), $rand(0,1)$ is a random value within [01] and $X_{\min}$, and $X_{\max}$ are the decision bounds of parameter X.

Gradient search rule (GSR)

The GSR in GBO provides random behaviors which subsequently enhances the diversion ability of the model in the optimizer. As provided in Eq. (2), direction of movement, the primary location of searching agent, the site of trajectory (x_n^{m}) are evaluated based on the GSR.

$$X1_n^{\mathrm{m}} = \chi_n^m - randn \times \rho_1 \times \frac{2\Delta x \times x_n^m}{(x_{worst} - x_{best} + \varepsilon)} + rand \times \rho_2 \times (x_{best} - x_n^{\mathrm{m}}) \tag{2}$$

Where;

$$\rho_1 = 2 \times rand \times \alpha - \alpha \tag{3}$$

$$\alpha = \left| \beta \times \sin\left(\frac{3\pi}{2} + sin\left(\beta \times \frac{3\pi}{2}\right)\right) \right| \tag{4}$$

$$\beta = \beta_{\min} + (\beta_{\max} - \beta_{\min}) \times \left(1 - \left(\frac{m}{M}\right)^3\right)^2 \tag{5}$$

Where β_{min} and $\beta_{\max}$ are 0.2 and 1.2, correspondingly, the current and maximum iteration values are m, and M. ε is a constant number ranging between[0,0.1].

$$\rho_2 = 2 \times rand \times \alpha - \alpha \tag{6}$$

$$\Delta x = rand(1:N) \times |srep| \tag{7}$$

$$step = \frac{(x_{best} - x_{r1}^m) + \delta}{2} \tag{8}$$

$$\delta = 2 \times rand \times \left(\left| \frac{x_{r1}^m + x_{r2}^{\mathrm{m}} + x_{r3}^{\mathrm{m}} + x_{r4}^{\mathrm{m}}}{4} - x_n^m \right| \right) \tag{9}$$

Where $rand\ (l:N)$ refers the random number with N dimensional, $r1, r2, r3$, and $r4$ ($r1 \neq r2 \neq r3 \neq r4 \neq n$) are arbitrarily elected integer from $[1N]$. x_{best} and x_{r1}^m are the step size. The new trajectory ($X2_n^m$) can be defined by replacing the location of (x_{best}) Best trajectory with existing trajectory (x_n^{m}) in Eq. (1);

$$X2_n^{\mathrm{m}} = x_{best} - randn \times \rho_1 \times \frac{2\Delta x \times x_n^{\mathrm{m}}}{(yp_n^m - yq_n^m + \varepsilon)} + rand \times \rho_2 \times (x_{r1}^{\mathrm{m}} - x_{r2}^{\mathrm{m}}) \tag{10}$$

Where,

$$yp_n = rand \times \left(\frac{[z_{n+1} + x_n]}{2} + rand \times \Delta x\right) \tag{11}$$

$$yq_n = rand \times \left(\frac{[z_{n+1} + x_n]}{2} - rand \times \Delta x\right) \tag{12}$$

At the next iteration, The novel solution ($x_n^{\mathrm{m}+1}$) is defined based on the locations 1_n^{m}, $X2_n^{\mathrm{m}}$, and the present location (X_n^{m}) as;

$$\chi_n^{\mathrm{m}+1} = r_a \times (r_b \times X1_n^m + (1 - r_b) \times X2_n^m) + (1 - r_a) \times X3_n^m \tag{13}$$

$$X3_n^{\mathrm{m}} = X_n^{\mathrm{m}} - \rho_1 \times (X2_n^{\mathrm{m}} - X1_n^{\mathrm{m}}) \tag{14}$$

Gradient-Based Optimization (GBO) refers to a class of optimization algorithms that use the gradient (or approximate gradient) of a function to find the optimal solution. The general idea is to iteratively update the parameters of the function to minimize or maximize an objective function.
The main steps involved in a gradient-based optimization algorithm are as follows:

1) *Initialize Parameters*
   - Start with an initial guess of the parameters. These are the values that we are going to optimize.

2) *Compute the Gradient*
   - Calculate the gradient (or partial derivatives) of the objective function with respect to the parameters. The gradient provides information on the direction in which the function is increasing or decreasing.

3) *Update Parameters*
   - Update the parameters using the gradient. This is typically done using a step size or learning rate to control the size of the update.

4) *Check for Convergence*
   - After each update, check if the change in the parameters is small enough, or if the objective function has reached a satisfactory value, to stop the iteration.

5) *Repeat*
   - Repeat steps 2–4 until convergence or until a stopping criterion (such as a maximum number of iterations) is met. The below are pseudo code of the GBO algorithm

```
# Pseudo Code for Gradient-Based Optimization (GBO)
# Define the objective function and its gradient
def objective_function(theta):
   # Function to minimize (e.g., mean squared error, loss function, etc.)
   return f_value
def gradient_of_function(theta):
   # Function to compute the gradient of the objective function
   return gradient_value
# Initialize parameters
theta = initial_guess   # Random or predefined initial values of parameters
learning_rate = 0.01    # Step size for updating parameters
tolerance = 1e-6        # Convergence tolerance
max_iter = 1000         # Maximum number of iterations
# Main GBO loop
for iteration in range(max_iter):
   # Calculate gradient at the current point
   grad = gradient_of_function(theta)
      # Update parameters
   theta = theta - learning_rate * grad
      # Check for convergence (small change in theta)
   if abs(grad).max() < tolerance:
      print("Convergence reached at iteration", iteration)
      break
# Return the optimized parameters
return theta
```

Local escaping operator (LEO)

The LEO is integrated into GBO to enhance its ability to provide optimum solutions to complex optimization problems. It assists in escaping from the local optimal solution. The LEO used to produce the fittest solution (X_{LEO}^{m}) that includes a randomly created location (x_{k}^{m}), best location (x_{best}), the locations $X1_{n}^{m}$ and $X2_{n}^{m}$, and two random locations x_{r1}^{m} and x_{r2}^{m}. The solution X_{LEO}^{m} is constructed based on the following manner.

Whereas f_1 denotes the even random integer, f_2 implies the uniformly distributed random value with mean of 0 and standard deviation (SD) of 1, pr indicates the probability, and u_1, u_2, and u_3 are three random integers that are shown below:

$$u_1 = \begin{cases} 2 \times rand if \mu_1 < 0.5 \\ 1\ otherwise \end{cases} \quad (15)$$

$$u_2 = \begin{cases} rand if \mu_1 < 0.5 \\ 1\ otherwise \end{cases} \tag{16}$$

$$u_3 = \begin{cases} rand if \mu_1 < 0.5 \\ 1\ otherwise \end{cases} \tag{17}$$

Where $rand$ indicates the random value within [0,1], and μ_1 is a number within [0,1]:

$$u_1 = L_1 \times 2 \times rand + (1 - L_1) \tag{18}$$

$$u_2 = L_1 \times rand + (1 - L_1) \tag{19}$$

$$u_3 = L_1 \times rand + (1 - L_1) \tag{20}$$

Where a binary parameter within the range of 0 or 1 is L_1. If the μ_1 and μ_2 parameters are less than 0.5, then L_1 value is 1, or else, 0. This can be mathematically modelled as follows:

$$x_k^m = \begin{cases} x_{rand}\ if\ \mu_2 < 0.5 \\ x_p^m\ otherwise \end{cases} \tag{21}$$

$$x_{rand} = X_{\min} + rand(0,1) \times (X_{\max} - X_{\min}) \tag{22}$$

Where x_{rand} signifies the novel solution, an arbitrarily chosen performance of the population ($p \in [1,2,\cdots,N$ is x_p^m as:

$$x_c^m = L_2 \times x_p^m + (1 - L_2) \times x_{rand} \tag{23}$$

Where binary parameter L_2 ranges within [0,1].

B. **Process Involved in Unequal Clustering**

The GBOUCA-HP approach evaluates a fitness value that relies on energy and distance metrics. Primarily, the node sends crucial energy at a certain signal intensity and the node develops this communication and calculates the distance to all the nodes. In addition, BS receives this communication, afterward computes and transmits E_{ave}. E_{ave} refers to the average RE of alive node. CH has been selected by reject radius (R_j) and competition radius (R_c).

The mathematical formula of R_c is defined as:

$$R_t = \left(1 - 0.3 \times \frac{d_{max} - d(i,BS)}{d_{max} - d_{nin}}\right) \times R_{max} \tag{24}$$

Whereas $R_{\max}$ stands for the maximal R_c that is determined in progress. $d_{\max}$ and $d_{\min}$ depicts the higher and lesser of $d(i,BS)$. R_c reflects the outcome of $d(i,BS)$ on clustering. If $d(i,BS)$ is lesser after the inter-cluster communication load gets heavy.

$$R_j = \alpha \times \beta \times R_c \tag{25}$$

At this point, α and β denote the variables. α reflects the result of RE. The node is a huge RE and is reduced in α. E_i represents the RE of i^{th} nodes.

$$\alpha = \begin{cases} \max\left[\frac{1}{2}, \left(1 + \frac{E_{ave} - E_i}{E_{ave}}\right)\right], E_i \geq E_{ave} \\ \min\left[\frac{3}{2}, \left(1 + \frac{E_{ave} - E_i}{E_{ave}}\right)\right], E_i < E_{ave} \end{cases} \tag{26}$$

β reflected the performance of AN counts. Node with further ANs is lesser in β.

$$\beta = \begin{cases} \max\left[\frac{1}{2}, \left(1 + \frac{N_{ave} - N_i}{E_{ave}}\right)\right], N_i \geq N_{ave} \\ \min\left[\frac{3}{2}, \left(1 + \frac{N_{ave} - N_i}{N_{ave}}\right)\right], N_i < N_{ave} \end{cases} \tag{27}$$

N_{ave} signifies the average node counts from the circle of that the radius is R_c that is measured as follows. N_i represents the node counts from the circle of that the centre is i, the radius is R_c and $d(i, RNs)$ stands for the average distance from i to this node.

$$N_{ave} = \frac{\pi \times N \times R_C^2}{S^2} \tag{28}$$

t_i reflects the outcome of $d(i, RNs)$. A node taking smaller $d(i, RNs)$ is lesser in it.

$$\mathrm{t_i} = \frac{d(i,\cdot RN_S)}{R_S} \times t_0 \tag{29}$$

In which, t_0 implies the time constant. The node that has chance of existence of a CH is named a CH candidate (CHC). Primarily, all the nodes were delayed for t_i. But the waiting, node frequently receives communications. Smaller the R_j is the superior opportunity that the node gets $CH.$ k refers to the better count of CHs. If k CH has been elected or waiting hours is over t_0, next CH chosen is accomplished. A non-CH node elects a neighbouring CH to link its cluster. Wireless Sensor Networks (WSNs) encounter several significant obstacles that must be resolved for effective optimization in practical applications. Environmental unpredictability, including temperature swings, humidity, and physical obstacles, may profoundly influence signal transmission and energy consumption, necessitating algorithms to perpetually adjust to these dynamic settings. Moreover, interference and noise from external devices in outdoor environments may hinder communication, resulting in packet loss and necessitating dynamic route changes, a challenge that static algorithms may find difficult to address. Node failures provide a significant challenge, since sensor nodes situated in adverse settings are susceptible to physical damage and battery exhaustion. Although adaptive algorithms, such as those using reinforcement learning, provide possible answers, real-time network reconfiguration to address abrupt failures continues to pose a considerable difficulty. Scalability is a significant issue, since an expanding network results in increased computing complexity, especially for methods like genetic algorithms, which may become inefficient with network growth. Moreover, several sophisticated algorithms impose supplementary communication and processing burdens, thereby undermining the advantages of optimal routing, particularly in energy-limited contexts. Efficient energy management is essential because to the diverse energy usage of nodes, with some using solar power and others relying on batteries. The integration of energy harvesting complicates energy management, since variations in available energy might affect node availability and network dependability. The difficulty of implementing sophisticated optimization algorithms, which frequently requires substantial computing resources and specialized knowledge, might impede their use in resource-constrained settings, particularly when integration with current infrastructure is required. Addressing these problems requires a compromise of algorithmic efficiency, real-time flexibility, and practical implementation factors.

4. RESULT ANALYSIS

The experimental evaluation of the GBOUCA-HP technique is investigated briefly. The experimental evaluation of the GBOUCA-HP technique is conducted in a detailed and comprehensive manner to assess its performance in optimizing energy consumption, mitigating hotspots, and enhancing the overall lifetime of Wireless Sensor Networks (WSNs). We set up a series of simulations using varying network conditions, including different node distributions, network sizes, and energy levels. The evaluation focuses on comparing the GBOUCA-HP technique with existing methods in terms of key performance metrics, including energy consumption, network lifetime, and hotspot mitigation efficiency. The network topology consists of randomly distributed nodes, with a defined base station and energy models based on realistic sensor node characteristics. A series of experiments were performed under various scenarios to analyze the robustness of the technique under diverse conditions such as node failures, environmental interference, and varying traffic loads. We measured performance outcomes such as energy efficiency, throughput, packet delivery ratio, and the time until the first node fails (which serves as an indicator of network lifetime). To ensure the reliability and validity of the results, statistical analysis was performed, including variance and standard deviation calculations for the primary metrics (e.g., energy consumption and hotspot mitigation). Furthermore, a comparison with other state-of-the-art techniques such as LEACH, HEED, and PSO-based methods was included to highlight the advantages of the GBOUCA-HP technique. The results show a significant improvement in energy efficiency, hotspot mitigation, and network longevity compared to these existing methods. Detailed visualizations and numerical results are presented to provide a clear understanding of the performance and effectiveness of the proposed technique.

The energy consumption (EC) results of the GBOUCA-HP technique is compared with other algorithms in Table 1 and Figure. 2 [14]. These accomplished outcomes denote that the I-PSO algorithm consumes more energy whereas the HH-DAP and QDAEER systems have utilized somewhat reduced energy. Although the ITSAUC-HSE model managed to consider decreased EC values, the GBOUCA-HP technique offers least EC values of 0.575J, 0.761J, 0.906J, 1.036J, and 1.106J under 50-400 nodes, respectively.

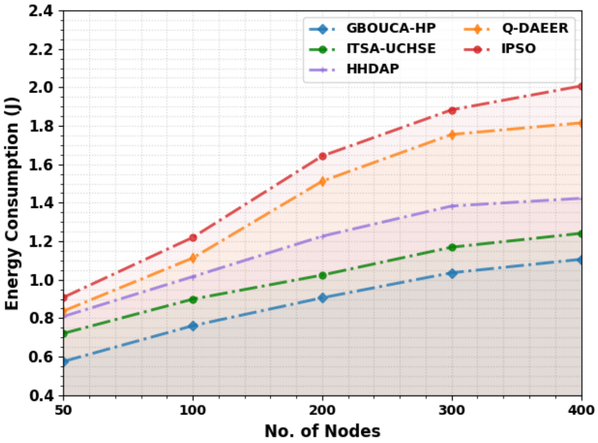

Figure 2. EC outcome of the GBOUCA-HP model under varying nodes

Table 1. Ec Results of The Gbouca-Hp System Compared with Other Algorithm Under Varying Nodes

Energy Consumption (J)					
No. of Nodes	GBOUCA-HP	ITSAUC-HSE	HH-DAP	QDAEER	I-PSO
50	0.575	0.721	0.809	0.837	0.908
100	0.761	0.899	1.016	1.113	1.220
200	0.906	1.024	1.226	1.512	1.643
300	1.036	1.169	1.383	1.755	1.883
400	1.106	1.241	1.423	1.815	2.007

Table 2. Nan Outcome of The Gbouca-Hp Model Compared with Other Techniques Under Various Rounds

Number of Alive Nodes					
No. of Rounds	GBOUCA-HP	ITSAUC-HSE	HH-DAP	QDAEER	I-PSO
0	100	100	100	100	100
100	100	100	100	100	100
200	100	100	100	100	100
300	100	100	100	100	100
400	100	100	100	100	97
500	100	100	97	93	94
600	100	100	92	76	92
700	100	98	65	20	66
800	100	95	42	13	1
900	97	79	28	2	1
1000	85	53	3	2	0
1100	74	33	0	0	0
1200	21	0	0	0	0

The number of alive nodes (NAN) results of the GBOUCA-HP technique is compared with existing models in Table 2 and Figure. 3. These outcomes depict that the GBOUCA-HP technique reaches higher NAN values. With 700 rounds, the GBOUCA-HP technique display increased NAN of 100 whereas the ITSAUC-HSE-HH-DAP, QDAEER, and I-PSO algorithms show minimized NAN of 98, 65, 20, and 66. In line with, 800 rounds, the GBOUCA-HP algorithm display improved NAN of 100 but, the ITSAUC-HSE, HH-DAP, QDAEER, and I-PSO systems get decreased NAN of 95, 42, 13, and 1. Meanwhile, based on 900 rounds, the GBOUCA-HP method gains improved NAN of 97 but, the ITSAUC-HSE-HH-DAP, QDAEER, and I-PSO systems get decreased NAN of 79, 28, 2, and 1. Finally, with 1000 rounds, the GBOUCA-HP technique provides raised NAN of 85 however, the ITSAUC-HSE-HH-DAP, QDAEER, and I-PSO methods obtain diminished NAN of 53, 3, 2, and 0, respectively

The average lifetime nodes (ALT) outcomes of the GBOUCA-HP system can be determined with the comparison of existing algorithms in Table 3 and Figure. 4. These achieved outcomes represent that the GBOUCA-HP method provides greater ALT values. According to FND, the GBOUCA-HP algorithm obtains better ALT of 773 rounds whereas the ITSAUC-HSE, HH-DAP, QDAEER, and I-PSO techniques indicate decreased ALT of 670, 476, 453, and 361 rounds. Meanwhile, based on HND, the GBOUCA-HP system get higher ALT of 1173 rounds but, the ITSAUC-HSE, HH-DAP, QDAEER, and I-PSO techniques offer lessened ALT of 1044, 770, 642, and 714 rounds. Also, with LND, the GBOUCA-HP technique acquire increased ALT of 1444 rounds then, the ITSAUC-HSE, HH-DAP, QDAEER, and I-PSO algorithms give lessened ALT of 1205, 103, 904, and 805 rounds.

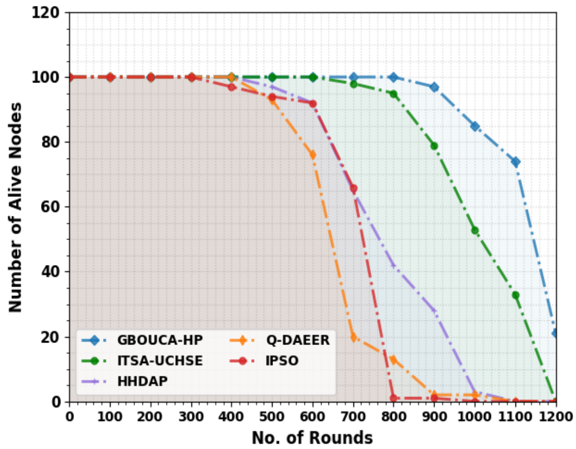

Figure 3. NAN outcome of the GBOUCA-HP model under number of rounds

Table 3. Alt Outcome of The Gbouca-Hp System Compared With Other Algorithms

Avg. Lifetime in Rounds					
-	GBOUCA-HP	ITSAUC-HSE	HH-DAP	QDAEER	I-PSO
FND	773	670	476	453	361
HND	1173	1044	770	642	714
LND	1444	1205	103	904	805

Table 4. Athr Outcome of The Gbouca-Hp System Compared With Other Algorithms Under Various Nodes

Avg. Throughput					
No. of Nodes	GBOUCA-HP	ITSAUC-HSE	HH-DAP	QDAEER	I-PSO
50	39.13	35.51	34.66	33.13	31.57
100	36.08	32.33	28.04	24.05	21.97
200	30.78	27.05	23.70	20.81	19.03
300	27.80	22.07	18.40	15.50	13.97
400	22.18	15.67	10.68	9.16	7.02

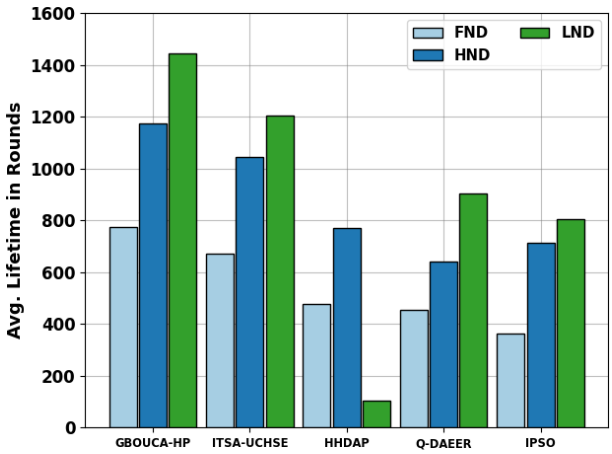

Figure 4. ALT outcome of the GBOUCA-HP model compared to other algorithms

A comprehensive average throughput (ATHR) comparison outcome of the GBOUCA-HP system can be determined under varying nodes in Table 4. These accomplished outcomes signify that the GBOUCA-HP technique offers superior ATHR values. On 50 node, the GBOUCA-HP method gains improved ATHR of 39.13 although, the ITSAUC-HSE, HH-DAP, QDAEER, and I-PSO algorithms show reduced ATHR of 35.51, 34.66, 33.13, and 31.57. Meanwhile, based on 200 node, the GBOUCA-HP technique get boosted ATHR of 30.78 whereas the ITSAUC-HSE, HH-DAP, QDAEER, and I-PSO systems offer the lowest ATHR of 27.05, 23.70, 20.81, and 19.03. Also, with 400 node, the GBOUCA-HP system acquire increased ATHR of 22.18 however, the ITSAUC-HSE, HH-DAP, QDAEER, and I-PSO algorithm obtain minimized ATHR of 15.67, 10.68, 9.16, and 7.02.

5. CONCLUSION

This article presents the GBOUCA-HP strategy, a metaheuristic approach aimed at optimizing energy consumption, alleviating hotspots, and prolonging the lifetime of Wireless Sensor Networks (WSNs). The GBOUCA-HP technique utilizes the Generalized Bacterial Foraging Optimization (GBO) algorithm, which combines diversification and intensification search strategies with gradient-based Newton's method, facilitating adaptive Cluster Head selection based on node energy levels and computational capabilities. Comprehensive simulations were conducted under diverse network settings, revealing that GBOUCA-HP far surpasses current methodologies across several critical criteria. GBOUCA-HP demonstrated enhanced energy efficiency, with energy consumption consistently lower than other algorithms across diverse node densities, such as 0.575J for 50 nodes in contrast to 0.721J for ITSAUC-HSE. The strategy surpassed others in preserving a greater quantity of alive nodes (NAN), with GBOUCA-HP sustaining 100% alive nodes for up to 800 rounds, whilst other techniques shown a significant decline. Furthermore, GBOUCA-HP enhanced the average longevity of nodes (ALT) to 773 rounds for FND, 1173 rounds for HND, and 1444 rounds for LND, markedly exceeding alternatives such as ITSAUC-HSE and I-PSO. Furthermore, GBOUCA-HP demonstrated superior throughput (ATHR) at varying node densities, achieving a value of 39.13 with 50 nodes, far surpassing other approaches. The GBOUCA-HP approach shown efficacy in alleviating hotspot problems, facilitating a more uniform energy distribution across nodes and consequently averting premature node failures. GBOUCA-HP shown significant improvements in energy consumption, network longevity, throughput, and hotspot mitigation, positioning it as a viable option for efficient and durable Wireless Sensor Networks across diverse real-world applications. Its capacity to optimize energy consumption while prolonging the operational lifespan of the network establishes GBOUCA-HP as a formidable strategy for future developments in WSN technology.

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