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Designing of K-means based M-ICHB energy efficient DEEC clustering protocol for heterogeneous WSN network

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Abstract - Wireless sensor networks, clustering-based networks are crucial for lowering each sensor node's energy usage. Furthermore, it is commonly known that a longer network life-time is an important parameter in evaluating the protocol's efficiency. This guarantees that each SN's data on the network is correct. We are unable to sense an SN once it has died in a zone, making it vulnerable to event detection. As a result, a protocol is said energy efficient must have a lengthy network lifespan.Second, a heterogeneous WSN once it is operative, a protocol must be intelligent enough to manage heterogeneous nodes in the WSN network. This might be due to a number of radio communication issues, the occurrence of unpredicta-ble events, or the network field's physical features. The Multi-level MIDEEC protocol ad-dressed the many constraints of the standard protocol, namely, DEEC, by modifying the number of nodes and WSN field size, and produced significantly more efficient outcomes in terms of energy consumption and network longevity. As an extension of the Multi-level MIDEEC protocols for heterogeneous WSNs models utilising an optimised K-means algo-rithm, we present the Optimized K-means based M-ICHB DEEC (OKMB-DEEC) protocol. By varying number of nodes and WSN field size enhances protocol's energy efficiency and network durability, according to the simulation results. These offer a complete solution for creating energy-efficient protocols for applications that demand a lengthy network lifespan.

Keywords - Clustering, Optimised K-means algorithm, Network lifetime, OK-MICHB algorithm, heterogeneous network, WSN

1. INTRODUCTION

Researchers have gained more interested in deploying small sensor nodes (SNs) in a range of applications via wireless sensor networks during the last several years. Temperature, light, humidity, motion, vibration, and other phenomena all be sensed using these sensor nodes, which have low-powered, small-size batteries (Akyildiz *et al.* 2002). The core features of these SNs are data detection from the real world, local data processing, and wireless data transfer capabilities (Anastasi *et al.* 2009).

A wireless sensor network (WSN) is created when hundreds of SNs are placed in an unstructured design with the objective of monitoring a specified area. These SNs are quite well to perform out their jobs in hostile, demanding, and extremely sensitive circumstances with too little human interaction for long periods of time. WSNs are used for a variety of purposes, including armed services or battleground surveillance, target detection, traffic monitoring and control, natural catastrophe forecasting, environmental monitoring, and structure health monitoring.

A WSN's lifetime is limited since each SN has a finite amount of power. This entails the creation of energy-efficient protocols suitable for prolonging the lifetime of each SN on the network. In order to build such successful techniques in this discipline, clustering approaches are essential. Organizing these SNs into tiny sub-groups to produce network clusters has been widely done and lauded by the academic community in clustering approaches during the last two decades. Each cluster is led by a cluster head (CH), who serves as a communication and data transmission link between SNs and base stations (BS). The SNs in the network benefit from a good clustering strategy since it allows them to spend less energy. Rather than wasting energy communicating directly with the BS, SNs send one‘s sensed data to their CHs, who would then combine the data packets into significant information using mathematical computations such as accumulation, combination, and so on, and then send these packet data to the BS via multi-hop or communicate directly. This method reduces energy consumption on each SN, reduces wasteful message forwarding to the BS, and keeps the network active for longer periods of time.

Various energy-efficient methods for either homogeneous or heterogeneous networks have been developed in recent years. Homogeneous networks, on the other hand, are made up of SNs with the same energy at the beginning of the network, while heterogeneous networks comprise SNs with varying energy. A homogeneous model is a sort of WSN that starts out with the same energy resources as each SN, but as the network grows, it evolves into a heterogeneous model. Because to radio communication characteristics, the possibility of random events, or morphological network field properties, each SN cannot spend the same amount of energy resource. Notably, it demonstrates a significant issue in designing energy-efficient protocols that may perform well in both homogeneous and heterogeneous networks. We have proposed algorithms for a heterogeneous network research paper.

WSN models can be classed as either centralised or distributed, depending on the clustering approach used. A significant node, such as BS, handles the major events in centralised models, such as clustering technique, network partitioning, searching CHs, and calculating the ideal number of CHs. This technique, however, has a number of serious flaws, notably network-wide knowledge needs, nodes' energy awareness of the dominant node, the dominant node's failure potentially shutting down the entire network, scalability difficulties in large networks, and so on. Distributed WSN models have grown in prominence in network modelling as a result of their ability to address these difficulties effectively. Due to the difficulty of node energy unawareness, most protocols in the distributed model must utilise some type of estimation/randomized methodologies for choosing CHs, implying that this concept still has a lot of room for development.

Researchers have been paying a lot of attention to meta-heuristic optimization algorithms in recent years because of their ability to identify optimal solutions and resolve complex uncertainties in any discipline. These algorithms may give competent solutions in the field of WSNs, such as enhanced routing pathways, proper coverage, fault-tolerant networks, cluster creation with the optimal number of clusters, and creating energy-efficient networks. Bacterial foraging optimization algorithm (BFOA) (Passino 2002), Particle swarm optimization (PSO) (Kennedy and Eberhart 1995), artificial bee colony (ABC) (Karaboga and Basturk 2007) and ant colony optimization (ACO) (Dorigo and Di Caro 1999) to name a few, have all had a significant impact on performance with such concerns and have produced better results than existing algorithms. A variety of clustering protocols were created based on these optimization methodologies, the bulk of which employ a centralised approach. Scalability concerns affect centralised clustering techniques in particular (Zungeru et al. 2012; Afsar et al. 2014). Developing a distributed meta-heuristic-based clustering technique based on this knowledge increased confidence in offering better answers to WSNs.

The most critical issue in WSNs is network lifetime, which is controlled by network energy either directly or indirectly. By clustering sensors into clusters, the most efficient use of network energy may be obtained. A leader node, also called as cluster head, and multiple sensor nodes make up each cluster. The unification and accumulation are generally done by the cluster head. In order for the network to have a longer lifespan, it must have enough energy. The variety of sensors in the observing region can be raised to enhance network energy. Although raising the number of sensor nodes boosts network energy, the cost is substantial since installing each extra sensor costs ten times as much as the batteries. As a result, increasing the life of the network by putting some high-battery sensors is more appropriate and cost-effective.

2. Materials and Methods

First, we suggest an optimised K-means clustering method in this research, which is an optimization of the K-means clustering technique (Aziz *et.al* 2017). The Elbow approach, which illustrates the graph between sum of square distance (SSD) within the cluster and different values of K, helps to get perfect number of clusters. This K-means method also clusters data in a confined way. Second, to deal with the issue of energy unawareness in distributed WSN models, we merged the Optimized K-means based Modified CH election using BFOA (OK-MICHB) method with a distributed approach based on stability-based clustering algorithms to pick cluster heads in each cluster. Furthermore, we may utilise the OK-MICHB technique to find the best SNs (in terms of energy) in all clusters that could potentially serve as CHs, and then construct an ideal collection of CHs that effectively covers the whole network field. Third, employing optimised K-means and the OK-MICHB algorithm on the DEEC protocol. In comparison to the multi-level MIDEEC protocol, this proposed protocol has improved energy efficient clustering formation in a confined manner and CH selection in every cluster without using estimation/randomized algorithm, provides elongated network lifetime, maintains CH selection in each round, and allows a higher data packets at the BS, and is fully distributive in nature. Fourth, by altering the number of nodes and WSN field size, we compared our proposed protocol (OKMB-DEEC) to the multi-level MIDEEC protocol.

Network model for multi-level heterogeneity

Each SN in a multi-level heterogeneity model has a variable starting energy level under the close-set of [E_{ini}, $E_{ini}(1 + \tau_{max})$], where E_{ini} specifies lowest limit of the boundary and parameter τ_{max} aids in the calculation of the maximum energy value. Each SN is given a starting energy of $E_{ini}(1 + \tau_i)$ at the start of the network. It demonstrates that SN has τ_i times more energy compared to E_{ini}'s bottom boundary limit. In multi-level heterogeneity, the assignment of starting energy levels for various types of SNs is taken into account. Now, the total combine energy of all nodes initially in the network in Eq.1 (Qing *et al.* 2006) is given by,

$$E_{com} = \sum_{i=1}^{N} E_{ini}\,(1 + \tau_i) = E_{ini}(N + \sum_{i=1}^{N} \tau_i) \quad (1)$$

Proposed work

While designing a network architecture to acquire data from a target region, N number of small SNs are dispersed in a square field. Cluster construction is done using an optimised K-means algorithm at the start of the network. Once the clusters are produced, the shape of the clusters stays constant over all rounds.

The OK-MICHB method is being used to pick cluster heads from each cluster. Using the OK-MICHB method, the cluster head will change every round in that particular cluster. In order to start the network, each sensor node perceives, gathers, and sends data after CH selection. Each SN is given the authority to detect the environment (for example, humid, temperature, motion, and so on), collect data, and transfer it to the relevant CHs. CHs utilise an automated approach to merge raw data into meaningful information and convey it to the BS in a single-hop transmission after receiving data packets. The data gathered at BS will eventually be analysed or used to take appropriate action.

Optimized K-means and OK-MICHB-based protocol for heterogeneous multi-level DEEC WSN is notable. The suggested protocol's entire flowchart is shown in Fig. 1.

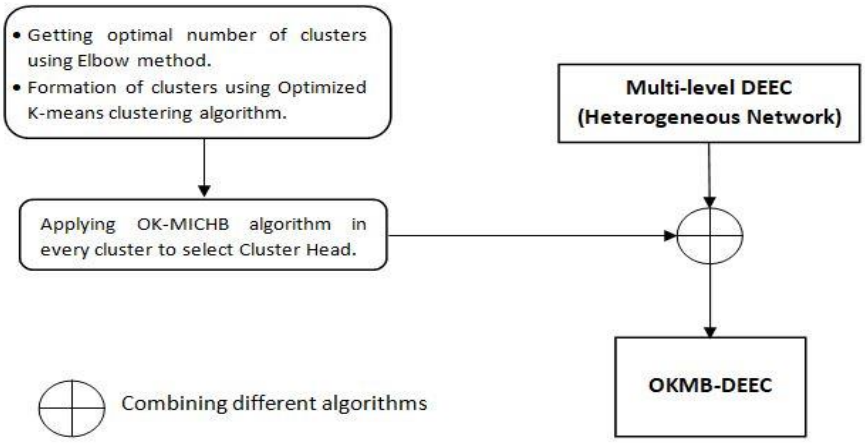


Fig.1

Proposed protocol flowchart

Optimized K-means algorithm:

The K-means algorithm for clustering the WSN network we obtain the optimal cluster value using the Elbow method (Umargono *et al.* 2019) with initial random centroid deployment in the WSN network.

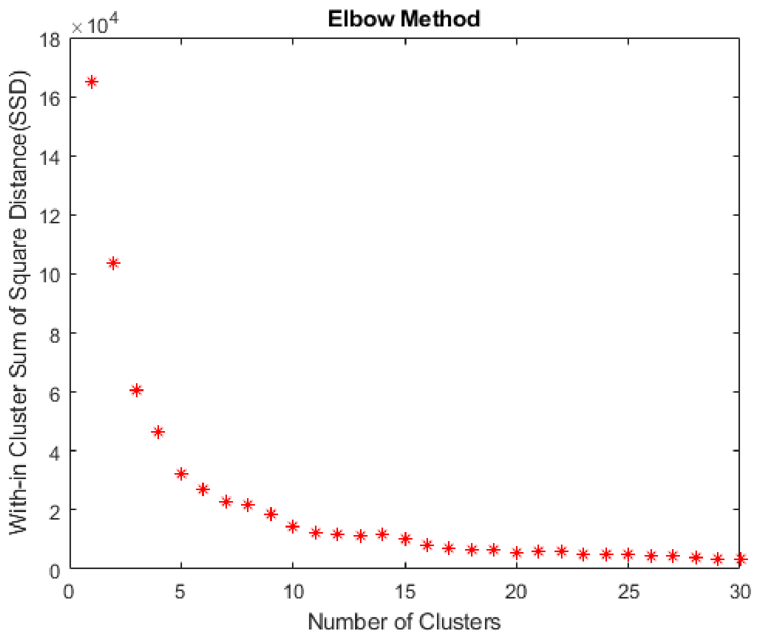


Fig.2

Elbow-method graph

We can see in Fig.2 that the change in SSD value after $K=20$ is negligible. As a result, the best cluster value (K_{opt}) is 20.

We defined initial 20 known arbitrary centroids at equal distance in the WSN network field to optimise K-means approach to compute more compact cluster in the WSN network. The use of a known arbitrary centroid will assist to avoid having two centroids so close together, as well as reducing the number of iterations.

The procedures involved in the WSN network field's optimised K-means algorithm.

- Step-1: K_{opt} = 20 must be specified.
- Step-2: Deploying 20 initial arbitrary centroid points at equal distances to cover the whole WSN network.

The blue dot in Fig.3 shows the randomly placed sensor nodes, whereas the red cross denotes the initial determined arbitrary centroids at equal distance to cover whole network.

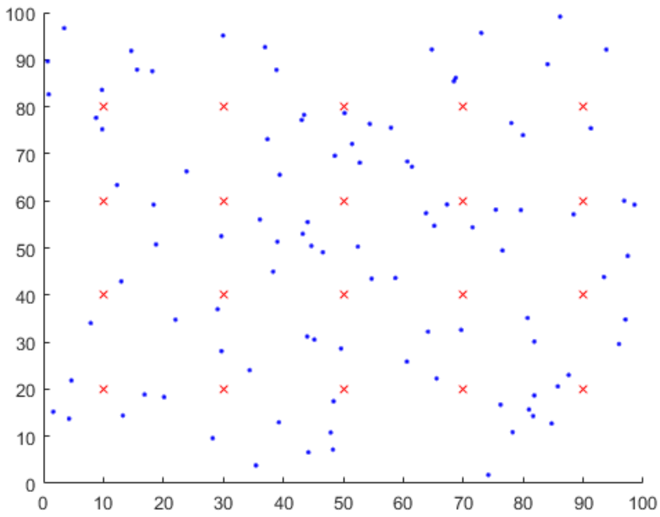


Fig.3

Initial defined arbitary centroid

- Step-3: The distance among sensor nodes with centroids is calculated by Euclidean distance.
- Step-4: Sensor nodes are grouped according to their closest centroid.
- Step-5: Using the means formula, find the new arbitrary centroid coordinate.
- Step-6: Clustering is complete when the new centroids coordinates are the same as the prior centroids.

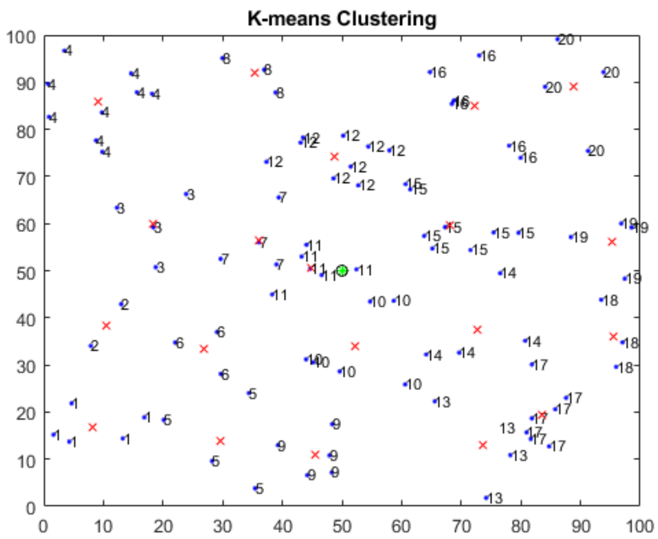


Fig.4

Optimized K-means clustering with final arbitrary centroid position

The green circle in the accompanying Fig.4 represents the position of the base station (50,50). The sensor nodes with the same number in the WSN network belong to the same cluster. In the network, there are twenty clusters, and this grouping will remain consistent over the rounds. The CH selection from the relevant cluster was detailed in the next section.

Optimized K-means based ModifiedIntelligent Cluster Head selection using BFOA (OK-MICHB) algorithm for CH selection:

We expand the capabilities of the M-ICHB method (Gupta and Sharma 2018) by using the OK-MICHB algorithm to find better CH nodes for producing improved network lifetime in WSNs. The OK-MICHB algorithm searches for SNs with greater residual energy, which act as CH nodes in that particular cluster for that round.

OK-MICHB mode of operation in particular cluster:

Our primary goal in using the OK-MICHB method is to spot the nodes with the better energy cost $E(\Psi)$ in each cluster, where SPN (SPotting Number) of each SN in the network is represented by Ψ. Chemotaxis mode of operation (Passino 2002) is required for the evolution of this algorithm, in which a single artificial bacterium in each cluster (i.e., a controlling message) shifts from one SN to other in search of a higher nutrient concentration (i.e., a better energy cost node) in that cluster.

For $(M \times M)\ m^2$ field we are using bacteria equal to optimum number of cluster value $(K_{opt}) = 20$. There is asingle bacteria for every cluster. The location of each bacterium is below (Gupta and Sharma 2017):

$$X(x) = \{\alpha^k(x) | k = 1,2,\ldots,20\} \qquad (2)$$

Where,

x = Chemotaxis step within the cluster

k = bacteria in the respective *k-th* cluster number

The energy cost of the sensor node where the *k-th* bacterium resides during the *x-th* chemotaxis step is $E(k, x)$. Throughout the chemotaxis approach, the M-ICHB algorithm only employs *swim* mode, which assists in transporting the population of fake *E. coli* bacteria on numerous SNs one after the other at a particular region. It searches for better energy cost nodes that can serve as CHs in the current round of the network.

At the start of each round, 20 SNs are used to start a population of bacteria, with each cluster containing a bacterium in a random position.

Eq.3 by Gupta and Sharma (2017) describes the location of each bacterium,

$$\Theta^k(x) = \Phi^k(SPN) \qquad (3)$$

where, $\{k = 1,2,\ldots,20\}$ inidicates *k-th* bacterium at *x-th* chemotaxis step and Φ^k symbolizes SPN of the SN where the *k-th* bacteria in the relevant cluster resides.

Random vector $R(k)$ is procreated to each k-th bacteria with the SPN of the SNs in the appropriate cluster: $\{k_i = 1,2,\ldots,n_{k_i}\}$ where, k_i is the cluster number and n_{k_i} represents total nodes in the k_i-th cluster.

Furthermore, each bacterium k in its associated random vector $R(k)$ changes from one node to the next in quest of the better energy cost $E(k,x)$. Eq.4 defines the movement of a bacterium k in a computational chemotaxis process,

$$\Theta^k(x+1) = [\Phi^k_{k_i+1}(SPN)]^{R(k)} \qquad (4)$$

where, $\Phi^k_{k_i+1}$ represents movement of *k-th* bacterium on other SNs $\{k_i + 1, \ldots, n_{k_i}\}$ in random vector $R(k)$.

Bacteria k moves from one SN to other (within the cluster) in quest of a better energy node, storing the energy cost $E(k, x)$ of the latest SN that was visited in a variable E_{last} as well as its SPN value under the *x-th* chemotactic step. When baterium finds the better energy cost node, it replaces the current value of E_{last} with $E(k, x + 1)$ and saves the SPN value. Otherwise, it the random vector $R(k)$ moves on to the next SN for more searching.

CH selection procedure:

Let $\alpha_i = 1/\kappa_i$ represent the average chance for an SN (n_{k_i}) to become CH in κ_i rounds. When every SN (n_{k_i}) has the equal energy at the start of a homogeneous network, the average probability α_i can be regarded comparable to α_{opt}. As the network becomes older, it begins to resemble a heterogeneous network, with each SN altering its residual energy. As a result, the chances of SN becoming CH should alter for each round and the higher residual node's value α_i should be greater than α_{opt}.

Using the OK-MICHB method, a bacterium is initiated in each cluster at the start of each round by any SN in the cluster. This ensures WSN's distributive character. Each bacterium's location is specified in Eq (3). After the population of bacteria has been initiated, a random vector $R(k)$ corresponding to each bacterium k is produced in each cluster. It stores the SPNs of SNs $\Phi^k(SPN)$, which are used to find the *k-th* bacteria that started in that cluster. In its random vector $R(k)$, each bacteria k shifts from one SN to other in search of a better residual energy node. Eq. 4 describes the movement process. During the moving process in a random vector, bacteria k saves the remaining energy of the last visited SN, as well as its SPN value in that cluster, in variable E_{last}. Furthermore, compares the residual energy value of the following SN in the random vector with E_{last}. If the remaining energy of a freshly visited SN is larger than E_{last}, the bacterium updates E_{last}, saves the SPN of the recently visited SN, and moves on to the next SN for more searching. Otherwise, if E_{last} is larger than the residual energy of the recently visited SN, it moves to the next SN in the random vector for even further search without making any modifications to E_{last}. OK-MICHB describes the whole operating model in detail.

The average chance of an SN becoming CH in a particular cluster during the search for a better remaining energy node in a random vector *R(k)* is given as,

$$\alpha_i = \alpha_{opt} \times \frac{Re(\theta^k(x+1))(r)}{Re(\theta^k(x)(r))} = \alpha_{opt} \times \frac{Re[\Phi^k_{k_i+1}(SPN)]^{R(k)}(r)}{Re[\Phi^k(SPN)](r)} \tag{5}$$

Where, $Re[\Phi^k_{k_i+1}(SPN)]^{R(k)}(r)$ represents the remaining energy of each SN $\Phi^k_{k_i+1}(SPN)$ in a random vector *R(k)* obeserved during searching step at *r-th* round in respective cluster. $Re[\Phi^k(SPN)](r)$ represents the remaining energy of SN $\Phi^k(SPN)$ at which *k-th* bacterium has been originated at *r-th* round. Each SN probability-based minimum value for determining whether to become a CH in a round is provided as, based on Eq.(5).

$$T(n_{k_i}) = \begin{cases} \dfrac{\alpha_i}{1-\alpha_i \times \left(r mod\left(\frac{1}{\alpha_i}\right)\right)} & if\ n_{k_i} = U \\ 0 & otherwise \end{cases} \tag{6}$$

where, U represents a set of SNs n_{k_i}(i.e sensor nodes present in the respective of k=1,2,…,20.) that has not been CH for last κ_i rounds and eligible for the same. Moreover on the basis of Eq. (5), the rotating epoch κ_i can be expressed as

$$\kappa_i = \frac{1}{\alpha_i} = \frac{Re[\Phi^k(IDN)](r)}{\alpha_{opt} \times Re[\Phi^k_{k_i+1}(IDN)]^{R(k)}(r)} = \kappa_{opt} \times \frac{Re[\Phi^k(IDN)](r)}{Re[\Phi^k_{k_i+1}(IDN)]^{R(k)}(r)} \tag{7}$$

Where κ_{opt} is the reference rotational epoch for an SN n_{k_i} to transform into a CH, which is equal to $1/\alpha_{opt}$. Specifically, the rotating epoch κ_i changes for each SN n_{k_i} due to the fact that higher remaining energy nodes have shorter rotating epochs, implying that higher remaning energy nodes are eligible to operate as CHs more frequently than lower energy nodes.

Also, nodes near the BS will calculate the distance between respective CHs and the BS and then compare the two distances; if the distance between the node and the CH is greater than the distance between the node and the BS, the node will send data to the BS directly; otherwise, the data will be sent to the CH.

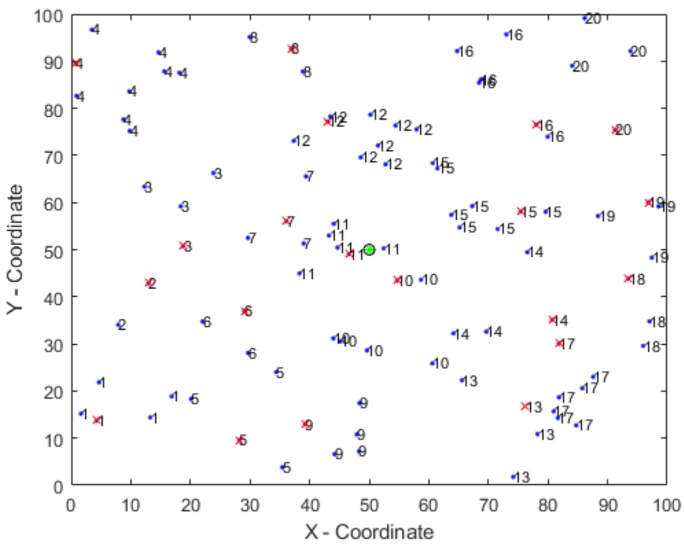


Fig. 4

Cluster Head in respective cluster

In above figure every cluster having a node with red cross depicts the CH of that cluster in a single round. Hence, CH will chosen in cluster itself while clustering remains same throughout the rounds.

The *Model* used for energy consumption in this OKMB-DEEC protocol and also the simulation parameters are same as used in MIDEEC protocol (Gupta and Sharma 2018).

Table 1

Simulation parameters

Parameters Description	**Value**
Network field size *(M×M)*	100×100m^2, 200×200m^2
Value of Nodes *(N)*	100, 200 & 500
Base Station Location	(50,50) for 100×100 & (100,100) for 200×200
Initial energy to each node *(E_{ini})*	Varying between (0.5 to 2)J& (0.5 to 3)J
Optimal distance *(l_0)*	87.7m

The Multi-level MIDEEC protocol uses optimal number of clusters (c_{opt}) (Amini *et al.* 2012; Kumar *et al.* 2014):

$$c_{opt} = 177.43 \times \sqrt{N/M^2} \qquad (15)$$

where,

N= number of nodes, M= Length of WSN field.

Case-1: For 100×100m^2 WSN field by varying number of nodes the c_{opt} value is listed below in the table.

N	c_{opt}
100	18
200	25
500	40

Case-2: For 200×200m^2 WSN field by varying number of nodes the c_{opt} value is listed below in the table.

N	c_{opt}
100	9
200	13
500	20

RESULTS AND DISSCUSSION

By altering the number of nodes and field size in MATLAB, this section compares the simulated results and performance of OKMB-DEEC to multi-level MIDEEC. The suggested protocol is well-suited for applications in which energy efficiency and maximum longevity are required to send data packets to BS over long periods of time with limited battery in sensor nodes. In wireless communication links, we employ ideal MAC layer for simplicity and neglect sig-nal collision and interference effects.

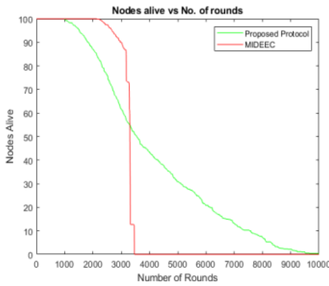


Fig.5(a)

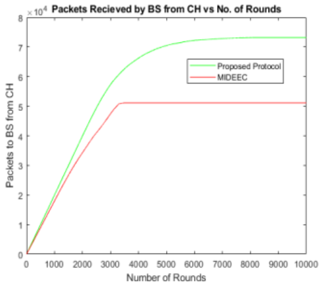


Fig.5(b)

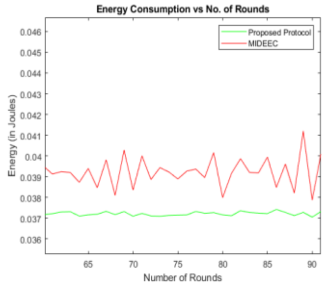


Fig.5(c)

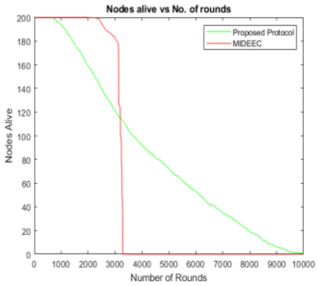


Fig.6(a)

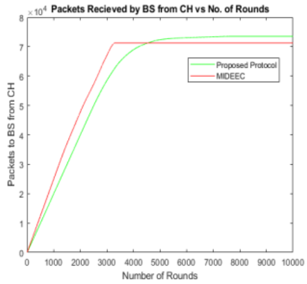


Fig.6(b)

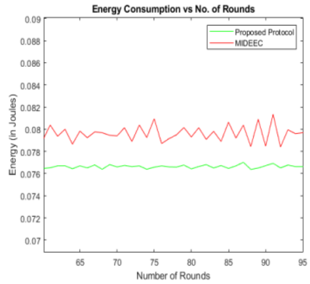
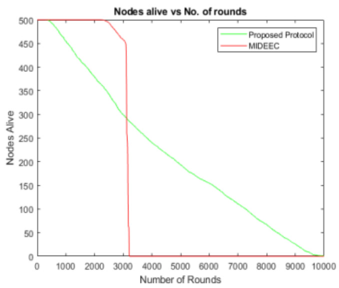
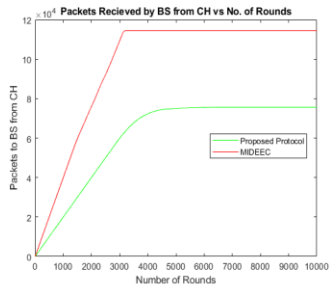


Fig.6(c)





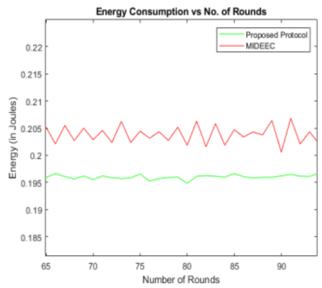


Fig.7(a) Fig.7(b) Fig.7(c)

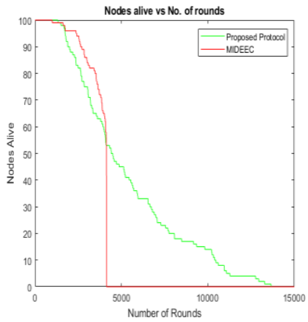
From Figure 5(a) to Figure 7(c) the each sensor node energy is varied between (0 to 2)J for 100×100 WSN field. Figure 5(a) to 5(c), 6(a) to 6(c) & 7(a) to 7(c) show the plot for N=100, 200 & 500 nodes, respectively. In the graph 5(a), 6(a) & 7(a) we obtained the alive node graph with respect to number of rounds and value of First Dead Node and Last Dead Node are listed below in the table.

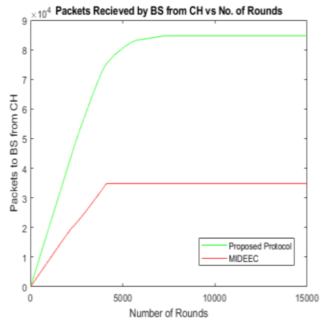
Number of nodes (N)	**First Dead Node (FDN)**		**Last Dead Node (LDN)**	
	Proposed protocol (OKMB-DEEC)	**MIDEEC protocol**	**Proposed Protocol (OKMB-DEEC)**	**MIDEEC protocol**
100	1189	2280	9422	3315
200	753	2278	9398	3218
500	403	2349	9818	3152

From the above table we can say that for N=100,200 & 500 nodes the network lifetime is improved by 184%, 192% &211% (i.e. measured with respect to last dead node of MIDEEC), respectively.

Figure 5(b) and 6(b) shows that the data packets send to BS from CH of proposed protocol are also improved but in Figure 7(b), the MIDEEC protocol is having greater number of data packets sent to BS from CH.

Figures 5(c) through 7(c) demonstrate that our suggested protocol uses less energy than the MIDEEC approach.





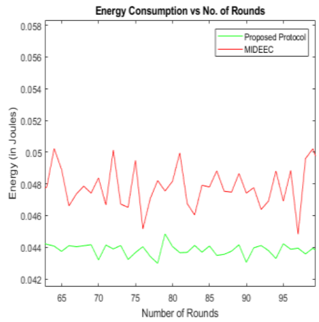
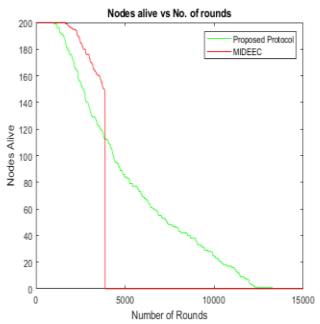
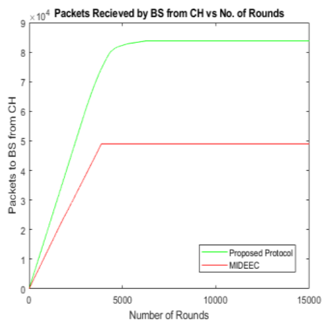


Fig.8(a) Fig.8(b) Fig.8(c)





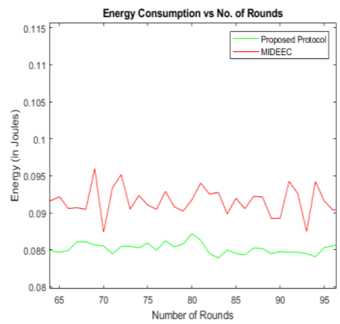


Fig.9(a) Fig.9(b) Fig.9(c)

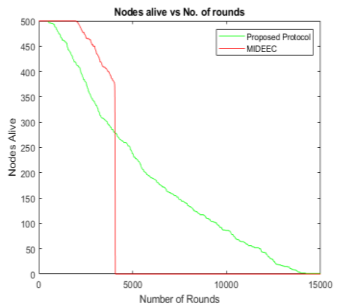


Fig.10(a)

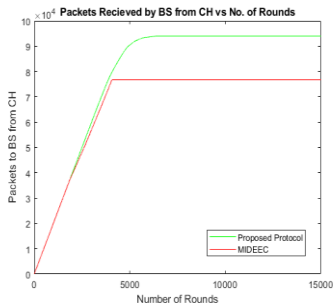


Fig.10(b)

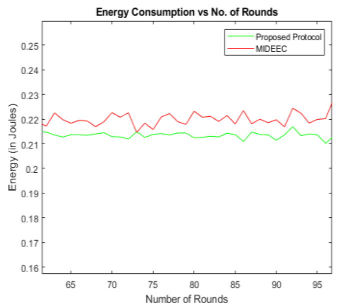


Fig.10(c)

From Figure 8(a) to Figure 10(c) the each sensor node energy is varied between (0 to 3)J for 200×200 WSN field. Figure 8(a) to 8(c), 9(a) to 9(c) & 10(a) to 10(c) show the plot for N=100, 200 & 500 nodes, respectively. In the graph 8(a), 9(a) & 10(a) we obtained the graph of alive node with respect to number of rounds and value of First Dead Node & Last Dead Node are listed below in the table.

Number of nodes(N)	**First Dead Node (FDN)**		**Last Dead Node (LDN)**	
	Proposed protocol (OKMB-DEEC)	**MIDEEC protocol**	**Proposed Protocol (OKMB-DEEC)**	**MIDEEC protocol**
100	1488	993	13651	4128
200	1162	1653	13261	3876
500	503	1989	13670	4070

From the above table we can say that for N=100, 200 & 500 the network lifetime is improved by 230%, 242% & 236% (i.e. measured with respect to last dead node of MIDEEC), respectively and also above table depicts that for N=100 the stability region is also improved.

The data packets sent to BS from CH of the protocol are enhanced, as shown in Figures 8(b), 9(b) and 10(b).

Our suggested protocol is clearly more energy efficient than the MIDEEC protocol, as shown in Figures 8(c), 9(c) and 10(c).

Comparative analysis of proposed and multi-level MIDEEC protocol under varying initial energy of nodes, number of nodes and and WSN field dimension:

Total amount of energy (J)	**Nodes (N)**	**WSN field Dimension (M*M)m^2**	**Protocol**	**LND**
125	100	100*100	Multi-level MIDEEC (Gupta and Sharma 2018)	3315
125	100	100*100	OKMB-DEEC	9422
250	200	100*100	Multi-level MIDEEC (Gupta and Sharma 2018)	3218
250	200	100*100	OKMB-DEEC	9398
630	500	100*100	Multi-level MIDEEC (Gupta and Sharma 2018)	3152
630	500	100*100	OKMB-DEEC	9818
180	100	200*200	Multi-level MIDEEC (Gupta and Sharma 2018)	4128
180	100	200*200	OKMB-DEEC	13651
345	200	200*200	Multi-level MIDEEC (Gupta and Sharma 2018)	3876
345	200	200*200	OKMB-DEEC	13261
880	500	200*200	Multi-level MIDEEC (Gupta and Sharma 2018)	4070
880	500	200*200	OKMB-DEEC	13670

CONCLUSION:

The suggested protocol's network lifespan is increased in all scenarios, and it is also significantly more energy efficient than the Multi-level MIDEEC protocol, as seen in the table above. Using an optimised K-means method, you may enhance clustering in a more constrained fashion with fewer iterations. The OK-MICHB method is used to discover the CH without the need of any estimate or randomised algorithms, resulting in a simple CH election.

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