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Original Article

Investigating QoS in Mobile Ad Hoc Networks through Scikit-Learn K-Means Clustering: A Performance-Oriented Approach

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***Abstract* -.** *Mobile Ad-Hoc Networks are incapable of energizing themselves due to their limited energy. The effort is to develop an energy-adequate power management plan for the MANET. Cluster heads may malfunction or operate incorrectly as a result of power problems while based on different cluster routing methods. Consequently, during information collecting and interaction, the cluster heads encounter instability. Finding the unstable cluster heads and swapping out for another node to use the re-configurable clustering technique is the primary goal of this study. In order to correctly define the cluster heads, the proposed a Scikit-Learn's K-Means clustering method. The anomalous or superfluous modifications in cluster heads and the shift in the cluster nodes in the count are detected by the suggested in Scikit-Learn's K-Means technique. The proposed work represents Scikit learning k-means clustering in MANET and calculates QoS parameters such as Energy, Throughput, Delay and Packet delivery ratio. By leveraging Scikit-Learn's K-Means Clustering (SLKMC), a novel approach in MANET can achieve an optimized trade-off between energy, delay, PDR, and Throughput, making it a practical and efficient choice for QoS enhancement as Energy efficiency is expected to be up to 10-30% energy savings by reducing redundant communication. The delay is reduced with anticipation of a 15-25% decrease in average delay with efficient cluster-based routing. Packet Delivery Ration might improve by 5-20%, ensuring more reliable data delivery. Throughput is improved coordination and reduced collisions can enhance Throughput by 10-25%. Thus, the expected benefits quantify the impact of these enhancements in terms of QoS metrics and improve Network Performance.*

***Keywords* -** *Scikit Learn K-Means Clustering algorithms, Expectation maximization, K-means caveats*

1. Introduction

A MANET is a network in which nodes use multi-hop routes and peer-to-peer packet transfer [1, 2]. It does not require a fixed station or any kind of wireless backbone infrastructure to function. Therefore, MANETs have a lot of potential for use in these situations, such as sensor dust, emergency response, disaster assistance, warfare communications, and survival search. However, creating routing protocols for MANETs is a difficult procedure because of their mobility and frequent topology changes, particularly in large-scale networks. The clustering approach used sensors with comparable strengths and capabilities to create clusters. Furthermore, one of the highest-quality nodes is chosen as the CH, while the others function as members. The chosen cluster head was in charge of storing all the data that needed to be sent. The appropriate recipients receive the transmitted messages. Wireless nodes are necessary for energy optimization in MANETs. AODV routing protocol uses an individual path between the source and the destination. Although several paths have various cost indicators, it usually chooses the one with the lowest cost. Since using a single way to transmit data to its destination is insufficient, multipath routing was developed to get around this restriction. The multipath approach transfers data packets by choosing the optimal path among a number of possible routes. A fundamental unsupervised machine learning method, K-Means clustering is well-known for its ease of use and effectiveness in classifying datasets into discrete groups according to similarity. The K-Means technique and its application using the Scikit-Learn library have been studied in this study, emphasizing its methodical approach to finding significant patterns in data. The best alternative path is chosen for data transfer if the original path becomes complicated, has errors, or is busy during the transfer.

In summary, Scikit-Learn-supported K-Means clustering is still an essential tool for data scientists, providing strong pattern identification skills for various applications. To fully utilize machine learning's potential in addressing real-world problems, future research should concentrate on improving clustering algorithms. Due to the more changeover in the physical area, a mobile node in a MANET can be joined and exit the network. Additionally, mobile nodes move differently, and the host's speed and direction affect the operation topology [13]. MANET is more alluring than traditional networks because of features like fault tolerance in the event of connection failures, router-free access, rapid connectivity, and affordability. All of these benefits-free movement, no restrictions on location, and the ability to communicate without worrying about specifics-allow MANET to achieve ubiquitous and pervasive computing with ambient in different intelligence.

In Figure 1, MANET sends or receives messages, such as path requests and path replies, to neighbor nodes that are connected to source nodes and wish to broadcast with destination nodes. It keeps doing this until it locates a path to the destination node. The current routing technique results in a large control overhead in situations where the network is extremely thick or has an excessive number of nodes. A cluster is formed to overcome the extra overhead, which is a small collection of nodes where routing is started by the cluster head instead of regular nodes. Ultimately, routes are established, and data transit will occur via cluster nodes rather than single nodes. After the mobility of nodes are grouped together, a cluster head is selected from among them. Dynamically, networks, however, the cluster head scheme can face performance issues due to the frequent changes in network topology. This can lead to instability and increased overhead in maintaining the clusters.

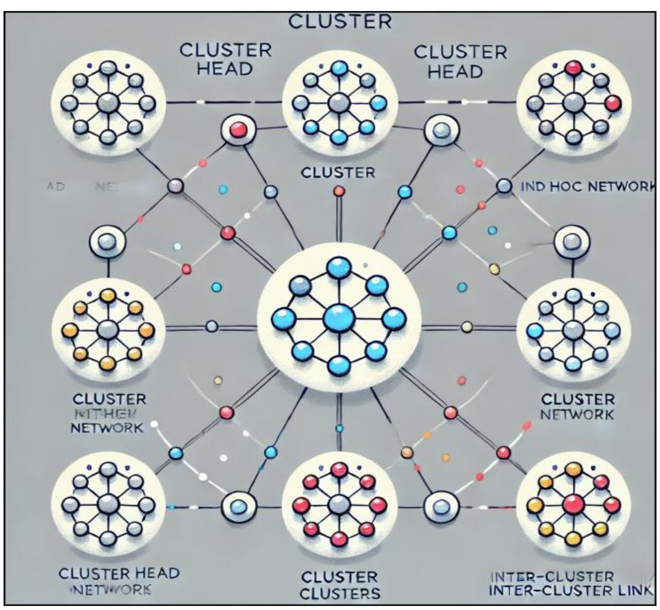

Fig. 1 Cluster designing in manet network

2. Related Study

This work proposes EVO, a novel evolution-based routing parameters. Genetically, more programming is utilized to create these parameters automatically. Features pertaining to traffic and mobility are used in the development of this statistic. EVO-AODV is a modified version of AODV that uses the evolved, more featured metrics between communication with finepoints to rank and choose routes for the safe distribution of messages.

By choosing the best CH-weighted clustering method and considering several important routing issues, this study suggests that CBRP increases cluster stability and enhances the fulfillment of the conventional CBRP. Additionally, the suggested protocol recommends Re- CH to improve the cluster's stability and, indirectly, the network infrastructure if the cluster head fails.

This paper suggests a unique unequal clustering route protocol for WSN that considers balance energy. This protocol is called Unequal Clustering based on Network Partition and Distance. In order to reduce duplicate broadcasts and enhance the route discovered processing, Basurra [8] later suggested a single-hop clustering algorithm to give zonal broadcasting techniques. A review of several routing types has previously been completed in an article [11].

Malar et al. [4] presented bio-inspired techniques to appreciate the MANET rout process in a different investigation. To create an energy-efficient routing system in MANET and make better use of the energy, they employed the Ant colony optimization technique. [5] This research uses the k-means method in conjunction with a new neural network to resolve the cluster-making and cluster head selection problems within networks, depending on the state of the art mentioned.

Agarwal et al. [12] used characteristics including trusting, balancing of load, energy usage, mobility, and battery utilization in their trusted weight-based clustering technique. An agent-based secure improved enforcement method for MANET in AB-SEP was proposed by Bisen and Sharma [5, 6]. The main benefits mentioned were improved node performance, reduced energy usage, and the ability to detect malicious network activity [9].

3. Materials and Methods

A clustering method puts related data points in one group according to their traits and attributes. The general procedures for data clustering are as follows:

1. Get the nodes ready in the network.
2. Make a metric for similarity.
3. Execute a clustering algorithm.
4. Analyze the findings and modify the clustering.

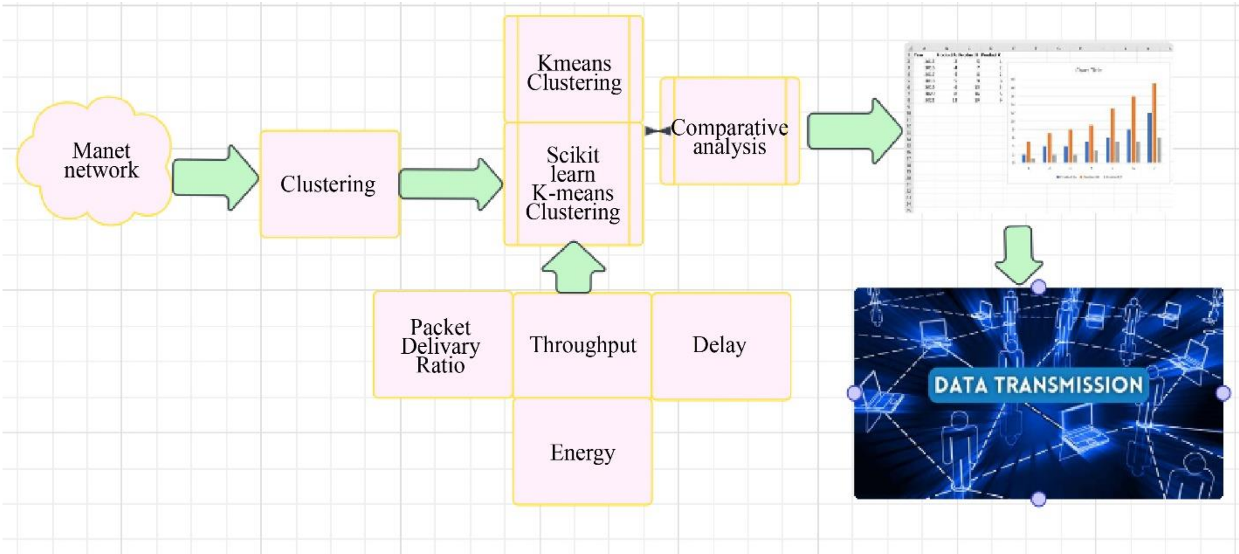

Fig. 2 A Block diagram representing the proposed methodology in MANET using Scikit-learn K-means clustering

Data is gathered from MANET. Nodes that offer information like positions or signal strengths can be laptop computers, smartphones, or Internet of Things devices. Node data with properties (such as signal strength and position) is an example of input. The data preprocessing stage is before clustering, where data may need to be pre-processed to remove noise, fix missing values, or standardize values. Scikit-learn Framework utilizes Scikit-learn, a Python machine learning package that provides tools for building and assessing models. Cluster Centres starts the choice of K initial centroids, which can be made randomly or via an initialization technique like K-Means++, which directs the clustering process. The network assigns each data node to the nearest centroid using a distance metric, commonly Euclidean. For every data point assigned to centroids, cluster mean is computed to reupdate the centroid coordinates. After that, the centroids are moved. The assignment and update processes are repeated after the centroid update until there is little variation in the centroids (convergence). MANET nodes that are clustered. The nodes are arranged into clusters supervised by a centroid after convergence yields the final clusters. This shows how nodes are rearranged based on similar parametric design and proximity. This shows how nodes are arranged based on similarity and proximity. Evaluation of Performance in clustering, quality is asses using evaluation parameters such as PDR: silhouette score, more inertia, and Davies-Bouldin index. Inertia, silhouette score, and cluster validity are important metrics.

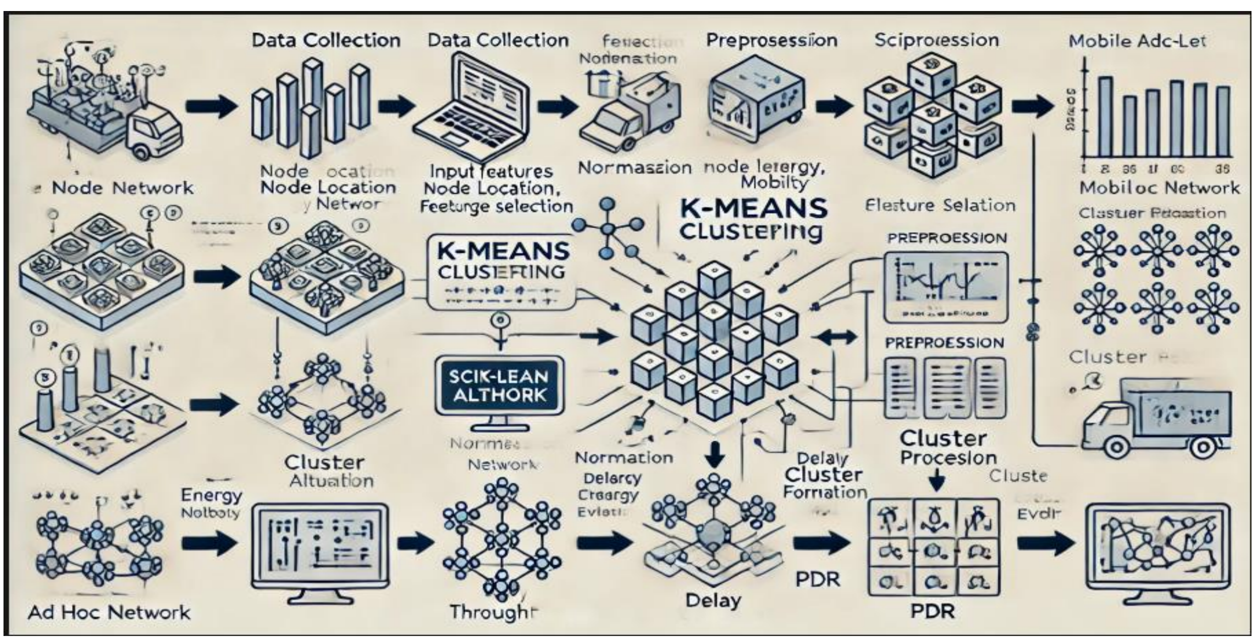

Fig. 3 QoS parameter analysis in MANET with Scikit-Learn K-Means Clustering (SLKMC)

Figure 3 depicts the visualization of the MANET network with node location feature selection pre-procession unit with more latency. Quality of service parameters can be evaluated by Scikit-Learn K-Means Clustering in manet with cluster procession and cluster actuation, and input feature of random node selection parametric calculation can be done by Scikit-Learn K-Means Clustering (SLKMC) such as throughput, node delay, PDR and energy of node.

3.1. Flow Chart for Cluster Head Selection Using Scikit-Learn K-Means Clustering in MANET

Using Scikit-Learn's K-Means Clustering, the flowchart illustrates the Cluster Head Selection Process in a MANET. Below is a synopsis of every step

1. Collect Node Data Input: Compile pertinent information from each network node: Position: The node's geographic location. Energy: The node's remaining battery power. Mobility: The node's pattern of movement or stability. Goal: Clustering and assessing a node's fitness as a CH depends on data.
2. Preprocessing Data Tasks: Make sure all attributes (position, energy, and mobility) are on the same scale by normalizing and scaling the data. This phase is essential to the K-Means algorithm's efficient operation. The goal is to prevent bias toward qualities with wider numerical ranges by preparing the data for clustering.
3. The K-Means Clustering Algorithm should be used: The K-Means algorithm in Scikit-Learn clusters nodes should be used according to how similar their attributes are (e.g., position, energy, mobility). The result is that Clusters of nodes are created, and each cluster has a centroid, or the average location.
4. Create Clusters and Determine Centroids Clusters: Nodes grouped together according to how similar and close they are. Centroids: Show where each cluster's centre is. Because nodes close to the centroid are more central and appropriate, they serve as a useful tool for identifying possible cluster heads.
5. Assess the Node Criteria:
   Energy: CH should have sufficient energy to manage the added burden.
   Centrality: For efficient communication with other nodes, the node should be near the centroid. Mobility: To maintain stability in its role as the cluster head, the node should have little mobility. The goal is to make certain that the cluster head of choice satisfies all prerequisites for optimum performance.
6. Choose the cluster head choose the node that best meets the requirements (low mobility, high energy, and high centrality) based on the evaluation. The chosen node will serve as the cluster's leader and be in charge of coordination and communication.
7. Assign the role of Cluster Head. Assign the chosen node the cluster head's responsibilities. The node is formally designated to serve as its cluster's communication relay.
8.

The flowchart describes an efficient and systematic process for forming clusters and selecting the most suitable cluster head in a MANET. This process ensures optimal communication, reduces energy consumption, and improves the overall network's Quality of Service (QoS) by:

- Balancing workloads.
- Minimizing communication delays.
- Enhancing Throughput.

Fig. 4 Flow chart to optimized cluster formation and leader node selection using Scikit-Learn K-Means Clustering in MANET

4. Mathematical Calculations

Scikit-Learn's K-Means Clustering technique divides data points into k clusters using mathematical equations. An outline of the main mathematical terms and ideas is provided below:

Step 1 : Minimizing the Within-Cluster Sum of Squared Distances (WCSS), or inertia, is the aim of K-Means represented as :

$$J = \sum_{i=1}^{k} \sum_{x \in C_i} | x - \mu_i|^2$$

Where:

- J: Objective function (inertia).
- k: cluster numbers.
- Ci: data node points in the i-th cluster.
- x: A node in cluster Ci
- μ_i: It is an i-th cluster centroid

$$\sum_{i=1}^{k} x - \mu_i|^2$$

The squared Euclidean distance between the centroid of a cluster and a point μ_i

Step 2 : Calculating the Centroid, The mean of data points in the cluster with its centroid:

$$\mu_i = \frac{1}{|C_i|} \sum_{x \in C_i} x$$

Where:

- μ_i: Centroid
- |Ci|: No of data points represent cluster i
- x: Data points to cluster i.

Step 3 : Step of Assignment, The Euclidean distance is used to allocate each data point to the closest cluster:

$$Ci = \{x \ || x - \mu\_i |\char`^2 \le | x - \mu\_j |\char`^2, \ \forall j, \quad 1 \le j \le k\}$$

Step 4 : Optimization Through Iteration Iteratively, the K-Means algorithm:

Depending on the distance to the centroids, data points are assigned to the closest cluster. Determines the mean of the points in each cluster to update the position of the centroid. Repeats until either a max no of iterations is achieved or centroids converge, meaning there is no discernible change in the centroids.

Step 5 : Metric of Distance, The Euclidean distance is the default distance metric used by Scikit-Learn's K-Means:

$$|x - y| = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}$$

Where x and y are data points in dimensional n space,

Step 6 : Criterion of Convergence

$$|\mu_i^{(t+1)} - \mu_i^{(t)}| < \varepsilon$$

Where, ε is a tiny cutoff point. The number of iterations has reached its maximum. These mathematical underpinnings enable K-Means in Scikit-Learn to effectively divide data into clusters.

5. Simulations and Result

Scikit learns K-Means clustering is a dataset divided into a predefined number of clusters (k) using an unsupervised learning technique. Cluster centroids are initialized, data nodes are assigned to the nearest centroid, and the centroids are then updated using the mean of the assigned points. Until convergence, this iterative process will continue. Although K-Means is easy to use and effective for big datasets, it can be sensitive to initialization and requires the number of clusters to be predetermined. Furthermore, it assumes that cluster forms are spherical, which could not work for all data distributions. K-Means is a useful tool for finding patterns in data overall, but its settings need to be carefully considered.

5.1. Observations in Mathematics with Numerical Perspectives

PCA-Based Dimensionality Reduction: calculate t from datasets in the covariance matrix. Calculate the matrix's Eigen values and Eigen vectors. Based on explained variance, select the top k principle components (i.e., components that account for the majority of the variance). The original dataset should be projected onto the reduced k-dimensional space.

5.2. Interpretation of Cluster Formation

The outcomes of using K-Means clustering on a dataset are compiled in the cluster construction table. Each column and its meaning are explained in detail below: the average data point inside a cluster is the centroid. They are essential to comprehending the features of clusters. The number of points distorted point distribution could suggest that some clusters are scarce or dominant. WCSS: Better-defined clusters with compact data points are indicated by lower WCSS values across clusters.

Table 1. Cluster centroids interpretation

Cluster ID	Centroid Coordinates	Number of Points	Within-Cluster Sum of Squares (WCSS)
1	(4.2, 2.8, 3.1, 1.5)	50	23.45
2	(5.8, 3.2, 4.7, 1.9)	45	21.34
3	(6.1, 3.4, 5.6, 2.3)	40	19.67
4	(5.0, 3.0, 1.4, 0.2)	65	25.78
Total		**200**	**90.24**

The total row aggregates all clusters:

Total points: 50+45+40+65=200
Total WCSS: Sum of WCSS for all clusters 23.45+21.34+19.67+25.78=90.

These values provide an overall assessment of clustering quality.

1. Covariance Matrix

$$\Sigma = \frac{1}{n}(X^{\top}X)$$

Where Σ is the covariance matrix of the dataset X.

2. Eigen Decomposition

$$\Sigma v = \lambda v$$

λ: Eigenvalues (variance explained by the principal components).
v: Eigenvectors

3. Dimensionality Reduction: Project data onto the top k eigenvectors:

$$Z = X.W$$

Z: Reduced k -dimensional data.
X: Original data matrix.
W Matrix of the top k eigenvectors.

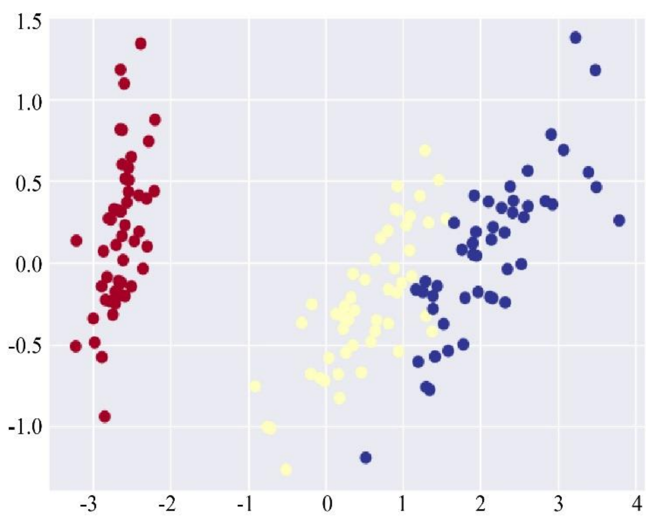

Fig. 5 Dimensionality of K-Means Clustering with reduction using PCA

Figure 5 depicts effective clustering for high-dimensional datasets while preserving important information by combining PCA with K-Means. No of samples is 200, centres are 4, random_state are 0, cluster std are 0.60.

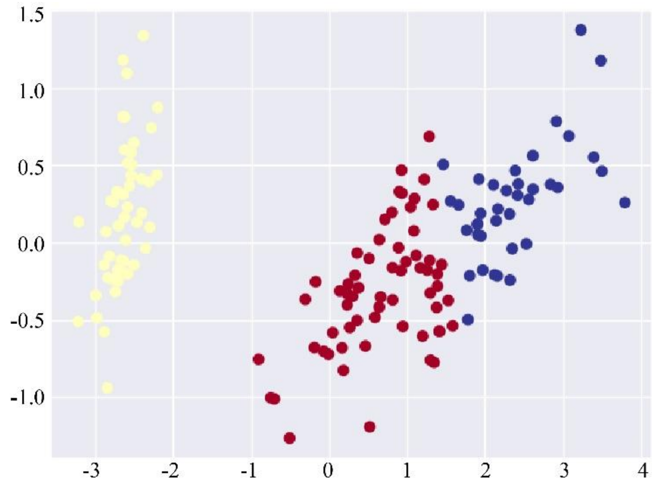

Fig. 6 Generation of a synthetic dataset with four clusters and visualize it in a 2D scatter plots

Figure 6 represents K Means clustering, which is the process of identifying data groups using only the properties of the data-not the labels. The K Means algorithm is comparatively simple to comprehend. In order to allocate each point to the cluster centre that is closest to it, look for the centred cluster and have mean points within the network. Here, 4 clusters should be scattered in 2-dimensional plots with synthetic data sets.

Dataset Reduced by shape: (150,2) means two components:
0.361 x sepal length (cm) + -0.085 x sepal width (cm) + 0.857 x petal length (cm) + 0.358 x petal width (cm)
0.657 x sepal length (cm) + 0.730 x sepal width (cm) + -0.173 x petal length (cm) + -0.075 x petal width (cm)

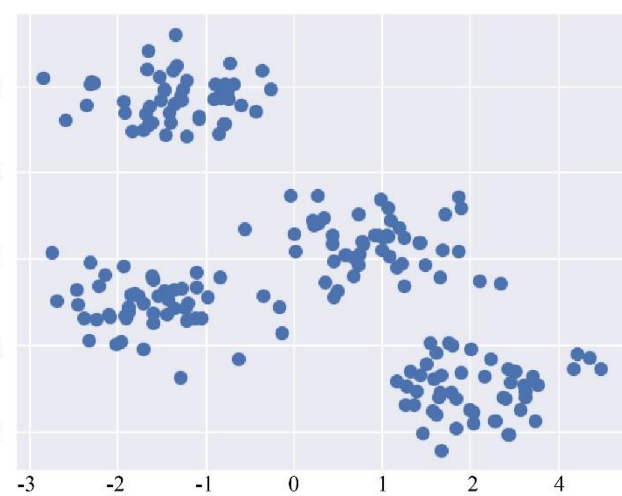

Fig. 7 scikit learn K means clustering algorithm implementation

Figure 7 depicts that there will be 4 clusters designed according to the same group's allotments with the same structural process. Identifying data clusters using only the properties of the data-not the labels. The K Means algorithm is comparatively simple to comprehend. In order to allocate each point to the cluster centre that is closest to it, cluster centres are looked for, which are the mean of the points within them. Cluster std=0.60 with rainbow, random state=0, N samples=200, and centres=4.

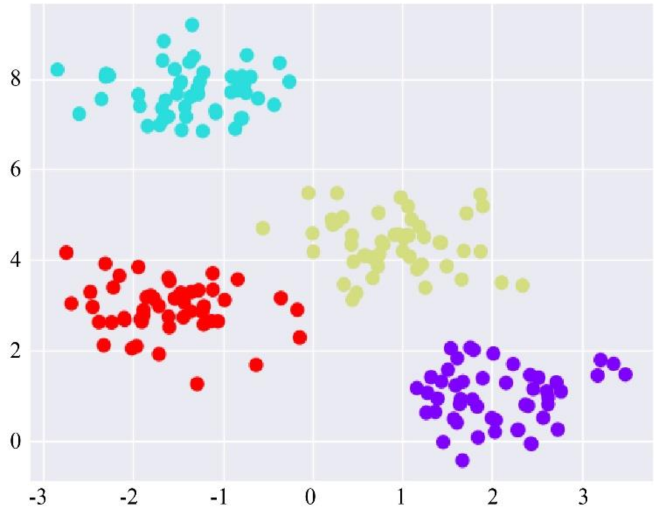

Fig. 8 Representation of clusters with the K-Means algorithm along with expectation maximization

Figure 8 represents 4 clusters with an Expectation-Maximization strategy to reach the solution of K-Means. The two-step Expectation-Maximization method operates as,

1. Identify a few cluster centers
2. Continue until convergence is achieved. A. Different points are assigned to the closest cluster centre. B. Use the mean to set the cluster centres.

5.3. Algorithm Implementation

K Means Clustering_ MANET (D, k)

Input: Dataset D containing node positions and metrics (Throughput, Energy, Delay, PDR),

Number of clusters k

Output: Cluster assignments, centroids, and performance metrics (Throughput, Energy, Delay, PDR) for each cluster

Step 1 : Load the dataset D containing node attributes:
- Node positions: X, Y
- Throughput: Throughput[i]
- Energy: Energy[i]
- Delay: Delay[i]
- PDR: PDR[i]

Step 2 : Prepare the features for clustering:
- Select relevant features for clustering (e.g., X, Y positions of the nodes)
features = Extract ([X, Y]) # Extract X and Y positions for clustering

Step 3 : Initialize the K-Means algorithm:
- Use KMeans from Scikit-Learn to fit the features and define the number of clusters (k)
kmeans = KMeans(n_clusters=k)

Step 4 : Fit the K-Means model to the dataset and predict cluster assignments:
cluster_assignments = kmeans.fit_predict(features)

Step 5 : Add the cluster assignments back to the dataset:
- D['ClusterID'] = cluster_assignments

Step 6 : For each cluster, compute the performance metrics (Throughput, Energy, Delay, PDR):
For i = 1 to k:
cluster_nodes = Data points assigned to cluster i
Calculate metrics for cluster i:
-Throughput[i] = mean (Throughput of all nodes in cluster i)
- Energy[i] = mean(Energy in nodes in cluster i)
Delay[i] = mean (Delay in nodes in cluster i)
PDR[i] = mean (PDR in nodes cluster i)

Step 7 : Calculate the centroid (mean position) for each cluster:
For i = 1 to k:
centroid[i] = mean ([X, Y] nodes in cluster i)

Step 8 : Return the final results:
Cluster Assignments: Data points' corresponding cluster ID
-Cluster Centroids: Centroids of each cluster
- Performance Metrics: Throughput, Energy, Delay, PDR for each cluster

Step 9 : Optional: Visualize the clusters and centroids:
- Plot the nodes in each cluster with different colors
- Mark the centroids with red crosses

5.4. Mathematical Calculations for QoS Parameters

In MANET, several performance metrics are commonly used to evaluate the efficiency and effectiveness of the network. Here are definitions and formulas for Throughput, delay, energy consumption, and Packet Delivery Ratio (PDR).

5.4.1. Throughput (kbps)

The rate at which information is successfully sent via a network in a specific period of time is known as Throughput. Bits per second (bps) are typically used to quantify it.

$$Throughput = \frac{Total\ data\ Received}{Total\ Time}$$

5.4.2. Packet Delivery Ratio (PDR)

The packets successfully delivered to the destination divided by the number of packets sent from the source are known as the PDR. It is crucially indicated for evaluation of the network's dependability.

$$\left[\mathrm{PDR} = \frac{\text{Number of Packets Delivered}}{\text{Number of Packets Sent}} \times 100\%\right]$$

5.4.3. Energy Consumption

Energy consumption in MANETs refers to the energy utilized by the node in the network to transmit, receive, and process data. It is crucial for battery-powered devices.

$$Energy \ = (P_{tx} \times t_{tx})$$

5.4.4. Delay

The time taken for a packet to go from its source to destination is referred to as delay. It consists of several elements, including propagation and transmission delays.

5.4.5. Transmission Delay

$$Transmission\ delay \ = \frac{Packet\ Size}{Transmission\ Rate}$$

5.4.6. Propagation Delay

$$\left(Propogation\ Delay \ = \frac{\text{Distance}}{\text{Propagation Speed}}\right)$$

5.5. Simulating Parameters

Table 2. Simulating Parameters

Parameters	Value
Network area:	1000 x 1000 m²
Simulation time:	100 s
Traffic:	CBR
No of Nodes	50
Mobility	Random waypoint model.
Average Throughput (Kbps)	251.0202267
Average PDR (%)	94.07955989 %
Average Energy (J)	17.49503883
Average delay (ms)	24.37ms

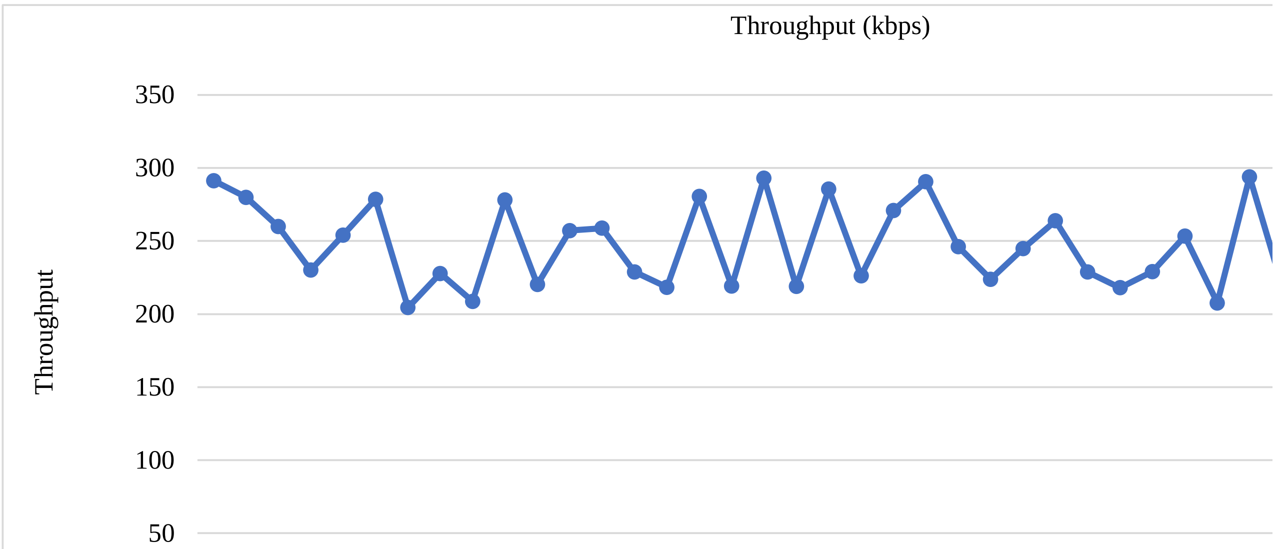

Fig. 9 Throughput or overhead versus network size (number of nodes)

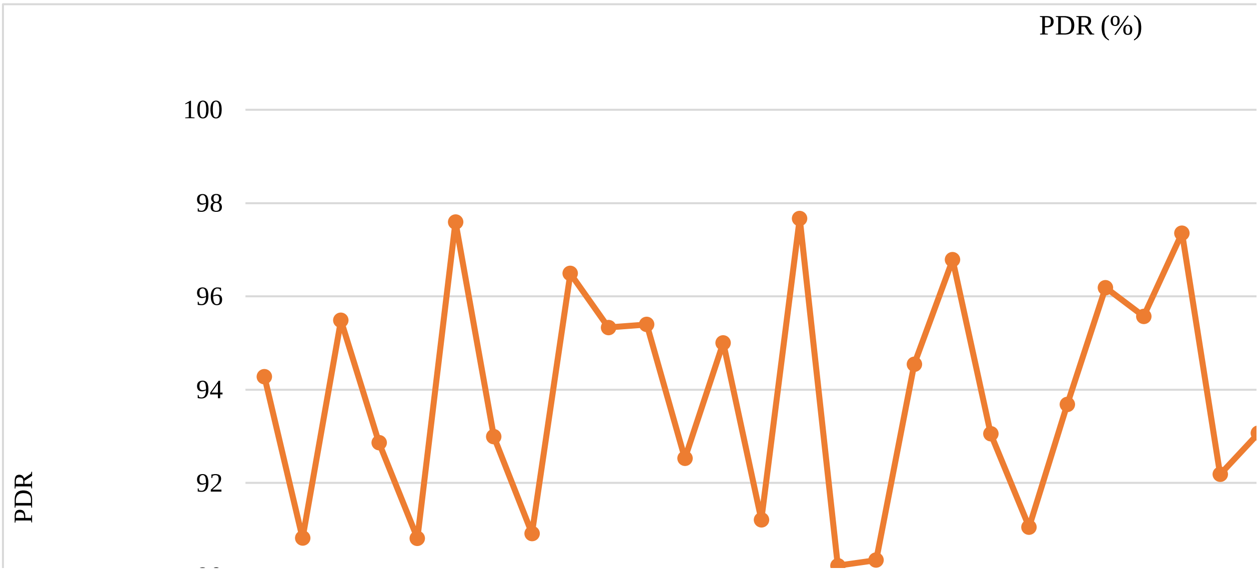

Fig. 10 Packet Delivery Ratio (%) versus node speed (m/s)

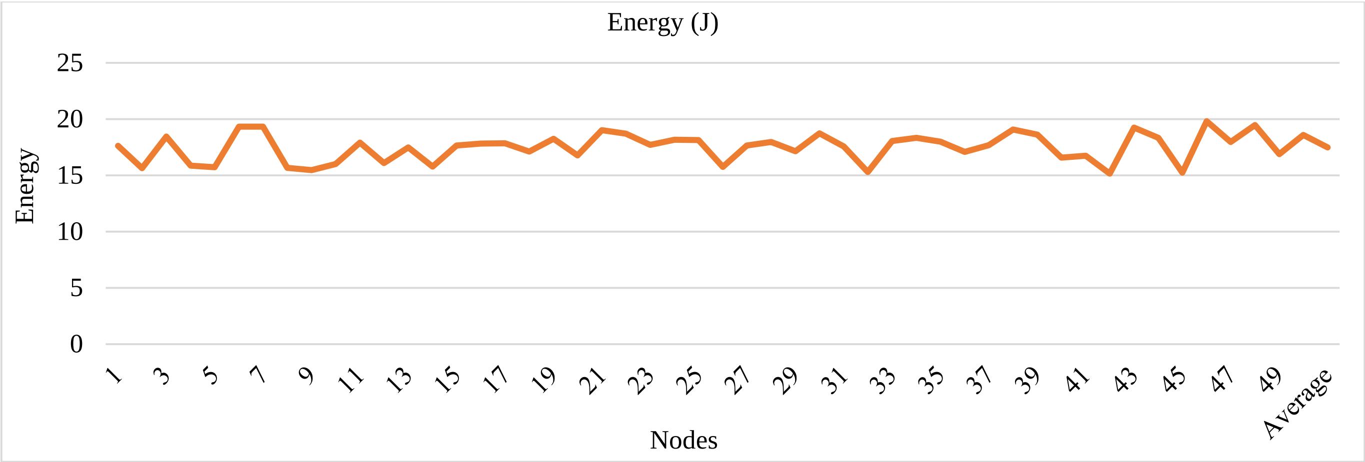

Fig. 11 Energy calculation with graphical representation

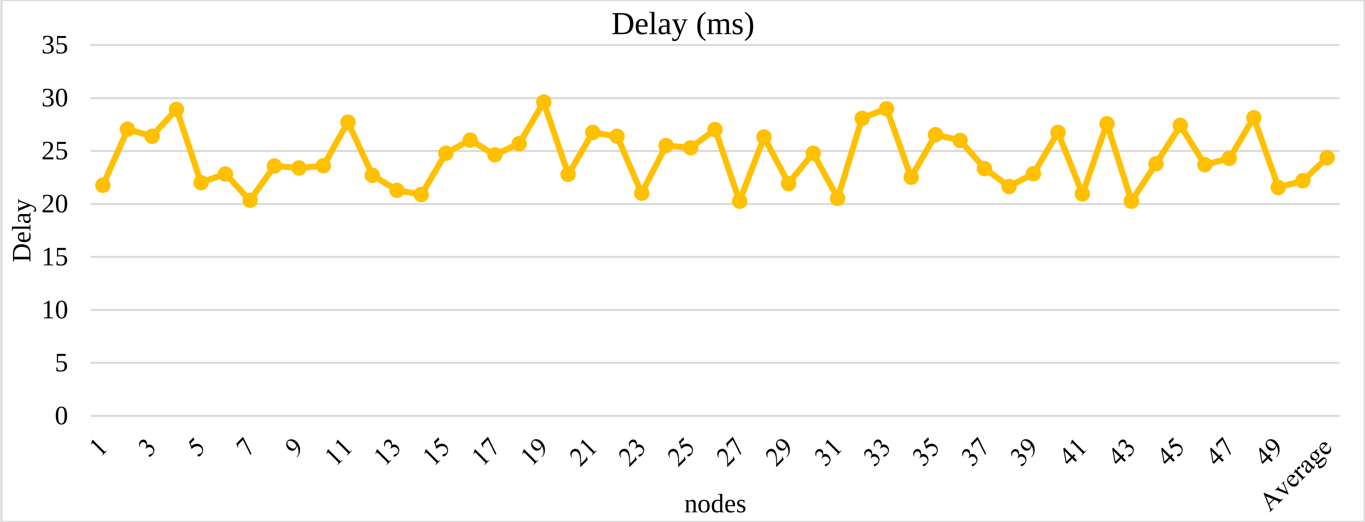

Fig. 12 Delay calculation with graphical representation

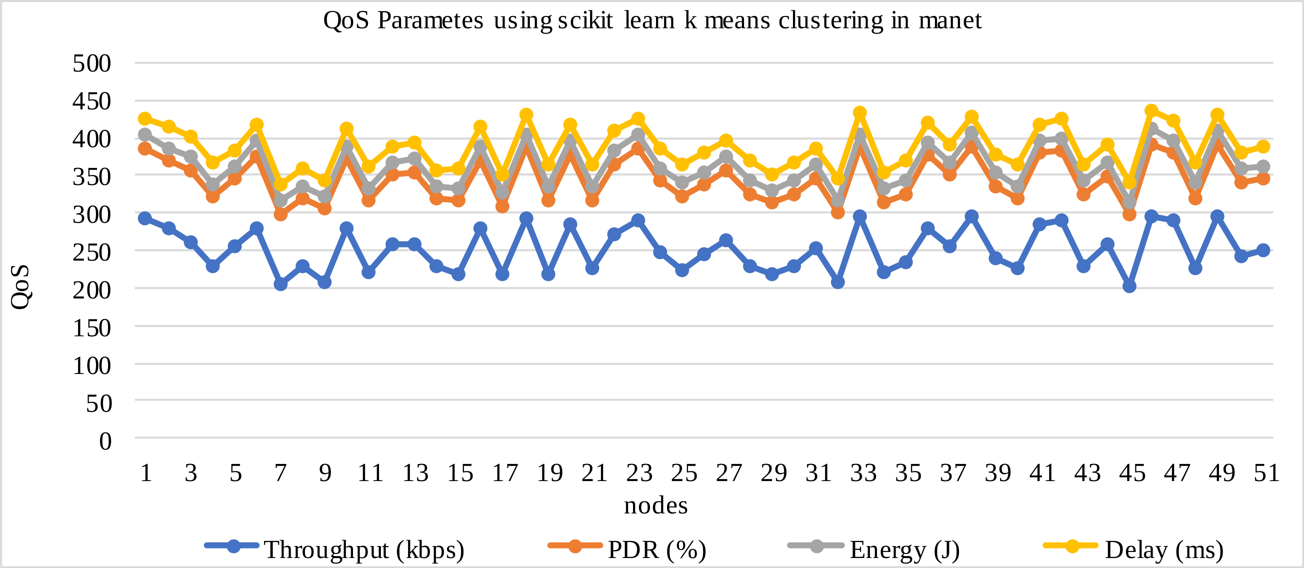

Fig. 13 Quality of services parameters graphical representation using Scilearn K-Means Clustering in MANET

6. Conclusion

An effective method of formation of clusters and the election of stabled CHs with more energy levels among MANET nodes was presented in this research. It implemented the scikit learn k-means clustering algorithm to group nodes according to their distance from one another. Each cluster is then subjected to a network with nodes, and the cluster head is selected based on factors like energy, packet drop, mobility, and the number of neighbour nodes. Node determined by scikit learns k means to be cluster heads with greater energy levels and longer stability. This process decreased the re-affiliation of cluster member nodes and the repetitive selection of cluster heads. Compared to traditional methods, these novel Scikit learn k means cluster integrations improved PDR, Throughput, routing overhead, and CH stability while also making communication ubiquitous and strengthening the system.

Thus, verified Quality of service parameters conclude as efficient values of

Throughput	:	200 kbps $\leq$T $\leq$300 kbps
PDR	:	90% $\leq$PDR $\leq$98%
Energy	:	15 J $\leq$E $\leq$ 20 J
Delay	:	20 ms$\leq$D$\leq$30 ms.

The analysis of the above code and graphs provides insight into the performance and behavior of a MANET. Clustering helps understand the spatial distribution of nodes, while metrics provide a detailed view of network performance. The high variability in the metrics highlights the dynamic nature of MANETs and the challenges in achieving consistent performance across all nodes. The average values provide a useful baseline for evaluating network conditions and identifying areas for optimization.

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