An Energy-Efficient Clustering Model for Wireless Sensor Networks Using Modified K-Means Algorithm

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Abstract: Wireless Sensor Networks (WSNs) are becoming essential for many applications, ranging from smart cities to environmental monitoring. WSNs comprises a collection of deployed sensor nodes to execute specified objectives in a certain area. Since batteries can only hold so much energy, one of the most crucial topics of research is how to use energy efficiently in order to extend the lifespan of sensors. One of the most popular methods for lowering energy consumption is clustering, and clustering routing protocols are methods for preserving energy to increase the lifetime of a wireless sensor network. The K-Means algorithm is one of the clustering techniques that requires prior knowledge of the clusters. This study proposes a mathematical model to determine the optimal number of clusters in WSNs, reducing energy consumption by up to 97%. Choosing the number of clusters at random could use more energy and reduce the network lifetime. This paper seeks to present a new approach for determining out the optimal number of clusters in a WSN. The proposed model tests the WSN performance by using a mathematical model and implementing it as a simulation technique in MATLAB. It considers the key WSN characteristics, including the deployed area size (100 × 100), the number of rounds (100, 200, 300, 400, and 500), and the number of sensor nodes (500). This study demonstrated that our revised approach to selecting the number of sensor network clusters reduced overall energy consumption by 97% when compared to the conventional model, hence increasing the networks' overall lifespan.

1 INTRODUCTION

Wireless Sensor Networks (WSNs) are made up of many small sensors, electrical and actuator devices, and activation nodes. These sensing electronic devices can detect and gather data on phenomena such as the speed of the wind, pressure, temperature, and other similar features in a particular sensing field [1]. The processed information is subsequently delivered to the Base Station (BS). WSN sensors are small and have a low production cost. As a result, WSNs have a wide range of efficient and sometimes sensitive uses, particularly in the armed forces, healthcare, and environmental fields. WSNs have limited resource systems which need good management and efficient utilization of all of their resources [2]. WSNs face two key extensive constraints: the first one is the low energy resources of the sensors, which are not rechargeable, and an exceedingly limited battery. The second constraint is susceptibility to failure. However, the data transmission process consumes the most energy [3, 4]. One possible method for reducing communications and hence reducing energy consumption is to arrange the network in clusters [5]. Hence, clustering is a common technique that is used to obtain efficient resource allocation and good scalability in WSNs. The major problem in networks that are based on the clustering technique is how to decide what is the best number of clusters with the objective of minimizing energy consumption [6]. The optimal number of clusters in the WSN environment is essential because if the given number of clusters, which is input to the K-Means algorithm, is less or greater than the optimal value, the produced result will not be suitable for balancing distribution in the sensor network [7]. Advantages of centroid models such as K-Means are that convergence is guaranteed and they are specialized in clusters of different sizes and shapes, but they have a disadvantage: the K-value is difficult to predict [8]. Clustering in WSN is grouping sensor nodes into clusters and selecting a Cluster Head (CH) for each cluster, where each CH is responsible for gathering data from its own sensor nodes and sending them to the BS or to other CHs. Clustering has many advantages such as grouping sensors, reducing the number of nodes responsible for transmitting data, and decreasing energy consumption [9]. Clustering in sensor nodes has been widely used to solve the scalability, energy, and lifetime issues of sensor networks [10]. Clustering is an algorithm that is used to separate, classify, or group objects depending on attributes/features into K number of groups. K is a positive integer number. Grouping is achieved by reducing the sum of squares of distances between data and the corresponding cluster centroid. It is also called the centroid method [11]. K-Means is a method of cluster analysis using a previously determined number of clusters. It requires advanced knowledge of ‘K’. The use of the K-Means algorithm as a clustering technique for cluster formation ensures good clustering and minimizes the overheads when the channels are re-elected.

Advantages of K-Means are that convergence is guaranteed and it is specialized in clusters of different sizes and shapes [12]. To get good energy consumption management during the communication process and endure transient failures, many methods for clustering used in WSNs have been proposed in the literature. Motivated by the research described in the preceding part, we utilized a mathematical model to offer a viable and useful solution for a wireless sensor network. The rest of this paper is organized as follows: Section 2 reviews the related work, Section 3 describes the K-Means Algorithm, Section 4 presents the methodology and the proposed model, Section 5 discusses the results and discussion, and Section 6 concludes the study.

2 RELATED WORK

Heinzelman et al. [13] presented a low-energy adaptive clustering hierarchy (LEACH), which is currently regarded as the most famous clustering protocol for WSNs, as a means of deploying a WSN. There are two kinds of nodes in a hierarchical topology: cluster heads and cluster members. A single node is designated as the cluster head in each cluster that is made up of member nodes [14]. The primary responsibility of the cluster head is to receive signals from cluster members and transmit them to other cluster heads or the base station [15, 16]. The authors in [17] introduced a system called (HEED) Hybrid Energy-Efficient Distributed Clustering that selects the cluster head by using an iterative clustering process; they utilized a hybrid of residual energy and communication cost in terms of node proximity to neighbours or node degree. This achieves uniform cluster head distribution across the network and incurs low message overhead. The same approximation that was used by the LEACH approach is used by this method to get the optimum number of clusters (k). The authors of [18] presented a systematic analysis based on the cost for sensor nodes that are organized in clusters by using single-hop or multi-hop communication modes. For each mode of communication, they tried to formulate guidelines to get the optimal number of clusters. In [19, 20], clustered networks with dynamic hierarchy were introduced. They tried to determine the best number of clusters that reduces the overhead of the routing process. They defined the overhead of the routing process as the amount of information that is needed to describe the change in a network topology. They tried to minimize the routing overhead by determining the optimal number using an information-theoretical approach with mobility prediction and without mobility prediction. In [21], the authors introduced a sensor network that depends on multi-cluster technology; this network is applied for source extraction. They used the Particle Swarm Optimization (PSO) algorithm to cluster the sensors. They also proved theoretically that there is a unique optimal number of clusters that achieves the lowest energy consumption. In [22], the authors showed an analytical method to get the optimum number of clusters of dense wireless sensor networks by using a cross-layer optimization method. In [23], the authors tried to get the suitable number of clusters that can achieve well-balanced memberships. In [24], the authors divided a data set into a set of clusters by using an objective function-based method. [25] tried to propose fuzzy-based clustering. Fuzzy c-Means (FCM) and its derivatives encounter two problems: cluster validity and local minima, which have a direct impact on the formation of the clustering.

3 K-MEANS ALGORITHM

3.1 Overview of the K-Means Algorithm

Among the promising and successful clustering techniques is K-Means [26]. The process involves grouping nodes in the network into many clusters, with each cluster being based on two parameters: the number of desired clusters and the Euclidean distance, which is used to find the cluster that is closest to each node [27]. The cluster center must be the cluster head's position, and the node's residual energy is the basis for choosing the cluster heads for the k-Means clustering algorithm. The k-Means clustering technique in wireless sensor networks is predicated on an iterative optimization of the classification nodes' distance. From a collection of N nodes, the method creates K clusters. The K-Means algorithm's objective function is [28- 29]:

$$F = \sum_{r=1}^{k} \sum_{x1 \in Cr}^{n} (x_i - ch_r)^2 \quad (1)$$

The Euclidean distance is used in K-Means clustering, where *Cr* is the set of nodes that are belong to of cluster r:

$$d(x_i, CH_r) = \sqrt{(x_i - CH_r)^2} \quad (2)$$

The K-Means method therefore just looks for the global minimum of CH_r . CH_r is the cluster head when x_i is a cluster node [30–35].

3.2 Steps for k-Means Algorithm

The K-Means clustering algorithm works in five stages. First, it determines how many clusters to create in a wireless sensor network. Next, it randomly selects the cluster head for each cluster. Finally, it uses the Euclidean distance to determine which cluster is closest to each node [36]. Advantages of K-Means are convergence is guaranteed and specialized in clusters of different sizes and shapes. K means is an iterative clustering algorithm that aims to find local maxima in each iteration as shown in Figure 1. The field-deployed wireless sensors were represented by $\{x_1, x_2, x_3, \ldots, x_n\}$, whereas the cluster head, originally selected at random, was represented by $\{CH_1, CH_2, \ldots, CH_k\}$.

1) Specify the desired number of clusters *K*: Let us choose *k*=2 for these 5 data points in 2-D space.
2) Randomly assign each data point to a cluster. Set the clusters' center at random, CH_r, where r = 1,...,*k*, and $k < n$.
3) Compute cluster centroids. Using the Euclidean distance, assign each data point to the nearest cluster:

$$C_j = j: d(x_j, ch_r) \leq d(x_j, ch_l), l \neq r, j = 1..n. \quad (3)$$

4) Re-assign each point to the closest cluster centroid. Re-compute cluster centroids. The cluster middles Chi for each cluster k are updated using:

$$ch_i = \sum \left(\frac{1}{c}\right) \sum_{j=1}^{ci} x_i \quad \ldots. \quad (4)$$

Repeat steps 4 and 5 until no improvements are possible.

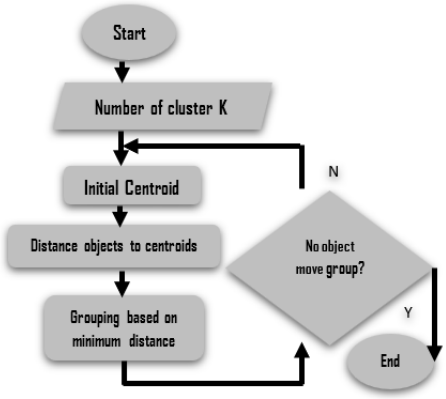

Figure 1: K-Means Algorithm Mechanism [36].

4 METHODOLOGY

The primary goal of the suggested strategy is to minimize the amount of energy used for data transfers. Although a K-Means method was developed for use in database environments, we wish to modify it so that it may function in wireless sensor environments without altering the algorithm's basic structure. When selecting the initial centroids at random, the majority of the centroid techniques now in use, like K-Means, have the following disadvantages [37-38]:

- An empty cluster.
- User desired clusters as input to the algorithm.
- The unbalanced workload on the clusters.
- Non-selection of optimal CHs count.

This approach describes how the K-Means algorithm is modified and optimized for WSNs, with a focus on balancing energy efficiency and network performance via careful cluster formation and centroid selection. a set of adjustments meant to determine the ideal number of clusters (K) in accordance with a WSN's unique requirements. The suggested model modifies K by taking important factors affecting WSN functionality into account. The ideas that follow are made to adapt the K-mean algorithm in order to get around these issues and adapt K-means for WSN.

An indicated model is used in this study to determine k based on the suggested WSN environment. K can be determined by taking into account several factors that affect WSN settings.

4.1 Sensing Coverage and Cluster Formation

Each sensor node's sensing region is shown as a circle with a radius equal to the sensing radius, or R. The following (5) can be used to get each sensor's coverage area:

$$A_s = R^2 * \pi, \tag{5}$$

where R is the sensing radius and A_s is the sensing node's area. Equation 6 is proposed as a means to assess the coverage probability.

$$P = \frac{A_s}{A}, \tag{6}$$

where (6) can be used to calculate the coverage probability (P) of a sensor node inside a specified region of interest (A).

4.2 Determining the Optimal Number of Sensor Nodes (N)

(N) is particularly important since putting additional sensor nodes would raise costs even if using fewer sensor nodes would result in poor coverage. Thefore, to ensure adequate coverage of the region while minimizing costs, the optimal number of sensor nodes (N) required to cover a specific area is found via using (7).

$$N = \frac{A}{As}\ . \tag{7}$$

Where *(N)* is the ideal number of sensor nodes, (A_s) is the sensing area of a node, and *(A)* is the total area of interest.

4.3 Determining the Optimal Number of Clusters (K)

The optimal number of clusters, denoted as K, is a critical input for the K-Means algorithm and is calculated using the following (8):

$$K = N * P, \tag{8}$$

where K is the optimal number of clusters, N is the ideal number of sensor nodes, and P is the coverage probability.

4.4 Modified K-Means Algorithm for WSNs

Once the optimal number of clusters K has been determined using the equations outlined above, the modified K-Means algorithm is applied (Fig. 2).

Input	
	Parameters Setting, Sensor nodes
	Area, R, K
Output	
	BER Calculation
Initialization	
	Compute *As* by Eq.5
	Compute *P* by Eq.6
	Compute *N* by Eq.7
	Compute *K* by Eq.8
Process	
1.	Start
2.	Centroid (Modified steps to obtain K)
3.	Distance objects to centroids (Euclidean)
4.	Grouping based on minimum distance
5.	If No object move group?
6.	Got to start
End	

Figure 2: Algorithm 1: Modified K-Means.

The steps for the modified algorithm are as follows:

- Initial Centroid Selection. Instead of random centroid selection, the algorithm chooses centroids based on coverage and distribution, ensuring that empty clusters are avoided;
- Cluster Formation. The network is partitioned into clusters based on the calculated K. Each sensor node is assigned to the nearest cluster centroid to minimize intra-cluster distances;
- Cluster Head Selection. An adaptive method is used to select cluster heads, considering energy efficiency and load balancing across the network. This prevents unbalanced workloads and ensures that energy consumption is evenly distributed among the nodes;
- Re-Clustering. Dynamic re-clustering is employed to adjust the network structure as nodes deplete their energy, ensuring sustained performance and longer network lifetime. Consequently, as seen in algorithm 1. By using the value of K determined from the proposed mathematical model, the network is divided into

optimal clusters. The modified K-Means algorithm then forms clusters that are suitable for the region of interest, balancing between too few clusters (which may lead to poor coverage) and too many clusters (which may increase energy consumption due to an excessive number of cluster heads).

5 RESULTS AND DISCUSSION

5.1 Experimental Setup

In the experimental phase, we implemented the K-Means clustering algorithm using the Matlab simulator over a region of interest (100 x 100 units). Two different approaches were used to determine the value of *K* (the number of clusters):

1) Random *K* Selection. The value of *k* was selected randomly;
2) Mathematical Model for *K* Selection. The second method involved calculating *K* based on the proposed mathematical model, which considers coverage probability, sensor node distribution, and the area of interest, as discussed in previous Section. For the simulations, 500 sensor nodes were deployed randomly across the region. We tested both the traditional K-Means algorithm and the proposed modified K-Means algorithm over 100 to 500 rounds. A coverage probability parameter *P=0.5* was used to randomly determine the number of clusters, ensuring consistent comparison across different scenarios.

While Table 2: used the updated K-Means echnique to get the energy usage measure. The ideal number of clusters was established using the suggested model throughout a range of rounds from 100 to 500. For Example: Consider a scenario with a sensing radius (R) of (15m) and an area of interest (A) measuring (100*100) m2.

Table 1: Energy Consumption using the traditional K-Means algorithm.

Number of nodes	Clustering method	Number of rounds	Total energy consumption (J)
500	K-Means	100	1.435
		200	2.871
		300	4.301
		400	5.759
		500	7.171

$A_s = R^2 * \pi$ = $(15)^2$ *3.14 = 706.5 m^2

$P = \frac{A_s}{A}$ = 706.5 / 10000 = 0.07

$N = A/A_s$ = 10000 / 706.5 = 14

$K = N * P$ = 14 * 0.07 = 1

Table 2: Modified K-Means.

Number of nodes	Clustering method	Number of rounds	Total energy consumption (J)
500	Modified K-Means	100	0.040
		200	0.018
		300	0.121
		400	0.161
		500	0.202

5.2 Energy Consumption Analysis

Energy efficiency is one of the critical factors in evaluating the performance of Wireless Sensor Networks (WSNs). We used total energy consumption as the primary metric for comparison between the traditional K-Means clustering algorithm and the proposed modified algorithm. Energy consumption was calculated based on the communication and computation energy costs during cluster formation and data transmission. Therefore, we can find the Energy saving percentage between two approaches via this formula: [41]

$$Energy\ saving\% = \frac{E_{old}-E_{new}}{E_{old}}\% = \left(1-\frac{E_{new}}{E_{old}}\right)\%,, \quad (9)$$

where (E_{old}) is represent to the total Energy Consumption for common K- mean, while (E_{new}) is refer to the total Energy Consumption for our approach, and from Table 1, Table 2 , and (9), we can obtained on the Table 3, and Figure 3.

The results show a consistent trend: the proposed algorithm reduces total energy consumption by optimizing cluster formation and selecting cluster heads more effectively. As the number of rounds increases, the energy savings become even more significant. The difference in the total energy consumption metric between the modified K-Means algorithm and the K-Means method is shown in Figure 3. Energy efficiency is one of the critical factors in evaluating the performance of WSNs. We used total energy consumption as the primary metric for comparison between the traditional K-Means clustering algorithm and the proposed modified algorithm. Energy consumption was calculated based on the communication and computation energy costs during cluster formation and data transmission. The results show a consistent trend: the proposed

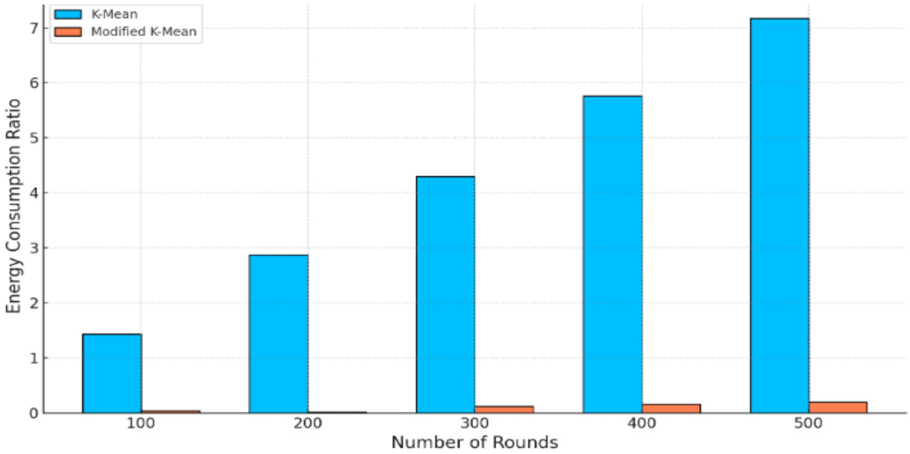

Figure 3: Energy consumption for two approaches (conventional K-Means approach and modified K-Means).

algorithm reduces total energy consumption by optimizing cluster formation and selecting cluster heads more effectively. As the number of rounds increases, the energy savings become even more significant.

Table 3: Energy saving percentage for applying the modified K-Means algorithm.

Number of nodes	Number of rounds	E_{old} for conventional K-Means (J)	E_{new} for modified K-Means (J)	Energy saving %
500	100	1.435	0.040	97.2%
	200	2.871	0.108	96.2%
	300	4.301	0.121	97.2%
	400	5.759	0.161	97.2%
	500	7.171	0.202	97.2%

5.3 Cluster Distribution and Load Balancing

Another key observation from the experiments was the impact of cluster distribution on the network's performance. In the traditional K-Means algorithm, random centroid selection often resulted in unbalanced clusters, with some clusters covering larger areas and consuming more energy. This led to uneven load distribution, where certain sensor nodes depleted their energy more quickly, causing a reduction in network lifetime. A bar chart comparing total energy consumption for the K-Means and the modified K-Means across multiple simulation. In contrast, the K-Means algorithm addressed this issue by using an optimized number of clusters and adaptive cluster head selection. By taking into account factors such as coverage probability and area of interest, the proposed algorithm formed more balanced clusters. As a result, sensor nodes shared the workload more evenly, prolonging the network's overall lifetime and enhancing performance. Based on the results reported in Tables 1, 2 as well as Table3 and the observations in Figure 3, the following conclusions are drawn:

- The improved K-Means algorithm outperforms the total energy consumption metric than conventional K-Means about at least 97%.
- Optimal cluster selection adds to longer network lifetimes, emphasizing the importance of this strategy in network sustainability.

Also, scalability was another important factor evaluated during the experiments. As the number of sensor nodes and the size of the region increased, the proposed algorithm maintained its performance advantage over the traditional K-Means algorithm. This scalability was mainly due to the ability of the modified algorithm to adjust the number of clusters dynamically, ensuring optimal performance even as network conditions changed. In terms of network longevity, the proposed algorithm outperformed the traditional approach in all test cases. By reducing energy consumption and balancing the workload among nodes, the network remained operational for longer periods, even in high-density environments or under prolonged testing. The results of the research show how well the suggested modified K-Means algorithm works to increase WSNs' durability, scalability, and energy efficiency. In order to lower communication overhead and guarantee more evenly distributed energy consumption among clusters, the cluster selection mathematical model (value of K) was essential. It is evident from comparing the suggested model with the conventional K-Means technique that random cluster formation and Centro's selection are ineffective for WSN situations, where energy conservation is crucial. The modified algorithm not only reduces energy consumption but also improves network performance through more intelligent cluster formation and adaptive cluster head selection.

6 CONCLUSIONS

In this paper, we proposed and evaluated a new mathematical model for determining the optimal number of clusters in WSNs, aiming to address one of the most pressing challenges in WSN design: energy efficiency. WSNs, being inherently energy-constrained due to their reliance on battery-powered sensor nodes, require intelligent clustering mechanisms to reduce communication overhead and extend network longevity. Our model was specifically developed to dynamically adapt to variations in network size and deployment density without requiring prior knowledge of the number of clusters. To validate the effectiveness of the proposed approach, we conducted a series of simulation experiments using MATLAB, where 100 to 500 sensor nodes were randomly distributed over a fixed 100×100 m² area. The model's performance was evaluated against traditional analytical and random clustering methods. Key evaluation metrics included energy consumption, network lifetime, and the stability of the clustering mechanism across varying node densities and operational rounds. The simulation results demonstrated that our model significantly outperforms conventional methods, achieving up to a 97% reduction in energy consumption. This substantial energy saving leads directly to a longer operational lifetime for sensor nodes and improved network resilience. Moreover, the balanced load distribution among clusters prevents premature node failures, thereby preserving network functionality for extended periods. The model also showcased excellent scalability, maintaining consistent performance across different deployment sizes and configurations. In addition to the quantitative performance gains, the proposed model contributes to the broader field of WSN research by offering a generalized, adaptable framework for cluster optimization. Unlike static clustering algorithms such as K-Means, which require pre-defined cluster counts and are not adaptive to dynamic conditions, our model integrates key network characteristics to derive the optimal number of clusters in a resource-aware manner.

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