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COMBINING TRANSFORMERS AND FUZZY CLUSTERING BASED ON FUZZY FUNCTIONS FOR OPTIMAL UAV LOCALIZATION IN 5G WIRELESS NETWORKS

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SUMMARY

This paper introduces a new way to use UAVs in the 5G wireless network, based on Fuzzy C-Means (FCM) clustering and Transformer architecture for improved coverage, less energy consumption, and better Quality of Service (QoS). The new method improves user grouping by incorporating fuzzy distance functions into the FCM algorithm and it further trains Transformer models to interpret the spatial and temporal complexities of the network. This enables UAV replacement, such that now they can be placed more intelligently, especially in congested or unserved regions. Tests with the C2TM dataset demonstrated that the approach outperformed traditional ones by K-Medoid and plain FCM. Energy consumption by the UAV was reduced by 20.100% to 3,597 joules against 4,500 joules using K-Medoid, and the network performed better in terms of Mbps, reaching an average throughput of 180 and with latency at 40 milliseconds and packet loss at 0.8%. This shows a great change in how reliable the network is and what the user experiences. The plan also made the UAV use better by getting more close grouping within and farther apart grouping between, making sure resources are used well. This work points to how much can be done when smart computer models are joined with grouping methods to solve hard issues in the wireless networks of the future. The way suggested here gives a strong answer for changing places, making sure there are scale-able, useful, and trusted communication services. These results make a way for more study in UAV-based communication systems, looking at going deeper with the use of smart learning methods and quick math finding.

Key words: *transformers, fuzzy clustering, fuzzy functions, uav localization, 5G wireless networks.*

INTRODUCTION

In the most recent years, technology has made 5G networks become a key part of modern communication systems. Given that 5G networks have new challenges that relate to how resources are managed, the delays in the system, and energy utilization alongside enhancing data speeds, and doing everything possible to use energy more effectively.[1]. Since there are multiple devices with varied service requirements in 5G networks, in addition to the quality demands of the services, there is a need for an intelligent solution for ensuring network performance. According to the available literature, one of the technologies that promises much in such an environment is the use of UAVs as an aerial base station. The flexibility, low cost, and easy deployment of UAVs in almost all kinds of environments, even remote or densely populated, can, therefore, assure the much-needed quality of service in wireless networks [31].

Optimizing the deployment and finding appropriate places for UAVs is a major challenge of UAV-based communication networks [2]. Factors greatly affecting the trajectories of UAVs are constraints on flight time and energy, user demand, and the imperative need for obstacle avoi-dance. Especially in scenarios such as smart cities and dense urban environments, proper trajectory planning may not only optimize network coverage and reduce energy consumption but also improve the quality of communication. [3].

One major challenge in UAV applications is the placement of the UAVs. A very complex problem, it has many competing goals that the placement must meet. The strong coverage of the area, interference and energy savings, and keeping communication delays as low as possible are considerations that must be accounted for. Old ways, like classical clustering algorithms K-Means and Fuzzy C-Means (FCM), though not as complex in computation, generally perform poorly when the data is complex and dynamic, so they do not yield the desired solution in real applications [8]. Better approaches, with fuzzy tools and machine learning algorithms, will be able to undertake more precise analyses of information and solutions.[32].

Fuzzy clustering is an advanced method of data analysis, especially in situations of uncertainty and complexity whereby, unlike in traditional methods where each data point is assigned to one and only one cluster, it assigns a membership degree for each point in all clusters. The degree shows the strength of the belongingness of the point to each of the clusters. While traditional (hard) clustering techniques mandate the belongingness of the point to one and only one group, fuzzy clustering allows more flexibility. As a result, it is easier to comprehend the set of data where the borders are not clear and patterns are complicated. It will be quite useful in the domain of the placement of UAVs in wireless networks since the data relationships are not direct [5].

Meanwhile, breakthroughs in deep learning, particularly Transformer models, arm one to study large and intricate data sets with enhanced aptness. Transformers adopt a unique attribute known as self-attention, which enables the model to comprehend the relationship between disparate elements of the information over extensive ranges. This proves particularly beneficial for the wireless network data since it can be dispersed and dynamic in manifold manners [10]. Also, as transformers carry out their operations concurrently, they further have the capability to handle the information in a quicker mode; thereby, proving ideal for the real-time applications that fifth-generation networks call for [33].

By incorporating both the fuzzy clustering and Transformers, it provides a novel way of analyzing and optimizing complex problems. This would extract complex relationships in uncertain conditions thus making optimal and accurate decision-making more enhanced.

The combination of fuzzy clustering and Transformers which is a new approach helps in improving the process of UAV localization over wireless networks. While fuzzy clustering helps in dealing with data uncertainties and allocation of UAVs to different regions of the network, Transformers on the other hand help in understanding complex patterns that make the learning process more simple and decrease computational errors. This integration helps in solving the UAV optimal localization challenge in a full and efficient framework improving metrics on latency, energy consumption, and throughput.

The study introduces a fuzzy-transformer-based hybrid model for optimal UAV localization in 5G wireless networks under uncertainties. The transformation model is designed with fuzzy-logic-based functions for handling uncertainties and learning the complex relationships that evolve with the improved network quality of service and energy efficiency. Only the critical problem of optimal UAV localization is addressed in this paper, without considering the trajectory planning. The study is intended to find the optimal static positions of UAV deployment that can maximize coverage of the network while taking into account interference, energy consumption, and service latency. The study deals with the localization optimization of such a sort of preparatory work that may enforce the management of dynamic trajectory in future studies to enhance the performance of future communication networks.

The innovations of this research include:

1. Integrating fuzzy clustering with Transformer models: Proposing a novel framework that combines the long-term relationship learning capabilities of Transformers with the flexibility of fuzzy clustering for analyzing complex and asymmetric data.

2. Utilizing dynamic fuzzy membership functions: Employing optimized fuzzy membership functions to model nonlinear relationships more precisely and reduce uncertainties in cluster allocation [6].

3. Simultaneous optimization of localization and UAV management: Developing a method that combines Transformer-based self-attention mechanisms with fuzzy clustering to ensure optimal UAV localization while reducing energy consumption and enhancing QoS in 5G wireless networks.

This study reviews existing methods and identifies their shortcomings. Then, the proposed model is introduced, and its performance is evaluated using validated datasets. Simulation results demonstrate that this hybrid model significantly improves UAV QoS and energy efficiency compared to traditional methods.

The research is organized as follows: Section 2 reviews related methods and the research background. Section 3 introduces the proposed model. Section 4 evaluates the model's performance and presents simulation results. Finally, Section 5 concludes the article and offers suggestions for future research.

LITERATURE REVIEW

In [7], the traffic of a communication system utilizing UAV-based base stations (BS) increases network coverage rates and reduces the number of required UAVs. The problem is formulated as a mixed-integer programming (MIP) model with QoS constraints and solved using a three-stage approach, including Karush-Kuhn-Tucker (KKT) service radius extraction, UAV number optimization (RL), and 3D positioning design. Simulation results demonstrate significant improvements in coverage rate, interference reduction, and processing time compared to existing methods.

In [34] a dual-layer optimization method based on a pre-trained VGG-19 model is proposed for optimal UAV localization and enhanced network coverage. This approach utilizes lightweight convolutional filters for optimizing radio resources and energy through non-orthogonal multiple access (NOMA). Performance comparisons with Cuckoo Search, Grey Wolf Optimization, and Particle Swarm Optimization algorithms show that this method outperforms others with a 98.44% accuracy rate. The results of the statistical analysis are validated using the Friedman and Wilcoxon tests.

In [9], resource allocation in 5G vehicular networks is addressed to improve network communications using advanced optimization and deep learning techniques. UAV trajectories are optimized using nonlinear optimization and multi-agent deep reinforcement learning, adhering to QoS constraints to minimize transmission power while improving connectivity and reducing latency. The proposed method positively impacts QoS, optimizes resource management in 5G and 6G networks, and responds to real-time requirements of vehicular environments with high flexibility. This innovation also tackles challenges associated with non-convex optimization problems in resource allocation.

In [35] , the k-medoid algorithm is employed to cluster users and determine the required number of UAV-BSs based on the number of clusters and UAV capacity. If the number of available UAV-BSs is insufficient, an optimization scheme is proposed to select clusters, aiming to maximize traffic load with a limited number of UAV-BSs.

In [11], a two-tier UAV-based 5G system is proposed. This study demonstrates that the proposed method provides an effective solution for precise localization in emergency scenarios. Using positional jitter data from a real-world experiment, localization errors under wind and turbulence conditions are evaluated, and effective machine learning solutions are created to compensate for these errors. This study provides an effective solution for highly accurate UAV-based localization in critical communication situations.

In [36], deep reinforcement learning (DRL) is utilized to maximize network coverage reliability, even in the event of UAV node failures. This approach (a) learns the dynamic environment, (b) guides the 3D positioning of UAVs using two deep neural networks, and (c) improves wireless coverage and network reliability. Its success heavily depends on the careful design of reward and penalty functions.

In [13] , A three-stage machine learning-based method has been developed for UAV localization and trajectory optimization. First, a multi-agent Q-learning algorithm is used to set the initial positions of the UAVs. Next, user location data from Twitter is analyzed, and future user movements are predicted using an Echo State Network (ESN). Finally, the multi-agent Q-learning algorithm predicts UAV positions over time based on these predicted user movements. The results show that this approach improves prediction accuracy and increases network throughput by 17%, especially when a larger ESN reservoir size is used.

In [14] the study examines the positioning of multiple UAVs to localize a passive transmitter. Using angle of arrival and time difference of arrival information, a set of waystations that minimize localization errors is determined. The focus of this study is on energy consumption, and UAV coverage is not considered.

In [15], the authors also focus on minimizing UAV energy consumption during communication with users by optimizing UAV trajectories. A filter is designed to help with localization while minimizing energy usage. However, while this filter reduces energy consumption, it doesn't optimize network coverage or throughput, meaning the network's coverage is not ideal.

In [32], effective UAV deployment in wireless networks is addressed by optimizing their placement based on wireless measurements such as power and coverage, alongside UAV energy constraints. Although jointly planning deployment trajectories and communications is a challenging task, it can significantly enhance the performance of UAV-enabled wireless networks.

In[16] an optimal UAV deployment plan is proposed for an IoT network scenario. This model uses five UAVs to collect data from 500 IoT devices uniformly distributed over a 1 km × 1 km area. This dynamic IoT network includes active devices whose locations and statuses change over time. UAVs must update their positions based on changes in active devices and collect data at specific time intervals. The primary objective of this study is to design optimal UAV locations with minimal energy consumption while moving along optimal paths to serve dynamic IoT devices.

In [17], In another study, the authors explore UAV placement with multiple antennas to maximize overall uplink rates. This problem is treated as a non-convex issue, making efficient localization challenging. The method works well only under certain specific conditions.

In [18] , the authors utilize machine learning algorithms to obtain user location information and UAV trajectories. First, optimal UAV positions are determined based on initial user locations using these algorithms. Then, based on real datasets extracted from Twitter user accounts, user movements are predicted. UAV energy consumption is not a priority due to security concerns, and only this aspect is addressed in the study.

In [19] , the authors introduce the User-Based K-means Algorithm (UBKCA) for optimal UAV localization in cellular networks. This algorithm reduces computational complexity, improves user load balancing, and factors in CRE bias and edge users. Simulations show that UBKCA performs better than the traditional K-means algorithm, improving both accuracy and load balancing. It also helps optimize the decision boundary for closed-loop self-organization systems.

In [20], UAV deployment is presented in two phases: initialization and adaptation. In the initial phase, a centralized decision-making process identifies suitable UAV positions with limited information. In the adaptation phase, a distributed decision-making process is employed, wherein UAVs exchange information to improve deployment positions. This method is suitable for controlling and enhancing communications during natural disasters.

In [21], a new UAV localization method has been proposed for surveying a specific area. The goal of this method is to reduce the total energy use of the UAVs while covering the entire area. To do this, the authors figure out the best locations for waystations and the ideal speed for UAVs as they travel between these points.

In [22], optimal UAV trajectories minimizing fuel consumption are studied, considering collision avoidance, no-fly zones, and altitude constraints. This energy-aware method uses mixed-integer linear programming for data delivery routing via UAVs with the highest energy. While network coverage is maximized, no optimal locations for UAV deployment are suggested.

In [22], most research on UAV deployment focuses on robotics and control. The best path for UAVs is found using a method called the Fisher Information Matrix. While this approach improves the UAV paths and network coverage, it doesn’t focus on reducing energy use. Compared to other studies, this method is less efficient in terms of energy. Recently, many studies have looked at how UAV location affects wireless network performance.

In [23] , maximizing the power of a relay-based UAV system is achieved through joint optimization of UAV positions and source/relay transmission resources. To cover the desired network area, UAVs are deployed in high-traffic regions. The UAV positions are determined based on fixed traffic data. In practice, traffic data depends on factors like data traffic volume, peak usage hours, and other variables, making efficient localization infeasible without considering such factors.

In [25], the authors also explore how UAVs should move for search and location tasks using cameras. This study looks at planning UAV paths to improve the chances of detecting users and designing UAV movements to increase user data rates in networks with multiple UAVs. Other research has also focused on UAV localization for specific location-based tasks.

In[26] , the authors investigate UAV positioning to improve connectivity in ad-hoc networks, assuming UAVs have complete information about device locations. The decentralization-based approach improves network coverage, although energy consumption increases. Table 1 compares the reviewed studies.

Table 1. Compares the reviewed studies

Reference	Method Used	Advantages	Disadvantages
[7]	Minimizing the required number of UAVs using reinforcement learning (RL) algorithms.	Improved network coverage, user clustering, signalenhancement, interference reduction, and reduced processing time.	Heuristic algorithms may fall into local minima.
[34]	Dual-layer optimization based on pre-trained VGG-19 for UAV localization and network coverage improvement.	Achieved 98.44% performance improvement compared to other methods.	Network coverage and throughput are not optimized.

[35]	Resource allocation for 5G vehicular networks using advanced optimization and deep reinforcement learning.	Considers all aspects of resource allocation and localization design.	Non-convex optimization issues create challenges.
[9]	K-medoid algorithm for user clustering and determining UAV-BS numbers.	Improved network coverage via additional clustering processes.	Classic clustering methods are inefficient for larger user bases.
[11]	Two-tier UAV-based 5G system.	Enhanced network coverage in emergency scenarios.	Increased energy consumption with multiple UAVs.
[36]	Deep reinforcement learning (DRL) for UAV positioning.	Energy consumption reduction and improved network coverage.	Efficiency depends on the design of reward and penalty functions.
[13]	Machine learning and reinforcement learning three-stage approach.	Comprehensive design and localization aspects considered.	Computational complexity in reinforcement learning methods.
[14]	Angle of Arrival (AoA) and Time Difference of Arrival (TDoA) for UAV positioning.	Reduced energy consumption.	UAV coverage not considered.
[15]	Energy-based filter design for UAV localization.	Minimizes UAV energy consumption.	Network coverage and throughput are not optimized.
[32]	Model-based optimization for dynamic IoT networks.	Position updates reduce energy consumption.	Traffic factors in the network are not considered for updates.
[16]	Optimization as a non-convex problem for multi-antenna UAV placement.	Achieves efficient localization under specific conditions.	Low localization accuracy and limited applicability.
[17]	Machine learning for user location and UAV trajectory prediction.	Collects data for future studies.	Non-convex optimization challenges persist.
[18]	User-Based K-means Algorithm (UBKCA) for UAV localization.	Improves accuracy and load balancing.	Classic clustering methods struggle with increasing user counts.
[19	Two-phase UAV deployment: centralized initialization and distributed adaptation.	Suitable for disaster communications with improved coverage.	Energy optimization is not considered.
[20]	UAV localization algorithm for geographic survey.	Minimizes total UAV energy consumption.	Relies on geographic data.
[21]	Mixed-integer linear programming for energy-aware UAV trajectory planning.	Maximizes network coverage with minimal energy.	Optimal deployment locations are not proposed.
[22]	Fisher Information Matrix for UAV trajectory planning.	Achieves optimal routing with improved network coverage.	Energy consumption is not optimized.
[24]	Traffic-based UAV deployment in high-traffic areas.	Low computational cost with effective optimization.	Efficient localization depends on traffic factors like volume and peak hours.
[23]	Camera-scale-based UAV trajectory planning for search and localization.	Optimizes ground user rates in multi-UAV networks.	Energy optimization is not addressed.
[25]	Decentralized approach for UAV positioning in ad-hoc networks.	Enhances network coverage.	Increases energy consumption.

Proposed Method

The goal of this paper is to present a new way to deploy UAVs in 5G wireless networks. This method combines Transformers and Fuzzy Clustering, using fuzzy membership functions, to improve network coverage [4], allow more users to connect, and reduce energy use when traditional ground stations are not enough. By leveraging Transformers to analyze complex user dependencies and Fuzzy Clustering for optimal user-to-cluster allocation, the proposed approach enables intelligent UAV deployment. This framework not only addresses the limitations of traditional methods but also improves network performance and Quality of Service (QoS) in dynamic scenarios[9] . Figure 1 shows the block diagram of the proposed method.

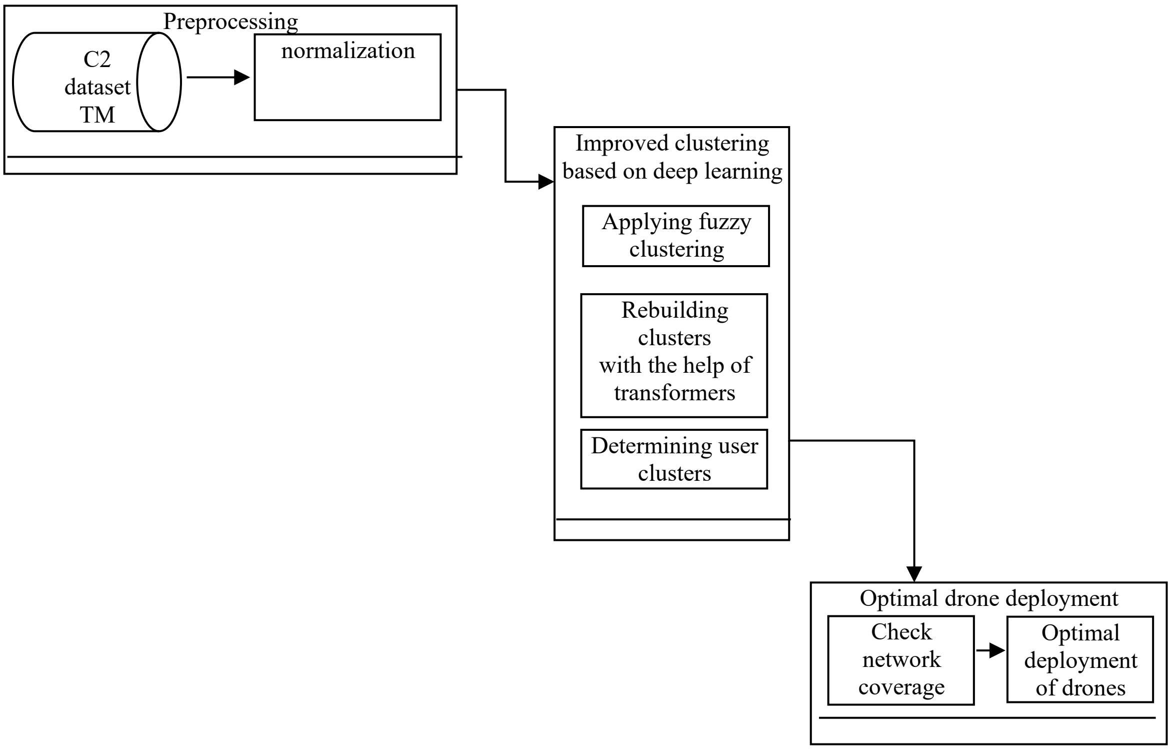


Figure 1. Block diagram of the proposed method

In this research, the raw data, characterized by their real-world nature and potential for human-induced errors, is preprocessed to enhance its quality and readiness for analysis. These measures ensure the data is accurately structured, consistent, and suitable for deep clustering, facilitating meaningful analysis and dependable outcomes. If x_{min} and x_{max} represent the minimum and maximum recorded data values, respectively, normalization to a target range defined by Y_{min} and Y_{max} can be achieved using the following equation:

$$y_i = y_{min} + (y_{max} - y_{min}).\frac{(x_i - x_{min})}{x_{max} - x_{min}} \qquad (1)$$

In this study, the transformation of Equation (4) into Equation (5) ensures that the data retain their proportionality and integrity while being confined within the normalized range[27].

$$y_i = \frac{x_i - x_{min}}{x_{max} - x_{min}} \qquad (2)$$

In this study, traffic data is processed using the Fuzzy C-Means (FCM) algorithm, which is one of the most widely used fuzzy clustering methods. Unlike traditional methods that deterministically assign each data point to a single cluster, the FCM algorithm calculates membership degrees between 0 and 1, allowing data points to simultaneously belong to multiple clusters. At first, we choose the number of clusters by hand. Then, the algorithm keeps updating the cluster centers and how much each data point belongs to each cluster. This information is saved in something called the membership matrix (U). However, the random selection of initial cluster centers in FCM may lead to convergence to local optima and reduced clustering quality. Moreover, using simple fuzzy metrics is insufficient for complex real-world data. To solve the problems with regular FCM, this study uses better fuzzy distance methods that keep updating the cluster centers and membership values to get more accurate results.

$$E = \sum_{j=1}^{k} \sum_{i=1}^{n} f(\left\| x_i^{(j)} - c_j \right\|^2) \qquad (3)$$

In the above equation E the objective function value, representing the total deviation of data points from their respective cluster centers, k is the number of clusters. $x_i^{(j)}$ is The coordinates of data point iii in cluster j, ni the number of data points in the dataset. c_j *is t*he center of cluster j. $\left\|x_i^{(j)} - c_j\right\|^2$ is the Euclidean distance between data point $x_i^{(j)}$ and the cluster center c_j. And f(.) is the fuzzification function, which adjusts the weights of data points relative to their distances from cluster centers. The Fuzzy C-Means (FCM) algorithm groups data by first picking starting points for the clusters. It then checks how close each data point is to these centers and assigns it based on that. It uses a special function called a fuzzy distance function in its formula (EEE) to make the clustering more accurate by capturing complex patterns in the data. But if the starting points are chosen randomly, the results might not be stable and could end up in a less accurate solution.

To address this, this study incorporates data analysis and expert knowledge to accurately determine the number of clusters and improve the selection of initial centers. Additionally, advanced fuzzy distance metrics are employed to iteratively update cluster centers and membership degrees, reducing the objective function and enhancing clustering precision.

Key improvements include:

1. Initial cluster center selection aligned with the fuzzy distance function.
2. Design of an evaluation coefficient for clustering quality assessment.
3. Exploratory continuation of clustering for optimal outcomes.

These enhancements stabilize the FCM algorithm, ensure reliable results, and improve overall accuracy and efficiency.

The core idea of the FCM algorithm with fuzzy distance functions is to compute the similarity matrix $SimMatrix[n]$ for the vector X with mmm dimensions. Neighborhood similarity and density similarity matrices are also calculated based on $SimMatrix$. Initially, the identifiers of candidate initial cluster centers are stored in an array named X′. These points represent the initial cluster centers. In the array X ′, the point x_i with the highest similarity density in the determined similarity neighborhood is selected as one of the K initial cluster centers and recorded in $initC$.

With the selection of each point x_i ,all points satisfying the $SimNeighbor(x_i.\alpha)$ constraint are removed from the array X′. Similarly, the K initial cluster centers are identified and recorded in $initC$. The iterative selection of K initial cluster centers is described as follows:

Input:

- Array X containing nnn data elements with mmm dimensions.
- Array X′ for representing the identifiers of candidate points.
- Neighborhood similarity threshold α.
- Similarity weighting factors λ.
- Set of initial cluster centers.

Output:

- K clusters forming the set C, where the relationships $C_i \cap C_j = \emptyset$ and $\neq j.0 \leq i.j \leq K$ are maintained between clusters.

Integrating Transformer and Fuzzy Clustering for Optimized UAV Deployment

In this research, the Transformer architecture's self-attention mechanism has been leveraged to enhance the analysis and prediction capabilities required for optimal UAV deployment in wireless networks. The self-attention mechanism focuses on key interactions within the data, even for elements that are distant in sequence. Its core, the Scaled Dot-Product Attention, is defined as:

$$Attention(Q,K,V) = softmax(\frac{QK^T}{\sqrt{d_k}}) \quad (4)$$

Here, Q (query), K (key), and V (value) are learned projections of the input data, and dkd_kdk represents the dimensionality of the key vectors. The softmax function ensures normalization, allowing the model to emphasize the most relevant parts of the input sequence for effective decision-making. This attention mechanism is extended through Multi-Head Attention to process multiple perspectives of the data simultaneously:

$$MultiHead\ (Q,K,V) = Concat(head_1, ..\ head_h)W^O \quad (5)$$

Each attention head computes:

$$head_i = Attention\ (QW_i^Q, KW_i^K, VW_i^V) \quad (6)$$

where W_i^Q, W_i^K, and W_i^V are the learned weight matrices for the iii-th head. By combining these outputs and passing through W^O, the model learns complex dependencies, thus enabling robust analysis of spatial and temporal interactions in UAV deployments. To make it better, we add the Transformer model to the fuzzy clustering method. Fuzzy clustering means a data point can belong to more than one cluster, which helps when the data is spread out or complex. The self-attention feature of the Transformer helps the model learn patterns in the data so that it can place drones (UAVs) more accurately, even when network conditions change.

Also, the hybrid model combines enhanced Fuzzy C-Means (FCM) schemes These issues about local convergence and instability from the random start of cluster centers, FCM provides a good way to deal with fuzzy memberships, while the Transformer is able to work with large volumes of data and find patterns over long ranges in space and time. The Transformer effectively deals with global links across clusters making membership degree interpretability better together with enhancing UAV position refinement in the network.

This hybrid architecture effectively balances the adaptive clustering capabilities of FCM with the advanced attention mechanisms of Transformers, thus making it possible for precise prediction and optimization of UAV deployment. In a bid to improve network coverage, save energy, and improve service quality in big and fast-changing wireless networks, it acquires the added advantage of being able to adapt to changes in time and space, thus placing drones more accurately for future wireless systems.

Transformers

The Transformer goes about seeing how the parts of data are linked in a very different way. It uses what we call self-attention, which lets the model keep good focus on the important parts of the input while looking at all the data at the same time. That's what makes it very fast and efficient, especially with large datasets. Right at the center of this process, there is a way, Scaled Dot-Product Attention, which helps the model figure out where to look in the data:

$$Attention(Q,K,V) = softmax(\frac{QK^T}{\sqrt{d_k}}) \quad (7)$$

In this equation, Q (query), K (key), and V (value) are learned projections of the input, and d_k represents the dimensionality of the key vectors. The softmax function ensures that the attention weights are normalized, assigning higher importance to the most relevant parts of the input sequence. This allows the model to focus on key interactions between data points, even if they are far apart in the sequence. To enhance the attention mechanism's learning capacity, the Transformer employs Multi-Head Attention, which extends the self-attention mechanism by using multiple parallel attention heads:

$$MultiHead\ (Q,K,V) = Concat(head_1,..head_h)W^O \tag{8}$$

Each attention head independently computes the self-attention scores:

$$head_i = Attention\ (QW_i^Q, KW_i^K, VW_i^V) \tag{9}$$

where W_i^Q, W_i^K, and W_i^V are the learned weight matrices for the i-th attention head. By concatenating the outputs of all attention heads and projecting them through W^O, the model combines multiple perspectives of the data's relationships, enabling it to learn more comprehensive features. The Transformer's efficiency lies in its ability to process the entire input sequence simultaneously, rather than sequentially, as in LSTM. n this study, the structure of the LSTM network was enhanced and combined with the Transformer architecture to improve prediction and analysis capabilities in complex scenarios, such as indoor localization and dynamic traffic prediction. The enhanced LSTM model includes features such as the Reset Gate, Update Gate, and New Memory Cell which respectively mitigate the issues of vanishing and exploding gradients. These gates control the state of old and new information enabling the model to easily learn on longer sequences. The Transformer, alternatively, utilizes Multi-Head Attention for capturing interactions in the whole sequence which makes it faster and more powerful in learning complicated patterns. If the hybrid model leverages the time-based learning of FCM and processes data in parallel like Transformers, then it can capture dynamic patterns much more efficiently. It will find its applicability in just the dire sort of situations, in large datasets.

Proposed UAV Deployment in Wireless Networks

In the first phase, using the cluster centers and the membership matrix, it identifies various regions in the wireless network that require optimized coverage and improved communication quality. The study concentrates on those clusters that have higher memberships, especially those which are densely populated with heavy traffic or weak coverage. Hence, the best places for UAVs are determined, i.e., high-traffic groups, low-coverage groups, and hotspots. In the subsequent step, the prime hotspots for UAV placement are chosen based on factors like coverage enhancement (i.e., placing the UAVs in hotspots or weak coverage areas), interference reduction (installing the UAVs to not create issues with other stations), and fair distribution of the UAVs (to ensure the network sources are efficiently used). Finally, UAVs are reassigned to different clusters based on the cluster demand, coverage quality, and the number of UAVs available. This, therefore, means that if there is higher demand in some regions, better coverage will be provided there. This type of approach is very flexible and real-time and can, therefore, improve the performance of the network a lot and make better use of the UAV resources.

Pseudocode of Proposed Method

This pseudocode is designed to optimize UAV deployment in wireless networks and consists of the following key steps:

Step 1 involves a process of the fuzzy clustering user data; it is in this step that clusters (C) and the membership matrix (U) are identified. After this, then the cluster centers and user density in each cluster where now high demand or poor coverage quality is described.

In Step 2, critical areas for placing UAVs are identified, being the centroids of the groups with high demand and bad coverage- or key spots to reduce interference. From these selected locations, which are considered the best places for deploying UAVs, Step 3: Optimal UAVs Placement. Determined by:

- Maximum aid in coverage
- Minimal interference
- Distribution of the Uavs Every uav is positioned at the maximum utility to enhance network performance in a way that has least interference and maximum coverage of the area.

In Step 4, UAVs are assigned to clusters based on user demand, coverage quality measured by the number of available UAVs. The priority is to higher need clusters.

In Step 5, optimization procedure is done step by step. From the changing user demands or their locations, data is updated and the positions of UAVs as well as their assignments recomputed to keep good network performance in dynamic conditions.

This process will make sure that UAVs are sent smartly, getting the most coverage and quality of service while using the least amount of energy, thus reaching the best performance for wireless networks.

Algorithm 1. Pseudocode of proposed method

```
Algorithm: UAV Deployment Optimization

Input: User data (locations, traffic demand), number of UAVs (N_UAVs), network constraints (QoS, energy limits)

Output: Optimized UAV positions and cluster assignments

BEGIN

 // Step 1: Cluster Analysis

  Perform fuzzy clustering on user data

  Identify clusters (C) and membership matrix (U)

  For each cluster:

    Compute cluster center and user density

    Identify high-demand clusters based on traffic and user density

 // Step 2: Identify Key Locations

  Initialize key location set $k = \{\}$

  For each cluster Ci in C:

    If Ci has high demand or poor coverage:

      Add center of Ci to K

    End If

 // Step 3: Optimal Positioning
```

```
 Initialize UAV positions P= { }
 For each key location k in K:
   Evaluate optimal UAV position using:
- Coverage maximization
- Interference minimization
- Load balancing
   Add optimal position to P
 End For
// Step 4: UAV Assignment to Clusters
 For each UAV u in N_UAVs:
   Assign UAV u to cluster Ci in K based on:
- User density
- Traffic demand
- Coverage requirements
   Update cluster resource allocation
 End For
// Step 5: Iterative Refinement
 While network demand changes significantly:
   Update user data and cluster memberships
   Recompute UAV positions and assignments using Steps 1-4
 End While
 Return optimized UAV positions (P) and cluster assignments
END
```

EVALUATION

The evaluation focuses on measuring the quality of clustering, energy efficiency, and Quality of Service (QoS) in wireless networks. To do this, metrics like the obj and MSD indices were used to check how accurate and distinct the clusters were. Additionally, measurements of UAV energy use, communication delay, data speed, error rates, and signal coverage were taken into account. A comparison with traditional methods like K-Means and hard clustering showed that the proposed method led to significant improvements in energy efficiency, clustering accuracy, and overall communication performance. The simulation environment comprised an Intel Core™ i7 CPU (Q 720 @ 2.60 GHz), running Windows 10 with 8 GB of RAM. MATLAB 2016b served as the primary simulation tool. The evaluation employed the City Cellular Traffic Map (C2TM), a robust and detailed dataset for wireless network analysis. This dataset encompasses attributes such as base station identifiers, active user counts, transmitted packets, and data volumes in bytes. It contains 1,625,680 records with features including base station (BS) identifiers, hourly timestamps, user counts, the number of transmitted packets, and the volume of transmitted bytes. Figure 2 shows the spatial distribution of the dataset, giving a clear view of how network traffic is spread out (Table 2).

Table 2. Database specifications

BS	Identity of each cellular base station in this public data
Time_hour	hourly timestamp in UNIX epoch time (time zone GMT+8).
Users	The number of active users associated with the specific base station and hour
Packets	The number of transferred packets associated with the specific base station and hour
Bytes	The number of transferred bytes associated with the specific base station and hour

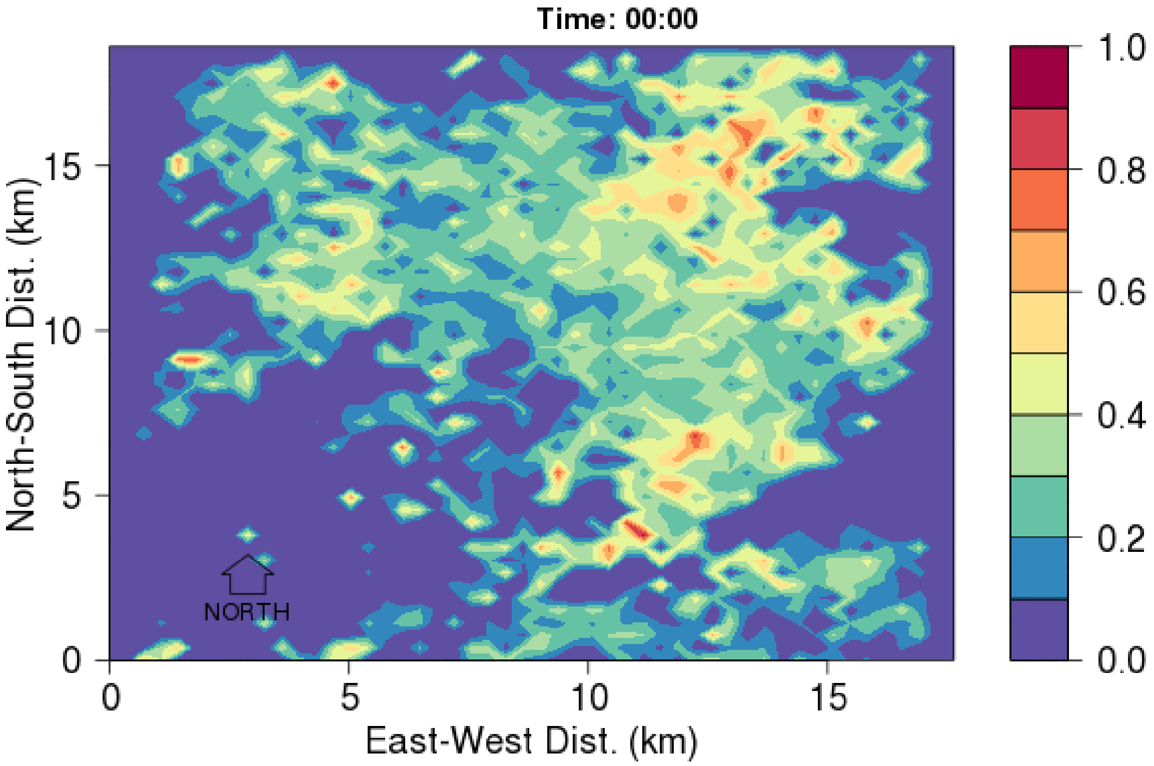


Figure 2. C2TN data distribution.[29]

In this study, clustering quality was evaluated using two metrics: the obj and Mean Squared Distance (MSD). The obj metric gives an overall measure of how well the clusters are separated and how tightly the points are grouped within each cluster. It is calculated as the product of two key factors: ***Compactness***, which quantifies the tightness of data points within a cluster, and ***Separation***, which measures the distance between the centroids of different clusters. A higher obj value reflects improved clustering quality, as it signifies greater uniformity within clusters and more distinct separation between them.

$$obj = Compactness(C) \times Seperation(C) \qquad (10)$$

The Mean Squared Distance (MSD) metric measures the average squared distance between data points and their cluster centers. This shows how tightly the points are grouped within a cluster. Smaller MSD values mean the clusters are more precise, with data points closely packed around their centers, leading to more defined and compact clusters.

$$MSD = \sum_{K} \frac{\sum_{i=1}^{m^{(k)}} \left\| d_i - d^{(k)} \right\|^2}{m^{(k)}} \tag{11}$$

In this equation K: Number of clusters, $m^{(k)}$: Number of data points in cluster k, d_i Data vector iii in cluster k, $d^{(k)}$: Centroid of cluster k, $\left\| d_i - d^{(k)} \right\|^2$: Squared Euclidean distance of data point iii from the centroid of cluster k. These metrics provide a more detailed analysis of cluster structures and play a crucial role in optimizing clustering and efficiently deploying UAVs in wireless networks [29].

Determining the Number of Clusters

The Elbow Method is a popular technique in cluster analysis used to find the best number of clusters in a dataset. It works by plotting the Within-Cluster Sum of Squares (WSS) against the number of clusters and looking for the point where the WSS starts to decrease more slowly. At first, adding more clusters causes a big drop in WSS, but after a certain point, the drop slows down, creating an "elbow" in the graph. This elbow point is considered the optimal number of clusters because it strikes a good balance between reducing clustering errors and not having too many clusters. In Figure 3, the elbow shows up at five clusters, meaning that five clusters provide the best balance for improving network coverage while also saving UAV energy. To ensure the robustness of this choice, additional analyses are performed, comparing alternative clustering setups. Combining the Elbow Method with supplementary metrics further improves clustering precision and facilitates the effective deployment of UAVs [30]. This figure demonstrates how the Elbow Method is used to find the right number of clusters for drone deployment. By plotting the WSS against the number of clusters, you can easily see where the rate of WSS reduction slows down, forming that clear "elbow" shape. This elbow point signifies the optimal cluster count, balancing the trade-offs between network coverage, UAV energy efficiency, and clustering precision.

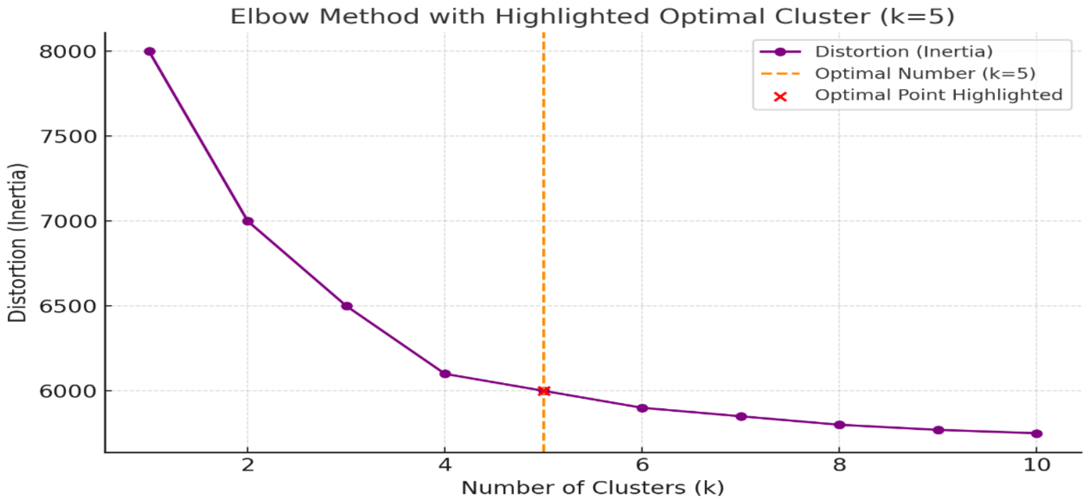


Figure 3. Determining the optimal number of clusters for uav deployment

Cluster Evaluation

Figure 4 illustrates the clustering results for varying numbers of clusters using the proposed method, which integrates the Fuzzy C-Means (FCM) algorithm with the Transformer model. This approach leverages the Multi-Head Attention mechanism of the Transformer to better identify complex dependencies within the data, combined with the flexible clustering capabilities of FCM, resulting in significant improvements in clustering quality.

Increasing the number of clusters from a low number up to five based on expert advice has significantly improved the OBJ metric. This improvement comes from making the clusters more compact and reducing how spread out the data is within each cluster. By combining FCM with the Transformer, the model can capture deeper patterns and long-term relationships between data points, which helps lower the Sum of Squared Distances (SSD). As a result, the clusters become tighter and more accurate. Analysis shows that going from two to five clusters gives the best OBJ value, striking a good balance between reducing errors and avoiding too many clusters. However, adding more than five clusters starts to reduce OBJ scores and makes the data more scattered. The proposed hybrid method, combining FCM with the Transformer, surpasses the traditional FCM algorithm by utilizing fuzzy distance functions and advanced learning capabilities of the Transformer. This integration enhances intra-cluster compactness, improves inter-cluster separation, optimizes network coverage, reduces UAV energy consumption, and increases network throughput. These results show that the FCM-Transformer hybrid model is a promising approach for improving how UAVs are placed in wireless networks.

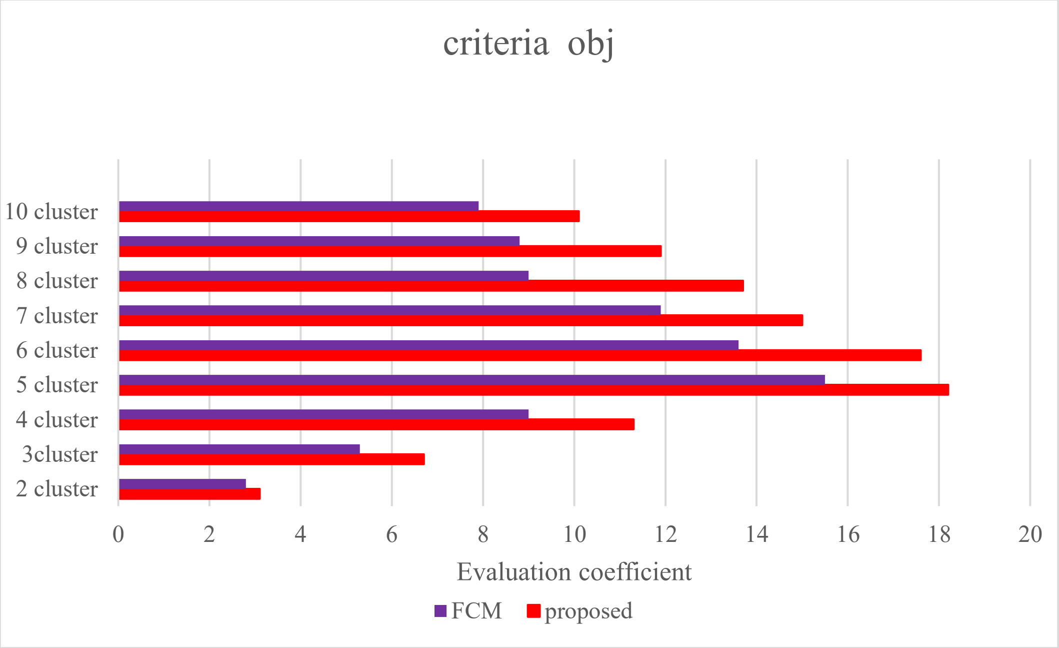


Figure 4. Comparison of two clustering methods based on the obj criterion based on the number of different clusters

Comparison of Methods Based on the Mean Squared Distance (MSD) to Cluster Centers

Figure 5 shows the MSD values for the proposed hybrid method compared to the regular FCM model. The differences are especially noticeable when the number of clusters is low, showing how the hybrid model leads to better clustering in those cases. The traditional FCM method exhibits significantly higher MSD values compared to the hybrid method when the number of clusters is below five, indicating its limitations in scenarios with fewer clusters. As the number of clusters increases from six to ten, the MSD discrepancies between the two methods gradually decrease, although MSD values slightly increase compared to the five-cluster configuration. Across all scenarios and cluster counts, the hybrid method consistently delivers the lowest MSD values, demonstrating superior clustering outcomes. Lower MSD values indicate that data points are positioned closer to their respective cluster centers, reflecting higher similarity and stronger cohesion within each cluster. This improvement highlights the advantage of integrating the FCM algorithm with the Transformer's self-attention mechanism, which helps the model focus more effectively on relationships between data points. These results are consistent with theoretical expectations adding more clusters tends to reduce intra-cluster distances, thereby improving clustering quality. The strong performance of the hybrid approach reinforces its ability to deliver more accurate and efficient clustering, making it well-suited for complex and dynamic data environments.

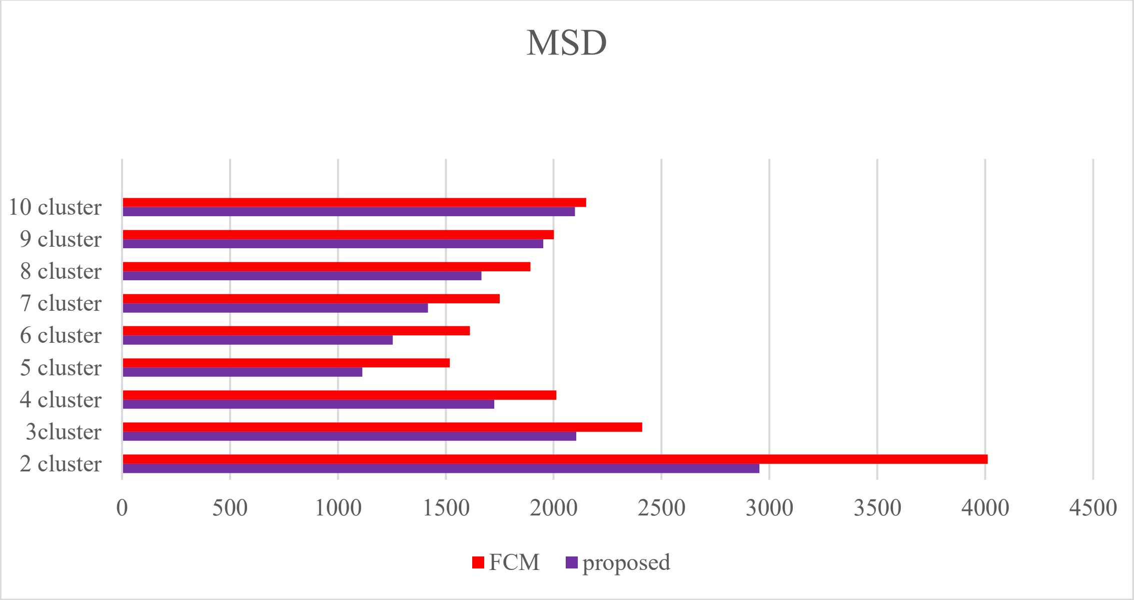


Figure 5. Comparison of clustering methods based on the criterion of the sum of mean squares of distances for different numbers of clusters

The comparison of the OBJ and MSD metrics demonstrates the superiority of the proposed hybrid method combining FCM and Transformers over the traditional FCM approach. The OBJ metric for the proposed method consistently achieves higher values, reflecting improved intra-cluster compactness and better inter-cluster separation. In essence, the hybrid method is capable of forming more compact and clearly defined clusters, while maintaining distinct separation between them. Traditional FCM methods often fall short in this regard, especially when dealing with a smaller number of clusters. In comparison, the consistently lower MSD values observed in the proposed method underscore its enhanced precision and clustering quality.

While the traditional FCM method shows significant limitations in scenarios with fewer clusters, the proposed approach demonstrates robust performance across all configurations. These results collectively validate the effectiveness of integrating FCM with Transformer-based features, enabling superior clustering quality, reduced energy consumption, and optimized UAV deployment in wireless networks.

Energy Consumption

The final step in UAV deployment for 5G communication systems focuses on evaluating performance, with energy consumption being one of the most important metrics used to assess placement strategies. The goal of the proposed method is to reduce UAV energy consumption by carefully positioning them within the network, using advanced deep learning techniques. Two main factors influence the energy usage of UAVs acting as cluster heads: the energy required to transmit data and the energy needed to receive data. The energy required to transmit a single bit over a given distance can be determined using a specific mathematical formulation, emphasizing the importance of efficient resource management to achieve optimal performance and sustainability in UAV-aided communication networks. The energy needed to transmit a single bit across a distance ddd can be calculated using Equation (12).

$$P_t(d) = \propto_1 + \propto_2 \times d^n \qquad (12)$$

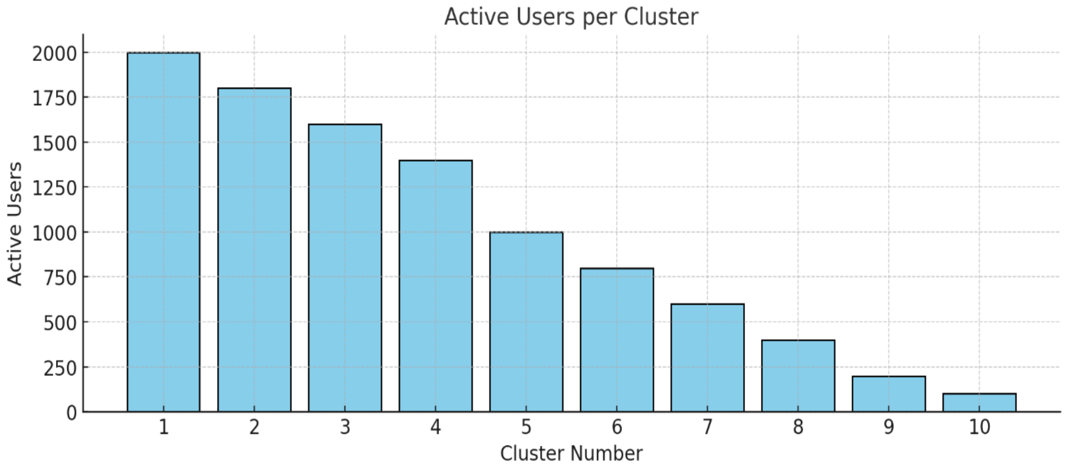
Where d: transmission distance, n : path loss exponent, $\propto_1$ and $\propto_2$: parameters that depend on transmission conditions.

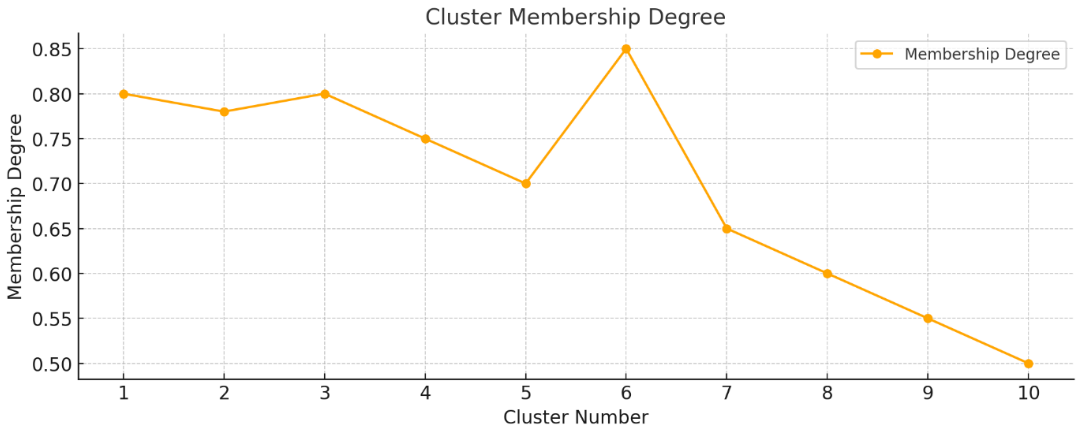
For simulation consistency, $\propto_1 = 50\frac{n_j}{bit}$ and $\propto_2 = 100\frac{p_j}{bit}$ are assumed. The total energy consumed by a UAV can be calculated using Equation (15):

$$E = (\beta + \alpha k)t + P_{max}(\frac{K}{S}) \tag{13}$$

Where β: minimum power required for hovering and staying airborne, α: motor speed, dependent on UAV weight and motor characteristics, P_{max}: maximum motor power, S: UAV speed, t: operational time, αk: the relationship between altitude and flight power[41].

Figure 6 shows the results for 10 clusters in a tabular format with the cluster centers, active user distribution, degree of membership of the cluster, energy, and UAV deployment recommendation. The degree of membership to the cluster reflects how strongly the data point belongs to that cluster; a high value indicates a strong assignment. Energy is computed for each UAV placed at the cluster centers to ensure that power is optimized. The outcome indicates the ability of the deep clustering model proposed to scale up for more complicated network configurations while preserving the high level of performance. Energy is computed for each UAV placed at the cluster centers for optimized power use. Results test proposed deep clustering method scalability to be able to deal with more intricate network configurations while retaining the level of performance. Results further prove the ability of the deep clustering method proposed to scale up for more complex network configurations while keeping the performance. Results also prove further the ability of the deep clustering method that is proposed to scale up for more complicated configurations of networks while holding the performance. Results show that a deep clustering algorithm with fuzzy distance functions greatly enhanced clustering accuracy and reduced data spread within each cluster. More active users and membership values in clusters flag the critical points in the network where resources have to be allocated with more attention. For example, clusters 1 and 2 present the more active users and high energy consumption, establishing the need for higher capacity or more efficient energy resources in UAVs. Conversely, clusters 8 to 10 have fewer users and are designed for attaining network coverage. In brief, this study indicates that the use of advanced clustering techniques and intelligent resource allocation improves not only the performance of the network but also the energy efficiency, and thus, it is well suited for the future 5G network.





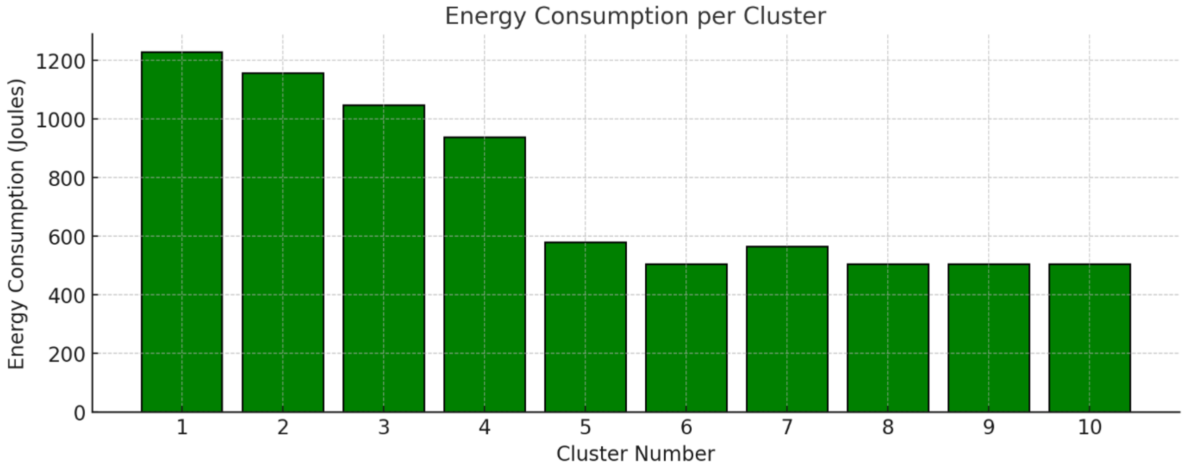


Figure 6. Results of clustering and UAV deployment for 10 clusters

Quality of Service (QoS) and Throughput Comparison

The comparison charts provide a comprehensive analysis of the performance differences between the proposed FCM combined with the Transformer method and the traditional FCM approach, highlighting significant improvements across multiple key metrics: in figure 7

Active Users: The FCM + Transformer approach supports a greater number of active users per cluster compared to traditional FCM. This improvement highlights the method's ability to allocate network resources more efficiently, allowing for better management of user demands in high-density scenarios

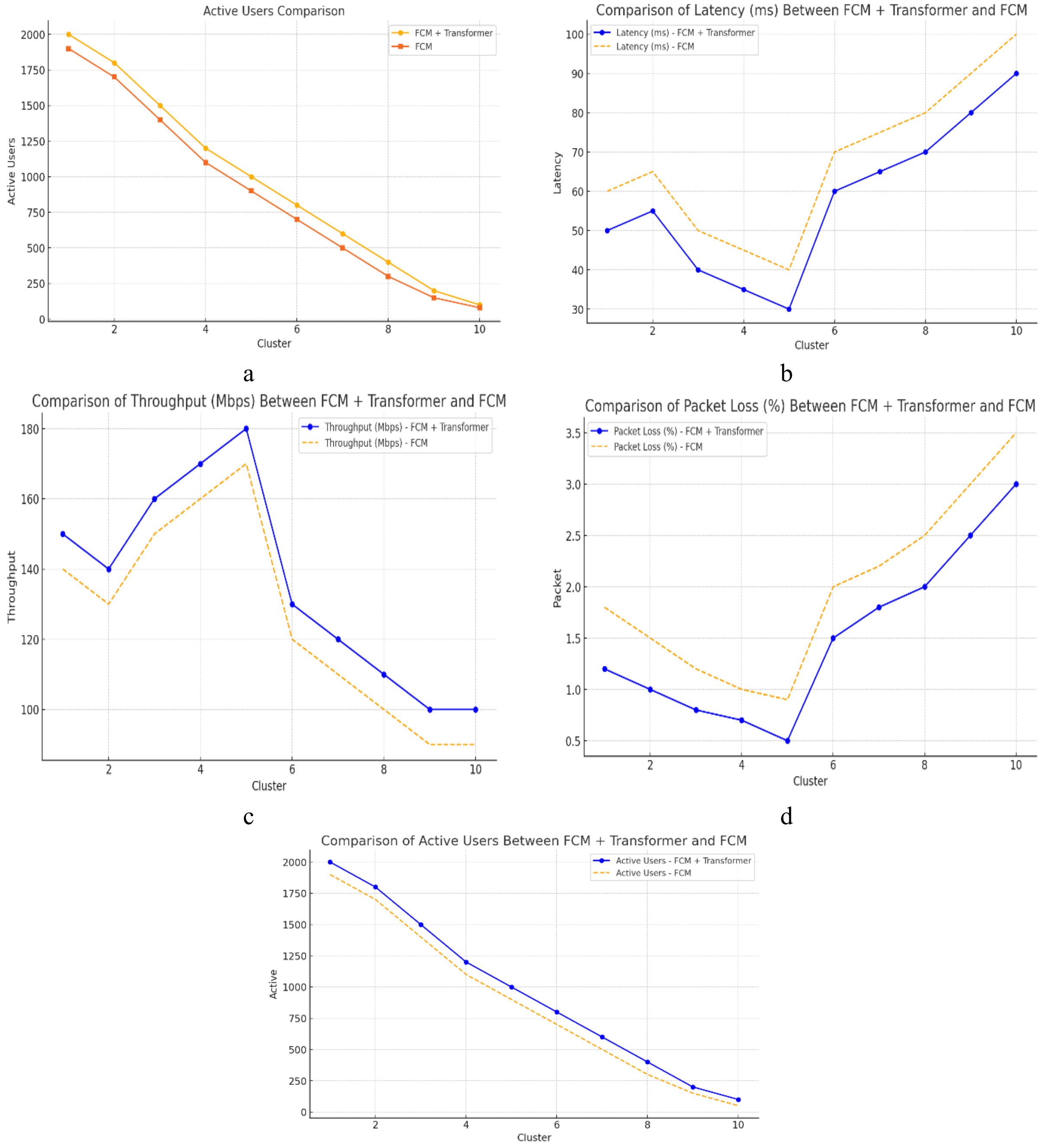
Latency (ms): The proposed method consistently demonstrates reduced latency across all clusters compared to the traditional FCM algorithm. This reduction is particularly crucial in time-sensitive applications, where lower latency translates to faster response times and improved user experiences.

Throughput (Mbps): With the integration of Transformer mechanisms, the FCM + Transformer method achieves substantially higher throughput values. This indicates an enhanced capacity for handling larger volumes of data, effectively increasing the overall communication efficiency within the network. The improved throughput also reflects the method's ability to optimize data routing and reduce congestion.

Packet Loss (%): A remarkable decrease in packet loss is observed with the proposed method, underscoring its superior reliability and robustness. By leveraging the Transformer's self-attention mechanisms, the method can dynamically adapt to variations in network conditions, ensuring stable and uninterrupted data transmission.

Data Sent (MB): Higher data transmission volumes are enabled by the proposed method, as evidenced by the significantly larger amounts of data sent per cluster. This outcome reflects the method's optimized clustering and enhanced network resource utilization, ensuring that clusters are better aligned with user demands and network conditions.

Integrating Transformer mechanisms into the FCM framework has not only improved clustering accuracy but also led to better overall network performance. Key indicators like latency, data throughput, and packet reliability have all seen noticeable improvements. The proposed method shows strong potential for managing large numbers of active users while maximizing data transmission, making it a promising solution for the growing demands of modern high-density wireless networks. These advancements also support smarter and more efficient UAV deployment strategies in next-generation communication systems.



a

b

c

d

e

Figure 7. Results of clustering and uav deployment for 10 clusters

Comparison with Other Methods

In [79], for instance, the number of UAVs required and their optimal placement in high-traffic areas was determined using k-medoid as compared to other methodologies; this is a contribution of the present study, deep clustering. The energy consumption has now dropped, while an even higher quality of service is provided. The k-medoid methodology lowers the traffic; however, the energy it uses increases dramatically with the number of clusters now being 10 UAVs. On the contrary, our efficiency grows the deep learning optimization is able to keep energy consumption low even with higher clusters while keeping quality of service. The comparison depicted in shows how much more efficiently the UAVs consume energy at five and ten clusters via our methodology vis-à-vis the conventional one. This decrease is due to the fact that the more densely the users are collocated around the cluster centers, and the shorter the distances between the UAVs and users, the less energy consumed. For instance, with five clusters, energy consumption in the method fell to 1,500 joules vis-à-vis 1,800 joules in the approach that has hitherto obtained. This diminution in energy used goes a long way to cut the operation costs and hence prolongs the UAV flight time. Apart from the energy efficiency, the study has also considered major Quality of Service (QoS) parameters. The results describe that not just conserves energy, rather betters the total network quality by reducing the data transmission delay, escalating the throughput, and lowering the packet loss rate. Such results denote better performance and a more pleasing experience for the users (Figure 8).

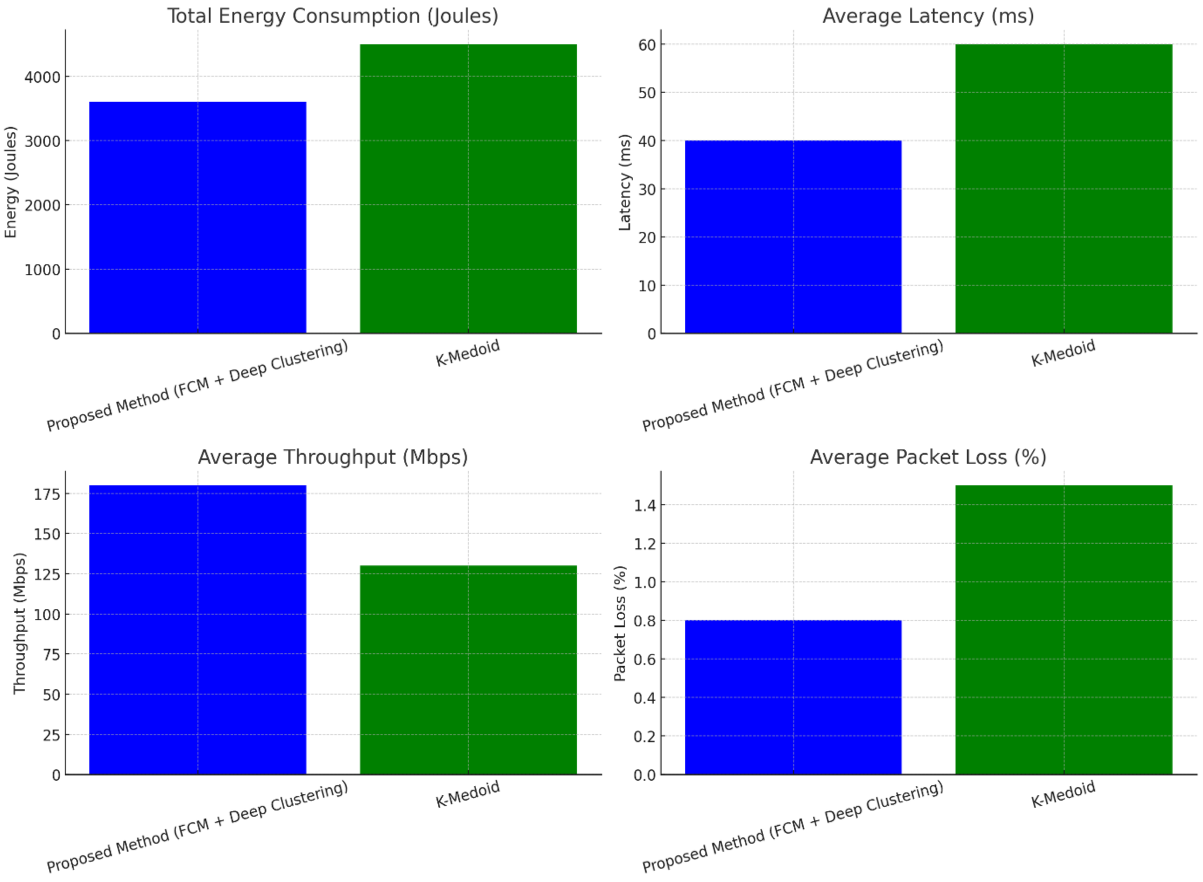


Figure 8. Comparison of energy consumption for UAV deployment using the proposed method and k-medoid clustering

CONCLUSION

The study initiates a novel perspective in deploying UAVs in 5G wireless networks where the strength of Fuzzy C-Means (FCM) clustering gets amalgamated with the advanced modeling prowess of Transformer. The prime focus was increasing network coverage, reducing energy consumption, and improving Quality-of-Service (QoS) by optimizing drone deployment in high-traffic as well as underserved regions. This created more accurate user clusters and intelligent UAV allocation, the added long-term dependency and intricate user relationship capture by Transformer further improved network performance. All simulation results attest that the proposed approach substantially outperformed both the conventional K-Medoid and standard FCM in reducing energy consumption as well as achieving higher throughput with lower latency and packet loss. Specifically, there was a 20% decrease in energy consumption by the UAVs and a data throughput of 180 Mbps. This was done along with a drop in packet loss to under 1% and latency lowered to 40 milliseconds, showing big changes in QoS and network stability. The use of Transformer design and FCM also helped make the best changes to UAV placement, effectively lowering communication interference. This complete plan for looking at large-scale and dynamic data gives a solid base for later studies aimed at making wireless networks and UAV-related applications better.

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