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Efficient Localization-based Clustering Approach for Increased Residual Energy and Enhanced Network Lifetime

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Abstract: Mobile Adhoc Networks are not without challenges such as limitations with scaling, and problems with excessive power consumptions which is mostly attributed to battery consumption. The movement of nodes causes an increasing use of energy, delay, and the shortened lifetime of nodes. A solution to these problems is a resource-efficient City Block-K Means Algorithm (CB-K Means) clustering method that prioritizes resource optimization and the lifespan of the network. These are localization, selection of Cluster Head (CH) and mobile node clustering. Mobile Node (MN) localization is performed using a Crossover and Mutation-based Jaya Optimization Algorithm (CM-JOA), followed by clustering through CB-K Means, where the CHs are selected with a linear scaling-based Satin Bowerbird Optimization Algorithm (LS-SBOA). The experimental results indicate that there is an improvement by 3.48% in the PDR (Packet Delivery Ratio), 7.3 percent packet loss, reduced clustering time of 3412ms and enhanced throughput of 889 bps.

Index Terms: MANET, Energy Efficient Routing, Network Lifetime, Resource Optimization, Energy Consumption.

1. Introduction

MANETs are emerging technologies [1, 2] used in areas with MNs without pre-existing communication or else network infrastructure, such as military battlefield networks, collaborative robotic mobile networks, along with vehicular networks [2]. These independent MN [3] work together to improve connectivity devoid of requiring a fixed base station [4] infrastructure. MANETs offer a dynamic topology, making Routing Protocols (RP) more challenging than wired networks [5]. With self-assertive portable nodes that can extend along with safeguard the complete network framework automatically, they offer secure communication, [6, 7, 9].

In MANET networks, RPs [10] must adapt to changing network requirements due to their highly mobile and dynamic nature. They guide packets through complex transmission processes, and are essential for ubiquitous devices' future [11, 12]. There are proactive, reactive, and hybrid RPs available [13], focusing on energy consumption and NL [14, 15]. Due to interference and mobility-related issues, wireless networks have higher complexity [16].

MANETs, which require energy conservation to prevent early dissolution and path breakup, are operating on batteries [17, 18]. This paper presents an efficient clustering algorithm for improved energy-efficient NL in MANETs. The algorithm considers clustering and routing as major problems in MANET design [19, 20], ensuring efficient communication and routing. The paper presents existing works, proposes an energy-efficient CB-K means clustering technique, discusses simulation results and concludes.

2. Literature Survey

[21] The study presents a resource-optimized geographic routing method for improved NL in MANET using a particle swarm. The Particle Size Optimization technique optimizes resource utilization and PDR, with the fitness function determining particle positions. The obtained result shows an improved energy consumption and PDR compared to existing methods.

[22] The study developed an energy-efficient multipath routing method using the Opposition Genetic-centric Fish Swarm Optimization (OGFSO) algorithm. Data routing costs were minimized by the K-medoid clustering algorithm in dense networks. The method improved energy efficiency and NL, but required large memory storage.

[23] The study presents an efficient artificial fish swarm-centric clustering system for MANETs, optimizing nodes into clusters with a specific CH. The low energy adaptive clustering hierarchy protocol enhances NL, but consumes the most time in selecting the optimal CH.

[24] The Dynamic Energy Ad-Hoc On-Demand Distance Vector (DE-AODV) RP was developed for MANET, focusing on energy-efficient along with trustworthy nodes for the shortest route path. Regarding PDR, network stability, and throughput, the system outperformed previous protocols, but became complicated with network size increase.

[25] The LEA-CMAC protocol, a Cooperative Medium access control (CMAC) protocol, was developed for MANETs to improve performance via cooperative transmission and multi-objective target orientation. Experimental results showed improved performance, but slow packet delivery through multiple paths.

[26] The study presents an energy-efficient multipath ant colony-centric routing algorithm for MANETs, utilizing meta-heuristic impact factors to provide robust paths and overcome resource constraints. The algorithm improved NL but could not read two layers of information.

[27] The study presents an energy-efficient route assigning method in MANET by employing a related node discovery algorithm. By selecting the steadiest node for a specific route, this method optimizes resource utilization, reducing energy consumption and improving NL.

3. Proposed Model

Here, this paper introduces an energy-efficient CB-K-Means clustering technique in MANET to augment NL. The method involves random initialization of MNs, using CM-JOA localization, optimal CH selection by employing LS-SBOA, and clustering using CB-K-Means. The proposed model is depicted in Fig. 1.

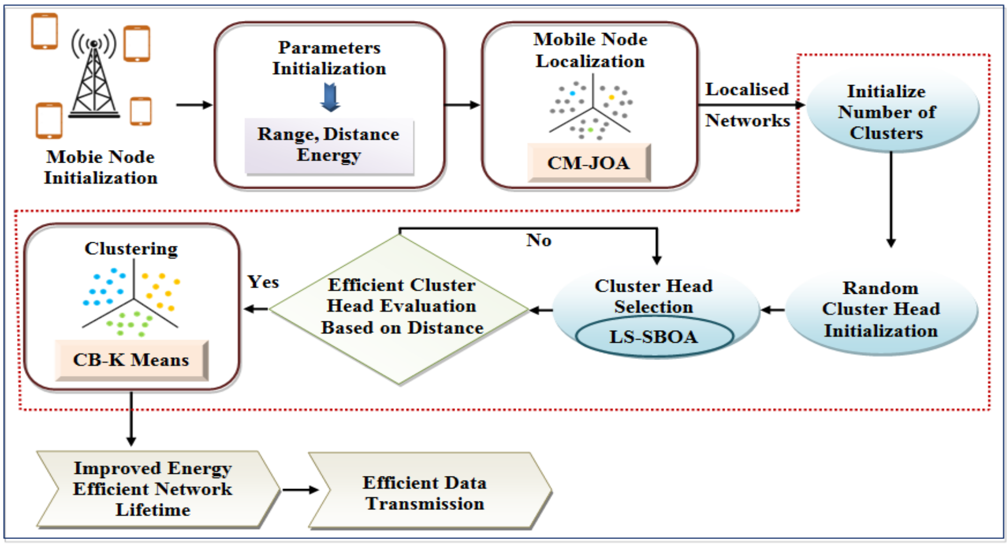


Fig.1. Proposed model

3.1. Mobile Node Initialization

MN initialization is a process of gathering the MNs and enforcing them as input. Primarily, all the MNs are randomly initialized as below,

$$M = \{m_1, m_2, m_3, \ldots, m_n\} \tag{1}$$

Here, M is for number of MNs, m_1 is the first MN, and m_n denotes the nth number of one MN. Next, necessary parameters are considered to the initialized MN.

3.2. Parameters Initialization

Parameter initialization is an essential step that can help in defining or classifying a particular system. After the MN initialization, the necessary parameters assigned to the MNs are Range, Distance, and Energy.

Range: As the device can join and communicate with all devices in range, the range of transmission of the device is an important parameter. For example, if there are 2 nodes A and B, then node A is in the transmission range of node B if A receives data from B. Similarly, B is in the range of A if B receives A's data. This shows that both nodes are in the transmission range of each other which is explained as,

$$\frac{P_A}{P_B} = \frac{Q_A Q_B}{d^2 \lambda^2} \tag{2}$$

Here, P_A signifies the power fed into the transmitting node A, P_B denotes the power fed into the receiving node B, Q_A is A's area, Q_B is B's area, d is distance between the nodes as well as λ implies the wavelength.

Distance: To obtain the estimated position of the unknown nodes, the distance parameter is initialized in MNs. By implementing proposed optimization algorithm, position of initialized MNs can be obtained.

Energy: The main aim of the energy parameter is to get the total energy consumed by the MNs while performing data-based operations. The total energy consumption by each node for transmission and reception of the data can be assessed with a function of node number in the network.

3.3. Mobile Node Localization

After parameter initializing, mobile node localization is processed. The process of determining the coordinates of MNs and relocating the MNs based on network coverage range is termed Localization. For estimating the coordinates and the distance of the target node, the proposed methodology uses crossover and mutation-based Jaya Optimization Algorithm (CM-JOA). Jaya Optimization Algorithm (JOA) is the best solution. It requires just common control parameters but not any algorithm-specific control parameters. JOA does not have the process to tune its parameters. So, in some critical scenarios, it cannot update the positions of the population based on fitness. So, the localization process is done by using CM-JOA. The Crossover and Mutation step is a hybrid of the existing JOA to improve the updating process.

Step 1: The proposed algorithm begins with the initialization of the population size $M = \{m_1, m_2, \ldots, m_n\}$, assigning the designed variables $(v = 1, 2, 3, \ldots, b)$ and the number of iterations $(i = 1, 2, 3, \ldots, c)$. The algorithm terminates based on maximum number of iterations. The objective function for the distance betwixt the target (X_t) along with the nodes (X) is defined as,

$$F(Z) = \sum_{t=1}^{n} (X_t^2 + X^2 - 2X_t X) \tag{3}$$

Here, $F(Z)$ signifies the object function and n signifies the number of nodes.

Step 2: A random population is generated according to the size of the population and designed variable numbers. The population size is the number of candidate solutions.

Step 3: The candidates with the best and the worst values of $F(Z)$ are identified based on the randomly generated population. In the proposed algorithm, Range is considered as a fitness value and it must be higher to obtain an optimal solution. The candidate with higher value of $F(Z)$ is the best and the candidate with lower value of $F(Z)$ is taken as the worst. It is equated as,

$$Z_{v,i,best} = \{Z_{v,i,best} \mid (F(Z) \in Z_{v,i})_{max}\} \tag{4}$$

$$Z_{v,i,worst} = \{Z_{v,i,worst} \mid (F(Z) \in Z_{v,i})_{min}\} \tag{5}$$

Where, $Z_{v,i,best}$ is taken as best solution and $Z_{v,i,worst}$ is taken as worst solution.

Step 4: For these best as well as worst solutions evaluated step (v), the proposed crossover and mutation technique is applied. It is illustrated below in Fig. 2.

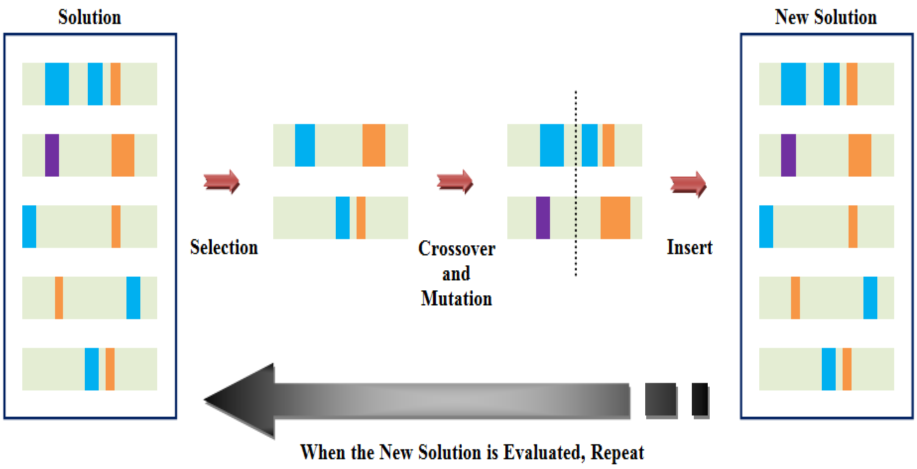


Fig.2. Crossover plus mutation process

After the application of the crossover and mutation process, the updated solution can be expressed as,

$$Z'_{v,M,i} = Z_{v,M,i-1} + f_{1,v,i}\left(Z_{v,best,i} - \left|Z_{v,M,i-1}\right|\right) - f_{2,v,i}\left(Z_{v,worst,i} - \left|Z_{v,M,i-1}\right|\right) \tag{6}$$

Where, $Z_{v,M,i-1}$ signifies v^{th} design variable value for M^{th} candidate during $i-1^{th}$ repetition, The terms $f_{1,v,i}(Z_{v,best,i} - |Z_{v,M,i-1}|)$ and $-f_{2,v,i}(Z_{v,worst,i} - |Z_{v,M,i-1}|)$ are respectively made use for the algorithm's movement to either search the best solution or to avoid the worst solution.

Step 5: The previous solution can be replaced if the iteration value is over-ruled by the modified value. Otherwise, the same previous solution will be kept. i.e.,

$$Z'_{v,M,i+1} = \begin{cases} Z'_{v,M,i}, & if\ F(Z)'_{v,M,i} > F(Z)_{v,M,i-1} \\ Z'_{v,M,i-1}, & otherwise \end{cases} \tag{7}$$

Step 6: The updated solution of $F(Z)$ helps to select the best as well as the worst candidates and then they are taken as inputs for the $(i+1^{th})$ loop.

Repeat Steps 4 to 6 until the termination condition is met to get the optimal solution.

The worst solutions are replaced by the best solutions based on the objective function in the Optimization Algorithm. Similarly, based on the optimal range, the initialized MNs are localized using CM-JOA. The localized network is represented as,

$$M_{loc} = \{m_{loc1}, m_{loc2}, m_{loc3}, \ldots, m_{locn},\} \tag{8}$$

Where, M_{loc} implies number of localized MNs and m_{locn} signifies the localized nth number of a MN.

3.4. Clustering

The City Block–K-Means Algorithm is applied for clustering rearranged MNs to in order to enhance residual energy and NL. Yet, due to varying sizes and densities of clusters, the existing algorithm struggles with data clustering. Thus, by using the City Block – K-Means Algorithm (CB-KM), Clustering is carried out [18]. Primarily, the clusters' set $\{L_1, L_2, L_3, \ldots\}$ is defined and CHs are initialized randomly. No precise answer offered by random CH initialization.

Therefore, the Linear Scaling based Satin Bowerbird Optimization Algorithm (LS-SBOA) selects the optimal CH for each cluster depending on the highest residual energy [8], the biggest number of neighbor nodes, along with the least distance as of the base station [9].

The clustering process's '2' stages are CH selection along with cluster formation.

A. Cluster Head Selection

The Satin Bowerbird Optimization (SBO) is a population-based algorithm that estimates the global optimum for an optimization problem. In the SBOA, during their mating season, an adult male begins to build bowers on their land with different materials. Females are attracted to a bower after visiting several bowers, due to the fascinating nature of the bower and the gestures set out by the male. SBOA has related problems with low optimization accuracy and reduced convergence speed. In order to overcome such an issue, the linear scaling technique is introduced in the mutation process of SBOA. The stages of the proposed algorithm are designed based on the life of a satin bower bird, and are discussed below:

Generation of Random Initial Population

The proposed algorithm starts with the random initial population through the consideration of both the lower and upper limit parameters. The positions for bower are depicted as the initial population (i.e., the number of MNs initialized). Every position is described as a node (vertex) by a dimensional vector, which needs optimization.

Probability Determination

Each bower's attraction is computed as a probability. To select a bower, the value of the probability of fitness is used. The values of probability and fitness of each population can be calculated using the mathematical expressions,

$$X_e = \frac{\psi_e}{\sum_{n=1}^{B} \psi_n} \tag{9}$$

$$\psi_e = \begin{cases} \dfrac{1}{1+g(\nabla_e)}, & g(\nabla_e) \geq 0 \\ 1+|g(\nabla_e)|, & g(\nabla_e) < 0 \end{cases} \tag{10}$$

Here, X_e implies the probability of the e^{th} solution, ψ_e signifies the value of fitness for the e^{th} solution, B signifies the bowers number, and $g(\nabla_e)$ signifies the cost function value of the e^{th} position. Now, compute the cost function and is a function to be optimized. The Fitness value needs to be always positive.

Elitism

It allows for preserving the best solution at every stage of the optimization process. The bowers resulting from the experienced male building have higher fitness value than the ones built by non-experienced. Here, the position of the best bower built by birds is considered as the elite for each loop of the algorithm. Since the elite bower possesses the maximum fitness, they must be allowed to control other bowers' positions. The bower's new position can be computed using the expression given below if there are any changes in the bower position.

$$\phi_{eh}^{new} = \phi_{eh}^{old} + \hbar_h \left[\left(\frac{\phi_{uh} + \phi_{elite,h}}{2} \right) - \phi_{eh}^{old} \right] \tag{11}$$

Here, φ_{eh}^{new} implies the new e^{th} bower solution for the vector's h^{th} member, φ_{eh}^{old} is the old solution, φ_u determines the target solution among all the solutions in the current iteration, φ_u is the target value evaluated by employing the roulette wheel process, entails that a solution with a higher probability will have a greater chance of being chosen, φ_{elite} indicates the elite position stored in the current iteration and $\hbar_h$ describes the attractiveness in the target bower. The attraction power $\hbar_h$ is obtained using the mathematical equation,

$$\hbar_h = \frac{w}{1+X_u} \tag{12}$$

Here, w implies the maximum step size, X_u signifies the probability obtained from equation 7, having the target bower at intervals66 of 0 to 1. If the X_u of the target bower is 0, the maximum step size occurs, where the increment is by w and the minimum step size occurs if the target bower probability is 1, where the increment is $\frac{w}{2}$.

Mutation

To eliminate the weak bower, the algorithm uses a mutation process. Now, random changes are applied to φ_{eh} with a certain probability. A normal distribution (d) is used with mean of φ_{eh}^{old} and variance of ϑ^2 as mentioned below,

$$\phi_{eh}^{new} \sim d(\phi_{eh}^{old}, \vartheta^2) \tag{13}$$

$$d(\phi_{eh}^{old}, \vartheta^2) = \phi_{eh}^{old} + \vartheta * d(0,1) \tag{14}$$

The value of ϑ, spatial width can be calculated by applying the linear scaling formula,

$$\vartheta = k * \left(\frac{c \;\; - c_{\min}}{c_{\max} - c_{\min}} \right) \tag{15}$$

Here, c_{max} and c_{min} are upper as well as lower bounds applied to the variables. The value of k is the difference betwixt the upper along with the lower bounds. At the end of each cycle, the initial population and the population obtained from changes are evaluated.

These '2' populations are mixed along with ordered regarding the cut-cost values derived as of the cost function. The new population is created and the others are deleted according to the previously defined number.

In Fig. 3., the LS-SBOA algorithm's pseudo code is shown.

```
Input : Initialized cluster heads φ_n
Output : Optimal cluster heads φ_opt(n)
Begin
      Initialize cluster head φ_n, step size w, maximun number of iteration e
      Assign bower position randomly
      Calculate the fitness value ψ_e
      Obtain elite value by finding best bower
      While (e < e_max)
      Compute the probability of the bower using equations 9 and 10
       For e = 1 to all bower
          For u = 1 to all element of bower
                Roulette wheel selection is used to pick a bower
                Calculate ħ_h using equation 12
                Update the position of bower using equation 11
          End for
       End for
       Evaluate the fitness value of the bowers
       Update elite value if it is better than the previous value
       End while
       Return optimal cluster heads φ_opt(n)
End
```

Fig.3. Pseudo-code of the LS-SBOA algorithm

The female bird visits several bowers before choosing the mating partner and the best bower according to the algorithm. Likewise, the optimal CH is chosen. The selected CH is evaluated based on (i) highest residual energy, (ii) maximum number of neighbor nodes, along with (iii) smallest distance from the base station. The selected optimal CHs are,

$$\phi_{opt} = \{\phi_{opt1}, \phi_{opt2}, \ldots, \phi_{optn}\} \tag{16}$$

Here, φ_{opt} implies the total number of selected optimal CHs.

B. Cluster Formation

It is a methodology in which the MNs are grouped together according to the distance, sources, etc. The MNs are distributed to a cluster using the CB-K-Means clustering algorithm.

The nodes closer to one another are assigned to the selected efficient CH centered on the distance betwixt the MNs and the cluster center for the number of clusters (L) initialized in the above step. The city block distance is shown as,

$$\delta = \left| \sum_{n=1}^{N} \left(M_{locn} - \phi_{opt\ n} \right) \right| \tag{17}$$

The input devices are categorized into several clusters by considering the minimum distance between the CH and the nodes. The above procedure is repeated until all the MNs are clustered. Next, the final clusters are formed as,

$$L_c = \{L_{c_1}, L_{c_2}, L_{c_3}, \ldots, L_{c_N}\} \tag{18}$$

Here, L_c implies the final cluster set, L_{c_n} signifies the n^{th} number of clusters.

As a result of clustering, the NL of the MANET has been enhanced and the energy efficiency of the networks is improved with efficient data transmission.

4. Results and Discussion

Here, the suggested model's performance is assessed. The suggested energy-efficient MANET is built in the Python workspace. It involves three stages in performance comparison between the suggested model and the current approaches.

4.1. Database Description

The dataset utilized in the suggested framework came from the CRAWDAD dataset, an outdoor MANET dataset of experiments used for comparing various RPs, including System and Traffic-dependent Adaptive Routing Algorithms (STARA), On-Demand Multicast RP (ODMRP), along with Ad-hoc On-Demand distance Vector (AODV). Time, Source, Destination, Protocol Length, and Info are all included in the dataset, which is in the '.pcap' file type.

4.2. Performance Analysis

This section compares the performance of the proposed CB-K-Means algorithm with that of the K-Means, Fuzzy-C-Means (FCM), Clustering Large Applications (CLARA), also with Partition Around Medoid (PAM) methods currently in use. The comparison is based on the following metrics: Packet Loss Ratio (PLR), Packet Delivery Ratio (PDR), throughput, Network Lifetime (NL), energy consumption, clustering time, and time delay. Next, the suggested LS-SBOA's performance is contrasted with that of the current Satin Bowerbird Optimization Algorithm (SBOA), with the Harries Hawks Optimization Algorithm (HHOA), Chimp Optimization Algorithm (CHOA), and Whale Optimization Algorithm (WOA) regarding fitness and Cluster Head selection time. At last, the suggested CM-JOA's performance is compared to the current mobile versions of the JOA, Crow Search Algorithm (CSA), Monarch Butterfly Optimization Algorithm (MBOA), along with Rock Hyraxes Swarm Optimization Algorithm (RHSOA).

Table 1. Performance of proposed CB-K Means algorithm with the existing methods

Metrics	No. of nodes	FCM	CLARA	PAM	K-Means	Proposed CB-K Means
Packet loss ratio (%)	100	25.3568	22.6635	17.7455	14.7849	8.3548
	200	27.4875	21.6634	18.6478	12.6258	7.4875
	300	28.3256	22.4859	16.4478	13.4875	8.5689
	400	26.4975	23.3568	16.3255	14.8566	6.6147
	500	27.4485	21.7485	17.4578	13.5668	7.3247
Packet delivery ratio (%)	100	81.2338	84.7837	88.3274	91.3375	97.5256
	200	82.1484	85.6249	89.2498	92.4536	95.4428
	300	80.3294	83.5488	87.4584	91.7529	96.3238
	400	81.4577	84.7519	89.6549	92.5144	95.8749
	500	80.3231	83.6534	88.6538	92.7572	96.2384
Throughput	100	1322	1633	2474	2874	3457
	200	1895	2478	2748	3477	4472
	300	2471	2865	3485	3846	4987
	400	2865	3425	3874	4365	5476
	500	3488	3765	4475	4978	5867

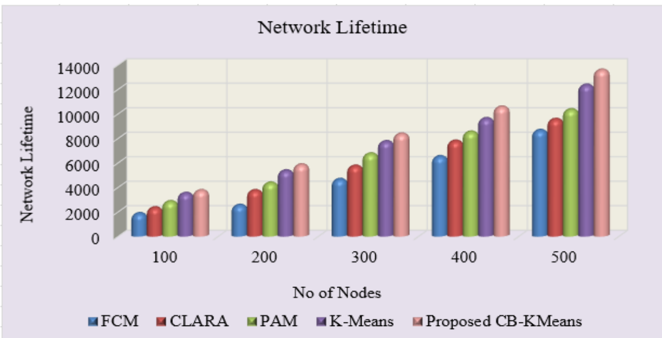
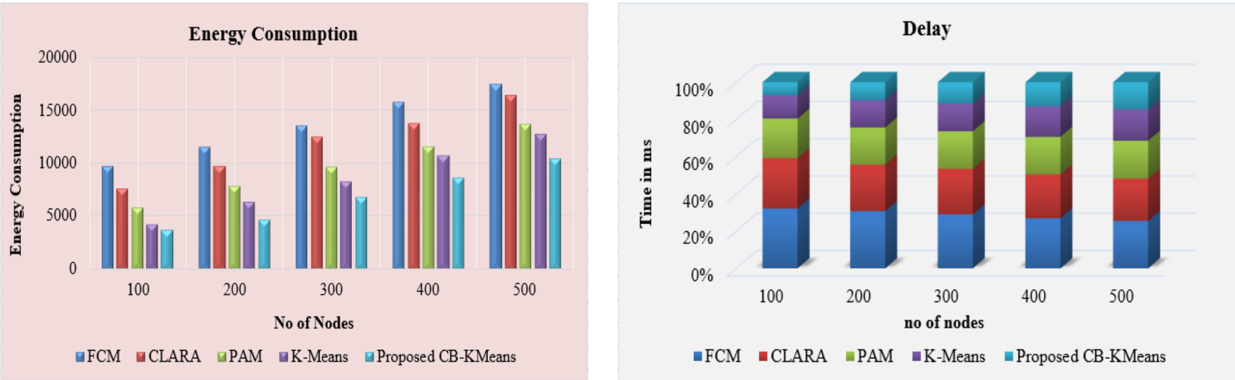


Fig.4. Network lifetime analysis of the proposed technique

Discussion: In Table 1, the comparison between the suggested CB-K Means algorithm and the current approaches is displayed. The ratio of lost packets to total the packets sent is termed the PLR. The suggested approach is less efficient with a loss percentage of 7.3% than the current methods regarding loss ratio percentage. The reduced PLR indicates that the strategy is working better. The ratio of the packets received at the destination to packets transmitted from the source is termed the PDR. There is a 3.48% increase in the PDR when comparing the proposed CB-K Means methods to the current K-Means method.

The throughput value of the suggested method shows a progressive rise of 889bps when weighed against the current approaches.

Discussion: An effective approach should have a longer NL. The number of nodes, which ranged from 100 to 500, was used to study the NL. For the case of 500 nodes, the proposed CB-K Means has a lifetime of 13583. However, for the same number of nodes, the NLs of the current approaches are 8659 (FCM), 9564 (CLARA), 10348 (PAM), and 12358 (K-Means). Likewise, the suggested solution has a longer NL for every number of nodes.



(a) (b)

Fig.5. Analysis of the proposed CB-K Means method and the existing methods based on (a) energy consumption and (b) time delay

Discussion: The energy consumption and response time delay are compared to the FCM, CLARA, PAM, and K-Means methods in order to demonstrate the efficacy of the suggested strategy. These figures should be minimal. These were examined by taking into account a range of 100 to 500 nodes. The suggested solution uses less energy of 10354J for 500 nodes than the current approaches. The time delays of the suggested method (2471 ms) are also less (4321 ms-FCM, 3847 ms-CLARA, 3458 ms-PAM, and 2845 ms-K-Means).

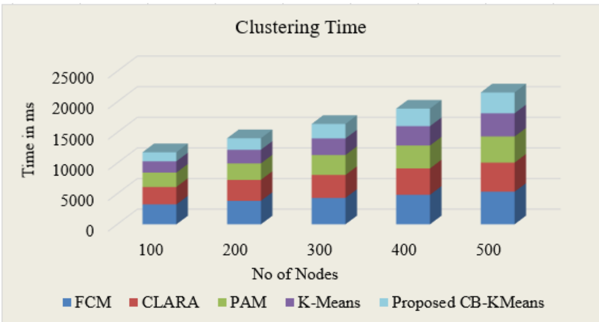


Fig.6. Graphical representation of clustering time analysis

Discussion: In Fig. 6, the graphical representation of the clustering time of the proposed along with the existing methods is shown. The proposed method takes a clustering time of 3412ms as compared to 3784ms (K-means), 5322ms (FCM), 4756ms (CLARA), and 4265ms (PAM) for clustering. As per the above analysis, the proposed method takes lesser time, for clustering, when analogized to the prevailing methods.

Table 2. Represents the CH selection time in milliseconds of the proposed LS-SBO and existing methods

Iteration	HHO	CHOA	WOA	SBO	Proposed LS-SBO
10	5432	4623	3625	2635	1634
20	11247	9254	7412	5231	3244
30	16647	13457	10256	7745	4875
40	22541	18345	14325	10452	6422
50	27452	22356	17458	13254	8045

Discussion: The CH selection time of the proposed and existing methods are presented in Table 2. The iterations ranges from 10 to 50. The proposed LS-SBO method takes the least time of 8045ms and shows a time difference of 5209ms in comparison to the existing SBO method for 50 iterations. Similar ways, the proposed method shows a time difference of 19407ms, 14311ms, and 9413ms compared to the existing HHO, CHOA, and WOA methods.

Table 3. Fitness vs Iteration for cluster head selection

Iteration	HHO	CHOA	WOA	SBO	Proposed LS-SBO
10	34	55	77	96	116
20	52	77	94	114	134
30	77	94	116	132	158
40	94	114	137	151	175
50	117	138	152	173	196

Discussion: The fitness vs iteration analysis is shown in Table 3. For the varying number of iterations, the proposed method, LS-SBOA, exhibits an improvement in the fitness value by 20 for 10 iterations, 20 for 20 iterations, 26 for 30 iterations, 24 for 40 iterations, and 23 for 50 iterations when compared to the existing SBO method. The existing ones, for the same number of iterations, have fitness values smaller than the proposed method.

Table 4. Fitness vs Iteration for mobile node localization

Iteration	CSA	MBO	RHS	JOA	Proposed CM-JOA
10	33	58	77	96	116
20	58	77	95	115	134
30	74	96	117	137	158
40	97	118	135	158	176
50	116	135	158	173	193

Discussion: The fitness vs iteration analysis of the existing approaches and the suggested CM-JOA method are depicted in Table 4. A range of 10 to 50 iterations is taken into account while evaluating the fitness value for MN localization. The CM-JOA approach outperforms the JOA, CSA, MBO, and RHS methods in terms of fitness value for all iterations. Table 4 shows that the suggested approach performed better when analogized to the current ones.

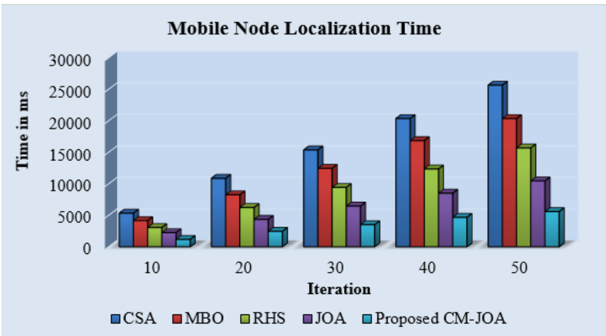


Fig.7. Illustrates the mobile node localization time

Discussion: Localization time is the amount of time required for MNs to determine their current location. Analysis of localization time of MNs was done using a range of iterations, from 10 to 50. The previous approaches require 25648ms for CSA, 20347ms for MBO, 15684ms for RHS, and 10457ms for JOA, while the suggested method achieves for the MNs the localization time of 5584ms for 50 iterations. Compared to the current methods, the proposed method requires less time.

5. Conclusions

This research suggests an effective clustering technique called localization-based CB-K-Means clustering in order to improve MANET's energy efficiency. Creating an effective model that will shorten response times and rates of energy consumption, also to extend NL, and boost nodes' residual energy – these are the important results of this work. This paper compares evaluation of performance of existing methods and the proposed CB-K Means, CM-JOA, and LS-SBO. As per the experimental findings, the proposed CB-K Means has a response time of 2471 ms, which is faster than that of the current techniques. Also, a reduced clustering time of 3412ms for the proposed method. The MN's localization time in the proposed method is 5584 milliseconds. Also, the suggested algorithm surpassed the current techniques across the board in every metric.

Declarations

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