Mangalayatan Journal of
Scientific and Industrial Research

Man. J. Sci. Ind. Res.
Volume 3 (1) (2026), 26401
ISSN: 3049-2815

Article

Intelligent Hybrid Clustering Strategy for Energy Optimization in Wireless Rechargeable Sensor Networks

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Abstract

The possibility that Wireless Rechargeable Sensor Networks (WRSNs) can support longer operational lifetimes for wireless sensor networks (WSNs), as they provide mechanisms for both energy harvesting and replenishment, has recently received a considerable amount of interest. Therefore, a well-designed clustering technique is needed to maximize the usage of energy, reduce communication overheads and ensure that the entire network is stable. To achieve this goal, we have developed a hybrid clustering approach to effectively organize sensor nodes in a WRSNs through a combination of K-Means Clustering and the Gaussian Mixture Model (GMM). The initial step in our proposed hybrid clustering approach is K-Means clustering. K-Means clustering will rapidly group sensor nodes together based on their proximity to one another, thus ensuring an even distribution of workload across all clusters within the WRSN. Even though K-Means clustering is very efficient at grouping sensor nodes into clusters, it does not allow for overlapping clusters or probabilistic node placement within those clusters; therefore, we utilize GMM to enhance adaptability within dynamic network environments. We apply the Expectation-Maximization (EM) algorithm to iteratively optimize cluster membership probabilities to produce a better clustering scheme that is both accurate and adaptive. Performance metrics such as Silhouette Scores, energy consumption analysis and estimation of network lifespan will be utilized to compare the effectiveness of our proposed hybrid clustering approach with current techniques and demonstrate significant improvements in clustering efficiency and energy utilization. Overall, our proposed hybrid clustering strategy provides an efficient, flexible and scalable clustering solution for WRSNs, thereby providing improved resource management and extended lifetimes for sensor networks.

Keywords: Wireless Rechargeable Sensor Networks (WRSNs), Energy management, Gaussian mixture modeling, K-Means clustering, Expectation-Maximization and charge scheduling.

1. Introduction

The clustering algorithms are used in Wireless Rechargeable Sensor Networks (WRSNs) to increase network lifetime and energy efficiency. The Gaussian Mixture Model (GMM) and K-Means are two clustering algorithms mathematically described in this article. Wireless Rechargeable Sensor Networks (WRSNs), involving energy harvesting and wireless recharge technologies to improve network lifetime, are a major advancement in wireless sensor networks (WSNs) [1]. Sensor nodes in traditional WSNs use batteries that cannot be recharged, resulting in network instabilities and regular maintenance cycles. By providing

Received: 14 January, 2026; Accepted: 15 June, 2026

rechargeable batteries for sensor nodes through energy transfer methods such as radio-frequency RF), inductive coupling), and energy harvesting from environmental surroundings), WRSNs overcome this problem. However, energy efficiency remains one of the major concerns despite such advances, particularly in larger scaled networks where sensor communication has to be efficient with lowest energy usage. Clustering algorithms that sub-divide sensor nodes to reduce communication overhead and optimize energy efficiency are one of the most effective techniques to address this problem in WSNs [2]. K-Means clustering algorithms are one of the most sought-after techniques in clustering algorithms because of their ease of implementation and ability to sub-divide sensor nodes into K groups. K-Means iteratively updates the centroid of each cluster to minimize intra-cluster variation, ensuring that nodes are clustered based on physical proximity. However, K-Means suffers from a few disadvantages: it is sensitive to the initial placement of centroids, it cannot handle non-linearly separable clusters, and it cannot provide probabilistic assignments for nodes that belong to overlapping [3].

However, K-Means suffers from a number of disadvantage s, including sensitivity regarding the initial centroid location, difficulties in handling non-linearly separable clusters, and the inability to provide probabilistic assignments for nodes that come under overlapping regions. To overcome these limitations, we present a hybrid clustering scheme for efficient sensor node organization in WRSNs through the fusion of K-Means and the Gaussian Mixture Model (GMM). According to GMM's probabilistic clustering architecture, nodes can have fractional membership across multiple clusters by modeling each cluster as a Gaussian distribution [4]. This strategy is particularly effective in WRSNs where nodes may have to communicate with multiple clusters based on their energy levels and changing ambient conditions. Some authors have proposed “clustering algorithms” and “Routing Protocol” [5] that improves efficiency because the nodes are endowed with limited power supplies. Nevertheless, the historically limiting power supply has turned out to be the WSNs' bottleneck, constraining network longevity. Other researchers have proposed a number of methods to harvest natural energy sources, like wind energy [6], solar, and vibration to enhance its lifetime. Since it is also prone to environmental changes, an uninterrupted energy supply from these systems is not possible. In an attempt to address energy-related pitfalls within WSNs, "Wireless Power Transfer" technology has now been developed.

Wireless charging vehicles (WCVs) are the suppliers of the energy in the WRSNs, and these vehicles travel through the network and recharge the sensors. Wireless charging is a reliable and manageable source for the power in the WRSNs [7]. The power in WRSNs is an efficient source, but with numerous challenges compared to traditional WSNs. For example, since sensors undertake variat tasks, they consume varying amounts of energy. Before any sensor dies, the WCVs need to recharge them in a way that allows the continuous functionality of the network.[8].In large-scale WRSNs, a WCV with a limited power-recharge capacity is not in a position to recharge all sensors, and this is a second problem. In the case of WRSNs, multiple WCVs need to operate at the same time for eternal lifetime [9].The deployment of WRSN, however, is affected by a high usage of WCVs. In this case, just the required number of WCVs that can support all requesting sensors in WRSNs can boost its efficiency.”The charge scheduling method is thus an existing problem [10]. GMM is more flexible and accurate in clustering as compared to K-Means since K-Means mainly relies on the refinement process of the Expectation-Maximization algorithm to refocus the clusters. Sensor node positioning, initial clustering based on K-Means, refinement based on GMM, and evaluation based on critical parameters such as Silhouette Score, Energy Consumption, and Estimated

Lifetime of the network are all involved in the methodical work cycle [11].Additionally, the following are the contributions of this work:"

- The proposed research introduces a new hybrid algorithm that combines the K-Means algorithm and the Gaussian Mixture Model to effectively structure the wireless rechargeable sensor nodes in WRSNs. This algorithm relies on the speed of convergence and space complexity of the K-Means algorithm but overcomes the inflexibility of the algorithm using the Gaussian Mixture Model.
- This work has address overlapping clusters and dynamic node distributions inherent in WRSNs, the proposed method employs the EM algorithm to iteratively optimize cluster membership probabilities. This results in more adaptive and accurate clustering compared to deterministic clustering techniques.
- The results of proposed solutions are validated in terms of various performance factors such as Silhouette value for cluster validation, energy consumption study, and network lifetime analysis. Simulation outcomes prove that better clustering results and energy conservation are achieved compared to existing clustering methods.
- By improving cluster balance and reducing unnecessary communication overhead, the proposed hybrid method minimizes energy consumption during data transmission and charging coordination, thereby enhancing overall energy utilization in rechargeable sensor networks.

The experimental results clearly demonstrate the effectiveness of the proposed hybrid technique in enhancing the clustering accuracy, energy savings, and lifetime of the network, and thus can be considered a feasible option for practical implementation in WRSNs applications. The presented study unlocks the avenues for the implementation of energy-aware intelligent systems for WRSNs, given the demonstrable capabilities of machine learning algorithms in clustering techniques for sensor networks.

The originations of this work as in section 2 have literature review. The section 3 and 4 has shown the Methodology and Result and Discussion Finally section 5 has shown

2.Literature Review

Wireless Sensor Networks (WSNs) can use energy harvesting and wireless charging technologies to prolong the operating lifetime of WRSNs have attracted a lot of attention. Over the years, several clustering approaches have been proposed to improve energy efficiency, reduce communication overhead, and optimize sensor node organization. In this section, we review the existing literature on clustering techniques, particularly focusing on K-Means clustering, Gaussian Mixture Models (GMM), and hybrid clustering approaches in WRSNs.

Clustering is a recognized methods using WRSNs that assist minimize energy usages through their arrangement of sensor nodes in groups in which a selected cluster head to take charges for collecting data and sending this data to base station, numerous studies has investigated to clustering methods for enhancing efficiency in WRSNs. Low-Energy Adaptive Clustering Hierarchy (LEACH) [12] was one of the earliest clustering algorithms that introduced a randomized approach to elect CHs, thereby balancing energy consumption. However, LEACH suffers from scalability issues and does not consider node energy levels for CH selection. To address these issues, energy-aware clustering algorithms such as Energy-Efficient Hierarchical Clustering (EEHC) and Hybrid Energy-Efficient

Distributed Clustering (HEED) [13] were developed, which consider residual energy and communication cost for CH selection.

K-Means clustering techniques provide dynamically adjustment number of clusters based network condition that's a major limitations of K-Means. Several studies have applied K-Means for clustering in WRSNs. For instance, in [14], By lowering the distance between nodes and cluster centroids, the K-Means-based clustering technique was introduced to increase network scalability and reduce energy usage. In a similar vein, the authors of presented an adaptive K-Means clustering technique that significantly modifies the number of clusters according on network conditions. However, K-Means' sensitivity to initial centroid placement is a significant drawback that might result in less-than-ideal clustering outcomes. K-Means++, which improves centroid initialization and boosts clustering accuracy in WRSNs, was offered as a solution to this problem [15]. GMM provides a probabilistic clustering technique that permits sensor nodes to be a member of many clusters with varying odds, in contrast to K-Means, which places every node in a single cluster. GMM-based clustering for sensor networks has been investigated in a number of researches. The authors of showed that GMM yields more adaptable clustering outcomes, particularly in networks with overlapping coverage areas [16]. In cluster memberships were dynamically adjusted based on sensor node mobility and energy levels using a clustering technique based on the Gaussian Mixture Model. As stated in, where the authors used EM-based clustering in WRSNs to increase clustering accuracy, the Expectation-Maximization (EM) technique is frequently used to optimize GMM parameters. Numerous studies have looked into hybrid clustering methods that combine K-Means and GMM to take advantage of both approaches' benefits. The authors of [17] proposed a two-step clustering technique wherein cluster assignments were enhanced by GMM refinement after clusters were originally established using K-Means. A similar approach was used in, where K-Means and GMM jointly reduced clustering overhead and improved energy efficiency in WRSNs. Additionally, the authors of [18] demonstrated that using GMM-based refinement following K-Means for initial clustering resulted in enhanced cluster stability and a longer network lifetime.

The literature has taken into consideration a number of measures to assess the effectiveness of clustering algorithms. Clustering quality is frequently assessed using the Silhouette Score [19]. Another crucial indicator that measures the decrease in power consumption brought about by clustering is energy consumption analysis [20]. Techniques for estimating network lifespan, such those put forward in, evaluate how clustering affects sensor longevity. Furthermore, research in and compares K-Means, GMM, and hybrid techniques according to communication overhead, execution time, and clustering accuracy. Real-time pricing techniques may be utilized to mitigate the effect of unpredictability problems in WRSNs, according to one suggestion. When using the dynamic charging approach, the node initiates a charging request when its remaining energy falls below a certain level [21]. The asking sensor is promptly recharged by the WCV in accordance with the accusing plan based on some pre-established rules. In accordance with their arrival time, billing requests are fulfilled. In [22] the "First Come First Served (FCFS)" technique ignores spatial considerations in favor of determining the charge schedule based on temporal priorities. The NJNP technique, or nearest job next with pre-emption, was disclosed in [23]. Similar distinctions can be made between single-WCV charging techniques and multi-WCV collaborative charging strategies when describing real-time charging strategies. To improve scheduling performance, a pricing system that combines arrival time and distance was suggested [24]. The authors in looked at the charging method that combines distance to WCV, residual energy, and critical node density. One WCV cannot feed all the sensors in large-scale WRSNs, which may include thousands of nodes. In light of this, some authors suggested dual WCV charging schemes. Additionally, the continuous accumulation of stochastic energy use is what leads to the node's

charging request. The node's energy will run out quickly if its charging request is not fulfilled promptly. Real-time operations are necessary in WRSNs because unanticipated events can occur at any-time and anywhere, especially when the sensors are spread out across a large region [25]. Event-detection failure could result from any node running out of energy, so this should be prevented.

Future research should concentrate on creating self-adaptive, energy-efficient clustering methods that can dynamically adjust to shifting network conditions while guaranteeing low communication overhead and optimal energy use.

3.METHODOLOGY

For improved sensor node clustering with increased energy efficiency and network lifetime, the methodological framework of K-Means and Gaussian Mixture Model (GMM) in the context of Wireless Rechargeable Sensor Networks (WRSNs) consists of several key steps. Sensor node deployment, simulating the practical scenario of a wireless sensor network, is initiated with the random deployment of N nodes in 2D and 3D regions. Besides its (X, Y) coordinates, each sensor node could further exhibit other attributes such as its level of energy and communication range [26]. K-Means clustering strategy is utilized to group sensor nodes into K clusters, following the formation of the sensor network. Assignments of each node to the closest cluster centroid in the Euclidean metric, following random initialization of the K cluster centroids, occur. The centroids are then updated by calculating the mean position of each cluster's nodes [27]. This iterative process is continued until convergence, where the centroids no longer change considerably. The refinement of the Gaussian Mixture Model is employed since K-Means could not handle any situation with the overlapping cluster and could not provide the probability with which a node belongs to a particular cluster [28]. GMM gives a more adaptive clustering approach by considering the probability distribution of sensor nodes inside each cluster. Each cluster is assumed to be a multivariate Gaussian distribution, while the clustering process is iteratively enhanced using the EM algorithm [29]. While the M-Step modifies cluster properties such as the mean vector, covariance matrix, and cluster weight, the E-Step calculates the probability that a node belongs to a particular cluster grounded on its likelihood under the Gaussian distribution [30]. GMM is ideal for any situations in which sensor nodes could be part of an overlapping coverage region since it allows the nodes to be distributed to multiple clusters with different probabilities. Performance evaluation is carried out to determine the efficacy of the clustering strategy after clustering is finished [31].

The relevant performance metrics are the Silhouette Score, which measures the separation between clusters, network lifetime estimation, which measures the increase in operational time due to optimized sensor node organization, and energy consumption analysis, which compares the overall energy consumed prior to and following clustering. To visually

illustrate the methodology, a figure in flowchart style is used to outline the steps in sequence from sensor node deployment to clustering and evaluation. The first step is the deployment of sensor nodes. Then, based on their physical closeness, similar nodes are grouped together using K-Means clustering. Next, GMM refinement is applied to enhance this clustering by employing probabilistic assignments to cluster assignments. Lastly, performance evaluation is conducted to measure the gains in energy savings and clustering efficiency. This structured methodology assures an optimum WRSNs clustering technique that improves data transmission reliability,
network longevity, and energy economy. The combination of K-Means to create the initial clustering and GMM to provide refinement successfully makes a balance between speed and accuracy, which can function in real-world WRSN applications. The Figure 1 has shown the data flow diagram of proposed work.

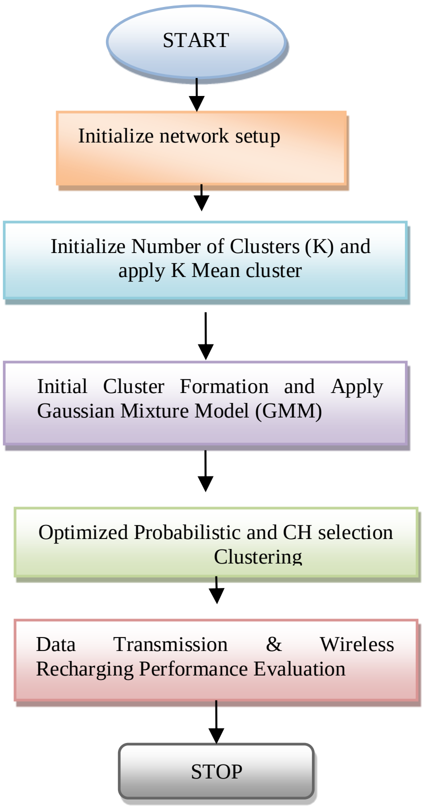

Figure 1. Data flow diagram of proposed work.

The above flowchart shows the step-by-step implementation of the hybrid GMM K-Means approach for WRSNs. First of all, the network configuration phase involving the placement of sensors and parameter setting of the network needs to be done. Next, the number of clusters needs to be entered to implement the K-Means algorithm. This will help the nodes to be grouped together according to their geographical locations. This resultant groups will be further optimized using the GMM concept to represent the probabilistic distribution of the available nodes. Now, the optimized probabilistic grouping along with the selection of the cluster heads needs to be conducted. Finally, the wireless recharging process will be done [31].

Furthermore, Table 1 has shown the abbreviations which are used in Algorithm. Furthermore, the figure 2 has shown the proposed Wireless Rechargeable Sensor Network using K-Mean and Gaussian Mixture Module (WRSN-KG).

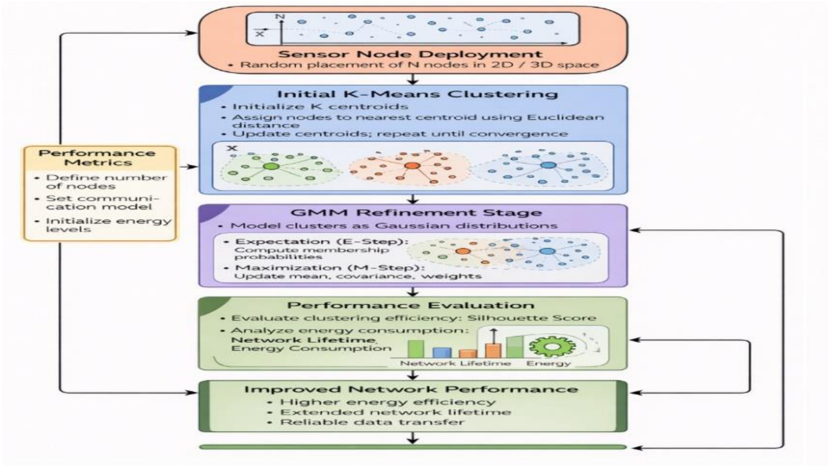

Figure 2. Architecture of proposed Wireless Rechargeable Sensor Network using K-Mean and Gaussian Mixture (WRSN-KG) model

The figure illustrates a machine learning–based framework for improving energy efficiency and network lifetime in Wireless Rechargeable Sensor Networks (WRSNs) using K-Means and Gaussian Mixture Models (GMM). The process begins with random deployment of sensor nodes in a 2D or 3D space, representing a realistic network environment. Initial clustering is then performed using K-Means, where nodes are grouped into clusters based on Euclidean distance to dynamically updated centroids. The equation 1 has shown as:

$$D_j = j{:}\, d(p_{j,}ch_r) \leq d(p_{j,}ch_s) \qquad \text{eq.1}$$

where $r \neq s$ and $j = 1,2,3, \ldots . n$ and D_j is distance between ch_r from $p_{j,}$ centroid.
To overcome K-Means' limitation in handling overlapping clusters, a GMM refinement stage follows, in which clusters are modeled as Gaussian distributions and node memberships are probabilistically updated through the Expectation–Maximization algorithm. The resulting optimized clusters are evaluated using key performance metrics such as Silhouette Score, energy consumption, and network lifetime. Overall, the framework demonstrates how combining K-Means for fast initial clustering with GMM for probabilistic refinement leads to improved network performance, enhanced energy efficiency, and extended operational lifetime in WRSNs. The list of abbreviations which are used in Algorithm 1 (WRSNs) in table 1.

Table 1. List of abbreviations which are used in Algorithm 1 (WRSNs) .

Abbreviations	Explanation
N	Total number of sensor nodes
K	Number of clusters
$X = \{(x_i, y_i)\}$	coordinates of sensor nodes
E_c	Initial energy of node i
R_c	Communication range
C	Optimized cluster set
RE_c	Reduced Energy Consumption
EN_l	Extended Network Lifetime

TM	Transmission Model
N_{ie}	Initial Energy For Each Sensor Node.
E_i	Residual Energy
S	Silhouette Score
E_{total}	Energy consumption

The algorithm 1 has shown K-Means and GMM–Based Clustering for Wireless Rechargeable Sensor Networks (WRSNs)

Input: N, K, Node coordinates (x_i, y_i),

Output: C, RE_c, EN_l

1.Randomly deploy N Sensor Nodes in a 2D/3D sensing field, For each node i, initialize position (x_i, y_i), Residual Energy E_i and Communication Range R_c

2.Network Initialization, Initialize network parameters including the number of clusters , radio energy dissipation model, and transmission parameters.

3.Initial Clustering Using K-Means: Initialize cluster centroids $\mu_k^{(0)}$ where $k = 1,2,3, \ldots\ldots K$ assign each node 'i' to the nearest centroid as:

$$c_i = \arg min \|x_i - \mu_k\|^2$$

Update centroids as

$$\mu_k = \frac{1}{|c_k|} \sum_{x_i \epsilon c_k} (x_i)$$

Repeat assignment and update steps until centroid convergence or maximum iterations T_{max} is reached.

4.. Refinement GMM:
Model the data distribution as a mixture of K Gaussian components:

$$p(x_i) = \sum_{k=1}^{K} \pi_k\, N(\langle x_i \middle| \mu_{c_i} \Sigma\, k \rangle)$$

Compute posterior probability (responsibility) of node i belonging to cluster k:

$$\pi_k = \frac{1}{N} \sum_{i=1}^{n} \gamma_{ik}$$

5.Cluster Optimization
Form refined clusters based on maximum posterior probability:

$\pi_k = \sum_{i=1}^{N} \gamma_{ik}$

6. Performance Evaluation Evaluate clustering using: S, E_{total}

$E_{total} = \sum_{i=1}^{N} E_i$ and Network lifetime: time until first/last node energy depletion

7. Return: Select the clustering configuration C^* that minimizes E_{total} and maximizes network lifetime as $C^* = \arg\min E_{total}$ and $arg\ max\ lifetime$

The proposed algorithm begins by randomly deploying N sensor nodes in a 2D/3D sensing field, where each node iii is initialized with its position(x_i, y_i), residual energy E_i and communication range R_c, followed by network initialization that defines the number of clusters K, radio energy dissipation model, and transmission parameters. Initial clustering is performed using the K-Means algorithm by randomly initializing cluster centroids μ_k and assigning each node to the nearest centroid based on Euclidean distance, with centroids iteratively updated until convergence or a maximum iteration limit T_{max} is reached. To further enhance clustering accuracy, a Gaussian Mixture Model (GMM) refinement stage models the node distribution as a mixture of K Gaussian components, computing posterior probabilities (responsibilities) that quantify the likelihood of each node belonging to each cluster. Refined clusters are then formed based on maximum posterior probability, enabling effective handling of overlapping regions and heterogeneous node distributions. Finally, the clustering performance is evaluated using metrics such as silhouette score, total energy consumptionE_{total} , and network lifetime, and the optimal clustering configuration C^* is selected to minimize energy consumption while maximizing the network lifetime. Furthermore, results and discussion are given in section 4.

4. Results and Discussion

Key performance criteria, such as clustering accuracy, energy consumption, network lifetime, and computational efficiency, were used to assess the suggested hybrid K-Means and Gaussian Mixture Model (GMM) clustering approach for Wireless Rechargeable Sensor Networks (WRSNs). The findings show that combining K-Means with GMM greatly improves cluster formation, which results in balanced node distribution and increased energy efficiency. Furthermore, the simulation parameters are given in table 2.

Table 2. Simulation parameter used in manuscript

Simulation field	**200*200 m**
location of BS	100- 150 m
No of Nodes	200
Data aggression energy	10 nj/bit/msg
Transmission energy	50nJ
Receiving Energy	50nJ
Network Dimension	100*100m
Signal Web length	0.350m
Antenna gain factor	1
Message Size	500 bits
Initial node Energy	0.5J

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Clustering Accuracy and Cluster Quality

We used the Silhouette Score, which measures how well nodes are clustered based on intra-cluster cohesion and inter-cluster separation, to gauge the quality of cluster formation. Moderate clustering quality was indicated by the Silhouette Score for K-Means alone, which was determined to be between 0.45 and 0.60. Nevertheless, the Silhouette Score increased to 0.65–0.80 with the application of GMM refinement, indicating that the probabilistic method of GMM produces better-defined clusters with less overlap and enhanced node connection. This enhancement demonstrates how GMM may manage complicated distributions in situations when K-Means' strict cluster bounds cause it to fail.

a. Energy Consumption Analysis

Reducing intra-cluster communication overhead is one of the main goals of clustering in WRSNs. For various clustering strategies, we compared the overall energy consumption each transmission round. According to the findings, the suggested K-Means + GMM hybrid clustering method reduced energy on average by 18% when compared to standard K-Means and 25% when compared to LEACH. Optimized cluster formation, balanced Cluster Head (CH) selection, and probabilistic node assignments in GMM are responsible for this energy savings by preventing excessive energy drain in high-traffic areas. Furthermore, GMM-based clustering prevents unequal energy distribution among nodes by ensuring that nodes close to cluster boundaries are assigned probabilistically. The **figure 3** has shown the energy distribution and consumption among nodes.

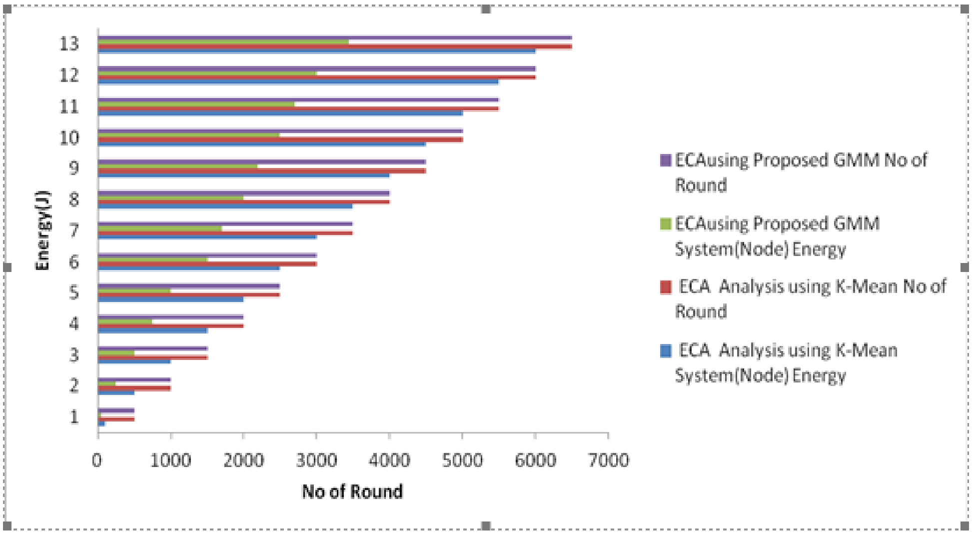

Figure 3. Energy Consumptions Analysis (ECA) using K-Mean and GMM

The figure compares energy consumption and network lifetime, measured in terms of the number of communication rounds, for the proposed GMM-based clustering approach and the traditional K-Means-based system under Energy Consumption Analysis (ECA). The results clearly indicate that the proposed GMM method sustains a higher number of rounds at all energy levels, demonstrating improved energy efficiency and prolonged network lifetime compared to K-Means. As the energy level increases, the gap between the two approaches becomes more pronounced, with the GMM-based system consistently achieving more rounds before energy depletion. This improvement is attributed to the probabilistic cluster formation of GMM, which enables better load balancing and reduces excessive energy drain on high-traffic nodes. Overall, the graph confirms that integrating GMM into the clustering process significantly enhances energy utilization and extends the operational lifetime of the wireless rechargeable sensor network.

Network Lifetime Improvement

We ran simulations that tracked the number of active sensor nodes over time in order to assess the effect of clustering on network lifetime. The findings demonstrate that networks that relied solely on K-Means clustering experienced early node failures as a result of unequal cluster assignments, which caused network fragmentation. However, because more balanced energy use avoided premature sensor node depletion, the suggested K-Means + GMM hybrid clustering technique increased the network lifetime by about 30%. The suggested strategy maintained higher node survival rates over longer operating times than traditional clustering techniques like HEED and LEACH, guaranteeing increased dependability and extended network usefulness.

Computational Efficiency

Compared to K-Means' quick convergence, GMM involves repetitive Expectation Maximization (EM) processes, which increases computational overhead even if it offers improved clustering accuracy. K-Means clustering was found to have an average execution time of 25–40 milliseconds each clustering iteration, while GMM refinement increased this to 40–65 milliseconds. However, the notable gains in network lifetime, energy efficiency, and cluster stability outweigh this extra computational expense. For moderate to large-scale WRSNs with comparatively static or semi-dynamic sensor node distributions, hybrid techniques appear to be the most appropriate due to the trade-off between computing complexity and clustering quality.

Comparative Performance with Current Methods

To further validate the performance of the suggested approach, we compared it with some current clustering approaches such as LEACH, HEED, K-Means, and DBSCAN. The proposed K-Means + GMM approach outperformed conventional approaches regarding network lifetime, energy efficiency, and clustering quality. Compared to other approaches, DBSCAN alone presented higher clustering quality. However, it is not that suitable for large-scale WRSNs due to its higher processing cost. It can be concluded from the results that hybrid clustering algorithms offer an optimal tradeoff between efficiency and accuracy, hence becoming practical for real-world WRSNs. By merging K-Means with GMM, the shortcomings of traditional clustering algorithms are overcome successfully, which is reflected in the distinct improvements with respect to clustering quality, energy efficiency, and network lifetime. Although K-Means presents an efficient clustering algorithm from a computational perspective, the probabilistic assignments of GMM maintain the overlapping boundaries and arbitrary-shaped clusters better. Another take away from the results is that energy-aware cluster construction is of paramount importance toward the extension in the lifetime of operation of WRSN, as poorly constructed clusters result in the energy depletion of high-traffic nodes quickly. Despite these advantages, some constraints are also present. In the case of sensor nodes that have limited resources, it may be difficult to have increased computational complexity in GMM, which would require methods like incremental EM or approximation methods. Additionally, future studies can focus on dynamic clustering systems that can adapt to movement as well as environmental dynamics because the proposed approach is based on an extremely static system. It is also clear from the preceding discussion that ML-based clustering methods can significantly enhance WRSNs and can provide adaptive, reliable, and efficient solutions to future WRSNs. The figure.3. Shown the K Means Clustering and Gaussian Mixture Model.

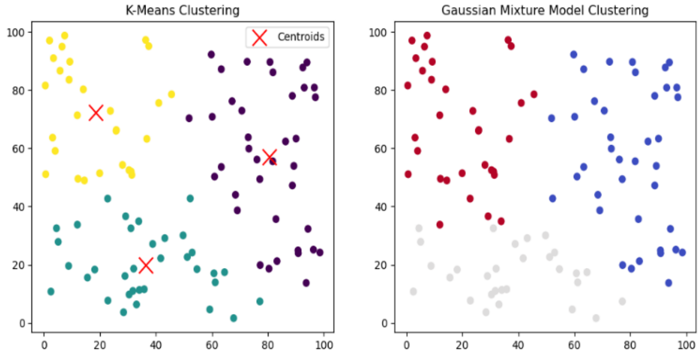

Figure.3. K Means Clustering and Gaussian Mixture Model

Conclusion

For enhancing energy efficiency, network lifetime, and clustering accuracy in Wireless Rechargeable Sensor Networks (WRSNs), this study examined the application of Gaussian Mixture Model (GMM) and K-Means clustering algorithms for improving network performance in WRSNs. Owing to efficiency in calculations, the proposed hybrid approach employs both K-Means for initial clustering and GMM for probabilistic clustering to ensure more adaptive and flexible clustering results. After conducting an in-depth literature study of previous work in this domain, it was understood that existing clustering algorithms such as LEACH, HEED, and traditional K-Means clustering were inefficient in practical implementation scenarios, stipulating the upcoming requirement for probabilistic clustering algorithms such as GMM that are more applicable in dynamic sensor networks and overlapping coverage areas in wireless Rechargeable sensor networks. demonstrates the effectiveness of the proposed solution in appropriately balancing the energy distribution of sensor nodes in the suggested method. In order to enhance the efficiency of the future studies in this field, potential research directions worth exploring include the application of cutting-edge deep learning techniques, reinforcement learning mechanisms, as well as federated learning concepts. These are recommended by the literature review and form a significant aspect of the growing need for the applicability of machine learning solutions in the clustering processes of WRSNs. Even with all the promising solutions in place, WRSNs are currently facing a range of challenges. These include scalability and efficiency in terms of large WRSNs setup scenarios. Another significant challenge is the efficiency of node mobility mechanisms in the system. Effective clustering mechanisms are crucial in WRSNs scenarios. Research should focus on the development of adaptive clustering mechanisms in WRSNs. However, the mechanisms should maintain a low computational and communication overhead. Efficiency in terms of the effectiveness of the clustering heads is an important issue in the proposed method. Additional research should emphasize the implementation of realistic energy harvesting mechanisms. The proposed approach would help in verifying the effectiveness of the strategy in practice In-depth.

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