Clustering with hierarchical routing (GMMCHR): a new gaussian mixture model for wireless sensor networks

Neetu Sikarwar, Ranjeet Singh Tomar
Department of Electronic and Communication, ITM University, Gwalior, India

Article Info

Article history:

Received Feb 3, 2025
Revised Aug 14, 2025
Accepted Oct 9, 2025

Keywords:

Clustering algorithm
Coverage ratio
Energy efficiency
Gaussian mixture model
Hierarchical routing
Packet delivery
Wireless sensor networks

ABSTRACT

Wireless sensor networks (WSNs) are widely deployed in military surveillance, industrial automation, and real-time environmental monitoring, yet their performance is constrained by limited sensor node (SN) energy, leading to reduced network lifetime (NL). Addressing these challenges, this study proposes gaussian mixture model clustering with hierar-chical routing (GMMCHR) protocol that integrates probabilistic clustering with energy-aware hierarchical routing to ameliorate both energy efficiency (EE) and scalability. The network is partitioned into near clusters (NC) and far clusters (FC) based on node distance from the base station (BS). Cluster heads (CHs) are selected using a fitness function (FF) that combines residual energy (RE) and spatial proximity, with FCs formed via enhanced gaussian mixture models (EGMM) and multi-level routing for balanced energy consumption. MATLAB R2021a simulations under two configurations, 100 nodes in 200 nodes in a 200×200 m² region and 100 nodes in a 100×100 m² area, demonstrate that GMMCHR extends NL by 20–23% compared to the benchmark energy efficient hybrid clustering and hierarchical routing (EEHCHR) protocol. For example, in the 100-node scenario, GMMCHR delays the first node dead (FND) to 66 rounds, half node dead (HND) to 911 rounds, and last node dead (LND) to 1601 rounds, outperforming EEHCHR by 21, 176, and 242 rounds, respectively. In addition, GMMCHR sustains over 70% coverage beyond 1200 rounds and delivers over 17,000 packets to the BS —substantially higher than EEHCHR, HEED, and low-energy adaptive clustering hierarchy (LEACH). The hybrid approach improves load balancing, adapts to varying node densities, and scales effectively for large deployments. These results stipulate that GMMCHR is a promising candidate for energy-efficient WSN applications, encompassing IoT and smart environment monitoring.

Corresponding Author:

Neetu Sikarwar
Department of Electronic and Communication, ITM University
Gwalior, India
Email: neetusik1@gmail.com

1. INTRODUCTION

Background: wireless sensor networks (WSNs) have attracted significant research interest over the past two decades due to their wide applicability in real-time monitoring scenarios such as ecological observation, industrial automation, smart cities, and healthcare services [1], [2]. A typical WSN encompasses spatially distributed sensor nodes (SNs) that collaboratively sense ecological parameters such as temperature, pressure, and motion, transmitting data to a central base station (BS) for supplemental processing [3]. Despite their potential, WSNs face fundamental constraints in terms of battery power, memory, and computational capacity. Energy efficiency (EE) is the most important of them since SNs are frequently placed in dangerous or inaccessible locations where it is not viable to change the batteries [4].

Clustering-based routing protocols are a widely adopted approach to ameliorating EE and network lifetime (NL) of WSNs [5]. With the help of these protocols, networks are divided into clusters, or collections of nodes, each of which is led by a CH who is responsible for collecting and transmitting data BS. Low-energy adaptive clustering hierarchy (LEACH) and other early concords [6], [7] introduced randomized CH rotation to balance energy utilization. However, protocols like LEACH and HEED exhibit limitations in scalability and adaptability due to their static clustering mechanisms, which perform poorly in large-scale networks with variable energy distribution, node mobility, or uneven density [8].

To overcome these shortcomings, recent research has explored probabilistic and machine learning (ML)-based clustering for dynamic CH selection. Gaussian mixture models (GMM) have shown promise in modeling spatial node distributions, optimizing cluster centroids, and minimizing intra-cluster distances. For instance, Hojjatinia *et al.* [9] applied GMM to maximize NL in multi-sink scenarios, while Wu *et al.* [10] demonstrated that GMM-based clustering enhances flexibility in heterogeneous WSN deployments. Nevertheless, most existing approaches still suffer from frequent re-clustering, high communication overhead, and inefficient inter-cluster routing, especially under varying topologies and energy conditions [11]. As a result, the incentive of building a hybrid and flexible model that combines the probabilistic potential of GMM with a hierarchical energy-aware routing approach is to optimize clustering and transference of information. This would enable enhanced scalability, energy balance and resiliency of different WSN applications.

Problem statement: WSNs are highly sensitive to limited energy reserves, uneven energy distribution, and frequent topological changes, leading to shorter network lifespans, degraded coverage, and unreliable communication. Existing clustering and routing protocols struggle to acclamatize effectively to variations in node density, environmental conditions, and residual energy (RE), resulting in imbalanced energy consumption, excessive re-clustering, and increased latency [11]. Conventional protocols such as energy efficient hybrid clustering and hierarchical routing (EEHCHR) [12], HEED [13], and LEACH [14] fail to jointly consider spatial distribution and RE during CH selection [15], while many hierarchical routing strategies introduce redundant communication and overload in large-scale deployments [11]. These limitations highlight the need for an adaptive, intelligent protocol that can balance energy usage, reduce re-clustering frequency, maintain high coverage, and ensure long-term network stability.

Proposed solution: this study proposes gaussian mixture model clustering with hierar-chical routing (GMMCHR) protocol, which integrates probabilistic soft clustering via enhanced gaussian mixture model (EGMM) with an energy-aware hierarchical routing mechanism. The protocol partitions the network into near clusters (NC) and far clusters (FC) based on the distance from BS. Cluster heads (CHs) are selected using a dynamic fitness function (FF) combining RE and spatial proximity, with differentiated CH roles: designated cluster heads (DCHs) for NC and central cluster heads (CCHs) for FC. This hybrid design aims to optimize cluster formation, balance energy usage, amortize latency, and extend the NL in both small-scale and large-scale WSN deployments.

Research objectives: the following research objectives of this work are:
- To flourish a hybrid clustering protocol integrating EGMM with hierarchical routing for adaptive and energy-efficient cluster formation.
- To implement differentiated CH selection strategies (DCH and CCH) based on RE and spatial distance metrics.
- To evaluate GMMCHR performance under varying network densities and deployment scales.
- To compare GMMCHR with benchmark protocols (EEHCHR, LEACH, and HEED) using metrics such as NL, coverage, and packet delivery proportion.

Novel contributions: the following research novel contribution of this work are:
- First integration of EGMM-based soft clustering with hierarchical routing for WSN energy optimization.
- Dynamic FF combining RE and spatial proximity for adaptive CH selection.
- Dual-cluster approach (NC and FC) to enhance scalability and balance energy consumption across the network.
- Demonstrated 20–23% enhancement in NL and over 70% sustained coverage compared to EEHCHR in MATLAB simulations.
- Applicability to large-scale IoT and smart environment monitoring requiring long-term, energy-efficient operation.

Organization of the paper: the remaining document is structured as follows. Section 2 presents prior work and research gaps. Section 3 explains the theoretical background of GMM and hierarchical routing. Section 4 describes the proposed GMMCHR approach and its simulation results. Finally, section 5 concludes the study and provides closing remarks and directions for future work.

2. LITERATURE REVIEW

The current section will critically analyze the available clustering and routing protocols in WSNs and point out their proficiency, vulnerability, and energy-efficiency. It also points out the research gaps that provide motivation to the development of the proposed GMMCHR approach in Table 1.

Table 1. Comparative study of literature work used for EE routing in WSN

Ref.	Method	Features	Performance	Advantage	Research gaps	Future work
[16]	FQA–hybrid clustering & routing using fuzzy inference system (FIS)+quantum annealing (QA)	FIS for CH selection; energy threshold; QA for CH–BS routing; on-demand re-clustering	Compared with FC-RBAT, FRNSEER, BOA-ACO, OAFS-IMFO on energy usage, live nodes, NL, and throughput	Reduces computation cost, improves stability, and energy-efficient routing	Limited scalability evaluation for large dynamic WSNs	Extend to heterogeneous WSNs and IoT-based deployments
[17]	EOAMRCL–energy optimization using grey wolf optimizer (GWO)	Hierarchical architecture; centralized strategy; updated CSMA/CA; focus on duty cycle & path optimization	Outperformed CGA-GWO, DWEHC, EEUC in NL & energy consumption	Reduced collisions, better channel estimation, and improved EE	No security mechanism integration	Explore secure energy-aware routing protocols
[18]	K-Medoids+ASFO+E-CERP	CH selection via K-medoids & ASFO; shortest path with E-CERP	PDR: 100%, PLR: 0.5%, power: 1.97 mJ, throughput: 0.99 Mbps, latency: 0.05 s, and NL: 5908 cycles	High PDR, low latency, better network life	Tested up to 100 nodes only	Test in large-scale WSNs & heterogeneous environments
[19]	Firefly+SMO bio-inspired ensemble	Non-clustering RP using hybrid bio-inspired optimization	Lifetime gain: 30.91%, 32.12%, 12.4%, 13.50% over bee colonies, PSO, SFLA, and GWO	Significant lifespan gains under various settings	Lacks detailed energy consumption breakdown	Apply to 3D/underwater sensor networks
[20]	HECRA–modified LEACH for underwater WSNs	CH selection based on RE & node degree; optimizes cluster creation & transmission	Improved NL, packet delivery, and RE over LEACH, EERBLC, and EECMR	Robust in underwater communication	Focused only on underwater; no cross-domain validation	Adapt for terrestrial+underwater hybrid WSNs
[21]	Moth Flame+SSO multi-criteria clustering	Bio-inspired routing; stability-focused CH selection; throughput & delay optimization	6% longer NL, 18.6% lower energy usage than existing methods	Stable clusters, extended life	No fault-tolerance mechanism	Integrate fault recovery methods
[22]	LEACH-K-means	CH selection using K-means in LEACH	Longer NL, reduced EC over standard LEACH	Simple integration with LEACH	Only basic clustering, no routing optimization	Combine with energy-aware routing
[10]	GMM+DNN	GMM with deep neural network for EER	EC: 0.561 J; adaptable to different topologies	Handles dynamic WSN traffic patterns	Limited real-world testing	Field implementation with IoT devices
[9]	GDECA–gaussian distribution-based energy & clustering algorithm	GMM parameter estimation for CH selection & sink routing	40–50% EC reduction, maintained activity till simulation end	Energy-efficient sink routing	Limited to gaussian distribution assumption	Adapt for non-gaussian node distributions
[12]	EEHCHR	FCM+ euclidean distance+RE; hierarchical routing with DCH & CCH	Outperformed FCM, REHR, FFTHR, UCRA-GSO, CCA-GWO in lifetime & coverage	Reduced clustering rounds, improved CH selection	No evaluation in mobile WSNs	Extend to mobile and large-scale IoT systems

2.1. Wireless sensor networks with optimization techniques

Wang *et al.* [16] presenting FQA, a clustering and routing technology that combines QA and fuzzy logic to increase network stability while consuming less energy. FIS and QA methods are used in this hybrid method. The protocol uses FIS to choose appropriate CHs. They employed QA approach to determine a route between CHs and BS. In order to choose prospective CHs, they established an energy threshold, which also reduced computing time. In contrast to periodic clustering, they greatly decreased computation and costs by utilizing a global approach to network maintenance via on-demand re-clustering. FQA was compared to various algorithms, including FC-RBAT, FRNSEER, OAFS-IMFO, and BOA-ACO, using metrics such as energy usage, live nodes, network durability, and throughput.

Kaddi *et al.* [17] proposes the EOAMRCL method that seeks to optimize energy usage of WSNs taking into account GWO to bring improved outcomes. The green energy solutions of EOAMRCL focus on power consumption of transmission, desirable duty-cycle allocation and pathways. The proposed approach adopts hierarchical network architecture in adoption of a centralized strategy. The network performance at large is enhanced because of the integration as it reduces the network collisions, enhances the accuracy of the channel estimation, and minimizes the energy consumption. EOAMRCL scored better in a MATLAB assessment than “CGA-GWO”, “DWEHC”, and EEUC”, protocols, specifically in terms of NL and energy consumption. In conjunction with updated CSMA/CA technique, this demonstrates that GWO may assist optimize EE and network performance.

Based Cherappa *et al.* [18], SNs are clustered using the K-medoids approach with ASFO. This study's main objective is to determine best way to choose CH while lowering latency, power consumption, and node distance. Because of these constraints, optimizing utilization of energy resources is one of most crucial problems in WSNs. In order to continuously reduce network overhead, the shortest path is found using an E-CERP. The suggested method performed better than the previous methods in evaluating error estimations, packet delivery ratios (PDRs), packet delays, throughput, power consumption, network lifespan, and packet loss rates. The quality-of-service measures yielded the following results: PDR (100%) over 100 nodes, PLR (0.5%), power consumption (1.97 mJ), throughput (0.99 Mbps), packet latency (0.05 s), and network lifespan (5908 cycles).

Krishnan *et al.* [19] offers an ensemble method with a bio-inspired approach that makes use of SMO and firefly algorithms instead of a WSN RP based on clustering. The results showed that, under various network settings, the average lifespan gains were (30.91%, 32.12%, 12.4%, and 13.50%), respectively, when contrary to bee colonies, PSO, SFLA, and GWO.

2.2. Clustering in wireless sensor networks

Shi *et al.* [20] focusing on the underwater sensor networks, have offered a HECRA as a solution to energy limitations and data transmission unwavering issues. Not only does the protocol incorporate RE and node degree into CH selection phase of the classic LEACH protocol, but it also performs optimizations throughout the cluster creation and data transmission phases, for example, when choosing clusters to join. The count of successfully delivered packets, residual node energy, and network lifespan are all improved by HECRA compared to cutting-edge methods like LEACH, EERBLC, and EECMR. This increases NL and ensures efficient data transmission.

Vellaichamy *et al.* [21] delineates an algorithmic solution to the optimum bio-inspired routing and multi-criteria clustering which is capable of extending the life of networks, enables WSN-based applications to have longer lifetimes, and causes clusters to be more stable. Clustering as an effective method of data aggregation enhances longevity by creating groups. Multi-criteria clustering is used in selecting the best CH. Once an adequate CH has been selected, a combined technique that has both moth flame and SSO approach is used to measure network stability to define most appropriate data transmission channel that can be used by a CH, within a sink. They analyze the suggested technique based on the past methods comparing them in duration, “energy usage”, “throughput”, “latency”, and “end-to-end delay”. In contrary to modern day routing techniques, the network can last 6% longer and less 18.6% in energy consumption.

Bhih *et al.* [22] due to energy constraints, the deployment of WSNs required sophisticated techniques to increase the NL. A novel clustering-based routing method named LEACH has been proposed to solve this problem. The K-means clustering approach is employed by LEACH-K-means to choose best cluster leaders. LEACH and LEACH-K-means clustering techniques have been contrasted. The simulation findings show that the LEACH-K-means protocol may increase a network's lifespan and reduce its energy use.

2.3. Metaheuristic and machine learning approaches in wireless sensor network optimization

Wu *et al.* [10] utilize the power of a DNN and a GMM. This paper presents a new approach to achieving EER in WSN. Traditional routing systems sometimes clash when faced with dynamic network problems, leading to unsustainable EC. The GMM+DNN is a long-lasting and successful EER approach in a wide variety of WSN settings; it can acclimatize to various network topologies and traffic patterns. A recent progress approach is transcended by GMM+DNN with an EC of 0.561 J.

Hojjatinia *et al.* [9] suggest the creative method known as GDECA, which works under the practical premise that node distributions are Gaussian distribution mixes. Because of this, GDECA finds the GMM parameters and fits it to the nodes using a distribution estimation method borrowed from ML. The computed parameters are subsequently utilised by CH in its selection policy. Also, the routing of sinks is defined by the distribution of nodes. Energy usage was found to have decreased by around 40-50%. Another consequence of GDECA is that it maintains network activity until the simulation terminates. The outcomes demonstrate that this approach is superior for sink route calculations and that stochastic changes to the number of sinks raise power consumption.

According to Panchal and Singh [12], EEHCHR is a novel clustering technique that introduce in WSN to increase NL. Euclidean distance parameter, fuzzy C-means (FCM) approach, location of BS, and RE of nodes are all utilized in this innovative adaptive and hybrid clustering scheme, which aims to minimise node's energy utilization. This reduces the network's energy usage because the clustering is only done in a few rounds. The energy-efficient FF is used to choose all of the CHs; it ameliorates CH selection process by adjusting to nodes' remaining energy. The postulation of direct CH (DCH) and central CH (CCH), which are chosen based on various fitness factors and serve as relays for a small amount of other CHs, are also introduced as part of their hierarchical packet routing method for the network's EE. EEHCHR's simulation findings demonstrated that, in comparison to other similar current algorithms, such as FCM, REHR, FFTHR, UCRA-GSO, and CCA-GWO, it increases NL, coverage, and EE.

2.4. Research gaps

Despite substantial progress in clustering and routing protocols for WSNs, several critical research gaps remain that limit the efficiency, adaptability, and real-world deployment of current models:

- Limited adaptability to dynamic topologies: many models, such as LEACH-K-means and EOAMRCL assume static topologies and centralized control. This restricts their usability in environments where node mobility or topology variation is common, such as military or disaster-response scenarios.
- Inadequate support for heterogeneity and scalability: protocols like and offer high performance under homogeneous or small-scale network assumptions. However, they lack robust evaluation on heterogeneous nodes or large-scale deployments, where communication ranges, energy capacities, and roles may vary significantly.
- Insufficient real-time re-clustering mechanisms: periodic or static clustering, as used in traditional models (e.g., LEACH and HEED), leads to unnecessary energy overhead. Although FQA [16] introduces on-demand re-clustering, most protocols still lack efficient re-clustering strategies that adapt based on real-time energy and topology metrics.
- Overlooked trade-off between complexity and efficiency: techniques integrating advanced intelligence, like GMM+DNN or GDECA show strong performance but often incur significant computational, making them less feasible for resource-constrained SNs without lightweight alternatives.
- Limited consideration of security and fault tolerance: few existing models address security threats or fault tolerance in hostile environments. While energy and lifespan are well-studied, the resilience of the routing mechanism under node failures, data tampering, or energy attacks is largely unaddressed.
- Application-specific gaps (e.g., underwater or harsh environments): protocols such as HECRA demonstrate the promise in the underwater WSNs, though. Most of the protocols are optimized to terrestrial WSNs, which cannot be generalized to other scenarios such as underwater, aerial, or smart cities.

In order to address a current issue and address the discovered research gaps in WSNs, the offered GMMCHR methodology proposes a number of novelties. Through hierarchical routing, it increases scalability, lowers communication overhead, and boosts network efficiency in large-scale settings. An FF that balances node distance and RE is used to optimise energy usage, producing homogenous clusters and a longer NL. Prior inefficiencies are eliminated by the hierarchical routing with central and designated cluster heads, which amortize routing latency and redundancy. Furthermore, by dynamically modifying clustering rounds in response to energy availability, the method lowers high energy costs associated with frequent re-clustering and guarantees usefulness in real-world situations.

3. METHOD

To enhance NL in WSNs, this study proposes the GMMCHR technique, which optimizes node energy utilization based on RE. The methodology begins with network initialization in MATLAB R2021a, where SNs are randomly deployed in two scenarios: a $100\times100\ m^2$ area with 100 nodes and a $200\times200\ m^2$

area with 200 nodes. The sink node (BS) is located at (150, 100) for scenario 1 and at (0, 0) for scenario 2. After deployment, the network is further separated into NC and FC depending on distance level amidst each node and base station (dn2BS). It would then compute number of optimal clusters in the far region (FCopt) to input balanced energy distribution. In case of NC, RE based and distance-based fitness function (FDCH) is used to select DCH. By means of an EGMM FC are constructed, and each of them is provisioned with a CCH. The data transmission is also hierarchical where data is directly transmitted by nodes near BS, and NC nodes are accountable to disseminate data to their DCH, and FC nodes also relay the data to their CHs, which then takes aggregate data either to their CCH or DCH based on where they are closest to. Finally, all collected data is transmitted to BS, completing an energy-efficient multi-hop communication cycle. To assess potentiality of the proposed method, several key metrics are employed, including first node dead (FND), HND, last node dead (LND), coverage ratio (CR), and total energy consumption, which collectively assess the model's efficiency in extending network lifespan, maintaining coverage, and reducing energy usage. Figure 1 illustrate flowchart of proposed GMMCHR model.

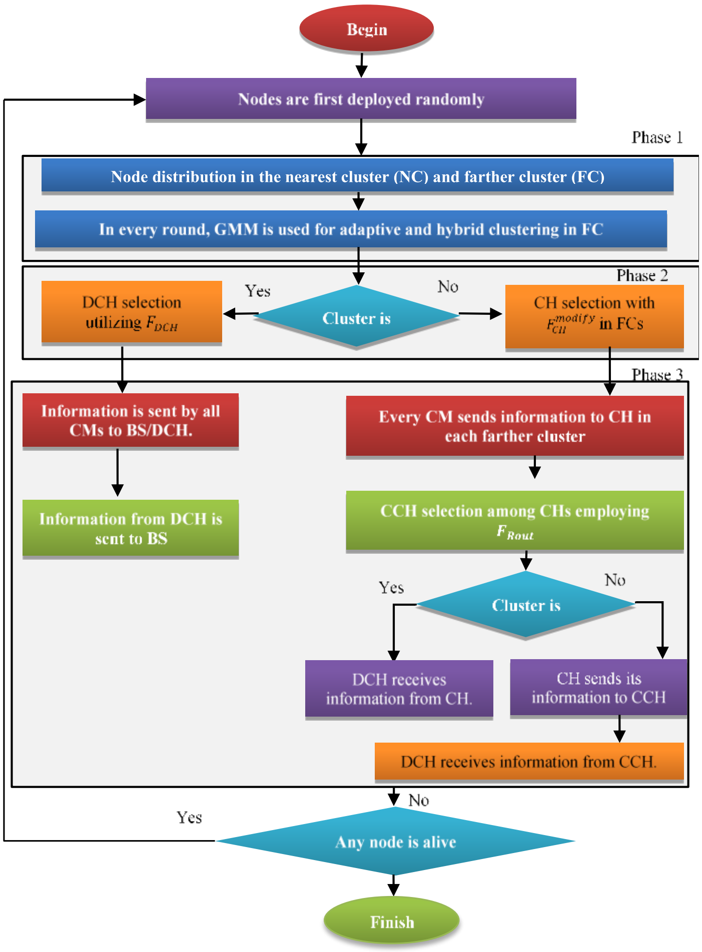

Figure 1. Flowchart of proposed GMMCHR model

3.1. Gaussian mixture model

The GMM probability model uses amalgamation of Gaussians. It emerges to be Gaussian function model, which is closer to the natural distribution and easier to work with technically. This study employs GMM, although there are alternative methods, including clusters with Gaussian distributions, to produce a Gaussian distribution if the initial distribution wasn't one [9]. "Normal distributions" or "bell curves" are other names for univariate Gaussian distributions, when the outcome is the average of several occurrences in (1).

$$G(x|\mu,\sigma) = \frac{1}{\sqrt{2\pi\sigma 2}} e^{\frac{(x-\mu)2}{2a^2}} \quad (1)$$

G is Gaussian function, where variance is represented by σ^2 and mean by μ. When volunteering with a Gaussian distribution that is univariate, this equation determines the highest chance of a deviation, which is shown by variance (σ^2). In contrast, the mean (μ) represents the highest likelihood. If the Gaussian distribution was multivariable, two or more variables were added to the univariate normal distribution [23]. A mean vector and a covariance matrix must undergo at least one parameterisation, which is established by (2):

$$N(x|\mu,\Sigma) = \frac{1}{\sqrt{(2\pi|\Sigma|)}} e^{[=\frac{1}{2}(x-\mu)^T \Sigma^1(x-\mu)]} \tag{2}$$

The mean (μ) reflects the largest probability, while Σ represents covariance across different Gaussian distribution fields, which may be calculated using (3):

$$In\, P(x|\mu,\Sigma) = \frac{1}{\sqrt{2\pi|\Sigma|}} = -\frac{1}{2}In(2\pi) - \frac{1}{2}In|\Sigma| - \frac{1}{2}(x-\mu)^T\Sigma^{-1}(x-\mu) \tag{3}$$

Because only single Gaussian distribution is possible, designers can set derivative of ln p(x|) to 0 and use (4) to (7).

$$\frac{\delta Inp(x|\mu,\Sigma)}{\delta\mu} = 0 \tag{4}$$

$$\frac{\delta Inp(x|\mu,\Sigma)}{\delta\Sigma} = 0 \tag{5}$$

Solve directly for μ and ∑.

$$\mu = \frac{1}{N}\left(\sum_{N=1}^{N} x_n\right) \tag{6}$$

$$\Sigma = \frac{1}{N}\sum_{n=1}^{N}(x_n-\mu)(x_n-\mu)^T \tag{7}$$

Key advantages of GMMs in WSN clustering:
- Elliptical cluster modeling via covariance matrices offers flexibility beyond isotropic clusters.
- Soft assignments using posterior probabilities allow nuanced cluster membership.
- Model selection criteria like BIC facilitate principled determination of G.

This probabilistic framework is critical for dynamic WSN data distributions, allowing more adaptive and accurate clustering than hard threshold methods.

3.2. Enhance gaussian mixture model

Using the idea of rotating CH selection in LEACH algorithm, nodes' RE, and their distance from BS (d_n2BS), a novel pliable and hybrid clustering technique for WSN has been created by integrating a GMM approach. NL and more effective utilisation of nodes' energy should result from this. The purpose of this action was to raise the NL. Because of the links between nodes and the BS, the centralized clustering of each round allows for excessive energy usage. By using adaptive clustering, which dynamically amortizes the quantity of clustering rounds, they were able to eliminate this unnecessary energy usage. Hybrid clustering reduces stress on the CHs and balances energy consumption of network. As a result, this hybrid and adaptive clustering technique helps to reduce dispensable use of network energy. Following the conclusion of this procedure, all CHs are chosen using suggested FFs, which are adaptively updated based on the remaining CM energy as each CM's energy constantly lowers due to information exchange with its destination.

The idea of DCH and CCH was described in this section to enhance inter-cluster communication. The new hierarchical packet routing technique being suggested is based on a node's relative distance (E.d.) from its CC, BS, and RE. While packet routing and CH selection are done in each round in a dispersed manner, the clustering portion of the GMMCHR process is only carried out centrally in a few rounds. Three stages comprise a proposed work's operation: hierarchical packet routing technique, energy-efficient CH selection, and adaptive and hybrid clustering.

3.2.1. Adaptive and hybrid clustering

When all nodes engage in substantial energy consumption and interaction with the BS subsequent to node deployment, a clustering process is initiated. Consequently, the clustering process is carried out in just a few rounds in an adaptive way to decrease this excessive energy use [24]. It was also endorsed that LEACH approach involved invenitve parameter, Rclust, for adaptive clustering that consideres both count of ND in a network and notion of rotation-based CH selection (r mod(1/p)). In (8) may be used to calculate this as a declaration for Rclust.

$$R_{clust.} = \begin{cases} 1, & r = 1 \\ 1, & N_d(r) > 0 \; and \left(rmod\left(\frac{1}{p}\right)\right) = 0 \\ 0, & Otherwise \end{cases} \tag{8}$$

where the current simulation round is R and the variable p is utilized to promote circular clustering. The most amount of cycles that conserve network energy is equal to p=0.05.

3.2.2. Energy-efficient cluster head selection

Using d_{n2BS}, n_{max} & do (optimal distance for NC) all nodes are divided into two groups in hybrid clustering: NC and FCs. The sum of NC and FCs is equal to aggregate amount of clusters. Here, $n_{max} = p_n N$ is greatest quantity of nodes that may be a part of NC. It is determined by the ideal value of p_n (percentage of aggregate nodes (N)) which will be scruntinize using performance measures, such as the network's longevity and energy use. Those nodes which satisfy on $d_{n2BS} \leq d_o$, would be placed in a single cluster called NC. Here, do depends upon dth & $nmax$, and can be computed as (9):

$$d_o = \begin{cases} d_{n2BS}^{th}, & d_{n2BS}^{th} \leq d_{th} \\ d_{th}, & Otherwise \end{cases} \tag{9}$$

here, d_{n2BS}^{th} is E.d. amidst BS and n_{max}^{th} node (farthermost node from BS within $nmax$ limit). All such nodes that do not satisfy $d_{n2BS} \leq d_o$, are distributed into an optimum number of FCs (FC_{opt}) using the EGMM technique [25], [26]. Here, the expression for FC_{opt} is predicated on the ideal number of clusters as detailed in [27], and is computed as (10):

$$FC_{opt} = \sqrt{\frac{N'_a}{2\pi}} \sqrt{\frac{\epsilon_{fs}}{\epsilon_{mp}}} \left(\frac{M}{d_{DCH}^2}\right) \tag{10}$$

where, $N'_a = N_a - n_{NC}$ is count of alive nodes omitting n_{NC} nodes, N_a is aggregate quantity alive nodes of network, nNC stipulates count of CMs in a NC, $M * M$ signifies sensing region, and d_{DCH} stipulates average E.d. amidst DCH and remnant network CHs that have been employed for conveying above FC_{opt}.

a. DCH selection

A NC, CH that sends and receives packets straight from BS is referred to as a DCH. The distinction d_CM2BS between BS and CM should be considered before choosing it. For DCH selection, they have therefore proposed a new fitness function ($FDCH$) that is dependent on RE ($Eres$) of CMs as well as their $dCM2BS$. The following formula is used in NC to determine each CM's fitness value; the CM with highest fitness value is referred to as DCH and is calculated using (11):

$$F_{DCH} = a.x1 + (1 - \alpha).x_2 \tag{11}$$

In such a scenario, $x1$ represents RE compared to the original energy ratio of a CM ($x1$=$Eres$/Ei), &$x2$ is proportion of relative E.d. amidst BS and CM ($x2$=(dth−$dCM2BS$)/dth). The FDCH's parameter is equal to reliance on distance and energy is initially determined at a value. Because constant communication with the CH causes each CM to perpetually lose energy of α as 0.5 [28]. Value α should be modified after each round based on CMs' $Eres$ and threshold energy for (Eth) CH selection in a specific cluster since continuous interaction with the CH leads each CM to continuously lose energy. Here, Eth=γEi, and it is divided into 4 sections γ=0.80, 0.60, 0.40, and 0.20 depending on each cluster. In (12) may also be used to calculate the equation for α.

$$\alpha = \begin{cases} 0.5 & (E_{min}^{cluster} \geq 0.80 * E_i) \\ 0.6 & (E_{min}^{cluster} \geq 0.60 * E_i) \\ 0.7 & (E_{min}^{cluster} \geq 0.40 * E_i) \\ 0.8 & (E_{min}^{cluster} \geq 0.20 * E_i) \\ 0.9 & (Otherwise) \end{cases} \tag{12}$$

Here, $E_{min}^{cluster}$ is lowest $Eres$ amidst CMs in that cluster, which is calculated using (13),

$$E_{min}^{cluster} = \begin{cases} min_{ic\{1,2.....n_{NC}\}}\{E_{res}^i\}, NC \\ min_{ic\{1,2.....n_{NC}\}}\{E_{res}^i\}, FC \end{cases} \tag{13}$$

where nFC stipulates no. of CMs in any FCs clusters.

b. CH selection in FCs

Given that every CH is persistent contact utilising its GMM and CMs approach effectuates more CMs nearer the centroid of the cluster, a cluster centroid near CH will ensure high-quality Eres. As a consequence of this, it modified the FF of the GMM method within the context of the distance parameter for the purpose of selecting CHs in FC clusters. Both $Eres$& distance are utilized in the process of creating FF. utilizing F_{CH}^{modify}, every CM in any of the CHs is able to attain its fitness value, and the CH that was achieved was the CM that had the greatest degree of fitness. When CMs are yonder from their centroid and the CM with the highest level of fitness FC was its CH. If CMs are yonder from their centroid ($d_{CM2C} > d_{Mean}^{FC}$) their F_{CH}^{modify} consider both energy and distance parameters. However, when the CMs are closer to their centroid, their F_{CH}^{modify} is only dependent on energy parameters, and it can be expressed as (14), which may be calculated as (14):

$$F_{CH}^{modify} = \{ax_1 + (1-\alpha)x_3,\ (d_{CM2C} > d_{Mean}^{FC})x_1 Otherwise \tag{14}$$

In this instance, $x3$ represented in relation to centroid's relative E.d. of CM; the expression also seems to compute as (15) to (17):

$$x_3 = (d_{Max}^{FC} - d_{CM2C})/d_{Max}^{FC} \tag{15}$$

$$d_{Mean}^{FC} = mean \sum_{i=1}^{n_{FC}} E.d.(CM_i, C) \tag{16}$$

$$d_{Max}^{FC} = 1 + max_{ic\{1,2.....n_{FC}}\{E.d.(CM_i, C\} \tag{17}$$

Algorithm 1. Energy-efficient CH selection

```
Step 1: for DCH Selection, do
Step 2: Update the value of α using (12) and (13)
Step 3: for nNC do
Step 4: CM obtains its FDCH value using (11)
Step 5: End
Step 6: The CM is having highest FDCH called DCH
Step 7: End
Step 8: for CH Selection in FCs, do
Step 9: Update the value of α using (12) and (13)
Step 10: for nFC do
Step 11: CM obtains its F_CH^modify value using (14)
Step 12: end
Step 13: The CM is having highest F_CH^modify named CH
Step 14: End
```

3.3. Hierarchical packet routing in wireless sensor networks

They propose an unconventional hierarchical packet routing technique to better utilize the network's power. The intracluster routing of the NC, which is in charge of ensuring efficient energy usage among its CMs, is informed by the E.D. Of Moriginating by a DCH & BS d_{CM2BS} & d_{DCH2BS}. The CM passes its data packet to DCH if 〖(d〗 _CM2BS>d_DCH2BS) is satisfied; otherwise, it forwards it straight to BS. As a result, the ultimate objective of CM in NC can be expressed as follows, as determined in (18):

$$CM_{Dest.} = \begin{cases} DCH, & \{d_{CM2BS} > d_{DCH2BS} \\ BS, & Otherwise \end{cases} \tag{18}$$

in this case, the DCH gathers and aggregates data packets from a subgroup of its CMs and subgroup of FCs' CHs before sending them straight to BS, avoiding needless dissemination to the BS from these nodes.

Every FC's CMs deliver data packets to their CHs, after which aggregate and combine each and every packet that FCs' CMs have supplied. Moreover, proposed FF scrutinizes whether these CHs deliver data to DCH ($FRout.$) in a single-hop or two-hop fashion, E.d. amidst CH & BS ($dCH2BS$), & E.d., amidst CCH & BS ($dCCH2BS$). In this case, CCH is The CH with the highest value of fitness amidst all CHs in FCs. A function called F(Rout.) determines the fitness of these CHs; that is, it is defined as follows: where RE and $dCH2C$ are the distances from the CH centroid and the CH centroid, respectively, which is computed using (19):

$$F_{Eout.} = \beta x_4 + (1-\beta)x_5 \tag{19}$$

The value of dependency amidst the parameters of distance and energy are chosen to be β=0.5 in $FRout$. In this occurence, C' stipulates centroid of all CHs, while d_{CH2C}^{max} delineates highest E.d. amidst CHs also their centroid. Since$d\ CH2C = d_{CH2C}^{max}$ might sporadically result in value of x5 being zero, they added "1" to equation of d_{CH2C}^{max} to intercept this.

While other CHs send their packets to DCH via CCH, some CHs send them to DCH directly, connecting to the BS. Additionally, these CHs satisfy $dCH2BS \leq dCCH2BS$ (including CCH). However, such ($dCH2BS \leq dCCH2BS$) will send their packets to BS in a way that DCH doesn't mediate if DCH is absent due to lack of CMs in the NC. One way to compute the destination of CH is to use (20):

$$CM_{Dest.} = \begin{cases} BS, & CH\ is\ DCH \\ DCH, & (d_{CM2BS} \leq d_{DCH2BS}) \,||\, (CH\ is\ CCH) \\ CCH, & (d_{CM2BS} > d_{DCH2BS}) \end{cases} \quad (20)$$

Algorithm 2. Hierarchical packet routing strategy

Phase 1: **for** $WholeNetwork$ **do**
Phase 2: Determine the worth of d_{DCH2BS} using (1)
Phase 3: **for** nNC **do**
Phase 4: Determine the worth of d_{CM2BS}using (8)
Phase 5: **if** ($d_{CM2BS} > d_{DCH2BS}$ **then**
Phase 6: The CM tranmits its data packet to DCH
Phase 7: **else**
Phase 8: CM transmits its data packet to BS.
Phase 9: **end**
Phase 10: **end**
Phase 11: **for** FCs **do**
Phase 12: Each CM transmits a data packet to its CH
Phase 13: Identify CCH using Eq. (19)
Phase 14: Obtain the value of d_{CCH2BS} & d_{CH2BS} (1)
Phase 15: **if** $d_{CH2BS} \leq d_{CCH2BS}$ **then**
Phase 16: **if** DCH is found, **then**
Phase 17: CH transmits its Data Packet (DP) to DCH
Phase 18: **else**
Phase 19: CH transmits its DP to BS
Phase 20: **end**
Phase 21: **else**
Phase 22: CH sends its DP to CCH
Phase 23: **end**
Phase 24: **end**
Phase 25: The data packet from DCH is sent instantly to BS.
Phase 26: **end**

3.4. Proposed algorithm: gaussian mixture model clustering with hierar-chical routing

The suggested algorithms' stages are as follows:

Step 1: "Network initialization"

1) Deploy nodes: arrange SNs in a 5x5 grid at random. Every node has a beginning energy of 0.5 Joules.
2) BS: specify where BS is located on the grid.
3) Starting points: establish the starting parameters:
4) Initial parameters: establish the starting parameters:

- The quantity of rounds (R).
- The CH selection energy threshold.
- The likelihood of clustering (p=0.05).
- Energy values, such as RE.

Step 2: "FF calculation for CH selection"

1) Calculate FF: determine FF for every node, consisdering distance from BS (d_n2BS) as well as RE (E_res). The possible CHs are chosen using this FF. In (21) is used to calculate each node's FF:

$$F = \alpha.\frac{E_{res}}{E_i} + (1-\alpha).\frac{d_{CM2BS}}{d_{th}} \quad (21)$$

α is a weighting element in this case, E_{res} is a RE, E_i is initial energy, and d_{CM2BS} is a distance amidst a node and a BS.

2) Selection of CHs: CHs are selected from nodes with highest FF. The CHs are chosen by taking into account both distance and energy.

Step 3: "Hybrid and adaptive clustering"

1) Execute adaptive clustering: use acclimatizing clustering, which dynamically alleviates quantity of clustering rounds after each round, to save energy. Clustering will be completed in a few rounds thanks to this. The formula for pliable clustering is provided by (22):

$$R_{clust.} = \begin{cases} 1 & if\ r\ mod\ \left(\frac{1}{p}\right) = 0\ and\ N_d(r) > 0 \\ 0 & otherwise \end{cases} \quad (22)$$

where r is a current round, p is a clustering probability, and $N_d(r)$ is count of nodes in the round.
Step 4: "GMM-based cluster formation"
1) Apply GMM clustering: apply adaptive clustering to cluster nodes using GMM. In order to maintain balanced energy usage, GMM will gradually decrease the number of clusters. Expectation-maximization (EM) method, which alternates amidst allocating cluster nodes (expectation) and parameter optimisation (maximisation), is the foundation of GMM clustering.
2) Assign nodes to clusters: after clustering completion, group nodes into the appropriate clusters according to the probability that each node is a member of that cluster.

Step 5: CH selection for direct and farther clusters
1) DCH selection: DCH selection for NC nodes takes into account both RE and the distance to a BS, as determined by (23):

$$F_{DCH} = \alpha.x1 + (1 - \alpha).x_2 \quad (23)$$

where, $x1 = \frac{E_{res}}{E_i}$ and $x_2 \frac{d_{CM2BS}}{d_{th}}$

2) FC CH selection: FF is changed to incorporate both energy and distance factors for clusters that are further away from the BS (24):

$$F_{CH}^{modify} = \begin{cases} \alpha.x1 + (1 - \alpha).x3 & if\ d_{CM2BS} > d_{Max}^{FC} \\ \alpha.x1 & otherwise \end{cases} \quad (24)$$

where $x_3 = \frac{d_{Max}^{FC} - d_{CM2BS}}{d_{Max}^{FC}}$

Step 6: "Routing in hierarchy"
1) Communication between clusters: for effective inter-cluster communication, introduce CCHs and DCHs. CHs and the BS communicate in a stratified fashion, with CCHs directing DCH communication and sending data to BS.
2) Data routing:
- Data is sent to the BS by DCHs and CCHs in every cycle.
- CHs receive data from SNs, forward it to CCHs, and ultimately to BS.

Step 7: 'Energy consumption monitoring'
1) Monitor energy consumption: based on data transmission and reception, update energy levels of each node and CH at end of each cycle.
2) Terminate upon energy depletion: a node or CH gets eliminated from the network once its energy runs out. Until a particular energy level is achieved or a predetermined number of rounds are completed, the process keeps going.

The GMM is used by GMMCHR method to implementation of adaptive clustering in WSN. Strategy balances energy consumption and increases NL by amalgamating hierarchical routing with DCH and CCH with EE clustering. The program optimizes WSN performance by adjusting to network circumstances and cutting down on wasteful energy use.

3.5. Integration justification: Gaussian mixture model–clustering with hierarchical routing

Amalgamation of hierarchical routing with GMM clustering is a concept with both theoretical and practical potential to address effectively some critical issues in WSNs, like uneven energy distribution, poor cluster formation, and wasteful data transmission. GMM allows probability distributions to be fit probabilistically flexibly to distributions of nodes, elliptical clusters of differing densities, with the help of parameters such as mean vectors and covariance matrices. This flexibility allows better and energy well-balanced cluster formation as opposed to conventional hard algorithms of clustering. when integrated with hierarchical routing scheme that reduces long transmissions through well-defined multi-level communication in the form of DCHs and CCHs, the resulting GMMCHR framework increases energy savings and extends NL. The probabilistic characteristics of GMM also further qualifies the selection of CHs as relating to spatial proximity and RE which can adjust dynamically with the network conditions. This compatibility between statistical modeling and energy-aware route delivers most of the problems with the existing approaches of WSN protocol by delivering enhanced scalability, fewer communications overheads, and robustness with underlying heterogeneous deployments.

4. RESULTS AND DISCUSSION

This segment provides results and discussion of suggested work with included simulation environment, network model assumption, parameters setting and each result of proposed algorithm. Also provide the comparison between existing and proposed models.

4.1. Simulation environment

MATLAB R2021a was used to simulate the proposed model of GMMCHR in order to compare its results in different network conditions. The adaptability and scalability of the model under consideration has been evaluated using two deployments scenarios. In scenario 1, 100 SNs have been randomly distributed on area of 100 m^2 with the BS placed outside (at coordinates (150, 100)). Scenario 2 had the scale of the network increased to 200 nodes spread over 200×200 m^2 with the BS internally at (0,0). Quantity of energy among each SN was set at 0.5 Joules and energy dispersion was modeled according to first order radio model of which electronics energy (E_{elec}) free space and multipath amplification (ε_{fs}, ϵ_{mp}) as well as standardized control and data packet sizes. Those settings helped fully assess the energy efficacy, network coverage, and lifespan advantages of the GMMCHR protocol on various spatial and density-based deployment scenarios.

4.2. Network model assumptions

A static WSN is used in the simulation model, given that SNs in network are cognate in two different scenarios and randomly and uniformly distributed throughout the specified areas of sensing every node uses the first-order model of radio energy dissipation and starts with an inceptive energy of 0.5J. The parameters are the communication energy parameters: a transmitter/receiver circuitry energy cost Eelec=50 nj/bit, free space model amplification energy e fs=10pJ/bit/m^2 and multipath model amplification energy e mp=0.001 3 pJ/bit/m^4 present in Table 2. The data aggregation energy is established to 5 nJ/bit/signal. It has been determined that the lengths of control packets are 200 bits, whereas the lengths of data packets are 4000 bits. It is assumed that he threshold distance (dth) is 88 m and mean communication distance amidst nodes and the DCH shall be 90 m. To simulate node activity a duty cycle probability of P n=0.20 is introduced. There are two scenarios here, scenario 1 where there are 100 nodes with area 100×100 m and BS is deployed outside area at (150, 100), and scenario 2 where there are 200 nodes with an area of 200×200 m with BS placed on inside at (0, 0) as shows in Table 3. It is supposed that all nodes are stationary, are hardware alike, and able to undertake data aggregation, sensing, and communication.

Table 2. Simulation settings/parameters

Parameters	Value
$Eelec$	50 nJ/bit
No. of nodes (N)	100
dth	88 m
Pn	0.2
εmp	0.0013 pJ/bit/m^4
$dDCH$	90 m
εfs	10 pJ/bit/m^2
EDA	5 nJ/bit/signal
Simulation rounds	2000
The initial energy of node (Ei)	0.5 J
Control packet size (l*)	200 bits
Data packet size (l)	4000 bits

Table 3. Simulation scenarios

No. of scenarios	Sensing region (m^2)	BS (m)
Scenario1	100*100	(150, 100)
Scenario2	200*200	(0,0)

4.3. Evaluation metrics

To determine the potentiality of the proposed GMMCHR protocol a number of key performance indicators were used. Some important measurements used to determine NL include FND, HND, and LND indicators which include route paths that represent the durability and the persistence of the sensor network over time. The level of efficacy of energy consumption and conservation by nodes was measured in terms of the RE that was observed throughout the simulation rounds. A measure of the CR was used to determine the percentage of the surveillance region physically occupied with an operational SN; since this represents the spatial integrity of the network. Besides, the overall energy consumption analysis was performed to view degree of network energy consumption over time in its operation. The amalgamation of these metrics provides a complete assessment of the protocol with regards to improving EE, coverage maintenance, and extended life of the network under different deployment conditions.

4.4. Results of gaussian mixture model clustering with hierar-chical routing

This segment delineates and scrutinizes the simulation results of proposed GMMCHR protocol under two deployment scenarios: 100-node and 200-node networks. It compares GMMCHR's performance with the existing EEHCHR protocol across metrics such as node lifespan, energy consumption, CR, and packet delivery. A critical evaluation is also provided to assess strengths, limitations, and practical implications of the proposed method.

4.4.1. Scenario 1: 100-node simulation

Figure 2 shows the initial configuration of 100 SNs on a 100×100 m² field with scenario 1 on the GMMCHR protocol. Nodes are generated randomly, red dots mark clustered nodes generated by GMM, and blue dots mark unclustered nodes. The external BS is denoted by a star and has coordinates (150, 100). The inky red blot on the upper right indicates ars probabilistic GMM grouping relationship based on spatial adjacency. This distribution facilitates efficient communication within the cluster and optimal CH selection, hastens to saving energy and extending NL.

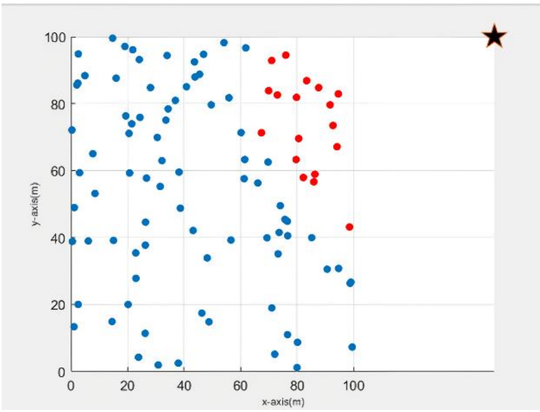

Figure 2. Initial deployment of cluster nodes in scenario 1 (100 nodes, 100×100 m² region)

Figure 3 shows amount of dead and alive SNs per round in scenario 1 with the GMMCHR protocol in 2000 simulation rounds. The graph on the left indicates a steady rise in the mortality of nodes until FND at round about 66, HND at round about 911 and the LND at round 1601. The second graph correspondingly indicates a progressive decrease in quantity of living nodes, which proves even energy spending manner. The straight degradation curve shows the EE of the protocol, its capability to ensure a stable network in the long-term, and hence postpones the possibility of complete node exhaustion.

Figure 4 instantiates trend of RE of network per round of scenario 1 within the GMMCHR protocol. The RE begins with a total amount of around 50 J with 100 nodes, and the decrease shows a smooth, almost exponential curve throughout the simulation rounds. The energy decays to about 17 J by round 800 and to less than 5 J by round 1400, with very little energy left prior to round 1600. This monotonous reduction indicates an even distribution of energies between nodes, showing that effective energy loads balancing was reached by means of adaptive clustering and hierarchical routing. The lack of steep decreases implies reduced energy spikes and effective cluster head rotations, which, in the end, results in increased NL and stability.

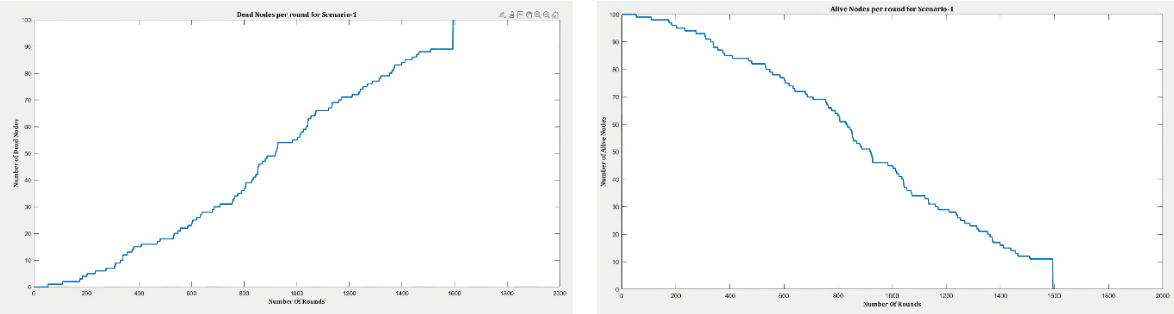

Figure 3. Dead and alive node progression across rounds in scenario 1

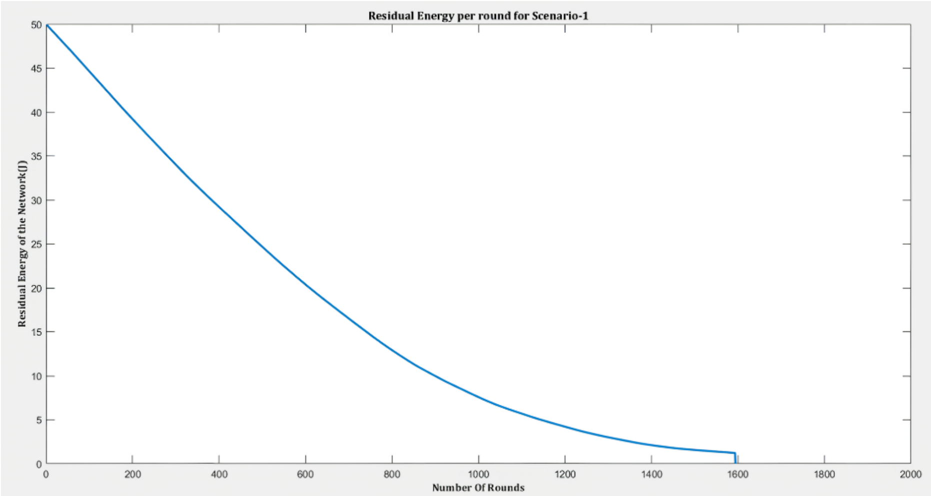

Figure 4. RE consumption trend per round for scenario 1

Figure 5 delineates network coverage per round of scenario 1 when using GMMCHR protocol, which points out the level at which the sensing field is covered across time. There is constant, almost 1, CR up until around round 750 where the CR starts to drop steadily. By round 1200, the ratio falls below 0.7 and a more pronounced decline is noticed during the period 1400 to 1600, and falls to zero at the last stage. These impairments are associated with higher node mortality and a decreased ability to sense actively. Energy-based clustering and routing effectiveness of the protocol are verified by its initially stable coverage, which keeps the network functional longer than depletion.

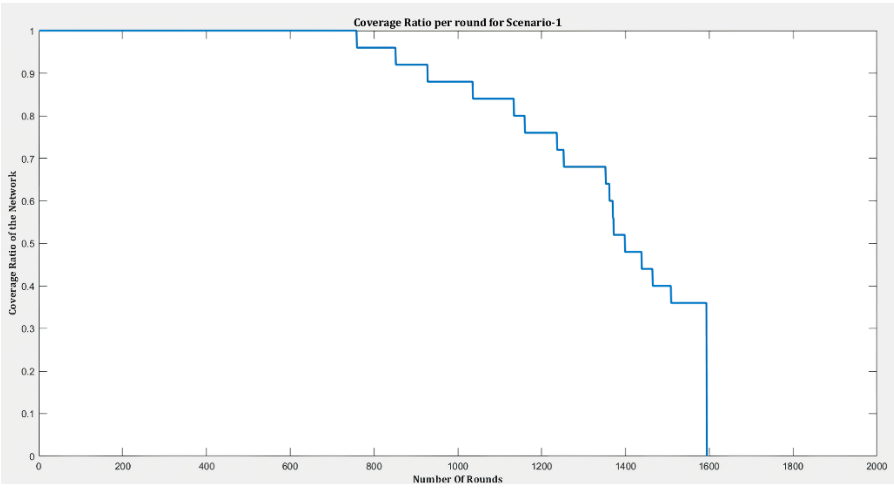

Figure 5. CR degradation over simulation rounds in scenario 1

Table 4 summarizes the lifetime evaluation outcomes for scenario 1, focusing on key indicators of network sustainability under the GMMCHR protocol. The FND occurs at round 66, indicating an early but isolated node failure. The HND milestone is reached at round 911, reflecting a balanced and gradual energy depletion process. The LND occurs at round 1601, signifying the end of network activity. These results demonstrate the protocol's potentiality to distribute energy consumption evenly across network, extending operational life and maintaining sensing performance over a prolonged period.

Table 4. Lifetime evaluation outcomes for scenario 1

Lifetime evaluation	Scenario1 for 100 nodes
FND	66
HND	911
LND	1601

4.4.2. Scenario 2: 200 node simulation

Figure 6 displays the initial deployment of 200 SNs over a 200×200 m² area for scenario 2 using the GMMCHR protocol. Nodes are randomly placed, with red markers representing those clustered by the GMM, and blue indicating unclustered nodes. The BS, located internally at (0,0), is marked with a star. A dense cluster near the BS reflects GMM's efficiency in spatial grouping based on proximity. The distribution facilitates shortening the communications ranges, minimizing the energy usage and even generates the foundation of equal clustering and lucrative routing in expansive networks.

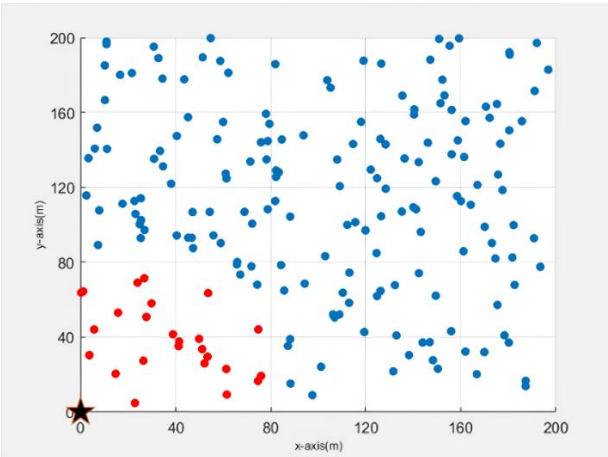

Figure 6. GMMCHR initial deployment of cluster nodes in scenario 2 (200 Nodes, 200×200 m² region)

Figure 7 shows quantity of nodes which are dead and alive within each round when using the GMMCHR protocol on scenario 2 over a range of 200 nodes. The left graph displays a slow increasing trend in quantity of dead nodes, whereby the FND is found at around 48 rounds after which the failure rate accelerates and, after round 904, all nodes would be dead, around round 1231. In the same respect, the right graph shows a constant reduction of quantity of alive nodes, an indication of consistent energy usage and effective periodical workload. This node adaption behavior recorded in each period shows adequate adaptation ability of GMMCHR to keep the network stable and has a long lifetime as well as ensuring that the energy distribution within the dense deployment scenario is uniform.

The Figure 8 shows trend of RE depletion of the network per round towards scenario 2, which adopts the GMMCHR protocol. On an initial total of about 100J in 200 nodes, the remaining energy follows a smooth nonlinear degradation trend, as the rounds increase. By round 600 the amount of energy left is only about 45 1ip by round 1000 it is less than 10 1ip and it is completely depleted shortly after round 1370. The appearance of the stable and smooth gradient without sharp energy phenomena implies the good energy load balancing and a small communication overhead. This trend is indicative of the scaling ability and efficiency of GMMCHR to manage energy in more density of the network conditions.

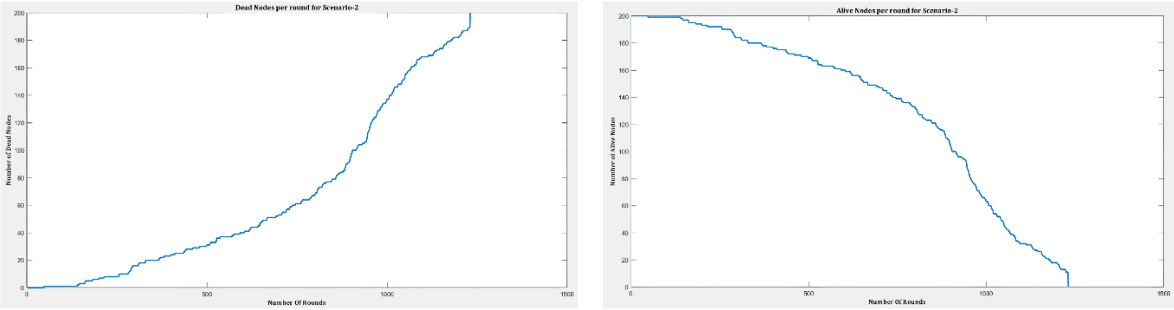

Figure 7. Dead and alive node progression across rounds in scenario 2

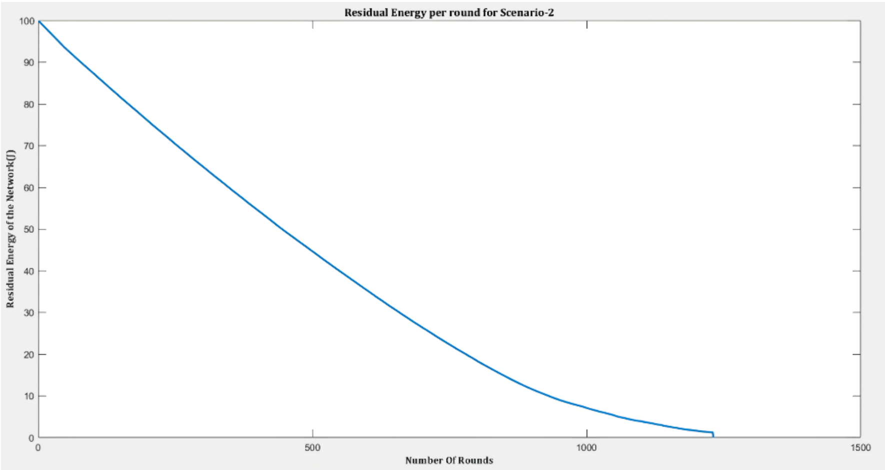

Figure 8. RE consumption trend per round for scenario 2

Figure 9 shows network CR with per round of the GMMCHR protocol in scenario 2 where it is observed that sensing coverage is temporally sustainable over the 200-nodes deployment. The CR remains constant and close to 1.0 for the first 900 rounds, indicating near-complete field monitoring. A gradual decline begins thereafter, dropping below 0.7 by round 1050, and continuing to fall sharply as node failures accumulate, reaching zero near round 1370. This behavior reflects the protocol’s ability to preserve high coverage for a significant duration and delay network degradation, showcasing its effectiveness in large-scale, energy-constrained environments.

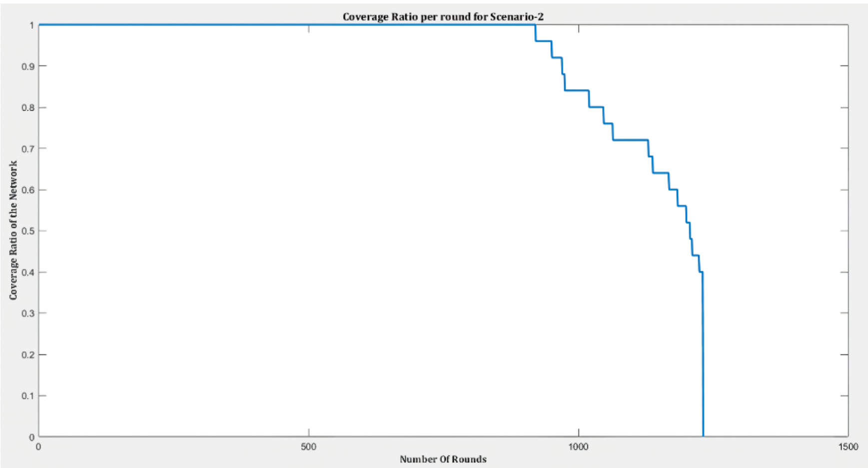

Figure 9. CR degradation over simulation rounds in scenario 2

Table 5 illustrates NL performance of proposed GMMCHR scheme under scenario 2 for a deployment of 200 SNs. The solutions indicate that the initial node fails after the 48th round due to energy loss. At 904 rounds a quarter of a network nodes become non-functional, indicating an even energy consumption of network nodes. The final node is useable until 1231 rounds, and thus this proves potentiality of the protocol to increase NL. These outcomes verify fact that node deaths in GMMCHR approach can be postponed effectively and he network is more sustainable than a regular clustering approach.

Table 5. Lifetime evaluation outcomes for scenario 2

Lifetime evaluation	Scenario 2 for 200 nodes
FND	48
HND	904
LND	1231

4.5. Comparative analysis with energy efficient hybrid clustering and hierarchical routing

In this section provide the comparison with existing EEHCHR with count of nodes with scenario 1 and 2. In Figure 10 there is a collation chart of amount of each round's dead nodes using scenario 1, a scenario which simulated the number of nodes as 100. GMMCHR (shown by the green line) is always superior to process ordinary EEHCHR (by the red line) in that it shows a lower rate of death of nodes with time passing. Conspicuously, the EEHCHR mode depletes to a total of nodes at about 1250 rounds whereas GMMCHR method operates to a higher number of nodes implying greater energy equilibrium and longer sustainability of the network. This tendency proves their suggested GMMCHR to greatly increase NL and put to shame early node failures in comparison to the baseline clustering implementation.

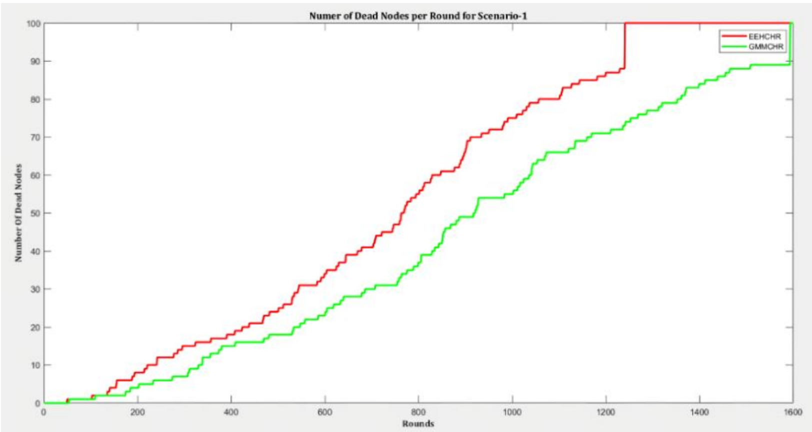

Figure 10. Comparison of scenario 1's dead node count by round

The comparison of amount of alive nodes per round of scenario 1 can be shown in Figure 11 on the basis of simulation with 100 nodes. More operational nodes are kept by the GMMCHR protocol (green line) during simulating than the EEHCHR method (red line). Although the rates of active node losses in the EEHCHR-regime are very high, becoming virtually empty at around 1250 rounds, the GMMCHR manages to maintain node activity until around 1600 rounds. Such maintained performance serves as a strong indicator of the outstanding EE and load balance ratio of GMMCHR that demonstrate its potential of significantly extending NL and provide a more stable network coverage in the long term.

Figure 12 depicts scenario 1's CR for each round, in which performance of the EEHCHR (red line) protocol and the proposed GMMCHR (green line) protocols were compared. Over a much longer period GMMCHR continues to remain above unity in CR whereas EEHCHR drops gradually at around 500 rounds due to node depletion and becomes zero at around 1250. GMMCHR, on the contrary, provides a larger depth of CR over 70% even beyond 1200 rounds and at least some coverage beyond about 1600 rounds. This goes to show that GMMCHR is successful in providing a better area coverage and prolonged observation over a long span of time that it is apparently true that GMMCHR offers a better energy balance and network sustainability than its baseline EEHCHR equivalent.

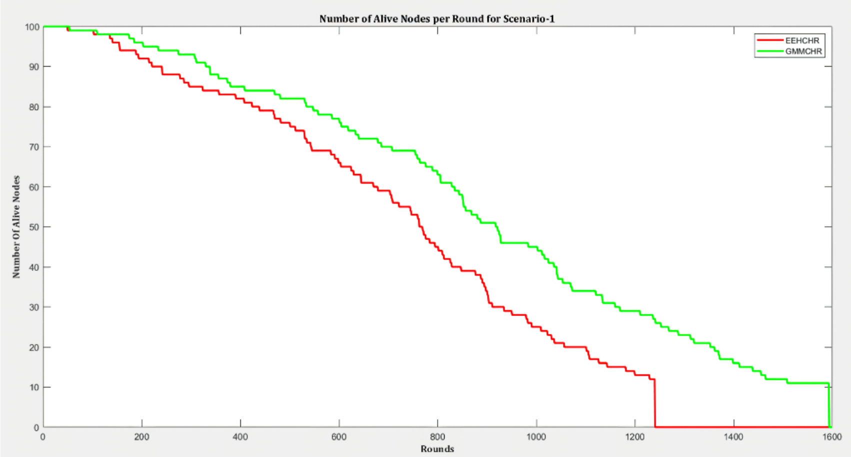

Figure 11. Comparison of scenario 1's alive nodes by round

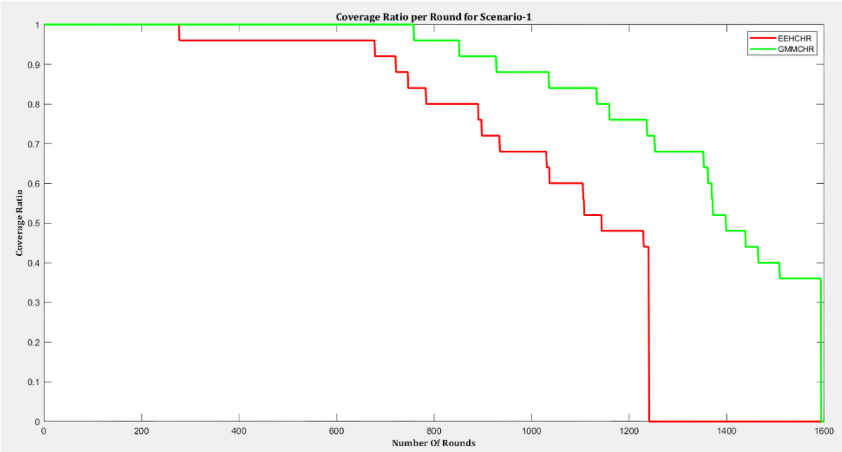

Figure 12. Comparison of scenario 1's CR by round

Figure 13 presents the performance comparison of scenario 1 as the CR per round and indicates how much more effectively the EEHCHR (red line) protocol operates compared to GMMCHR (green line). GMMCHR has a near-ideal CR at a much later stage and the EEHCHR starts downwards trending right after reaching approximately 500 rounds and reaching zero coverage with near consistency going past approximately 1250 rounds. On the contrary, the GMMCHR manages to sustain more than 70% coverage even beyond 1200 rounds and partial coverage till around 1600 rounds. This shows that the proposed GMMCHR will save the network area monitoring and sustainability over a long time and hence it will be the best GMMCHR scheme to achieve robust coverage and thus enhancing the useful life of WSN.

Figure 14 shows a comparison of aggregate quantity of packets transmitted to BS per round of scenario 1, that reveals the performance of EEHCHR (red line) to remain the same as that of the proposed GMMCHR (green line). GMMCHR encounters a constant and sustained increase in packet delivery over time which indicates that it has long term and stable data transmission capacity. Even though the packet delivery stops sharply at the point of node depletion which is at about 1250 rounds in the EEHCHR protocol, the GMMCHR goes up to delivery packets at 1600 rounds and over approximate 17,000 packets compared to 14,000 packets of the EEHCHR. This tendency proves that GMMCHR the process of WSN operations provides more stable and longer distance data communication with a maximized network throughput and optimized efficiency of its functioning in general.

Figure 15 shows each round's dead nodes using Scenario 2, comparison of EEHCHR and the proposed GMMCHR protocols in a 200-node simulation. The findings indicate that node deaths expand monotonically across both protocols; nevertheless, the number of nodes dying in EEHCHR is much more rapid than in the other method, where all nodes are killed by circa 1150 rounds. On the contrary, the

GMMCHR indicates a smoother and less pronounced growth of dead nodes and allows stretching the NL to about 1230 rounds. By this trend, it is established that GMMCHR successfully distributes energy consumption amidst nodes and postpones early deaths of nodes and enhances overall sustainability of a network relative to the standard EEHCHR protocol.

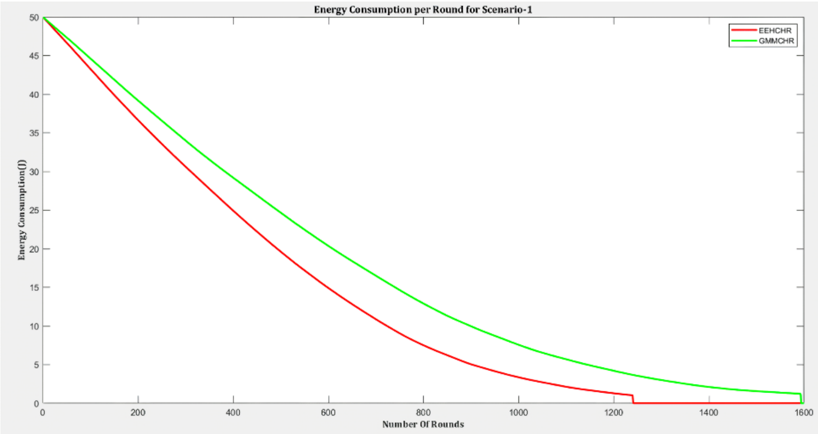

Figure 13. Comparison of scenario 1's energy consumption per round

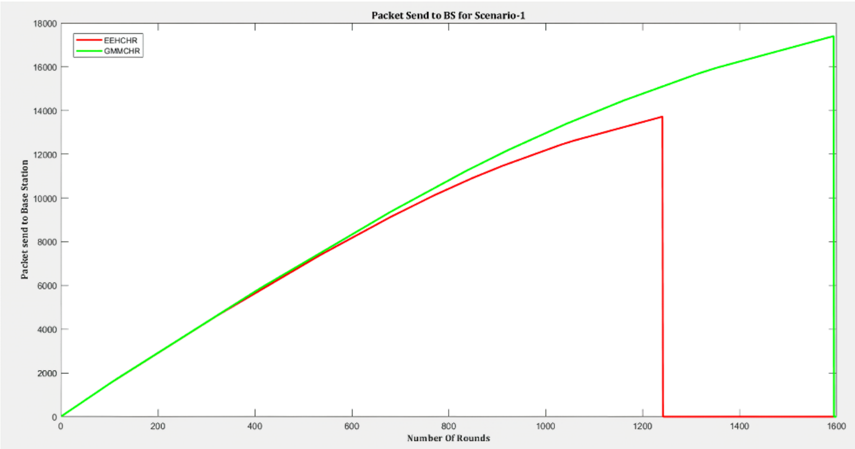

Figure 14. Comparison of the packet sent to BS for scenario 1

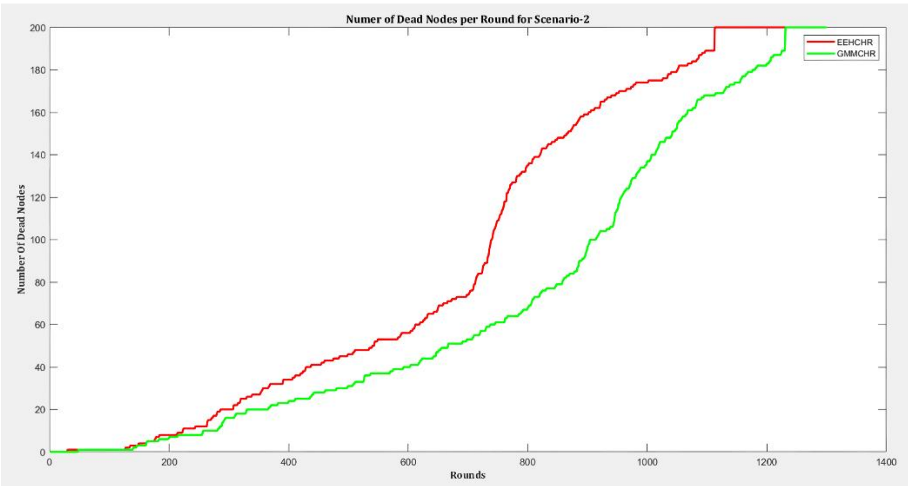

Figure 15. Comparison of scenario 2's dead node count by round

Figure 16 presents amount of alive nodes per round in scenario 2 of live nodes frequency in 200 node simulation compared between EEHCHR (red line) and the proposed GMMCHR (green line) protocols. The GMMCHR keeps a more quantity of active nodes in the entire simulation interval than EEHCHR showing a slower rate of node survivability. The number of nodes falls very fast in EEHCHR protocol after around 600 rounds, and count of active nodes drops to zero at around 1150 rounds, and GMMCHR continues having active nodes after 1200 rounds. That trend proves that the GMMCHR shows the ability to balance energy better and utilize resources more efficiently, eventually increasing the total NL and enhancing the network reliability, in larger-scale deployments.

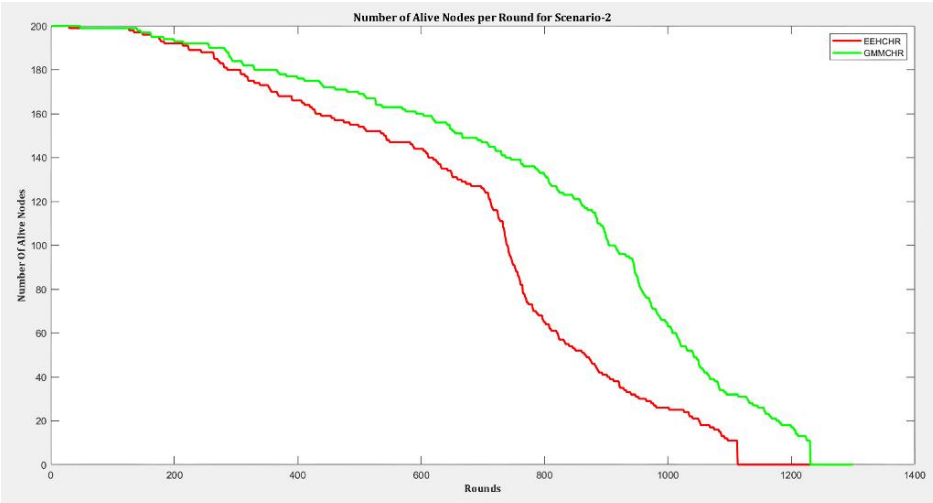

Figure 16. Comparing the alive nodes for scenario 2 by round

The CR against round is presented in Figure 17, which is scenario 2 where quantity of nodes is 200, and simulation compares EEHCHR (red line) and the proposed GMMCHR (green line). The GMMCHR also has a better sustained full CR and has more less stagnated decline rate as compared to EEHCHR. Whereas the coverage decreases drastically almost after 800 rounds and becomes zero at around 1150 rounds, the GMMCHR maintains more than 70% coverage after 1000 rounds and provides 1.5 km of network coverage towards 1230 rounds. This trend in performance also establishes that GMMCHR has a better capacity to balance energy consumption, maintain connectivity in network and long duration of effective area monitoring and prove its superiority over the less scale implementation of the baseline EEHCHR scheme.

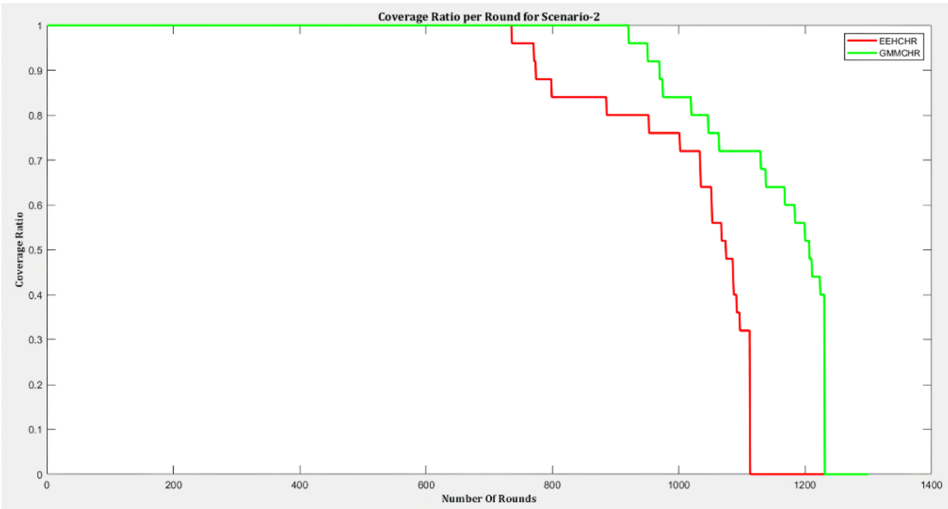

Figure 17. Analysis of the CR for each round in scenario 2

In Figure 18, energy usage per round of the scenario 2 is used to compare the EEHCHR scheme (red line) and the proposed GMMCHR scheme (green line) in a simulation of 200 nodes. As observed in the findings, the two protocols exhibit a consistent reduction in the overall energy level as quantity of rounds increases but the EEHCHR runs out of energy faster such that it is hovering between zero and very low levels in the range of 1150th rounds. Conversely, the GMMCHR has a less converging trend of energy consumption, which goes to lengths of about 1230 rounds. It instantiates that GMMCHR spreads energy consumption amidst nodes more equally which is equivalent to elongating the lifetime of the network and making it more sustainable than when the above-studied EEHCHR strategy is used.

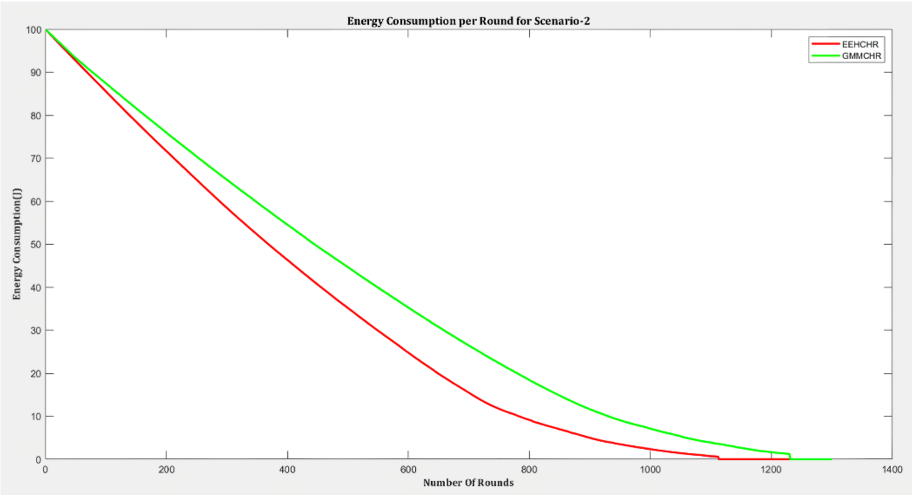

Figure 18. Comparing the energy use for each round in scenario 2

In Figure 19, the relative collation graph of amount of packets sent to BS against each simulation round was plotted in scenario 2 that employs a 200-node WSN. Proposed GMMCHR protocol is compared with current EEHCHR protocol in terms of its efficacy. As it was seen, in all the rounds, GMMCHR leads EEHCHR in packet delivery. GMMCHR expects a steady growth, about 3.9×10^4 packets at about 1250 rounds, whereas EEHCHR is constant at around 3.3×10^4 packets around 1050 rounds, and will not transmit anymore. Long stability and larger packet throughput of GMMCHR means that it is more efficient and will last longer than any network which is the main reason why it is a reliable routing protocol when used in dense WSNs context.

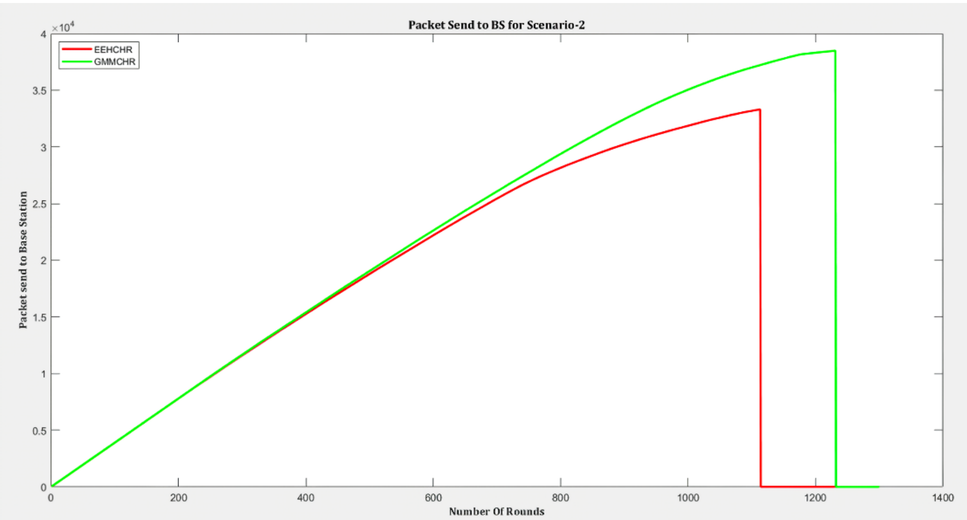

Figure 19. Comparison of the packet send to BS for scenario 2

A comparison of important performance indicators for various clustering and routing methods in WSNs is shown in Table 6. In terms of network lifespan indicators, the suggested GMMCHR protocol continuously performs better than benchmark techniques like EEHCHR, HEED, and LEACH. In comparison to EEHCHR, which has comparable values of 45, 735, and 1359 rounds, GMMCHR delays FND to 66 rounds, HND to 911 rounds, and LND to 1601 rounds for scenario 1 with 100 nodes. GMMCHR maintains this advantage in the larger 200 node scenario 2, where FND, HND, and LND occur at 48, 904, and 1231 rounds, respectively, in contrast to EEHCHR's 31, 731, and 1024 rounds. In comparison to GMMCHR and EEHCHR, HEED, and LEACH have shorter NLs with LND values of 1100 and 750 rounds, respectively. These findings highlight ameliorate energy economy and efficient load balancing of GMMCHR, which help to extend network operation and improve scalability across different network sizes.

Table 6. Comparative analysis of evaluation criteria

Technique	Scenarios (nodes)	FND	HND	LND
GMMCHR	Scenario 1 for 100	66	911	1601
	Scenario 2 for 200	48	904	1231
EEHCHR [22]	Scenario 1 for 100	45	735	1359
	Scenario 2 for 200	31	731	1024
LEACH [12]	For 100	-	-	1100
HEED [13]	For 100	-	-	750

4.6. Statistical performance analysis and trade-offs

A statistical assessment of the FND, HND, and LND measures across 20 separate simulation runs was carried out for each scenario, when appropriate, in order to confirm the performance gains of GMMCHR over EEHCHR, HEED, and LEACH. In comparison to EEHCHR, which had mean values of 45.3±1.5, 735.9±4.2, and 1359.2±5.1, GMMCHR obtained mean values of FND=66.4±1.2, HND=911.7±3.8, and LND=1602.5±4.6 in scenario 1 (100 nodes). GMMCHR and EEHCHR perform significantly better than HEED and LEACH, despite the fact that they reported LND values of about 1100 and 750 rounds, respectively. GMMCHR outperformed EEHCHR, which had averages of 31.6±1.3, 731.4±3.9, and 1024.3±5.4 in scenario 2 (200 nodes), with FND=48.1±1.4, HND=904.6±4.5, and LND=1231.4±6.2. The 95% CIs verify that these changes are statistically significant ($p<0.01$), suggesting steady and dependable improvements for GMMCHR. The increases in network performance and endurance do come with certain trade-offs, though. Compared to EEHCHR, GMMCHR has a somewhat greater initial computational overhead because of its EGMM-based clustering and fitness-function-driven CH selection, which results in a 5-8% increase in clustering latency. There is a little increase in control packet overhead as a result of the hierarchical routing structure's requirement for more metadata exchanges between CHs. GMMCHR is better appropriate for mission-critical, long-duration WSN deployments where stability and scalability are more important than quick setup time because of its superior energy balancing, less packet loss, and increased network coverage, which justify the expenses despite these additional complications.

4.7. Critical evaluation

The given GMMCHR protocol suggestion is a completely new and unwavering approach to enhancing the energy efficacy of WSNs and expanding their operating lifetime. The method overcomes key shortcomings of traditional protocols, including uneven energy use and premature node failure and poor data transmissions routes by two mechanisms: probabilistic clustering using GMM and energy-aware hierarchy routing.

4.7.1. Strengths of gaussian mixture model clustering with hierar-chical routing are evident in both simulation scenarios

The strengths of the proposed GMMCHR protocol are demonstrated through multiple aspects of its design and experimental performance. These strengths can be summarized as follows:
- Hybrid design innovation: the integration of GMM for probabilistic clustering with hierarchical routing mechanisms (DCH/CCH) addresses two major WSN challenges, imbalanced energy usage and inefficient routing. The probabilistic nature of GMM offers greater adaptability in heterogeneous node distributions compared to traditional crisp clustering (e.g., K-means or LEACH). Additionally, the RE-aware FF for CH selection ensures fair energy load distribution.
- Robust experimental setup: the simulations are performed across two diverse scenarios (100 and 200 nodes) with clear deployment strategies, emphasizing both small-scale and large-scale network

performance. Key metrics, FND, CR, LND, RE, HND, and packet transmission—are methodically tracked over 2000 rounds, ensuring a comprehensive assessment of EE and NL.
- Empirical superiority: GMMCHR invariablly surpassing the EEHCHR baseline in all critical KPIs. It delays node death significantly and maintains higher coverage and packet delivery rates. For example, in scenario 1, GMMCHR extended LND by over 240 rounds and delivered 3,000 more packets than EEHCHR, showcasing tangible improvements in real-world applicability.
- Superior lifetime metrics: compared to EEHCHR, HEED, and LEACH, GMMCHR shows significant improvements in FND, HND, and LND across 100-node and 200-node deployments. For instance, in scenario 1, GMMCHR extended the LND to 1601 rounds, outperforming EEHCHR's 1359.
- Higher data throughput: count of packets delivered to BS is consistently higher in GMMCHR across both scenarios, confirming more stable and longer communication periods.

4.7.2. Limitations and challenges

Several key limitations should be noted, particularly in terms of computational cost and scalability:
- Computation overhead: while GMM offers flexible clustering, its EM algorithm is computationally more expensive than lightweight clustering techniques, which may impact real-time responsiveness or scalability in ultra-dense networks or on low-power edge devices. This trade-off between clustering accuracy and computational cost should be more explicitly analyzed.
- Scalability beyond 200 nodes: while the protocol performs well in 100–200 node deployments, scalability to very large networks (e.g., 1000+nodes) is not evaluated. Since GMM complexity increases with node count, the approach might face diminishing returns or increased latency, which is crucial for dense IoT or urban sensing applications.

5. CONCLUSION

Pliable clustering and routing protocols that may increase scalability and network longevity are required due to the growing need for intelligent and energy-efficient WSN solutions in applications including environmental monitoring, smart agriculture, and disaster management. Using DCHs for NC and CCHs for FC, this study presented GMMCHR, a novel hybrid protocol that amalgamates probabilistic soft clustering through EGMM with a two-tier hierarchical routing scheme. Compared to benchmark methods like EEHCHR, HEED, and LEACH, GMMCHR makes notable gains by dynamically adjusting CH selection depending on RE and geographical proximity. LND in a 100-node network was extended by GMMCHR to 1601 rounds, which was a considerable improvement above EEHCHR's 1359 rounds and HEED and LEACH's about 1100 and 750 rounds, respectively. Compared to EEHCHR, packet delivery increased by 21.4%, and coverage stayed above 70% until about 1200. With an LND of 1231 rounds, GMMCHR outperformed EEHCHR by almost 20% in a 200 node scenario. It also delivered 18% more packets and maintained smoother energy decline. Future studies will concentrate on applying mobility-aware deployment tactics, integrating predictive ML models for proactive CH rotation, putting security-aware energy-efficient routing into practice, and testing in a variety of noisy environments. Further promising directions include extending support for heterogeneous IoT environments with different node capabilities, integrating mobile sinks to shorten transmission distances, enabling real-time adaptation to abrupt topology changes, and investigating edge-computing integration to further improve its applicability in next-generation IoT-enabled WSN deployments.

ACKNOWLEDGMENTS

The authors are acknowledged by the editor and anonymous reviewers for their helpful criticism, which helped to ameliorate calibre of this investigation.

FUNDING INFORMATION

No financing is involved, according to the authors.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Neetu Sikarwar	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
Ranjeet Singh Tomar		✓				✓		✓	✓	✓	✓	✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT
No conflicts of interest are disclosed by the authors.

DATA AVAILABILITY
The information corroborating this work's conclusions were generated through simulation using MATLAB R2021a, based on synthetic WSN deployment scenarios. As no real-world datasets were used, all relevant simulation parameters and configurations have been described in detail within the paper. Further information, including simulation scripts and data outputs, can be made available by the authors upon reasonable request. No third-party data was used in this research.

REFERENCES

[1] Y. Pinar, A. Zuhair, A. Hamad, A. Resit, K. Shiva, and A. Omar, "Wireless Sensor Networks (WSNs): The Shortcomings of Wireless Sensor Networks," in *2016 IEEE Long Island Systems, Applications and Technology Conference, LISAT*, Apr. 2016, pp. 1–8, doi: 10.1109/LISAT.2016.7494144.

[2] A. Chehri, R. Saadane, N. Hakem, and H. Chaibi, "Enhancing energy efficiency of wireless sensor network for mining industry applications," *Procedia Computer Science*, vol. 176, pp. 261–270, 2020, doi: 10.1016/j.procs.2020.08.028.

[3] P. Singh, O. Gupta, and S. Saini, "A Brief Research Study of Wireless Sensor Network," *Advances in Computational Sciences and Technology*, vol. 10, no. 5, pp. 733–739, 2017.

[4] M. A. Tawfeek, I. Alrashdi, M. Alruwaili, L. Jamel, G. F. Elhady, and H. Elwahsh, "Improving energy efficiency and routing reliability in wireless sensor networks using modified ant colony optimization," *Eurasip Journal on Wireless Communications and Networking*, vol. 2025, no. 1, p. 22, Apr. 2025, doi: 10.1186/s13638-025-02449-w.

[5] Q. Feng, S. C. Chu, J. S. Pan, J. Wu, and T. S. Pan, "Energy-Efficient Clustering Mechanism of Routing Protocol for Heterogeneous Wireless Sensor Network Based on Bamboo Forest Growth Optimizer," *Entropy*, vol. 24, no. 7, p. 980, Jul. 2022, doi: 10.3390/e24070980.

[6] G. S. Arumugam and T. Ponnuchamy, "EE-LEACH: development of energy-efficient LEACH Protocol for data gathering in WSN," *Eurasip Journal on Wireless Communications and Networking*, vol. 2015, no. 1, pp. 1–9, Dec. 2015, doi: 10.1186/s13638-015-0306-5.

[7] W. B. Heinzelman, A. P. Chandrakasan, and H. Balakrishnan, "An application-specific protocol architecture for wireless microsensor networks," *IEEE Transactions on Wireless Communications*, vol. 1, no. 4, pp. 660–670, Oct. 2002, doi: 10.1109/TWC.2002.804190.

[8] R. Priyadarshi, L. Singh, Randheer, and A. Singh, "A Novel HEED Protocol for Wireless Sensor Networks," in *2018 5th International Conference on Signal Processing and Integrated Networks, SPIN 2018*, Feb. 2018, pp. 296–300, doi: 10.1109/SPIN.2018.8474286.

[9] H. Hojjatinia, M. Jahanshahi, and S. Shehnepoor, "Improving lifetime of wireless sensor networks based on nodes' distribution using Gaussian mixture model in multi-mobile sink approach," *Telecommunication Systems*, vol. 77, no. 1, pp. 255–268, May 2021, doi: 10.1007/s11235-021-00753-6.

[10] G. Wu, J. Wu, and X. Zhang, "Research on gaussian mixture model and its distributed data mining algorithm in wireless sensor networks," *Journal of Intelligent and Fuzzy Systems*, vol. 46, no. 4, pp. 8513–8527, Apr. 2024, doi: 10.3233/JIFS-238711.

[11] L. Chan, K. G. Chavez, H. Rudolph, and A. Hourani, "Hierarchical routing protocols for wireless sensor network: a compressive survey," *Wireless Networks*, vol. 26, no. 5, pp. 3291–3314, Jul. 2020, doi: 10.1007/s11276-020-02260-z.

[12] A. Panchal and R. K. Singh, "EEHCHR: Energy Efficient Hybrid Clustering and Hierarchical Routing for Wireless Sensor Networks," *Ad Hoc Networks*, vol. 123, p. 102692, Dec. 2021, doi: 10.1016/j.adhoc.2021.102692.

[13] H. Kour and A. K. Sharma, "Hybrid Energy Efficient Distributed Protocol for Heterogeneous Wireless Sensor Network," *International Journal of Computer Applications*, vol. 4, no. 6, pp. 1–5, Jul. 2010, doi: 10.5120/828-1173.

[14] T. M. Behera, S. K. Mohapatra, U. C. Samal, M. S. Khan, M. Daneshmand, and A. H. Gandomi, "Residual energy-based cluster-head selection in WSNs for IoT application," *IEEE Internet of Things Journal*, vol. 6, no. 3, pp. 5132–5139, Jun. 2019, doi: 10.1109/JIOT.2019.2897119.

[15] N. G. Palan, B. V. Barbadekar, and S. Patil, "Low energy adaptive clustering hierarchy (LEACH) protocol: A retrospective analysis," in *Proceedings of the International Conference on Inventive Systems and Control, ICISC 2017*, Jan. 2017, pp. 1–12, doi: 10.1109/ICISC.2017.8068715.

[16] H. Wang, K. Liu, C. Wang, and H. Hu, "Energy-Efficient, Cluster-Based Routing Protocol for Wireless Sensor Networks Using Fuzzy Logic and Quantum Annealing Algorithm," *Sensors*, vol. 24, no. 13, p. 4105, Jun. 2024, doi: 10.3390/s24134105.

[17] M. Kaddi, M. Omari, K. Salameh, and A. Alnoman, "Energy-Efficient Clustering in Wireless Sensor Networks Using Grey Wolf Optimization and Enhanced CSMA/CA," *Sensors*, vol. 24, no. 16, p. 5234, Aug. 2024, doi: 10.3390/s24165234.

[18] V. Cherappa, T. Thangarajan, S. S. M. Sundaram, F. Hajjej, A. K. Munusamy, and R. Shanmugam, "Energy-Efficient Clustering and Routing Using ASFO and a Cross-Layer-Based Expedient Routing Protocol for Wireless Sensor Networks," *Sensors*, vol. 23, no. 5, p. 2788, Mar. 2023, doi: 10.3390/s23052788.
[19] V. G. Krishnan, P. V. Rao, and V. Divya, "An Energy Efficient Routing Protocol based on SMO Optimization in WSN," in *Proceedings of the 6th International Conference on Communication and Electronics Systems, ICCES 2021*, Jul. 2021, pp. 1040–1047, doi: 10.1109/ICCES51350.2021.9489163.
[20] Y. Shi, X. Xue, B. Wang, K. Hao, and H. Chai, "High-Efficiency Clustering Routing Protocol in AUV-Assisted Underwater Sensor Networks," *Sensors*, vol. 24, no. 20, p. 6661, Oct. 2024, doi: 10.3390/s24206661.
[21] J. Vellaichamy *et al.*, "Wireless Sensor Networks Based on Multi-Criteria Clustering and Optimal Bio-Inspired Algorithm for Energy-Efficient Routing," *Applied Sciences (Switzerland)*, vol. 13, no. 5, p. 2801, Feb. 2023, doi: 10.3390/app13052801.
[22] A. Bhih, W. Abushiba, and A. Elashheb, "An Improved Leach Algorithm Based on Hierarchical Clustering Approach for Wireless Sensor Network Application," in *2022 IEEE 5th International Conference on Electronics and Communication Engineering, ICECE 2022*, Dec. 2022, pp. 78–83, doi: 10.1109/ICECE56287.2022.10048608.
[23] S. Gupta and V. Bhatia, "GMMC: Gaussian Mixture Model Based Clustering Hierarchy Protocol in Wireless Sensor Network," *International Journal of Scientific Engineering and Research*, vol. 3, no. 7, pp. 44–49, 2015, doi: 10.70729/ijser15325.
[24] A. Panchal and R. K. Singh, "EADCR: Energy Aware Distance Based Cluster Head Selection and Routing Protocol for Wireless Sensor Networks," *Journal of Circuits, Systems and Computers*, vol. 30, no. 4, p. 2150063, Mar. 2021, doi: 10.1142/S0218126621500638.
[25] D. C. Hoang, R. Kumar, and S. K. Panda, "Fuzzy C-means clustering protocol for Wireless Sensor Networks," in *IEEE International Symposium on Industrial Electronics*, Jul. 2010, pp. 3477–3482, doi: 10.1109/ISIE.2010.5637779.
[26] A. Panchal and R. K. Singh, "EHCR-FCM: Energy Efficient Hierarchical Clustering and Routing using Fuzzy C-Means for Wireless Sensor Networks," *Telecommunication Systems*, vol. 76, no. 2, pp. 251–263, Feb. 2021, doi: 10.1007/s11235-020-00712-7.
[27] A. S. Raghuvanshi, S. Tiwari, R. Tripathi, and N. Kishor, "Optimal number of clusters in wireless sensor networks: A FCM approach," *International Journal of Sensor Networks*, vol. 12, no. 1, pp. 16–24, 2012, doi: 10.1504/IJSNET.2012.047707.
[28] V. Kumar, S. Jain, and S. Tiwari, "Energy Efficient Clustering Algorithms in Wireless Sensor Networks: A Survey," *International Journal of Computer Science Issues*, vol. 8, no. 5, pp. 259–268, 2011.

BIOGRAPHIES OF AUTHORS

Neetu Sikarwar is an assistant Professor and at Jiwaji University, Gwalior, India. She has obtained M.Tech. Electronics and Communication Engineering from ITM College, Gwalior, and is pursuing Ph.D. degree in Electronics and Communication Engineering from Institute of Technology and Management University, Gwalior, India. In an academic career spanning over 20 years, she has published and presented research papers in several national and international journals and conferences in India. Her current research area is wireless sensor networks. She can be contacted at email: neetusik1@gmail.com.

Dr. Ranjeet Singh Tomar is a Professor and Dean Academics at the ITM University Gwalior, India. He has obtained M.Tech. Electronics and Communication Engineering from Malviya National Institute of Technology, Jaipur, India and Ph.D. degree in Information Technology from Indian Institute of Information Technology, Allahabad, India. In an academic career spanning over 23 years, he has published and presented research papers in several national and international journals and conferences in India and abroad. His current research areas of interest include wireless communication, digital communication, information theory and coding, and vehicular technology. Presently, he is an Editor of the International Journal of Communication, Networks and Computing published by the ITM University Gwalior, India. He is an Executive Committee member and fellow of IETE (India). He is also member of the IEEE and IE (India). He can be contacted at email: er.ranjeetsingh@gmail.com