Iraqi Journal of Communications and Computer Networks
Vol. (2), Iss. (1), March 2026
e-ISSN: 3105-9252, p-ISSN: 3105-9244
DOI: https://doi.org/10.58564/IJCCN.2.1.2026.13

https://ijccn.net/

Research Article

Evaluation Study of MANET Cluster-Based Routing Protocols

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Citation: Aya Ayad Hussein, Goh Chin Hock, & Tiong Sieh Kiong. (2026). Evaluation Study of MANET Cluster-Based Routing Protocols . Iraqi Journal of Communications and Computer Networks (IJCCN), 2(1), 9–18.

ARTICLE INFO

Received:
Revised:
Accepted:

ABSTRACT

Cluster-based routing plays an important role in improving Quality of Service (QoS) and overcoming the energy consumption problems in Mobile Ad Hoc Networks (MANETs). This paper introduces a comparative analysis of two algorithms for node clustering: the supervised K-Nearest Neighbors (KNN) classifier and the unsupervised Fuzzy C-Means (FCM) clustering method. Their performance is calculated and simulated using basic key metrics for network simulation, such as end-to-end delay and energy efficiency, under rapidly varying node densities. Results demonstrate a clear trade-off: while FCM outperforms in creating clusters for data exploration, KNN, when adapted for routing, achieves outstanding performance in latency, exhibiting lower delay across all tested network sizes. The results found that it can provide critical insights for selecting the appropriate clustering algorithm to improve specific QoS parameters in MANET routing protocols.

Keywords: Clustering, Routing Protocols, KNN, Fuzzy C-Means, MANET, Energy Consumption

INTRODUCTION

Mobile Ad Hoc Networks (MANETs) are made of a group of nodes that communicate while moving independently within a framework that contains self-organizing and dynamically adaptable [1]. Communication in MANETs depends on multi-hop wireless links, which allow the devices to join or leave the network easily without centralized control or fixed infrastructure [2]. Based on these attributes, MANETs are highly suitable for scenarios where deploying the nodes in stable networks is not practical, such as disaster recovery operations, military and law enforcement exercises, mining activities, and different telecommunication applications involving wireless devices, computers, Internet of Things (IoT) platforms, and mobile phones [3]. ANETs have garnered attention due to their clear advantages, including network flexibility, cost efficiency, and coverage capabilities. These networks are self-configuring and allow devices to communicate without taking for granted a pre-existing infrastructure, which makes them suited for all dynamic and unpredictable environments. One of the primary benefits of MANETs is their adaptability and flexibility [4]. Mobile Ad Hoc Networks (MANETs) are highly flexible, capable of self-reorganization as nodes move or when node conditions are changed, making them valuable in scenarios such as disaster recovery, military operations, and remote monitoring where infrastructure is not available. Their scalability allows smooth integration of new devices, maximizes the ability of high coverage, and bridges isolated areas. MANETs also buttress cloud and edge computing by acting as intercessor between devices and centralized services, reducing costs and improving resource allocation. Routing in MANETs is generally sorted as hierarchical or flat, with hierarchical approaches employing clustering to minimize routing overhead in large, dense networks and maximize network lifetime. In this architecture, each node functions both as a router and a host [5]. The basic MANET clustering topology is shown in Fig. 1.

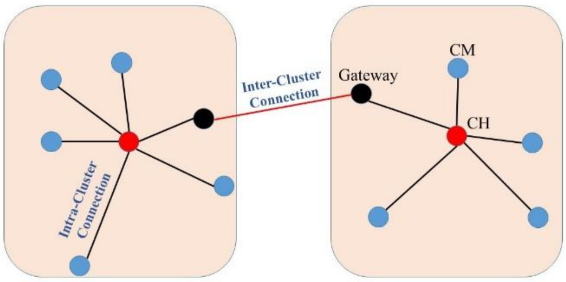

Fig.1 Clustering Topology of Mobile Ad Hoc Network

In flat routing, all nodes are considered equal in responsibility, which may result in network congestion and different challenges related to unflexibility, complexity, and scalability as the network grows in density. Routing nodes select best paths and forward packets with reliable data transmission; at the same time, frequent topology changes increase routing complexity. To manage these dynamics, MANETs establish routing protocols categorized as reactive, proactive, or hybrid, each designed to be modified to varying conditions [1]. Different studies have constraints on improving the efficiency of hierarchical protocols and give strength to network structures to improve overall performance [6]. Different authors have proposed several criteria for grouping nodes into clusters to be enifit of getting more efficient and optimal network structure. Such hierarchical clustering improves the performance of routing protocols by minimizing overhead and maximizing scalability. The choice of an appropriate metric is definitive, as different metrics, such as node density, energy level, and mobility, have been introduced to evaluate both logical and physical node specifications. An effective metric should smoothly create connections between nodes, accurately reflect their performance, and ultimately contribute to enhancing protocol efficiency [7].

Different clustering algorithms are used in MANET routing. This paper evaluates KNN and Fuzzy C-Means clustering algorithms. Table 1 presents the algorithm features of KNN and Fuzzy C-Means.

Table 1: Feature comparative table

Feature	KNN	Fuzzy C-Means
Type	Supervised classification / hard clustering	Unsupervised soft clustering
Node Assignment	Hard (one cluster per node)	Soft (partial membership in multiple clusters)
Computational Complexity	Medium to high (distance calculation with all nodes)	High (membership and centroid updates)
Adaptability	Medium (depends on K)	High (handles overlapping and dynamic clusters)
Stability in Mobile Networks	Low to medium	Medium to high
Applications in MANET	Cluster head selection, neighbor ranking, QoS routing	Adaptive clustering, energy-aware routing, mobility-aware handoffs

The evaluation in this paper provides the following contributions:

1- Evaluate the energy consumption of KNN and Fuzzy C-Means using different MANET topologies
2- Compute the network latency with different numbers of nodes
3- Suggest the best algorithm for different scenarios of MANET

The rest sections of this paper are described as follows: Section 2 illustrates the KNN algorithm. The structure of Fuzzy C-Means is presented in Section 3. Section 4 discusses the evaluation steps and simulation results. Finally, the paper's conclusion and the recommendation for future work are presented in Section 5.

KNN CLUSTERING ALGORITHM

The KNN algorithm is a supervised learning method primarily used for classification and regression. However, in clustering and network organization (such as MANETs), a KNN-based clustering approach can be adapted to form groups of nodes based on spatial proximity or other performance metrics. Each node identifies its *k* nearest neighbors using a distance metric (e.g., Euclidean distance, Manhattan distance, or hop count in networks) [8,9]. Nodes with similar neighborhoods are grouped into clusters. Figure 2 shows the KNN clustering algorithm structure.

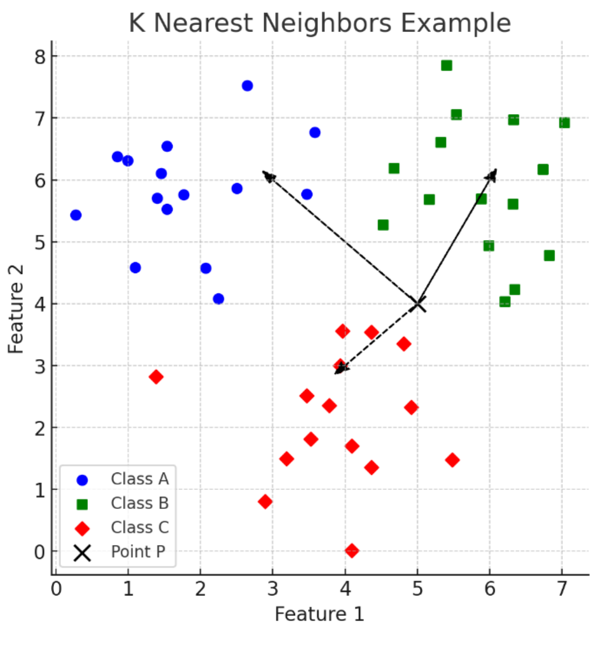

Fig.2 KNN Clustering scheme

KNN is highly regarded for its extreme simplicity and intuitive nature, making its predictions easy to explain. Its key advantage is the complete absence of an explicit training phase, as it simply memorizes the training data . This lazy learning approach allows it to instantly adapt to new data without costly retraining. The algorithm is remarkably versatile, effectively handling both classification and regression tasks with ease. It also manages multi-class problems naturally without requiring complex modifications. With well-structured data and proper tuning, KNN can achieve highly competitive and accurate results [10]. It features a short list of hyperparameters, primarily just the value of k and the distance metric. This makes the model straightforward to understand, tune, and implement for various scenarios. Furthermore, its instance-based method ensures no loss of underlying information from the original dataset. These traits collectively make KNN a powerful and transparent tool for many machine-learning applications. The classification steps of KNN are shown in Fig.3

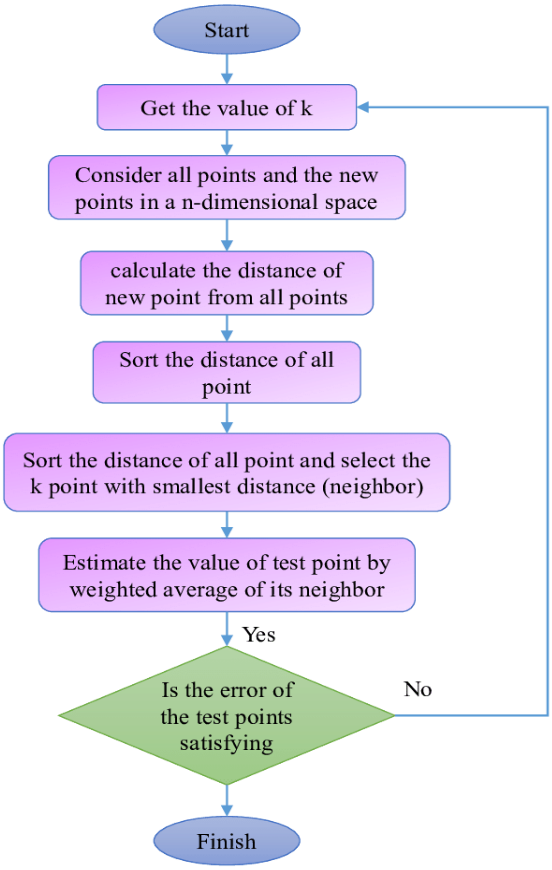

Fig. 3 KNN Classification Steps [11]

FUZZY C-MEANS ALGORITHM

The Fuzzy-C-Means algorithm is working as a centralized clustering technique; the master node (base station) calculates and allocates nodes into multi-clusters based on their location information. For a sensor network with N nodes distributed to c clusters: C1, C2, ..., Cm. The goal of cluster formation is to reduce and minimize the objective function:

$$J_m = \sum_{i=1}^{c} \sum_{j=1}^{N} u_{ij}^{m} \, dis_{ij}^{2} \qquad (1)$$

Where: u_{ij} is a sensor node j's degree of belonging to cluster i, and dis_{ij} represent the distance between the centroid of cluster i and node j. The degree u_{ij} of node j with respect to cluster is computed and fuzzyfied with a real parameter of m > 1 as below: [12]

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} (\frac{dis_{ij}}{dis_{kj}})^{\frac{2}{m-1}}} \qquad (2)$$

Euclidean distance is the distance from the sensor node to the center point. The goal is to minimize the spatial distance, the energy balance among sensor nodes is optimized. In the application scenario, the N sensor nodes are distributed in random form with an area of A×A m2. After the isolation is completed, these nodes will send a HELLO message to the main node (base station). The HELLO message will have the information of the node geographical location. The BS will compute the center of clusters as: [13]

$$Centriod = \frac{u_j^m \; pos(node_j)}{\sum_{j=1}^{c} u_j^m} \qquad (3)$$

The convergence is achieved when the difference between two successive iterations of the coefficient is less than or equal to a certain threshold value or a specified number of iterations. Following the formation of the clusters, the base stations select the nodes nearest the centroid that will become the CH. At the conclusion of the cluster formulation, the base stations contact the CH and determine which node is part of each cluster. The number of clusters can be determined by applying the following formula: [14] can be used:

$$K = \frac{\sqrt{N}}{\sqrt{2\pi}} \sqrt{\frac{e_{fs}}{e_{amp}}} \frac{M}{dis_{d\ to\ BS}^2} \qquad (4)$$

Where: $e_{fs.} = 10\text{pJ/bit/m}^2$, and $e_{amp.} = 100\ \text{pJ/bit/m}^2$

The complete Fuzzy C-Means clustering algorithm steps are presented in fig.4

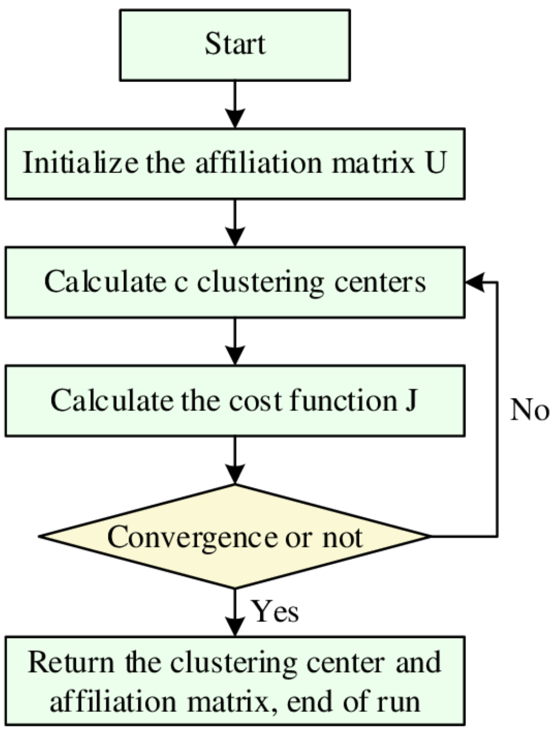

Fig. 4 Fuzzy C-Means Algorithm [15]

EVALUATION STEPS AND SIMULATION RESULTS

In this section, the evaluation steps will be listed as follows:

- Step No. 1: Create a network scenario with a different number of nodes and a different network size.
- Step No. 2: Compute the energy consumption and delay of the network scenario that is created in Step No. 1
- Step No. 3: Evaluate the results.

1- Network Scenario and Simulation Parameters: Table 2 illustrates the simulation parameters in this paper.

Table 2: Simulation Parameters

Parameters	value
N	25 to 250
TMax	60
VMax	2 m/s
Pause time	0.1
E_ele	50 x 10^{-9} J/bit
E_amp	100 x 10^{-12} J/bit/m^2
packetSize	4000 bit
E0	1
Network Size	100x100, 200x200
alpha	0.6
beta	0.4

Two network topologies are used, 100 x 100 m and 200x 200 m. Fig. 5 shows the node distribution of a 100 x 100 network using KNN and Fuzzy C-Means clustering algorithms.

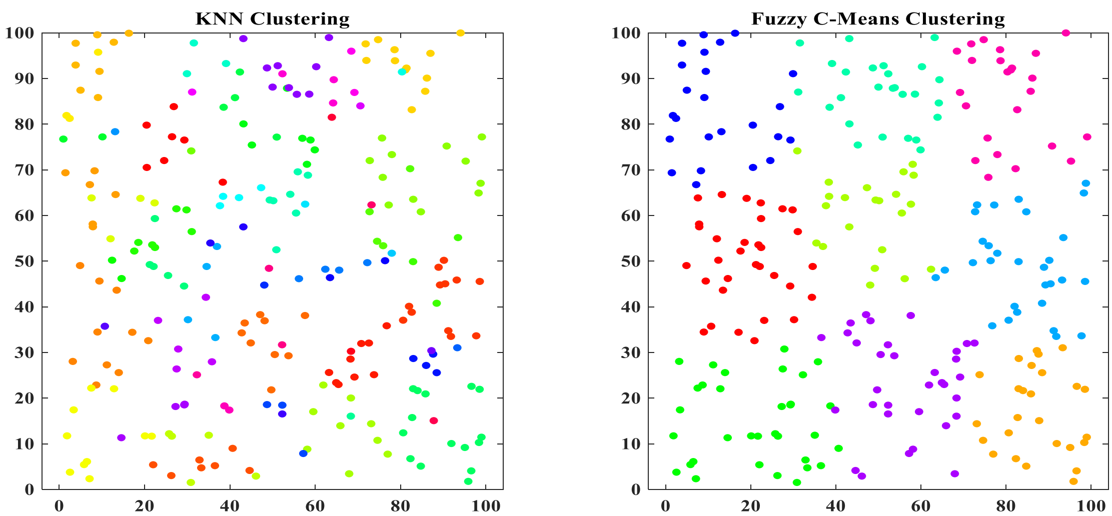

Fig. 5 Cluster nomination of KNN and Fuzzy C-Means with K=9

2- Energy consumption and transmission delay calculation for topology No. 1 (100 x 100) m

Fig. 6 and Fig. 7 show the KNN and Fuzzy C-Means clustering algorithms respectively

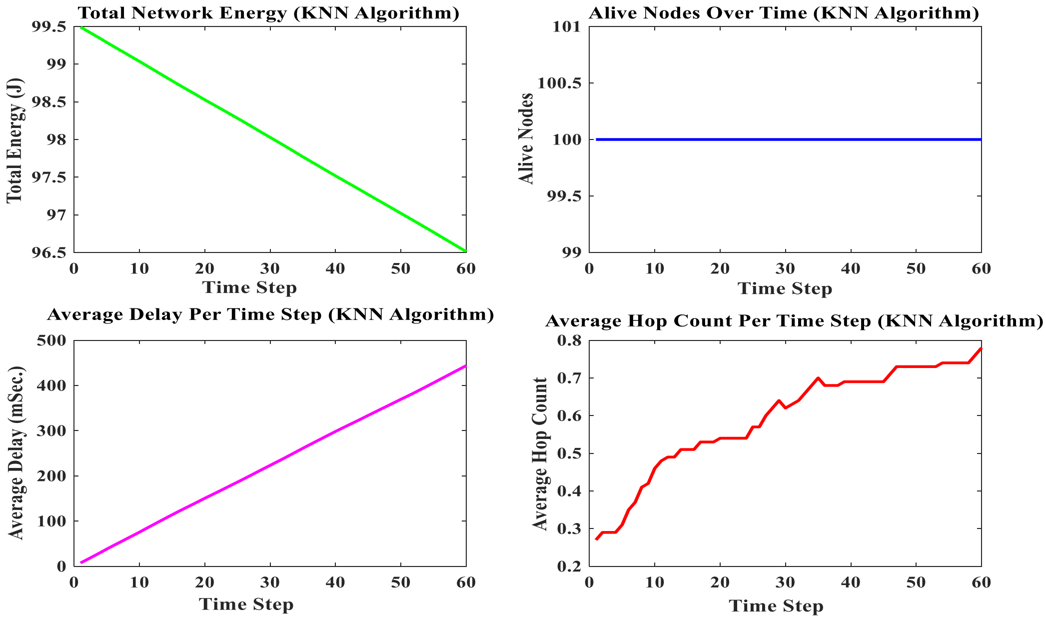

Fig. 6 Computation Result of KNN

Fig. 6 shows the performance of KNN over 60 time steps. Total network energy decreases steadily, indicating continuous energy consumption. All 100 nodes remain alive, meaning no node failures occurred during the simulation. The average delay maximized significantly during a period of time, causing high congestion or routing overhead. Finally, the average hop count increases moderately, suggesting longer multi-hop routes are desired as the network develops.

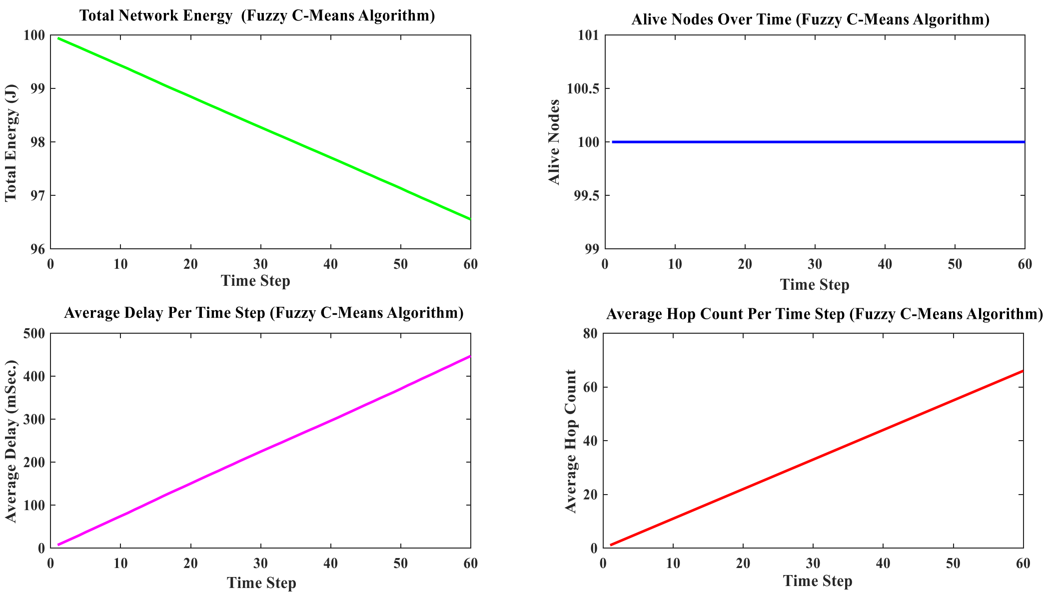

Fig. 7 Computation Result of Fuzzy-C-Means

Fig. 7 introduces FCM performance during 60 time steps. Total energy drops steadily from 100 J to 96 J, which indicates normal energy consumption. The number of alive nodes remains fixed at 100, showing no node death or failure. Average delay increases linearly, reaching about 500 slots, reflecting rising transmission latency. Average hop count grows sharply up to 17, suggesting longer and more complex routing paths. Overall, the network maintains stability in node survival but suffers from higher delay and routing overhead over time.

3- Transmission delay calculation for topology No. 1 (200 x 200) m with a different number of nodes.

The number of clusters for each algorithm is presented in Table 3.

Table 3: Number of clusters in 200x200 m topology

No. of Cluster			
Area	**No. of Nodes**	**KNN**	**Fuzzy C-MEANS**
200	25	5	5
	50	5	5
	75	6	6
	100	6	6
	125	7	7
	150	7	7
	175	8	8
	200	8	8
	225	9	9
	250	9	9

The comparative delay in this scenario is shown in Fig. 8

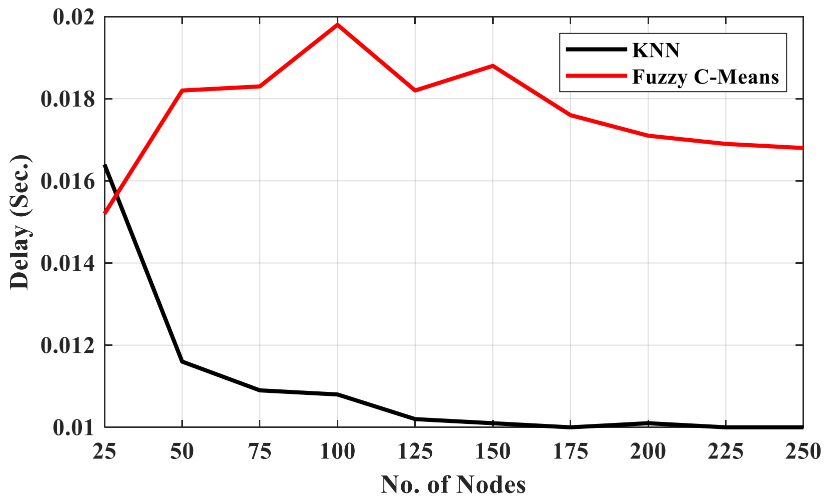

Fig. 8 Delay comparative result in 200 x 200 m topology

Fig. 8 compares the average delay (sec) of KNN and Fuzzy C-Means clustering in MANET as the number of nodes increases.

1. KNN achieves consistently lower delay, dropping sharply as node count increases and stabilizing near 0.01 sec beyond 150 nodes.
2. Fuzzy C-Means shows higher delay, fluctuating between 0.017–0.019 sec, especially peaking near 100 nodes.
3. Both algorithms start with similar delay around 25 nodes, but their performance diverges significantly with network growth.
4. KNN scales better with node density, as delay reduces with more nodes due to efficient neighbor-based clustering.

5. Fuzzy C-Means suffers from higher computational overhead and fuzzy membership assignment, leading to higher average delay.

Overall, KNN outperforms Fuzzy C-Means in terms of delay, especially in larger MANETs.

Conclusion and Future Work

This study offers an evaluation of the efficiency of two well-defined machine learning paradigms, the supervised KNN and the unsupervised FCM, for node clustering in MANETs. The paper aimed to determine their impact on crucial performance metrics, namely Quality of Service (QoS) through delay and overall energy efficiency. The simulation results show a clear and practical adjudication: the computationally simpler KNN algorithm consistently outperformed FCM in minimizing end-to-end delay during varying network densities. This causes the precise selection of a suitable candidate for MANET routing protocols, where low latency is the main concern. While FCM offers valuable theoretical satisfaction through its soft, probabilistic clustering approach, its computational overhead makes it less ideal for the dynamic and resource-constrained MANET environment.

Substantially, this comparison reveals that the optimal algorithm choice is determined by the specific network priority. If the primary objective is to reduce latency and ensure rapid, efficient packet delivery with high flexibility, KNN is clearly superior. If the application requires a deep, exploratory analysis of node relationships in which cluster overlap is meaningful, FCM's accurate approach remains relevant. The future work will focus on expanding a hybrid KNN-FCM model to leverage its combined strengths. We will also integrate the superior algorithm into a standard routing protocol to test its performance under tougher mobility and energy constraints network environment.

ETHICAL DECLARATION

Conflict of interest: No declaration required. **Financing:** No reporting required. **Peer review:** Double anonymous peer review.

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