DEAR-SFCM: Dynamic Energy Aware Radius Adaptive Subtractive Fuzzy C-Means Clustering Framework for Efficient and Sustainable Wireless Sensor Networks

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Abstract. *Managing energy efficiently in Wireless Sensor Networks (WSNs) is challenging because uneven energy use and early node failures weaken the network. To solve this issue, dynamic energy aware and radius adaptive subtractive fuzzy C-means clustering method (DEAR-SFCM) is designed to create more balanced clusters, enhance network stability and lifetime of sensor networks. It combines adaptive subtractive clustering, an energy distance weighted measure, and entropy regularized fuzzy membership updates to form clusters that better reflect both the energy levels and locations of sensor nodes. It has an adaptive radius control system that modifies the clustering radius as per the density of nodes, avoiding overcrowding in crowded areas and too many clusters in sparse ones. Also, the best nodes are appointed as cluster head (CH) by employing a multi criteria CH selection. When compared with existing state-of-the-art methods, DEAR-SFCM performs better in terms of energy balance, network lifetime, alive node and packet delivery rates. The results show DEAR-SFCM reduces hotspot formation, distributes communication tasks more evenly, and extends both the stable operating period and overall network duration. These improvements make DEAR-SFCM a strong and adaptable option for energy limited WSNs and future large scale Internet of Things (IoT) monitoring applications.*

Keywords

Cluster head selection, energy efficiency, fuzzy C-means, network lifetime, wireless sensor networks

1. Introduction

WSNs have evolved as a fundamental component of modern intelligent systems, supporting a numerous applications like environmental monitoring, healthcare data collection, military monitoring, smart agriculture and structural health evaluation. These networks consist of numerous sensor nodes distributed geographically and work together to detect, process, and forward sensed environmental data. WSNs faces problem with effective management of scarce energy resources. Extending lifetime of network while assuring delivery of data is a major design goal as sensor nodes typically run on batteries and occasionally situated in unreachable places. Clustering minimizes redundant transmissions, manages communication load, and enhances network scalability by bunching nodes into clusters and designating a CH responsible for data aggregation and communication with the sink [1].

Over the years, many clustering algorithms have been proposed [2], ranging from hierarchical and density based schemes to fuzzy and hybrid methods [3], thereby offering different strengths and shortcomings related to adaptability, robustness, and energy consumption. Clustering has been a very promising effective strategies for addressing energy limitations in WSNs. Among the various cluster formation strategies, Subtractive Fuzzy C-Means (SUBFCM) [4] and Hierarchical Agglomerative Clustering (HAC) [5] have attracted lot of attention. HAC is a deterministic, bottom up method that utilizes predetermined similarity measure and gradually combines the nearest node or cluster pairings. Though its rigid cluster structures is not suitable to adapt dynamic energy patterns and varied node distributions [6–11].

Existing hierarchical and fuzzy clustering methods mainly address either structural organization or membership flexibility. They do not consider residual energy into the estimation of initial cluster center, nor do they dynamically adjust neighborhood parameters as per local node density. This limitation becomes more critical in large-scale and dense WSN deployments, where static clustering assumptions often lead to unbalanced energy consumption and unstable clusters. The SUBFCM clustering technique, on the other hand, is a hybrid fuzzy clustering framework that combines the advantages of Fuzzy C-Means (FCM) [12] and Subtractive Clustering (SC) [13]. SC determines cluster centers directly from the data without any prior knowledge of number of clusters. The number of nodes within a certain radius is evaluated and cluster centers are more likely to be created in dense areas. SC is applied frequently to initialize fuzzy clustering algorithms due to its ability to determine initial centers.

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In large scale deployments, classical FCM may converge to local optima due to its sensitivity to initial center selection. SUBFCM gets around these restrictions by initializing FCM with SC, which leads to better energy allocation among sensor nodes and decreased computing complexity. According to earlier research, SUBFCM hybrids provide better choice in finding number of clusters and improve energy distribution, while only FCM based clustering increases energy consumption and prolongs network lifetime in comparison to hard clustering technique [14–16]. However, SC in WSNs does not consider residual energy and only relies on node density with a predetermined neighborhood radius, which may allow nodes with low energy appointed as cluster centers.This might result in unstable or unequal cluster formation.

Density based Multi hop Clustering (DMC) [17], Efficient Scalable Routing Hierarchical Agglomerative Clustering (ESR-HAC) [18], and Energy Efficient Hybrid Clustering with Heterogeneous Routing (EEHCHR) [19] are some of the clustering techniques that have been developed in addition to HAC, FCM, and SUBFCM to further optimize routing and extend network lifetime [20–22].

Although these algorithms provide useful features like multi hop energy balancing, hierarchical data forwarding, and heterogeneous energy handling, they still have drawbacks like lower Energy of nodes, adaptability to network topology, and inefficient CH selection in high density deployments. The need for dynamic, energy aware and density based clustering frameworks is increasing due to the complexity of WSN applications. These frameworks must sustain long term stability under a variety of operating scenarios.

More importantly, most existing approaches treat density awareness, energy awareness, and fuzzy optimization as independent design objectives rather than integrating them within a unified clustering framework. In addition, a novel aspect that remains largely unexplored is the use of an adaptive neighborhood radius to better capture local node distribution. Although existing clustering algorithms offer useful features such as multi-hop energy balancing, hierarchical data forwarding, and heterogeneous energy handling, they still suffer from several fundamental limitations when applied to large-scale and dense WSN deployments. In particular, many approaches rely on fixed neighborhood parameters, lack explicit integration of residual energy during cluster formation, and employ simplistic or partially energy-aware cluster head (CH) selection strategies. As a result, low-energy nodes may be selected as cluster centers or CHs, leading to premature node failures, uneven energy dissipation, and unstable cluster structures.

Consequently, there is a growing need for dynamic, energy-aware, and density-based clustering frameworks that can jointly consider spatial distribution, residual energy, and membership uncertainty while maintaining long-term stability under diverse operating scenarios. With a focus on energy efficiency, network lifetime, number of alive nodes, and overall data delivery ratio, this research proposes the DEAR-SFCM clustering strategy to overcome the above limitations by integrating energy-aware density estimation, adaptive-radius subtractive fuzzy clustering, and an energy distance position based CH selection mechanism within a single cohesive framework. This unified design enables balanced cluster formation, stable CH selection, and uniform energy dissipation, thereby significantly improving network reliability and sustainability compared to existing approaches.

With a focus on energy efficiency, network lifetime, alive nodes, and data delivery percentage [18], this work proposes the DEAR-SFCM clustering strategy to address limitations of existing methods through a unified energy aware and density adaptive fuzzy clustering framework. The main contributions of this work are deliberately organized into three tightly coupled and technically distinct components, each addressing a specific limitation identified in existing clustering approaches:

- An energy-aware density estimation model that integrates residual node energy with spatial distance during the subtractive clustering stage, enabling reliable identification of potential cluster centers and preventing the selection of low-energy nodes at the early clustering phase.

- An adaptive-radius subtractive fuzzy C-means clustering mechanism in which the neighborhood radius dynamically varies according to local node density, and fuzzy memberships are refined through energy-weighted optimization, resulting in balanced cluster formation and reduced centroid congestion.

- A multi-criteria cluster head selection rule based on residual energy, distance to cluster centroid, and distance to sink, ensuring stable CH election, reduced forwarding burden, and prolonged network lifetime.

The proposed approach DEAR-SFCM is evaluated against 5 existing methods FCM, SUBFCM, EEHCHR, ESR-HAC, and DMC under different node densities and sink placements to evaluate robustness and scalability. Performance indicators [18] including energy dissipation balance factor (EDBF), network lifetime, alive node trends, packet delivery rate, and node death indicators are examined to guide the selection of clustering schemes for large scale WSN deployments.

The rest of the paper is organized as follows, Section 2 reviews the existing literature on clustering techniques for WSNs. Section 3 comprises the methodology used to implement the proposed DEAR-SFCM framework. A thorough comparison analysis of the results along with an outline of the simulation setup and performance indicators is discussed in Sec. 4. The conclusion and future work related findings are presented in Sec. 5.

2. Related Work

In WSNs, clustering is a key idea to improve network durability, scalability, and energy efficiency. Various clustering algorithms with multiple approaches and performance measures have been explored and developed over the past decades. The HAC technique marked its adaptability under dynamic scenario of network. With significant improvements in data aggregation efficiency, Energy Efficient Hierarchical Agglomerative Data Aggregation (EEHADA) [23] model was developed to manage cluster formation and its maintenance, additional improvements to HAC based techniques have been made by Brust et al. in [24]. Fuzzy clustering provides flexibility in adapting circumstances by allowing nodes belong to various clusters. To exhibit low energy usage an Energy Efficient Hierarchical Clustering and Routing using Fuzzy C-Means (EHCR-FCM) [14] was developed. To enhance network longevity, energy efficiency and accuracy of clustering, a decentralized FCM based routing mechanism was developed which contributed to advancement in FCM algorithms [12], [16].

To maximize clustering in WSNs, metaheuristic algorithms inspired from natural processes startegy had been used in [25]. In order to gain balanced energy usage, multi criteria clustering technique was developed which took inspiration from natural bio phenomena. Later, cutting edge clustering methods have been revived and emphasized the effectiveness of swarm intelligence in CH selection. For effective cluster formation, the Improved Squirrel Search Algorithm (I-SSA) was implemented [26]. To decrease overhead of transmission in WSNs, modern advancements has explored compressive sensing (CS) at the CH in addition to energy efficient clustering. By taking advantage of spatial and inter channel correlations latest CS approaches like hierarchical and group based reconstruction models which enable efficient recovery, improved forwarding at reduced sampling rates [27], [28]. Thereby, CS technique lowers the amount of data for transmission, costs associated with communication, and energy usage. Combining such CS based reconstruction at CHs improves hierarchical and fuzzy clustering techniques [29], [30].

The foundation for energy efficient WSNs has been laid down by conventional clustering techniques like Low energy adaptive clustering hierarchy (LEACH) [31]. LEACH is a methodology that manages energy usage by rotating CHs. Due to its single hop communication, uneven cluster sizes, and random CH selection, LEACH is not scalable and consumes more energy in huge networks. For the purpose of routing, localization, and synchronization in sensor networks, distributed multi-hop clustering algorithm [32] clustering technique was developed that creates overlapping multi hop clusters as opposed to conventional disjoint ones. It is a randomized distributed algorithm that creates connected overlapping clusters with balanced sizes and adjustable overlap. The approximate rank order-wsn (ARO-WSN) [33] acquires O(n) computational complexity for large networks by combining distance based and hierarchical clustering. In comparison to LEACH, LEACH-Centralized, and K-means, experimental results demonstrate that ARO-WSN considerably lowers energy usage and increases network longevity. Hot spots, where nodes close to the base station rapidly deplete energy due to high forwarding, are a common problem for WSNs. Most schemes still choose CHs at random even though clustering aids in load balancing. Instead, to minimize hot spots and prolong network life, a trajectory method [34] chooses and rotates CHs depending on traffic patterns.

Several research work have also aimed at improving reliability and application deployment in WSNs. Synchronized industrial WSN communication using IEEE 802.11 was presented in [35], while adaptive radio channel selection for reliable and energy efficient communication was explored in [36]. Autonomous WSN deployment for smart city monitoring was demonstrated in [37]. In addition, modular software coordination for WSNs and fog-assisted infrastructures for emergency management were discussed in [38], [39].

These studies demonstrate the growing importance of efficient data acquisition, reliable communication, flexible software architectures, and application-driven design in modern WSN research. Traditional FCM [12] struggles with unbalanced datasets due to equal feature weighting and initialization sensitivity. Extending weighted FCM variant to the Distributed Weighted FCM (DWFCM) [40] to make WSNs more adaptible. Using average Euclidean deviation and diffusion based learning across six sensor nodes, DWFCM achieved better cluster quality and convergence than standard distributed FCM on synthetic and real datasets. A distributed WSN data stream clustering algorithm was introduced in [41] aimed at reducing energy consumption and extending network lifetime by trading communication for computation. The SUBFCM method performs distributed clustering and transmits only local cluster summaries. Its energy efficiency and clustering accuracy were evaluated against standard algorithms like FCM and K-means, with simulations and experiments demonstrating superior performance [42–44].

Recent studies have researched energy aware and intelligent clustering techniques to enhance the stability of WSNs. For example, [45] considered residual energy into a soft k-means model to improve stability of clusters and delay failure of node. Likewise, [46] highlighted the growing adoption of hybrid fuzzy learning approaches for handling dynamic network conditions. Metaheuristic based clustering has combined whale optimization with FCM to improve CH selection and network stability [47]. Other works focus on improving load balancing and energy distribution weighted multi-CH selection framework in [48]. Additionally, adaptive methods like reinforcement learning based CH selection [49] and unequal clustering with distance aware cluster sizes [50] have been proposed to address energy imbalance and hotspot issues in WSNs.

The key clustering techniques in WSNs are compared in Tab. 1, which summarizes the methodology, performance and limitations of each.

Clustering method	Methodology	Objective metrics	Performance summary	Limitations	Simulation platform
SUBFCM [4]	Subtractive clustering for initial center estimation followed by FCM refinement.	Lifetime improved by approximately 15–25% over FCM, with first node death delayed by about 20%.	Provides smoother clustering and better initialization than basic FCM.	Fixed global radius may cause improper clustering in heterogeneous regions.	MATLAB
HAC [5]	Bottom up merging of nodes using agglomerative similarity metrics.	Demonstrates longer network lifetime and more uniform energy dissipation than LEACH and LEACH-C.	Stable hierarchical clustering suitable for static deployments.	High computational complexity and slow reclustering in dynamic scenarios.	NS2
EHCR-FCM [14]	FCM-based clustering combined with hierarchical routing.	Network lifetime extended by approximately 15–30% compared to LEACH and energy consumption reduced by about 10–18% versus FCM.	Enhances energy efficiency and CH reliability through hybrid design.	Sensitive to parameter selection and fuzzy radius tuning.	MATLAB
DMC [17]	Density-based relay node selection with multi-hop forwarding.	Network lifetime higher than LEACH but lower than ESR-HAC under comparable scenarios.	Simple and fast cluster formation.	Rapid energy depletion and shortest lifetime in dense networks.	NS2
ESR-HAC [18]	Hierarchical agglomerative clustering with scalable routing.	For 200 nodes, the reported FND/HND/LND values are 637/709/732, while for 400 nodes they are 850/962/1048.	Stable multi-level clustering with strong central sink performance.	Additional routing overhead and sensitivity to asymmetric sink placement.	NS2
EEHCHR [19]	Energy-aware CH selection combined with multi-hop routing.	Lifetime increased by approximately 20–30% over LEACH and throughput improved by around 15%.	Improves early phase stability and packet delivery.	Performance degradation in high-density deployments.	NS2
EEHADA [23]	Hierarchical CH selection with data aggregation and compression.	Aggregation accuracy up to 97.52% with energy reduction of approximately 25–30%.	Improves aggregation efficiency and stability.	Additional delay due to compression operations.	MATLAB
LEACH [31]	Randomized CH election with single-hop communication.	Up to eightfold reduction in energy dissipation compared to direct transmission and Minimum Transmission Energy routing, with nearly twofold increase in network lifetime.	Lightweight and simple clustering mechanism.	Random CH selection leads to imbalance and limited scalability.	NS2
KOCA [32]	Overlapping multi-hop clustering with randomized CH communication.	First node death around 1900 rounds and packet delivery ratio between 90–95%.	Supports scalable overlapping cluster structures.	Overlapping increases routing overhead and energy cost.	NS2
ARO Clustering [33]	Rank-order clustering using optimized distance and energy metrics.	First node death improved by about 60% and last node death improved by about 67% compared to LEACH.	Strong performance in dense and heterogeneous deployments.	Computationally intensive ranking stage.	MATLAB
DWFCM [40]	Distributed weighted fuzzy C-means clustering with node weighting.	Energy consumption reduced by approximately 10–18% compared to FCM, with clustering accuracy reaching 90–95%.	Balances clusters through distributed fuzzy weighting.	Higher coordination and computational overhead.	MATLAB
FCM [41]	Iterative fuzzy objective minimization for cluster formation.	Baseline performance with earlier first node death and shorter lifetime compared to hybrid approaches.	Flexible fuzzy membership assignment.	Lacks energy awareness and sensitive to initialization in dense deployments.	MATLAB
DEAR-SFCM (Proposed)	Energy aware, density adaptive clustering SC and FCM, using residual energy, spatial distance, and adaptive radius fuzzy clustering for stable CH selection and improved network lifetime.	For 200 nodes, FND/HND/LND are 696/781/842 (centre) and 643/724/825 (edge) at 1 pkt/s, decreasing at 5 pkt/s. With 400 nodes, values increase to 921/1013/1099 (centre) and 912/985/1054 (edge), achieving about 5–12% lifetime improvement.	Achieves balanced energy dissipation, delays node death, and maintains stable clustering performance across varying node densities, sink placements, and traffic loads.	Additional fuzzy clustering computation may increase clustering overhead in very large scale networks.	NS2, NS3

Tab. 1. Comparative summary of key clustering techniques in wireless sensor networks.

3. Proposed Method

The proposed DEAR-SFCM framework is designed to overcome shortcomings of classical fuzzy clustering and traditional SC in WSNs: (i) the sensitivity of SUBFCM and related techniques to fixed radius density estimation, and (ii) the absence of mechanisms to incorporate energy heterogeneity into cluster formation. Traditional SC relies on a single global neighborhood radius, which often produces unstable or poorly distributed clusters in networks with non uniform node densities. Moreover, distance only dissimilarity metrics tend to select CHs that are spatially optimal but not necessarily energy sustainable. The following subsections describe the network assumptions, energy model, mathematical model, and the proposed clustering algorithm.

3.1 Network Model

The WSN considered in this work comprises of N homogeneous sensor nodes randomly located within an $M \times M$ sensing area. Nodes remain static after deployment and share identical initial energy and hardware capabilities. To represent both balanced and imbalanced prone scenarios,the base station (BS) is placed both at the geometric centre and along the boundary of the monitored region as shown in Fig. 1. Each node periodically senses its surroundings and generates fixed size k-bit data packets. These packets are forwarded to a designated CH through single hop communication. The received data is aggregated by CH which further transmits aggregated data to the BS using either direct or multi hop transmission, depending on distance and remaining energy.

3.2 Energy Model

The energy consumption of sensor nodes is modeled using the first order radio model [31], which gives the cost of both transmission and reception in low power wireless environments. The energy required to transmit a k-bit packet over a distance d is expressed in (1):

$$E_{\mathrm{TX}}(k,d) = \begin{cases} kE_{\mathrm{elec}} + k\varepsilon_{\mathrm{fs}} d^2, & d < d_0 \\ kE_{\mathrm{elec}} + k\varepsilon_{\mathrm{mp}} d^4, & d \geq d_0 \end{cases} \tag{1}$$

where $d_0 = \sqrt{\varepsilon_{\mathrm{fs}}/\varepsilon_{\mathrm{mp}}}$ denotes the threshold distance separating free-space and multipath propagation regions. The reception energy is modeled as (2):

$$E_{\mathrm{RX}}(k) = kE_{\mathrm{elec}}. \tag{2}$$

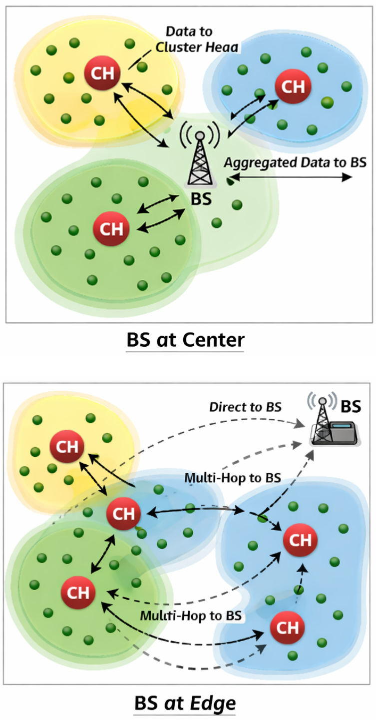

Fig. 1. WSN scenarios with centralized and edge sink placement.

To ensure consistency with prior WSN studies, the simulation includes radio model parameters which are used commonly, where the electronic energy is set to $E_{\mathrm{elec}} = 50$ nJ/bit, the free-space amplification factor is $\varepsilon_{\mathrm{fs}} = 10$ pJ/bit/m^2, the multipath fading coefficient is $\varepsilon_{\mathrm{mp}} = 0.0013$ pJ/bit/m^4, and the energy required for data aggregation is $E_{\mathrm{DA}} = 5$ nJ/bit. CHs includes an additional cost for data aggregation, described as (3):

$$E_{\mathrm{DA}}(k) = kE_{\mathrm{DA}}. \tag{3}$$

3.3 DEAR-SFCM

DEAR-SFCM introduces a solution which altogether solves the issues being addressed. First, DEAR-SFCM invloves an novel energy distance weighted measure, which weights spatial distances utilizing the remaining energy of nodes. Nodes with high energy therefore appear closer to cluster centres and receive higher membership values, aligning cluster formation with energy sustainability and reducing premature CH depletion. Second, a radius adaptive SC mechanism dynamically adjusts the neighborhood radius according to local node density. Dense regions naturally adopt a smaller radius to avoid centroid congestion, whereas sparse regions use a larger radius to prevent over splitting. This adaptability provides stable and nicely separated initial cluster centres across WSN deployments. Third, during improvement, the technique uses entropy stabilized fuzzy membership updates. Even when energy levels of nodes vary greatly, the entropy term developes smooth and stable cluster borders by discouraging sudden membership movements and improving numerical stability [18]. When combined all the three features, these metrics create clusters that are simultaneously topologically coherent, energy aware, and resilient to changes in varying network density.

3.4 Mathematical Model of DEAR-SFCM

A WSN with N nodes is considered located at $\mathbf{x}_k \in \mathbb{R}^2$. The aim is to divide them into c fuzzy clusters with centres $\mathbf{v}_i$ and memberships u_{ik}.

In order to intialize cluster centres based on density , the spatial similarity between nodes is first calculated using the squared euclidean distance (4) mentioned in [42] by James C. Bezdek.

$$d_{ik}^{(s)} = \|\mathbf{x}_k - \mathbf{v}_i\|^2. \tag{4}$$

Equation (5) introduces a novel energy distance weighted measure proposed in this work, where residual energy is incorporated into the distance computation to prioritize high energy nodes during clustering. Traditional euclidean distance (4) is reformulated to include energy awareness, making it more suitable for WSN environments.

$$D_{ik} = \frac{\|\mathbf{x}_k - \mathbf{v}_i\|^2}{E_k + \varepsilon} \tag{5}$$

where E_k is node's residual energy and ε is a small positive constant to avoid division by zero. Clustering is restricted towards greater energy nodes by this definition.

For robust initialization, a radius adaptive subtractive density measure is employed. An energy weighted Gaussian kernel is used to quantify density potential of each node, which takes into account nodes placed in dense and high energy regions:

$$P_k = \sum_{j=1}^{N} \exp\left(-\frac{\|\mathbf{x}_k - \mathbf{x}_j\|^2}{r_\mathrm{a}(k)^2}\right)\phi(E_j) \tag{6}$$

where $r_\mathrm{a}(k)$ denotes the adaptive neighborhood radius and $\phi(E_j)$ represents the energy weighting function. Nodes with higher potential are more likely to be selected as initial cluster centers.

Clustering error given by (7) and is derived from the classical FCM and it aims to reduce the value of objective function. Two modifications are made in this work: (i) energy based weighting w_k and (ii) an entropy based regularization term controlled by γ. Here, the degree of fuzziness is controlled by parameter m, $w_k = 1/(E_k+\varepsilon)$ reflects the effect of nodes rich in energy, and γ controls the smoothing of entropy.

$$J(U,V) = \sum_{i=1}^{c}\sum_{k=1}^{N}(u_{ik})^m w_k D_{ik} - \gamma \sum_{i=1}^{c}\sum_{k=1}^{N} u_{ik}\log(u_{ik}), \tag{7}$$

subject to the fuzzy constraints:

$$\sum_{i=1}^{c} u_{ik} = 1, \qquad 0 \le u_{ik} \le 1.$$

Equation (8) modifies the standard FCM centroid update rule by incorporating energy weights and the proposed energy distance measure.

$$\mathbf{v}_i = \frac{\sum_k (u_{ik})^m w_k \dfrac{\mathbf{x}_k}{E_k+\varepsilon}}{\sum_k (u_{ik})^m w_k \dfrac{1}{E_k+\varepsilon}}. \tag{8}$$

Membership values are updated repeatedly using standard FCM membership represented by.

An uncertainity control term in the objective function is introduced using entropy regularized fuzzy clustering. This enhances numerical stability and avoids over crisp membership. The method supports a smoother membership distribution by penalizing low entropy solutions, which enhances the working of dynamic WSN environments. During there is no entropy ($\gamma = 0$), Equation (9) is applied :

$$u_{ik} = \frac{(D_{ik})^{-1/(m-1)}}{\sum_{j=1}^{c}(D_{jk})^{-1/(m-1)}}. \tag{9}$$

When $\gamma > 0$, entropy smoothing is applied using (10), following entropy regularized fuzzy clustering concepts and adapted in this work to include the proposed energy weighted distance measure.

$$u_{ik} \leftarrow \text{Normalize}\left[\exp\left(-\frac{1}{\tau}(u_{ik})^{m-1} w_k D_{ik}\right)\right]. \tag{10}$$

The CH is appointed applying a multi criteria score that integrates membership strength, residual energy, and proximity to the cluster center. The node with the highest score (11) within each cluster is elected as the CH.

$$CH\_score_k = \lambda_1 u_{i^*k} + \lambda_2 \frac{E_k}{E_{\max}} - \lambda_3 \frac{\mathrm{dist}(\mathbf{x}_k, \mathbf{v}_{i^*})}{d_{\max}}. \tag{11}$$

Radius adaptive density estimation, energy integrated fuzzy clustering and entropy based membership stabilization measures are combined and developed in DEAR-SFCM. Regardless of different deployment scenarios, the proposed approach calculates reliable initial centers by dynamically modifying the subtractive radius. The change in cluster membership is made in a way that promotes longer functioning of network which is due to the energy distance hybrid measure. In the end, builtin instability of fuzzy clustering is reduced further by entropy regularization as depicted in Algorithm 1. When combined, these mechanisms offer DEAR-SFCM algorithm to offer a distinct advantage in WSN situations with varying energy profiles and unequal node placement.

Algorithm 1. DEAR-SFCM: Dynamic Energy Aware Radius Adaptive Subtractive Fuzzy C-Means.

1. **Initialize:** node coordinates, residual energies, radius r_a, threshold ξ, fuzziness m, entropy weight γ, and CH weights $\lambda_1, \lambda_2, \lambda_3$
2. **Phase 1: Radius-Adaptive Subtractive Clustering**
3. Update adaptive radius for each node based on local density
4. Compute density potential P_k for all nodes
5. Select node with maximum potential as first cluster center
6. Suppress neighboring potentials and iteratively select centers until threshold is met
7. Initialize cluster centers $\mathbf{v}$
8. **Phase 2: Energy-Aware FCM Refinement**
9. Initialize membership matrix $\mathbf{u}$
10. REPEAT
11. Compute spatial distance and energy-weighted distance D_{ik}
12. Update memberships using entropy-controlled rule
13. Update cluster centers using energy-weighted centroid
14. UNTIL convergence
15. Store final $\mathbf{u}$ and $\mathbf{v}$
16. **Phase 3: Cluster Head Selection**
17. FOR each node
18. Identify dominant cluster
19. Compute CH score
20. ENDFOR
21. Select highest-score node in each cluster as CH
22. **Phase 4: Data Transmission and Energy Update**
23. Member nodes transmit data to CH
24. CH aggregates and forwards data to base station
25. Update node energies using radio model
26. **Phase 5: Re-Clustering**
27. IF CH energy below threshold or interval reached
28. Restart from Phase 1
29. ENDIF
30. **Output:** cluster centers $\mathbf{v}$, membership matrix $\mathbf{u}$, and CH set

4. Results and Discussion

Performance evaluation of the suggested DEAR-SFCM algorithm with five key techniques of clustering SUBFCM, FCM, ESR-HAC, EEHCHR, and DMC is carried out in different deployment conditions. The results are examined using standard performance measures namely: EDBF, network lifetime, number of alive nodes, and percentage of packet-delivery. The evaluation considers networks with following scenarios:

- Varying node densities of (200 and 400 sensor nodes),
- Location of the sink node (centre and edge),
- Duty cycle (DC) (0.3–0.8) [44],
- Traffic load (low and high) [44].

In order to make fair comparison with prior clustering methods, the proposed DEAR-SFCM approach is implemented using the NS2 network simulation tool version 2.35. In order to make a fair comparison with prior clustering methods, the proposed DEAR-SFCM approach is implemented using the NS2 . Each simulation is done on a system running Ubuntu Linux 20.04.6 LTS (64-bit) with an Intel(R) Core(TM) i7-8550U CPU operating at 1.80 GHz and 8 GB of RAM. OTcl was used to create the simulation scripts. The simulation environment incorporates the TwoRayGround propagation model, IEEE 802.11 Medium Access Control (MAC) protocol, OmniAntenna antenna model, Ad hoc On-Demand Distance Vector (AODV) routing protocol, and the integrated NS2 EnergyModel configured according to the traditional first-order radio energy dissipation model. The operating conditions for examining behavior of cluster, energy usage, and CH selection in the WSN are described by the parameters shown in Tab. 2. These parameters are chosen based on commonly adopted values in established WSN clustering methods to ensure fair comparison and realistic network operation [18].

Parameters	Values
Size of network region	400 m × 400 m
Number of sensor nodes N	100–400
Number of the sink	1
Sensor node's initial energy	0.5 Joule
Essential transceiver energy E_{elec}	50 nJ/bit
Size of the data packets	2000 bits
Energy dissipation ε_{fs}	10 pJ/bit/m^2
Energy dissipation ε_{mp}	0.0013 pJ/bit/m^4
Distance threshold d_0	87
Coefficients α, β	0.4, 0.3
Weight factor γ	0.5
Maximum iteration MaxIteration	500
Mutation rate θ	0.3
Sink placement	Centre, Edge
Duty cycle (DC)	0.3–0.8
Traffic load	Low: 1 packet/s, High: 5 packets/s

Tab. 2. Simulation parameters.

4.1 Duty Cycle Sensitivity Analysis

In addition to the parameters listed in Tab. 2, a sensitivity analysis was conducted to examine the effect of duty cycle [44] on node lifetime. This analysis was performed for the 200 node edge sink configuration with a traffic load of 1 packet/s. Table 3 indicates that a moderate DC range of 0.5–0.6 provides the best trade-off between early node stability and overall network lifetime. Although DC = 0.6 yields marginally higher lifetime in some cases, the difference compared to DC = 0.5 remains within 1–2%, which lies inside normal simulation variability. Therefore, DC = 0.5 is adopted as the default value for subsequent experiments, as it ensures balanced sleep–wake operation, lower radio on-time, and reproducible performance even under the most demanding network conditions.

4.2 Multi-Scenario Stability Assessment Using FND, HND, and LND Metrics

The corresponding comparisons of first node dies (FND), half node dies (HND), and last node dies (LND) [18] for the proposed DEAR-SFCM and existing methods are summarized in Tabs. 4–7. To ensure validation, the proposed DEAR-SFCM protocol is evaluated under multiple scenarios: (i) 200 and 400 nodes, (ii) centre and edge sink placement, and (iii) 1 packet/s and 5 packet/s traffic load while fixing DC = 0.5.

It is evident from Tab. 4 and Tab. 5, DEAR-SFCM demonstrates the highest stability for both centre and edge sink placements (DC = 0.5, load = 1 packet/s). The method delays node death compared with existing approaches. For the centrally located sink, DEAR-SFCM improves FND by about 3.6%, HND by 2.4%, and LND by 2.4% in the 200 node scenario, while the gains for 400 nodes are approximately 1.1%, 1.2%, and 2.0%, respectively.

Duty cycle	FND	HND	LND
0.3	850	920	995
0.4	885	955	1025
0.5	912	985	1054
0.6	920	995	1065
0.7	905	980	1040
0.8	880	960	1030

Tab. 3. Effect of duty cycle on FND, HND, and LND for DEAR-SFCM with 200 sensor nodes and edge sink (load = 1 packet/s).

Method	Sink at centre Load: 1 packet/s			Sink at edge Load: 1 packet/s		
	FND	HND	LND	FND	HND	LND
DMC [16]	151	500	701	151	390	632
EEHCHR [18]	472	621	690	442	541	639
ESR-HAC [17]	640	712	739	572	641	711
FCM [35]	655	746	794	614	696	776
SUBFCM [3]	672	763	822	619	711	801
DEAR-SFCM (Proposed)	696	781	842	643	724	825

Tab. 4. FND, HND, and LND comparisons of the proposed DEAR-SFCM with existing methods for 200 sensor nodes.

Method	Sink at centre Load: 1 packet/s			Sink at edge Load: 1 packet/s		
	FND	HND	LND	FND	HND	LND
DMC [16]	211	552	891	199	681	850
EEHCHR [18]	689	811	933	671	851	890
ESR-HAC [17]	850	941	1042	831	949	991
FCM [35]	879	976	1056	879	961	1016
SUBFCM [3]	911	1001	1078	901	971	1042
DEAR-SFCM (Proposed)	921	1013	1099	912	985	1054

Tab. 5. FND, HND, and LND comparisons of the proposed DEAR-SFCM with existing methods for 400 sensor nodes.

The larger FND improvement indicates reduced early energy depletion due to the energy aware distance and adaptive clustering design, enabling high energy nodes to assume CH roles more frequently and improving load balance. With the sink at the edge, DEAR-SFCM again achieves the highest FND, HND, and LND. For 200 nodes, the delays are roughly 3.9% (FND), 1.8% (HND), and 3.0% (LND), while for 400 nodes the gains are about 1.2%, 1.4%, and 1.2%, respectively. These consistent gains show that the CH selection strategy considering energy, membership strength, and node position effectively distributes traffic and mitigates hotspot risk under asymmetric edge sink conditions. Overall, DEAR-SFCM ensures more balanced energy consumption and extended network lifetime across deployment settings.The improvements stem from the combined effect of energy aware membership, adaptive radius estimation, and energy distance based CH selection rather than a single optimization factor.

Tables 6 and 7 evaluate the stability of DEAR-SFCM under a higher traffic load of 5 packet/s for both 200- and 400-node deployments. Across all scenarios, DEAR-SFCM achieves the highest FND, HND, and LND values, indicating strong robustness under increased traffic and asymmetric sink placement. Although higher load reduces lifetime for all schemes, DEAR-SFCM maintains a consistent performance margin over competing methods, demonstrating good scalability under network stress.

For the 200-node network with a centrally located sink, DEAR-SFCM attains an FND of 650 rounds, improving upon SUBFCM by about 4.0% and FCM by roughly 6.6%. Corresponding gains in HND and LND confirm that the proposed design effectively postpones both early node failures and complete network exhaustion. When the sink is placed at the edge, all protocols experience reduced lifetime due to increased relay burden; nevertheless, DEAR-SFCM preserves clear superiority, with improvements of approximately 4.3%, 2.3%, and 3.4% over SUBFCM in FND, HND, and LND, respectively.

A similar trend appears in the denser 400-node deployment. With the sink at the centre, DEAR-SFCM improves FND by about 1.2% over SUBFCM and nearly 4.8% over FCM, while consistently extending HND and LND. Under edge placement, the proposed method again delivers the best stability, indicating effective mitigation of hotspot effects under heavier contention.

Method	Sink at centre Load: 5 packet/s			Sink at edge Load: 5 packet/s		
	FND	HND	LND	FND	HND	LND
DMC [16]	140	465	650	140	360	585
EEHCHR [18]	440	580	645	410	505	595
ESR-HAC [17]	595	665	690	530	600	665
FCM [35]	610	695	735	570	645	720
SUBFCM [3]	625	710	760	575	660	745
DEAR-SFCM (Proposed)	650	730	785	600	675	770

Tab. 6. FND, HND, and LND comparisons of the proposed DEAR-SFCM with existing methods for 200 sensor nodes.

Method	Sink at centre Load: 5 packet/s			Sink at edge Load: 5 packet/s		
	FND	HND	LND	FND	HND	LND
DMC [16]	195	520	840	185	650	800
EEHCHR [18]	645	760	875	630	800	835
ESR-HAC [17]	795	885	965	770	890	925
FCM [35]	825	910	975	815	900	950
SUBFCM [3]	855	935	1000	835	910	975
DEAR-SFCM (Proposed)	865	950	1020	845	925	990

Tab. 7. FND, HND, and LND comparisons of the proposed DEAR-SFCM with existing methods for 400 sensor nodes.

These gains under high traffic confirm that the energy aware membership and adaptive CH selection mechanisms of DEAR-SFCM distribute load more evenly and suppress premature energy depletion. Overall, the results verify that DEAR-SFCM remains scalable and energy efficient at elevated traffic levels and higher node densities.

4.3 Energy Dissipation Balance Factor

Across all deployment scenarios, DEAR-SFCM maintains an EDBF close to 1.0 for a noticeably greater duration compared to the other algorithms. A higher EDBF indicates more uniform energy utilization among sensor nodes and is therefore associated with prolonged network lifetime. Figures 2 and 3 illustrate the EDBF behaviour of DEAR-SFCM relative to existing schemes for 200-node networks with a centrally located sink (DC = 0.5, load = 1 packet/s). DEAR-SFCM begins to decline only around 740 rounds in 200-node networks and around 990 rounds in 400-node networks. This extended plateau indicates that the proposed energy distance formulation and entropy smoothed memberships effectively delay energy polarization within clusters, thereby sustaining balanced operation for a longer period. The behaviour also suggests improved resilience to early CH overloading, which is a common cause of instability in dense WSN deployments.

By contrast, SUBFCM and FCM show an earlier drop by approximately 20–40 rounds, corresponding to a 2–5% performance improvement for 200 nodes and 6–8% for 400 nodes. The relatively close initial behaviour of SUBFCM indicates that density based initialization alone can momentarily preserve balance; however, without continuous energy

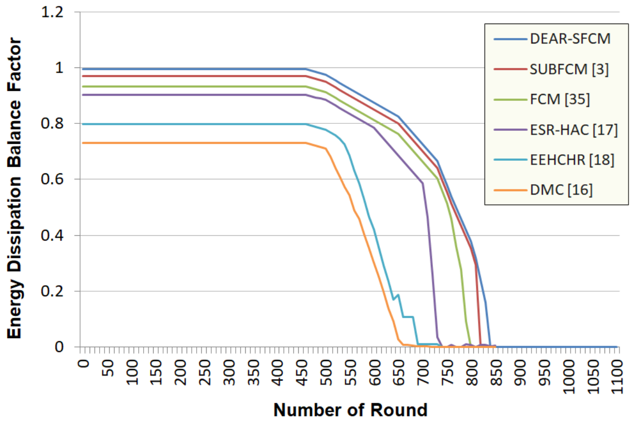

Fig. 2. EDBF comparisons of the proposed DEAR-SFCM with existing methods for 200 sensor nodes with a central sink (DC = 0.5, load = 1 packet/s).

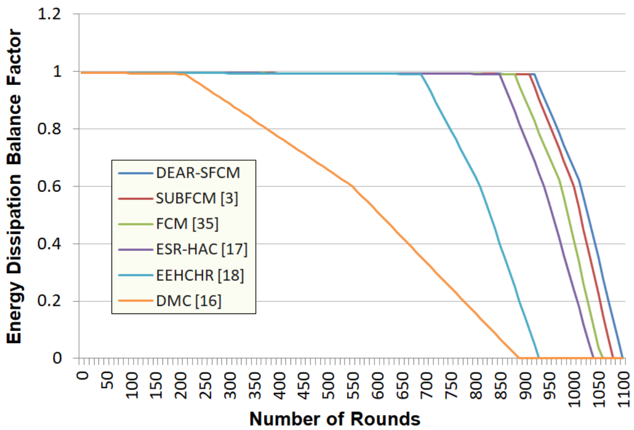

Fig. 3. EDBF comparisons of the proposed DEAR-SFCM with existing methods for 400 sensor nodes with a central sink (DC = 0.5, load = 1 packet/s).

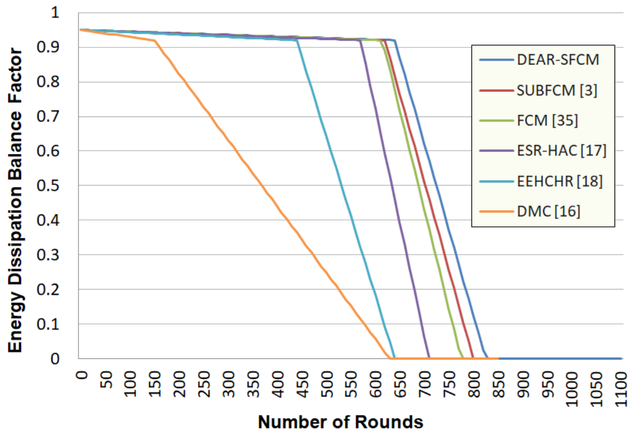

Fig. 4. EDBF comparisons of the proposed DEAR-SFCM with existing methods for 200 sensor nodes with an edge sink (DC = 0.5, load = 1 packet/s).

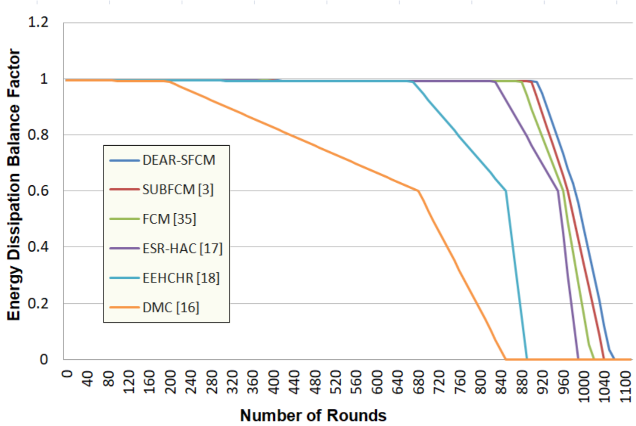

Fig. 5. EDBF comparisons of the proposed DEAR-SFCM with existing methods for 400 sensor nodes with an edge sink (DC = 0.5, load = 1 packet/s).

aware refinement, the network progressively drifts toward uneven energy depletion. ESR-HAC declines 50–80 rounds earlier, while EEHCHR and DMC experience markedly steeper drops, failing 200–300 rounds earlier in 200-node cases and 350–450 rounds earlier in 400-node scenarios. The sharper degradation of these schemes reflects their higher relay concentration on specific nodes, which accelerates hotspot formation and shortens the stable operating window. In contrast, the smoother decay profile of DEAR-SFCM indicates gradual and spatially distributed energy consumption rather than abrupt cluster collapse.

These differences translate to improvements of 30–45% for DEAR-SFCM even when the sink is placed at the network edge. Although edge placement typically increases routing imbalance, DEAR-SFCM maintains balanced dissipation up to 700–760 rounds (200 nodes) and nearly 900 rounds (400 nodes), as shown in Figs. 4 and 5. In edge sink scenarios, a brief mid round convergence with ESR-HAC is observed due to its hierarchical routing advantage that initially reduces transmission distance. However, the absence of adaptive energy aware cluster refinement leads to faster divergence as residual energy becomes unevenly distributed. The widening performance gap in denser deployments further indicates that DEAR-SFCM scales more effectively with node population by preventing localized congestion through its energy-distance driven clustering. These results highlight the ability of DEAR-SFCM to mitigate hotspot formation and maintain uniform energy consumption over extended operation.

4.4 Network Lifetime

With the sink located centrally (DC = 0.5, load = 1 packet/s), DEAR-SFCM extends the operational lifetime to approximately 840 rounds for 200-node deployments and nearly 1100 rounds for 400-node deployments, as shown in Figs. 6 and 7. SUBFCM and FCM terminate 20–50 rounds earlier, corresponding to improvements of about 3–6% and 5–8%, respectively. ESR-HAC ends 60–90 rounds earlier (7–10%), while EEHCHR and DMC exhibit the shortest lifetimes, ending 150–250 rounds (200 nodes) and 250–350 rounds (400 nodes) earlier, giving DEAR-SFCM an advantage of 20–35%.

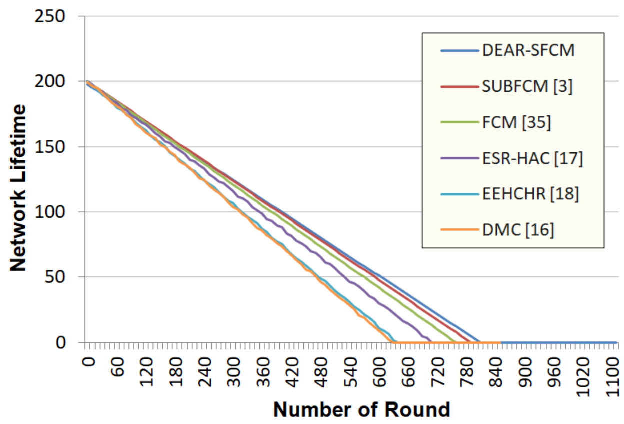

Fig. 6. Network lifetime comparisons of the proposed DEAR-SFCM with existing methods for 200 sensor nodes with a central sink (DC = 0.5, load = 1 packet/s).

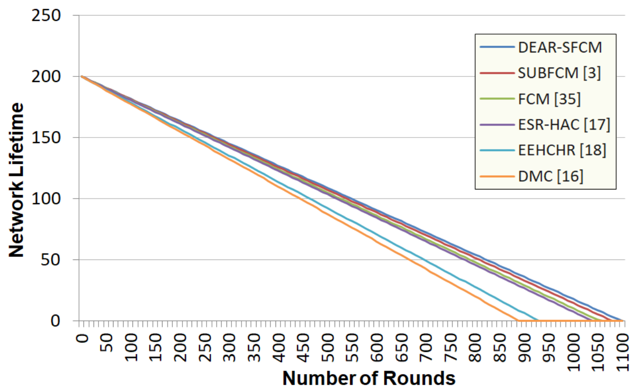

Fig. 7. Network lifetime comparisons of the proposed DEAR-SFCM with existing methods for 400 sensor nodes with a central sink (DC = 0.5, load = 1 packet/s).

The smoother decay of DEAR-SFCM indicates balanced CH rotation and controlled forwarding load. In contrast, the steeper drop in DMC and EEHCHR reflects relay concentration and faster energy depletion. A brief early-round proximity with ESR-HAC suggests initial routing efficiency, but its lack of adaptive energy awareness causes quicker later degradation.

When the sink is placed at the edge, all algorithms show reduced lifetimes due to uneven forwarding paths. Nevertheless, DEAR-SFCM remains the most resilient, maintaining operation for 820–840 rounds (200 nodes) and 1080–1100 rounds (400 nodes), as displayed in Figs. 8 and 9, respectively. The performance gain over SUBFCM and FCM remains within 4–7%, while ESR-HAC declines 80–120 rounds earlier (10–12%). EEHCHR and DMC again show the sharpest decline, ending 200–300 rounds earlier.

Although performance degradation occurs due to asymmetric paths, DEAR-SFCM sustains the longest operation. A minor crossover between SUBFCM and FCM in mid rounds indicates that density based initialization offers only temporary benefit. The larger gap in the 400 node case further confirms the scalability of DEAR-SFCM under higher density and traffic. These observations confirm the robustness of DEAR-SFCM in symmetric and asymmetric topologies.

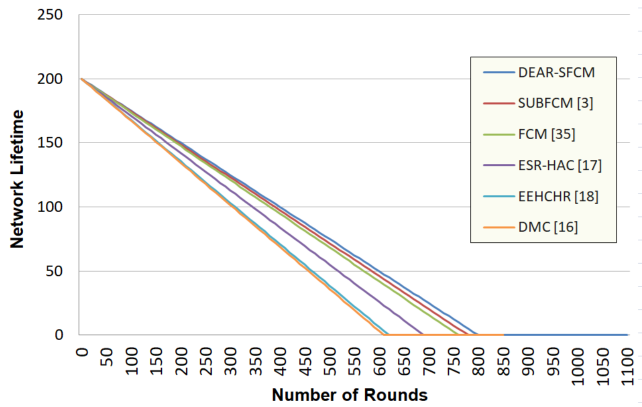

Fig. 8. Network lifetime comparisons of the proposed DEAR-SFCM with existing methods for 200 sensor nodes with an edge sink (DC = 0.5, load = 1 packet/s).

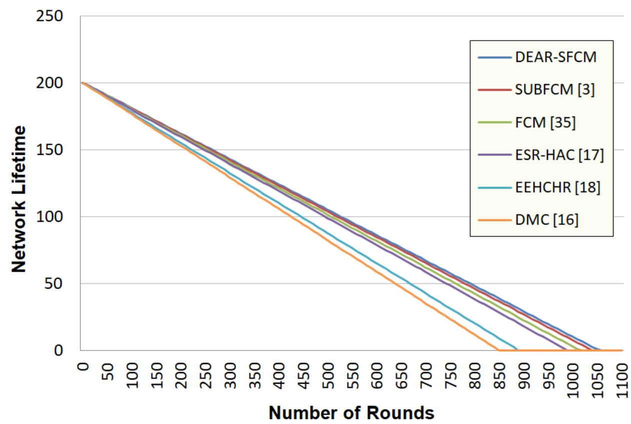

Fig. 9. Network lifetime comparisons of the proposed DEAR-SFCM with existing methods for 400 sensor nodes with an edge sink (DC = 0.5, load = 1 packet/s).

4.5 Alive Node Analysis

Figures 10 and 11 show the results for the number of nodes that remain alive over the rounds for centrally located sink with 200 and 400 nodes respectively and (DC = 0.5, load = 1 packet/s). With a central sink, the first node death occurs at approximately 690–710 rounds in 200 node networks and nearly 900 rounds in 400 node networks for DEAR-SFCM. DEAR-SFCM outperforms SUBFCM and FCM by 40–60 rounds (7–10%) and ESR-HAC by 70–90 rounds, while EEHCHR and DMC experience much earlier failures (200–400 rounds).

The extended flat region in the DEAR-SFCM curves indicates that a larger fraction of nodes remains operational for longer, reflecting well balanced energy dissipation across clusters. In contrast, the sharper decline in DMC and EEHCHR reveals concentrated relay burden that accelerates node death. Although SUBFCM and FCM initially track closely with DEAR-SFCM, their divergence in mid rounds suggests that density based initialization alone is insufficient to sustain long-term energy balance.

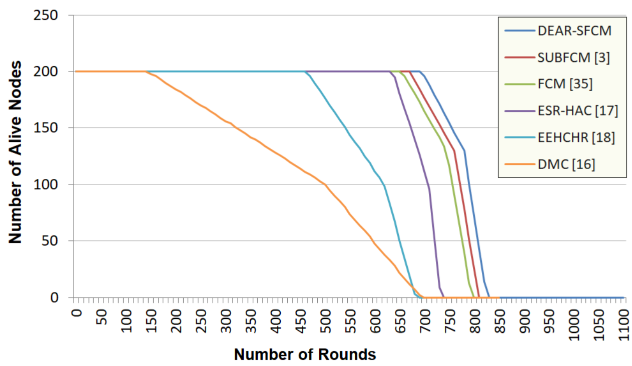

Fig. 10. Alive nodes comparisons of the proposed DEAR-SFCM with existing methods for 200 sensor nodes with a central sink (DC = 0.5, load = 1 packet/s).

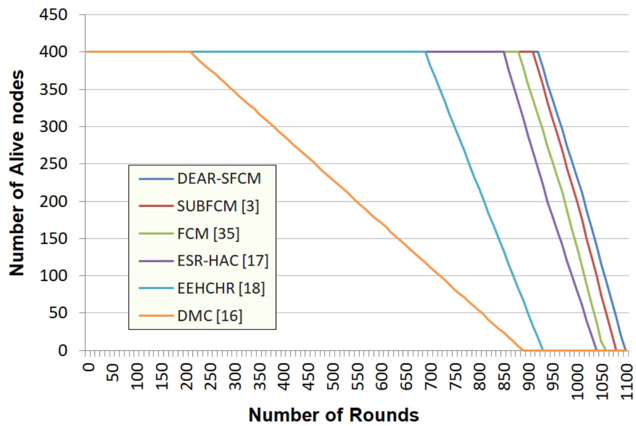

Fig. 11. Alive nodes comparisons of the proposed –SFCM with existing methods for 400 sensor nodes with a central sink (DC = 0.5, load = 1 packet/s).

A brief early round advantage of DMC (Fig. 10) is observed due to its multi-hop structure, which temporarily lowers transmission cost. However, the resulting relay concentration causes faster energy exhaustion and a steep later decline. DEAR-SFCM, by comparison, preserves smoother and more sustained node survival through energy aware membership and adaptive clustering, confirming its stronger long-term stability.

Under edge sink placement, as shown in Figs. 12 and 13, where routing imbalance is more pronounced, DEAR-SFCM maintains its advantage by postponing the FND to 680–700 rounds (200 nodes) and 880–900 rounds (400 nodes). The other methods degrade 30–120 rounds earlier, with DMC again showing the steepest decline.

Node failure is usually accelerated by edge placement, which increases traffic concentration close to forwarding pathways. The comparatively slow fall of DEAR-SFCM in this scenario shows that forwarding responsibilities are efficiently distributed by the energy aware clustering and CH selection technique, avoiding localized depletion. Additionally, in the 400 node scenario, the greater distance between DEAR-SFCM and other techniques validates enhanced scalability because the suggested mechanism remains stable even with increased traffic load and node density.

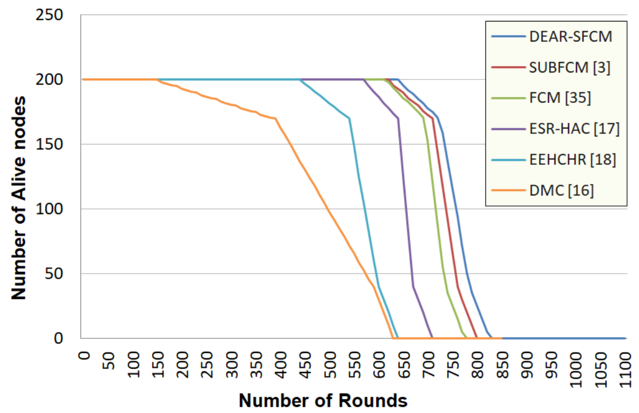

Fig. 12. Alive nodes comparisons of the proposed DEAR-SFCM with existing methods for 200 sensor nodes with an edge sink (DC = 0.5, load = 1 packet/s).

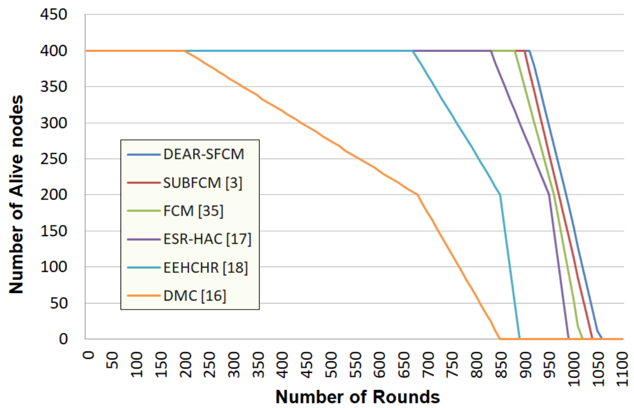

Fig. 13. Alive nodes comparisons of the proposed DEAR-SFCM with existing methods for 400 sensor nodes with an edge sink (DC = 0.5, load = 1 packet/s).

4.6 Packet Delivery Percentage (PDP)

By calculating the ratio of packets received at the BS to all packets transmitted by sensor nodes, PDP shows the reliability of data transmission in a WSN.

Figure 14 illustrates that DEAR-SFCM consistently achieves the highest PDP across all node densities and sink placements (DC = 0.5, load = 1 packet/s). PDP measures the reliability of data transmitted in a WSN as it measures the packet received by the BS over total packets sent. With the sink at the centre, DEAR-SFCM maintains PDP values between 95–98%, outperforming SUBFCM and FCM (93–96%) and exhibiting a 4–6% advantage over ESR-HAC. EEHCHR performs moderately, while DMC consistently records the lowest PDP, lagging by 10–15% points due to packet losses arising from its non-adaptive cluster formation.

The high PDP of DEAR-SFCM indicates that energy aware clustering not only balances consumption but also limits packet drops caused by early CH failure and frequent reclustering. SUBFCM and FCM show close performance at low density, but their lack of energy aware refinement leads to increasing packet loss as density grows.

When the sink is at the edge, overall PDP decreases slightly for all algorithms due to longer and asymmetric routing paths (DC = 0.5, load = 1 packet/s). Nonetheless, DEAR-SFCM sustains delivery ratios in the range of 93–96% as shown in Fig. 15, corresponding to improvements of 2–4% over SUBFCM and FCM and 4–6% over ESR-HAC. EEHCHR and DMC demonstrate pronounced degradation compared to the proposed method.

The steeper PDP drop in EEHCHR and DMC reflects relay overloading and higher retransmissions. In contrast, DEAR-SFCM maintains stable delivery through balanced clustering and energy-aware CH selection. These findings confirm that DEAR-SFCM's energy aware clustering and stable CH selection help to maintain high delivery reliability even under demanding network conditions.

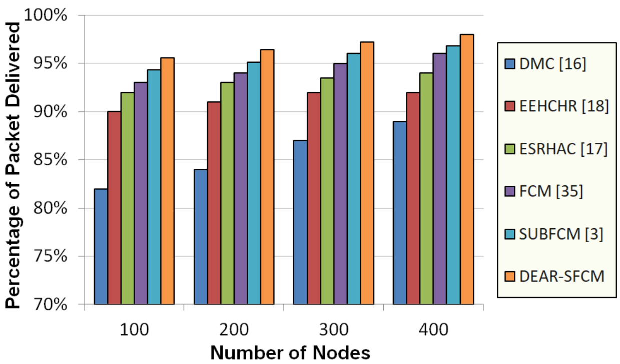

Fig. 14. Packet delivery ratio comparisons of the proposed DEAR-SFCM with existing methods under varying node densities with a central sink (DC = 0.5, load = 1 packet/s).

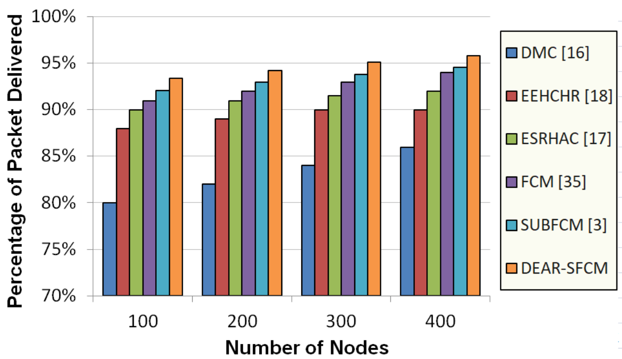

Fig. 15. Packet delivery ratio comparisons of the proposed DEAR-SFCM with existing methods under varying node densities with an edge sink (DC = 0.5, load = 1 packet/s).

Overall, the experimental results consistently demonstrate that DEAR-SFCM offers substantial improvements in energy balancing, stability period, lifetime extension, and packet delivery performance. These advantages establish DEAR-SFCM as a highly reliable and energy efficient clustering solution for WSN deployments.

4.7 Validation of Proposed Method DEAR-SFCM on NS3

To further assess the performance of the proposed DEAR-SFCM method in another simulation environment, the algorithm was also implemented in the NS3 simulator (version 3.47) [51], [52]. Table 8 presents the validation of the proposed DEAR-SFCM method using both NS2 and NS3 simulators under different configurations of node density, traffic load, and sink placement. The comparison focuses on three key network lifetime metrics: FND, HND, and LND. The observations are summarized as follows:

- **Lowest deviation case:** The smallest deviation is observed for 400 nodes with a traffic load of 1 packet/s and centre sink placement, where the reduction between NS2 and NS3 results is approximately 5.10%, 5.03%, and 5.00% for FND, HND, and LND, respectively.
- **Highest deviation case:** The highest deviation occurs under higher traffic conditions with edge sink placement, particularly for 200 nodes with 5 packets/s, where the reduction reaches approximately 10% across all lifetime metrics.
- **Effect of node density:** Increasing the number of sensor nodes from 200 to 400 significantly improves network lifetime in both simulators. For example, under 1 packet/s traffic and centre sink placement, the NS2 FND increases from 696 to 921 rounds, while the NS3 FND increases from 659 to 874 rounds, indicating improved load distribution and more balanced energy utilization.
- **Effect of sink placement:** The results consistently indicate that centre sink placement yields better network lifetime compared to edge placement. For instance, with 200 nodes and 1 packet/s traffic, the NS2 FND decreases from 696 rounds (centre) to 643 rounds (edge), primarily due to increased communication distances for a large number of nodes.

No. of nodes	Load	Sink placement	Results on NS2			Results on NS3			Deviation (%)		
			FND	HND	LND	FND	HND	LND	FND	HND	LND
200	1 packet/s	Centre	696	781	842	659	739	796	5.32	5.38	5.46
200	1 packet/s	Edge	643	724	825	598	674	764	7.00	6.90	7.39
400	1 packet/s	Centre	921	1013	1099	874	962	1044	5.10	5.03	5.00
400	1 packet/s	Edge	912	985	1054	839	907	970	8.00	7.92	7.97
200	5 packet/s	Centre	650	730	785	605	676	726	6.92	7.40	7.52
200	5 packet/s	Edge	600	675	770	540	608	693	10.00	9.93	10.00
400	5 packet/s	Centre	865	950	1020	804	884	947	7.05	6.95	7.16
400	5 packet/s	Edge	845	925	990	760	833	891	10.06	9.95	10.00

Tab. 8. Comparison of the proposed DEAR-SFCM method (duty cycle 0.5) on NS2 and NS3 simulators.

- **Effect of traffic load:** Increasing the traffic load from 1 packet/s to 5 packets/s leads to a noticeable reduction in network lifetime. For example, for 200 nodes with centre sink placement, NS2 FND decreases from 696 to 650 rounds, while NS3 decreases from 659 to 605 rounds, reflecting increased energy consumption caused by higher data transmission activity.

The results indicate that the proposed DEAR-SFCM method is largely simulator-independent, as it relies only on fundamental WSN parameters such as node coordinates, residual energy, and communication distance, which are available in common simulation frameworks including NS2 and NS3. The clustering formulation comprising density based initialization, energy weighted distance computation, entropy regularized fuzzy membership, and CH selection is implemented at the algorithmic level and does not depend on simulator specific modules.

However, slightly earlier node deaths are observed in NS3 (approximately 5–10%). This difference is mainly due to the more detailed packet level processing and realistic energy modeling implemented in NS3. In particular, NS3 accounts for energy consumption during packet transmission, reception, channel access, and protocol operations. As a result, nodes experience higher energy depletion in NS3, leading to earlier occurrences of FND, HND, and LND. Despite this difference, the overall performance trends remain consistent across both simulators, confirming the robustness of the proposed DEAR-SFCM method.

4.8 Ablation Study

To better isolate the contribution of each DEAR-SFCM component, an ablation study is conducted focusing on energy weighted membership, adaptive cluster radius, and energy distance aware CH selection. Three reduced variants V1 (energy weighted membership is removed), V2 (Removing adaptive radius estimation) and V3 (Eliminating the energy distance metric) are evaluated alongside the full model and existing schemes, as summarized in Tab. 9. The table qualitatively highlights the key design capabilities of the compared protocols.

Unlike conventional methods that emphasize isolated factors, DEAR-SFCM jointly integrates residual energy aware membership, adaptive radius control, and energy distance based CH selection within a unified framework. This coordinated design improves load distribution and scalability. In contrast, FCM lacks energy awareness, SUBFCM mainly enhances initialization, and hierarchical schemes such as ESR-HAC and EEHCHR incorporate energy information only partially. The comparison indicates that the performance gains of DEAR-SFCM arise from the integration of complementary mechanisms.

Tables 10–13 present the results obtained by selectively disabling key DEAR-SFCM components. All reduced variants show consistent degradation, confirming that each module contributes to network stability and lifetime.

The most significant FND drop occurs when energy weighted membership is removed (V1). In the 200 node central sink case, FND declines from 696 to 630 (9.5%), and in the 400 node central sink scenario from 921 to 860 (6.6%). This confirms that residual energy aware membership is the primary factor in delaying early node death by preventing repeated selection of weak nodes as CHs.

Removing adaptive radius estimation (V2) mainly impacts HND and LND. For the 200-node central-sink deployment, HND and LND decrease by 56 and 52 rounds, respectively. Similar trends appear in edge sink scenarios, indicating that adaptive radius primarily maintains cluster size balance and mid stage load distribution. Fixed radius clustering leads to uneven cluster populations and faster energy depletion during prolonged operation.

Eliminating the energy distance metric (V3) causes moderate degradation across metrics, with a stronger effect on LND. In the 400-node edge sink scenario, LND drops from 1054 to 1005 (4.6%), showing that ignoring the joint energy distance tradeoff increases long-range transmission cost and shortens lifetime.

Notably, the performance gap between the full model and ablated variants widens at higher node density and edge-sink placement. This trend highlights the increasing importance of the proposed mechanisms under heavier relay

Method	Residual energy awareness	Adaptive cluster radius	Energy–distance aware CH selection	Density-aware initialization	Load balancing capability	Scalability support
DEAR-SFCM (Proposed)	High	High	High	High	High	High
V1: w/o Energy-weighted membership	Nil	High	High	High	Medium	Medium
V2: w/o Adaptive radius	High	Nil	High	High	Medium	Medium
V3: w/o Energy–distance metric	High	High	Nil	High	Medium	Medium
SUBFCM [3]	Low	Medium	Nil	High	Medium	Medium
FCM [35]	Nil	Nil	Nil	Medium	Low	Low
ESR-HAC [17]	Medium	Low	Low	Low	Medium	Medium
EEHCHR [18]	Medium	Nil	Medium	Nil	Low	Low
DMC [16]	Low	Nil	Low	Nil	Low	Medium

Tab. 9. Feature comparison of DEAR-SFCM and existing clustering methods.

burden. Overall, DEAR-SFCM achieves its gains through the complementary interaction of its three core components rather than any single optimization.

Tables 14–17 report the ablation behavior under high traffic when (load = 5 packet/s). All schemes experience earlier node deaths, confirming that heavier traffic intensifies energy consumption. Nevertheless, the complete DEAR-SFCM model consistently maintains clear advantages over its reduced variants.

Method / Variant	FND	HND	LND
DEAR-SFCM (Proposed)	696	781	842
V1: w/o Energy-weighted membership	630	710	775
V2: w/o Adaptive radius	650	725	790
V3: w/o Energy–distance metric	645	720	785

Tab. 10. Ablation results of DEAR-SFCM variants for 200 sensor nodes with central sink (DC = 0.5, load = 1 packet/s).

Method / Variant	FND	HND	LND
DEAR-SFCM (Proposed)	643	724	825
V1: w/o Energy-weighted membership	585	665	760
V2: w/o Adaptive radius	600	680	770
V3: w/o Energy–distance metric	595	675	765

Tab. 11. Ablation results of DEAR-SFCM variants for 200 sensor nodes with edge sink (DC = 0.5, load = 1 packet/s).

Method / Variant	FND	HND	LND
DEAR-SFCM (Proposed)	921	1013	1099
V1: w/o Energy-weighted membership	860	945	1030
V2: w/o Adaptive radius	880	955	1040
V3: w/o Energy–distance metric	870	950	1035

Tab. 12. Ablation results of DEAR-SFCM variants for 400 sensor nodes with central sink (DC = 0.5, load = 1 packet/s).

Method / Variant	FND	HND	LND
DEAR-SFCM (Proposed)	912	985	1054
V1: w/o Energy-weighted membership	850	930	1000
V2: w/o Adaptive radius	870	940	1010
V3: w/o Energy–distance metric	860	935	1005

Tab. 13. Ablation results of DEAR-SFCM variants for 400 sensor nodes with edge sink (DC = 0.5, load = 1 packet/s).

Method / Variant	FND	HND	LND
DEAR-SFCM (Proposed)	650	730	785
V1: w/o Energy-weighted membership	585	660	725
V2: w/o Adaptive radius	605	675	740
V3: w/o Energy–distance metric	595	670	735

Tab. 14. Ablation results of DEAR-SFCM variants for 200 sensor nodes with central sink (DC = 0.5, load = 5 packet/s).

Method / Variant	FND	HND	LND
DEAR-SFCM (Proposed)	600	675	770
V1: w/o Energy-weighted membership	540	610	700
V2: w/o Adaptive radius	560	630	715
V3: w/o Energy–distance metric	550	625	710

Tab. 15. Ablation results of DEAR-SFCM variants for 200 sensor nodes with edge sink (DC = 0.5, load = 5 packet/s).

Method / Variant	FND	HND	LND
DEAR-SFCM (Proposed)	865	950	1020
V1: w/o Energy-weighted membership	810	895	960
V2: w/o Adaptive radius	830	905	975
V3: w/o Energy–distance metric	820	900	970

Tab. 16. Ablation results of DEAR-SFCM variants for 400 sensor nodes with central sink (DC = 0.5, load = 5 packet/s).

Method / Variant	FND	HND	LND
DEAR-SFCM (Proposed)	845	925	990
V1: w/o Energy-weighted membership	790	870	930
V2: w/o Adaptive radius	810	885	945
V3: w/o Energy–distance metric	800	880	940

Tab. 17. Ablation results of DEAR-SFCM variants for 400 sensor nodes with edge sink (DC = 0.5, load = 5 packet/s).

When energy weighted membership is removed (V1), FND degrades remarkably. In the 200 node central sink case, FND decreases from 650 to 585, and in the 400 node central-sink case from 865 to 810. This shows that residual energy aware membership becomes even more critical under heavy traffic, where weak nodes deplete rapidly if selected as CHs.

The absence of adaptive radius (V2) primarily affects mid and late network stages. In the 200-node edge-sink scenario, HND and LND drop by about 45 and 55 rounds, indicating that fixed-radius clustering causes persistent load imbalance that is amplified under high traffic.

Similarly, removing the energy distance metric (V3) shortens long-term lifetime. In the 400 node edge sink scenario, LND decreases from 990 to 940, confirming that neglecting the energy distance tradeoff increases transmission cost, especially under heavy data generation.

Overall, the larger performance gaps at load = 5 packet/s verify that DEAR-SFCM is particularly effective in traffic intensive real world scenario conditions. Stability, load balancing, and long term efficiency are jointly achieved only when all three components operate together.

5. Conclusion

DEAR-SFCM, an improved fuzzy clustering framework is proposed to solve uneven energy depletion in WSNs. FCM and SUBFCM have unstable membership convergence, energy distance measurements, and fixed cluster radius. DEAR-SFCM uses a hybrid approach that combines energy aware membership update with dynamic radius adaptation considering dense and sparse region to overcome the limitations. The approach improves cluster formation, resulting CH selection in a better way, and a more balanced distribution of energy. According to simulation tests, DEAR-SFCM often achieves increases of roughly 7–12% in stability period, 20–35% in network lifetime, and 4–8% in PDP, outperforming SUBFCM, FCM, ESR-HAC, EEHCHR, and DMC. These enhancements show how useful it is for long term field deployments, environmental monitoring, and large scale IoT sensing. Future research could further enhance adaptive CH selection by incorporating hybrid metaheuristics algorithm or AI based intelligent techniques which may include reinforcement learning. These developments could result in WSNs that are more intelligent, durable, and self managing.

Code Availability

To support reproducibility, the implementation code of the proposed DEAR-SFCM method is available at https://github.com/sheenakumar99/DEAR-SFCM

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