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Enhancing V2V Communication in Autonomous Vehicles with Novel Clustering and Fuzzy Logic Framework

by

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List of Abbreviations

AVs Autonomous Vehicles

CH Cluster Head

MVC Moving Vehicle Clustering

RSUs Roadside Units

SUMO Simulation of Urban Mobility

VANETs Vehicular Ad hoc Networks

Acknowledgment

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Abstract

Autonomous vehicles rely on a clustering-based packet forwarding framework to communicate with one another in infrastructure-less environments. This framework typically involves clustering the vehicles into groups using the K-Means algorithm, identifying each group's cluster heads (or leaders), and achieving inter-cluster communication through cluster heads. Since K-Means cannot handle arbitrary shapes and dynamic traffic conditions, the current clustering-based packet forwarding framework suffers from poor packet delivery ratios and network congestion. To tackle these problems, this paper proposes a novel density-based clustering algorithm named moving vehicle clustering (MVC) to cluster the vehicles in a network and identify the intelligent cluster head (CH) in each cluster with a novel fuzzy logic solution. The proposed framework achieves stable communication and optimized packet transactions. The experiments conducted using the Simulation of Urban Mobility (SUMO) and NS-3 network simulator demonstrate that the proposed framework significantly improves packet delivery ratios (over 85%), reduces delay, lowers queue sizes, and increases throughput.

Chapter 1

Introduction

1.1 Background and Overview

The development of autonomous vehicles (AVs) has marked a revolutionary transformation in the transportation sector. Unlike conventional vehicles that depend entirely on human control, autonomous vehicles employ sophisticated sensors, powerful processing units, and intelligent algorithms to perceive their environment and navigate without direct human intervention. These self-driving vehicles promise to enhance road safety by reducing human errors, which are a leading cause of traffic accidents. In addition to safety improvements, AVs offer potential benefits including increased traffic efficiency, reduced fuel consumption and emissions, and improved mobility for non-driving populations such as the elderly and disabled.

While autonomous vehicles are equipped with various sensors, such as cameras, LiDAR, radar, and GPS, these devices are limited to sensing the immediate surroundings. They are often constrained by line-of-sight and environmental factors. Critical driving scenarios often require information beyond the vehicle's onboard perception capabilities. For instance, detecting obstacles around corners, anticipating sudden traffic slowdowns ahead, or responding promptly to emergency vehicles demands a broader situational awareness.

1.2 Vehicular Communication Paradigms

Vehicular communication encompasses several paradigms, each contributing uniquely to the overall connected vehicle environment. Vehicle-to-Vehicle (V2V) communication allows direct information exchange between vehicles, facilitating immediate alerts such as collision warnings or cooperative driving strategies. For example, on a busy highway, if one vehicle brakes suddenly, it can immediately broadcast an alert to the vehicles behind it using V2V communication. This quick warning allows following vehicles to reduce speed preemptively, potentially avoiding rear-end collisions that might occur if drivers relied solely on their sensors.

Vehicle-to-Infrastructure (V2I) communication involves interaction with fixed roadside units or cellular base stations, which can assist in traffic management and data aggregation. Broadening this scope, Vehicle-to-Everything (V2X) communication integrates connections with pedestrians, cyclists, and network entities, creating a comprehensive ecosystem of cooperative road users. Among these, V2V communication plays a critical role, especially in environments lacking sufficient roadside infrastructure.

1.3 Challenges in Infrastructure-Less Vehicular Networks

While many vehicular networks rely on roadside infrastructure, such as cellular towers or dedicated units, infrastructure deployment is often costly, geographically limited, or infeasible in certain scenarios. Rural areas, mountainous regions, temporary construction zones, and disaster-stricken environments frequently lack established communication infrastructure. For instance, in a mountainous rural area, cellular towers and roadside units may be sparse or non-existent. Vehicles traveling through this region cannot rely on fixed infrastructure to exchange information. Instead, they form an ad hoc network where each vehicle communicates directly with its neighbors. Due to steep slopes and tunnels, wireless signals may be intermittently blocked, causing frequent disconnections and requiring the network to quickly reorganize itself.

Consequently, autonomous vehicles in these environments must form decentralized, infrastructure-less networks known as Vehicular Ad hoc Networks (VANETs), where vehicles communicate directly without centralized control.

Infrastructure-less VANETs exhibit unique characteristics that complicate communication design. The network topology is highly dynamic due to vehicle mobility, causing frequent changes in connectivity. Vehicle density varies widely across time and space, affecting network stability and communication quality. Furthermore, strict real-time requirements for safety-critical applications impose low-latency and high-reliability constraints on message exchange. Designing robust communication protocols under these challenging conditions remains an open research problem.

1.4 Clustering in Infrastructure-Less Vehicular Networks

Clustering has emerged as an effective technique to address the challenges of dynamic and large-scale vehicular networks. In clustering, vehicles are grouped into smaller, manageable clusters based on proximity or communication range, with a cluster head (CH) responsible for coordinating intra-cluster communication and acting as a gateway to other clusters. This hierarchical organization reduces network overhead, improves scalability, and simplifies routing.

For example, consider a busy urban intersection during rush hour. Vehicles approaching the intersection are grouped into clusters based on their physical proximity and communication range. One vehicle in each cluster acts as the cluster head, coordinating message exchange among cluster members. This organization reduces the number of redundant broadcast messages and ensures efficient data dissemination, preventing network congestion and improving communication reliability.

Clustering offers several benefits in vehicular networks, including enhanced network scalability, reduced communication overhead, improved message delivery reliability, and efficient utilization of bandwidth. However, clustering in vehicular networks is complicated by factors such as high vehicle mobility, varying traffic densities, limited wireless range, and the need for rapid adaptation to topology changes.

1.5 Limitations of Traditional Clustering Algorithms

Traditional clustering algorithms such as K-Means have been widely used due to their simplicity and efficiency. K-Means partitions vehicles into a fixed number of clusters by minimizing the distances between vehicles and cluster centroids. However, this approach presents several limitations in vehicular environments. For instance, using K-Means clustering in a city grid with traffic lights might result in clusters shaped as circles around centroids, ignoring the fact that vehicles align mostly along road lanes. Additionally, during peak hours when vehicle density surges, the fixed number of clusters may not adapt to increased traffic, leading to overloaded clusters and reduced communication quality. Isolated vehicles stuck at a traffic light might be forced into clusters where they do not share meaningful communication, degrading overall network performance.

Moreover, K-Means does not consider important factors like vehicle speed, direction, or link quality, which are critical for maintaining stable clusters in a mobile environment. It is also sensitive to outliers, which can distort cluster formation and affect the efficiency of communication.

1.6 Proposed Approach: Moving Vehicle Clustering and Fuzzy Logic-Based Cluster Head Selection

To overcome these challenges, this thesis proposes a novel Moving Vehicle Clustering (MVC) algorithm that leverages a density-based clustering approach tailored for the unique characteristics of vehicular networks. Unlike K-Means, MVC does not require prior knowledge of the number of clusters and can identify clusters with arbitrary shapes that better reflect real-world traffic patterns. For example, the MVC algorithm can dynamically detect a high-density traffic jam on a highway and form elongated clusters that follow the lane layout. Vehicles outside the jam, such as those in adjacent lanes or moving at higher speeds, are treated as noise or separate clusters. This flexibility ensures that clusters correspond more closely to real traffic situations.

Furthermore, the thesis introduces a fuzzy logic-based cluster head selection mechanism that evaluates multiple parameters, including vehicle speed and distance. By combining these metrics using fuzzy logic, the algorithm selects the most suitable vehicle to act as the cluster head, improving cluster stability and reducing the frequency of cluster head changes. For instance, the fuzzy logic method might select a vehicle moving steadily at a moderate speed with strong links to neighbors as the cluster head, avoiding fast-moving vehicles that frequently change positions. This leads to more stable clusters and enhances communication reliability.

1.7 Research Objectives

The main objective of this research is to design and evaluate an infrastructure-less clustering framework that facilitates efficient and stable communication among autonomous vehicles. To achieve this, the study aims to develop the Moving Vehicle Clustering algorithm, which can dynamically adapt to varying vehicle densities without relying on a predefined number of clusters. In addition, a fuzzy logic-based cluster head selection mechanism is proposed to intelligently incorporate multiple vehicle parameters, thereby optimizing cluster management and improving overall stability. The proposed framework is implemented and simulated using the NS-3 network simulator to thoroughly evaluate its performance. Furthermore, a comparative analysis is conducted against traditional clustering algorithms such as K-Means, focusing on key performance metrics including packet delivery ratio, communication delay, throughput, and network queue size.

1.8 Contributions

This thesis presents several significant contributions to the field of autonomous vehicular networks. First, it introduces a novel density-based clustering algorithm specifically designed to address the dynamic and irregular topology inherent in vehicular environments. Building on this, an intelligent cluster head selection mechanism is proposed, leveraging fuzzy logic to enhance cluster stability by incorporating multiple real-time vehicle parameters. Finally, the effectiveness of the proposed approach is thoroughly validated through comprehensive simulations and performance evaluations, which demonstrate its clear advantages over conventional clustering methods in infrastructure-less autonomous vehicle scenarios.

This thesis work was accepted at the IEEE International Conference on Fuzzy Systems (FUZZ-IEEE), 2025 [1].

1.9 Thesis Organization

The remainder of this thesis is organized as follows: Chapter 2 reviews related work on clustering and cluster head selection in vehicular networks. Chapter 3 presents the detailed methodology, including the MVC algorithm and fuzzy logic cluster head selection design. Chapter 4 describes the simulation setup, implementation details, and performance evaluation. Chapter 5 discusses the results and their implications. Finally, Chapter 6 concludes the thesis and outlines directions for future research.

Chapter 2

Literature Review

This chapter comprehensively reviews existing research related to communication in autonomous vehicle (AV) networks, particularly in infrastructure-less environments. The discussion is organized into three key thematic areas: (1) communication paradigms in AV networks, (2) clustering techniques for vehicular environments, and (3) cluster head (CH) selection strategies using fuzzy logic. This review highlights the state-of-the-art techniques, identifies key limitations, and sets the foundation for the novel approach proposed in this thesis.

2.1 Communication in Autonomous Vehicle Networks

Reliable and timely communication is fundamental to autonomous vehicles' safe and efficient operation. AVs rely on onboard sensors for environmental perception and communication systems to interact with other vehicles and external infrastructure. In well-equipped urban areas, communication predominantly utilizes Vehicle-to-Infrastructure (V2I) technologies, where Roadside Units (RSUs) serve as intermediaries for data dissemination and control. However, such infrastructure is often unavailable in rural, underdeveloped, or temporary settings, making Vehicle-to-Vehicle (V2V) communication critical for autonomous navigation and cooperative driving.

Extensive research has underlined the importance of V2V communication for enabling real-time data exchange related to traffic conditions, obstacle warnings, and route optimization [2–4]. V2V networks in infrastructure-less environments, however, face several challenges. These include high vehicle mobility, frequent topology changes, and fluctuating node densities, which make it challenging to maintain stable links and consistent connectivity [5, 6].

Several communication protocols have been introduced to address these challenges, ensuring high reliability, low latency, and scalability in dynamic environments [7, 8]. Protocols like Dedicated Short-Range Communication (DSRC) and Cellular-V2X (C-V2X) have made significant progress, but their effectiveness diminishes in scenarios with sparse vehicle distribution or lacking supporting infrastructure. Consequently, there is a growing need for decentralized, adaptive communication frameworks that operate robustly across varying traffic scenarios.

2.2 Clustering in Vehicular Networks

With the rise of autonomous vehicles (AVs), ensuring efficient and reliable communication in infrastructure-less environments remains a critical challenge. Traditional wireless communication frameworks, such as RSUs and cellular networks, are often unavailable in highly dynamic vehicular networks, necessitating decentralized communication. To address this, researchers have explored clustering-based techniques to enhance communication efficiency and reduce packet loss. Vehicle-to-vehicle (V2V) communication enables decentralized data exchange, but selecting adaptive clustering approaches remains challenging, as traditional methods struggle with dynamic network conditions [9, 10].

Clustering is a widely used technique to manage communication complexity in dynamic vehicular networks. The main idea is to group nearby vehicles into clusters, where one vehicle acts as the Cluster Head (CH) to coordinate communication. Clustering reduces network overhead, enhances stability, and improves routing efficiency.

Among clustering techniques, **K-Means** has been widely studied for structuring vehicular networks and reducing communication overhead [11]. While effective in some scenarios, K-Means has notable limitations:

- It requires the number of clusters (K) to be known in advance, which is impractical when vehicle counts fluctuate.
- It assumes clusters are spherical and evenly distributed, which is unrealistic in real-world road environments.
- It is sensitive to outlier vehicles, which may be misclassified and lead to communication inefficiencies.
- Frequent re-clustering is needed as vehicles move, adding computation and delay.

To address these limitations, researchers have investigated alternative approaches, including machine learning-based clustering and CH selection techniques [12]. While these methods offer adaptivity and learning capabilities, they often demand high computational resources and extensive training data, making them unsuitable for real-time or lightweight AV communication systems.

In contrast, density-based clustering techniques, particularly DBSCAN, have shown promise in vehicular scenarios. DBSCAN does not require the number of clusters to be specified in advance and can effectively detect clusters of arbitrary shapes while isolating noise points. These properties make it more suitable for road networks with uneven vehicle distributions and dynamic traffic flows. Moreover, DBSCAN adapts more naturally to changes in local vehicle density, making it an ideal foundation for clustering in infrastructure-less, real-time vehicular communication networks.

2.3 Cluster Head (CH) Selection Techniques

Cluster Head (CH) selection is vital in maintaining cluster stability and ensuring efficient intra- and inter-cluster communication. An ideal CH should be relatively stable (i.e., low mobility), highly connected, and optimally located within the cluster. Traditional CH selection schemes, such as those based on the lowest node ID, highest degree, or distance-based metrics, are static and often fail to adapt to dynamic vehicular environments, leading to frequent re-elections and increased communication disruptions.

To overcome these limitations, fuzzy logic has emerged as a powerful and adaptive tool for CH selection in dynamic networks. Fuzzy logic systems evaluate multiple input parameters simultaneously and apply heuristic rules to make real-time decisions, even under uncertainty and imprecise data [13–16]. In the context of CH selection, fuzzy logic typically considers factors such as:

- **Speed**: Slower vehicles are more likely to maintain cluster membership.
- **Direction**: Vehicles moving in similar directions stay connected longer.
- **Connectivity**: Highly connected vehicles serve better as CHs.

By assigning membership values and applying fuzzy inference rules, the system can evaluate the suitability of a node to act as a CH. Studies have shown that fuzzy logic-based CH selection improves overall network lifetime, reduces re-clustering frequency, and enhances packet delivery performance [17, 18].

Despite these advantages, the existing literature integrates density-based clustering and fuzzy logic-based CH selection only partially. Most prior works address these aspects in isolation, leaving a gap in developing a unified, intelligent clustering framework that combines the strengths of both techniques.

The reviewed literature demonstrates the importance of adaptive and intelligent communication frameworks for infrastructure-less AV networks. While traditional methods like K-Means clustering and static CH selection techniques offer basic organizational benefits, they fall short in handling the decentralized and highly dynamic nature of real-world vehicular traffic. Likewise, machine learning-based methods provide adaptivity but are computationally intensive and lack real-time applicability.

To bridge this gap, this thesis proposes a novel Moving Vehicle Clustering (MVC) algorithm, inspired by density-based techniques like DBSCAN, to dynamically adapt to vehicular topology without requiring pre-defined parameters. This is coupled with an intelligent fuzzy logic-based CH selection mechanism that considers real-time vehicle dynamics, such as speed, direction, and connectivity, to ensure robust and stable communication.

The proposed method addresses key limitations by integrating clustering and CH selection into a unified framework. Simulation-based evaluation in NS-3 further demonstrates the proposed approach's superior performance compared to traditional methods, validating its potential for deployment in real-world autonomous vehicle networks.

Chapter 3

Proposed Framework

The proposed framework optimizes communication in autonomous vehicular networks by leveraging a density-based clustering approach. This method ensures efficient data dissemination and network stability, even in infrastructure-less environments. The framework consists of three key steps:

1. **Moving Vehicle clustering of vehicles** using MVC to dynamically group vehicles based on their spatial proximity.
2. **Cluster head selection** using fuzzy logic, considering key parameters such as speed and coordinates of the vehicles to ensure optimal data transmission.
3. **Efficient intra-cluster and inter-cluster communication**, where cluster heads manage data exchange among vehicles and coordinate with other cluster heads to enhance network performance.

The following subsections provide a detailed explanation of each step.

3.1 Moving Vehicle Clustering

Step 1: Clustering the AVs

Definition 1 ***(Location Dataset.)*** *Let $V = \{v_1, v_2, \cdots, v_n\},\ n \geq 1$, be the set of vehicles in a road network. The location dataset, denoted as L_{ts}, represents the set of locations of all vehicles in V at a timestamp $ts \in \mathbb{R}^+$. That is, $L_{ts} = \{l_1, l_2, \cdots, l_n\}$, where $l_i = (x_i, y_i) \in \mathbb{R}^2$ denotes the spatial coordinates of vehicle $v_i \in V$ on a two-dimensional plane.*

Example 1 *Let $V = \{v_1, v_2, \cdots, v_6\}$ be the set of six vehicles in a road network. If the vehicle v_1 is located at the point $(10, 10)$ at a timestamp $ts = 1$ in a two-dimensional coordinate system, then its location $l_1 = (10, 10)$. Similarly, the location dataset containing the set locations of all vehicles at $ts = 1$, i.e.,*
$L_1 = \{(10, 10), (11, 13), (12, 14), (50, 50), (51, 53), (100, 100)\}$.

Definition 2 ***(Neighbors of a vechicle.)*** *Let v_i and v_j be two vehicles such that $v_i, v_j \in V$ and $v_i \neq v_j$. The vehicle v_j is said to be a neighbor of vehicle v_i if the distance*

Algorithm 1 MVC Algorithm

Require: Location dataset (L) at timestamp ts, maximum distance threshold ($maxDist$), neighborhood size ($minNS$)
Ensure: Clusters of locations and noise labelling at timestamp ts

Mark all locations in L as **unvisited**
for each location l in L at timestamp ts **do**
    if l is **visited then**
        continue to the next location
    Mark l as **visited**
    $Neighbors \leftarrow$ regionQuery$(L, l, maxDist, ts)$
    if $|Neighbors| < minNS$ **then**
        Mark l as **noise**
    else
        Create a new cluster C
        Add l to cluster C
        expandCluster$(L, l, Neighbors, C, maxDist, minNS, ts)$

between them is no more than the user-specified maximum distance ($maxDist$) threshold value. That is, v_j is a neighbour of v_i if $dist(l_i, l_j) \leq maxDist$, where $dist(.)$ is any distance function that satisfies the commutative property, such as Euclidean and Geodesic distance. Let $N_{v_i} \subseteq V$ denote the set of all vehicles in V neighbors to the vehicle v_i.

Example 2 *Let us consider the vehicles $v_1 = (10, 10)$, $v_2 = (11, 13)$, and $v_6 = (100, 100)$. Let the distance measure be Euclidean distance. For the vehicle v_1, $dist(v_1, v_2) = 3.16$ and $dist(v_1, v_6) = 127.28$. If the user-specified $maxDist = 5$, then we consider v_2 as the neighbor of v_1 as $dist(v_1, v_2) \ngtr maxDist$. In a similar way, the neighbors are calculated for all vehicles.*

Algorithm 2 expandCluster$(L, l, Neighbors, C,$ $maxDist, minNS, ts)$

for each location l' in $Neighbors$ at timestamp ts **do**
    if l' is **unvisited then**
        Mark l' as **visited**
        $Neighbors' \leftarrow$ regionQuery$(L, l', maxDist, ts)$
        if size of $Neighbors' \geq$ minNS **then**
            $Neighbors \leftarrow Neighbors \cup Neighbors'$
    if l' is not yet assigned to any cluster **then**
        Add l' to cluster C

Definition 3 ***(Core and noisy vehicle.)*** *A vehicle $v_i \in V$ is said to be a core vehicle if its neighborhood size is greater than or equal to the user-specified minimum neighborhood size ($minNS$). Otherwise, v_i is a noisy vehicle. That is, v_i is a core vehicle if $|N_{v_i}| \geq minNS$; otherwise noisy vehicle.*

Example 3 *Let the minimum neighborhood size ($minNS$) be 3. Vehicles v_1, v_2, and v_3 have at least three neighbors, so they are considered* core vehicles. *In contrast, (v_4) has fewer than three neighbors, which is classified as a* noisy vehicle.

Definition 4 ***(Cluster Formation.)*** *At each ts, starting from a core point l_i, its neighbors $l_j \in N(l_i)$ are examined. If l_j is unvisited and also a core point, its neighborhood is merged, i.e., $N(l_i) \leftarrow N(l_i) \cup N(l_j)$. This recursive process continues until no new core points are found, and all reachable points are added to the current cluster. Algorithm 1 and 2 detail the steps.*

Example 4 *The cluster formation begins at $(10, 10)$. If $(11, 13)$ and $(12, 14)$ are also core vehicles, the cluster becomes: $N((10, 10)) \cup N((11, 13)) \cup N((12, 14))$, forming a complete cluster (i.e., $\{v_1, v_2, v_3\}$). The cluster formation is recalculated every second.*

3.2 Selection of Cluster Head using Fuzzy Logic

After clustering vehicles using MVC, a fuzzy logic-based approach is employed to select the most suitable cluster head (CH). This method considers key parameters such as distance from the cluster centroid and vehicle speed, ensuring efficient and reliable data transmission. The fuzzy logic system evaluates these inputs to determine which vehicle within each cluster is best suited to act as the CH.

Step 1: Identify Cluster Centroids

For each cluster C_i, the centroid $(\bar{x}_{C_i}, \bar{y}_{C_i})$ is computed as the average position of all vehicles within the cluster:

$$\bar{x}_{C_i} = \frac{1}{|C_i|} \sum_{v_j \in C_i} x_j, \quad \bar{y}_{C_i} = \frac{1}{|C_i|} \sum_{v_j \in C_i} y_j \tag{3.1}$$

Example 5 *Consider cluster C_1 with three vehicles at $ts = 1$: $v_1 = (10, 10), \quad v_2 = (12, 14), \quad v_3 = (14, 12)$ The centroid coordinates are: $\bar{x}_{C_1} = \frac{10+12+14}{3} = 12, \quad \bar{y}_{C_1} = \frac{10+14+12}{3} = 12$ So, centroid $(\bar{x}_{C_1}, \bar{y}_{C_1}) = (12, 12)$.*

Step 2: Compute Distance and Speed Values

For each vehicle $v_j \in C_i$, the Euclidean distance from the centroid is calculated as:

$$d_j = \sqrt{(x_j - \bar{x}_{C_i})^2 + (y_j - \bar{y}_{C_i})^2} \tag{3.2}$$

Speed values s_j are extracted directly from the vehicular dataset to represent the mobility of each vehicle.

Example 6 *Using centroid $(12, 12)$, distances are: $d_1 = \sqrt{(10-12)^2 + (10-12)^2} = 2.83, \quad d_2 = \sqrt{(12-12)^2 + (14-12)^2} = 2.00, \quad d_3 = \sqrt{(14-12)^2 + (12-12)^2} = 2.00$ The vehicle speeds are: $s_1 = 20, \quad s_2 = 30, \quad s_3 = 40$ (km/h)*

Algorithm 3 FUZZY_CLUSTER_HEAD_SELECTION

Require: Set of vehicles C_i, where each vehicle v_j has position (x_j, y_j) and speed s_j at timestamp ts

Ensure: Selected cluster head vehicle v_{CH} at timestamp ts

if C_i is empty **then**
  return null
Compute the centroid $(\bar{x}_{C_i}, \bar{y}_{C_i})$ as:

$$\bar{x}_{C_i} = \frac{1}{|C_i|} \sum_{v_j \in C_i} x_j, \quad \bar{y}_{C_i} = \frac{1}{|C_i|} \sum_{v_j \in C_i} y_j$$

for each vehicle $v_j \in C_i$ **do**
  Compute distance from centroid: $d_j \leftarrow \sqrt{(x_j - \bar{x}_{C_i})^2 + (y_j - \bar{y}_{C_i})^2}$
$d_{\max} \leftarrow \max_{v_j \in C_i}(d_j), \quad s_{\max} \leftarrow \max_{v_j \in C_i}(s_j)$
for each vehicle $v_j \in C_i$ **do**
  Normalize: $d'_j \leftarrow \frac{d_j}{d_{\max}}, \quad s'_j \leftarrow \frac{s_j}{s_{\max}}$
  Fuzzify d'_j into *Low*, *Medium*, *High*
  Fuzzify s'_j into *Slow*, *Moderate*, *Fast*
  Apply fuzzy rules (e.g., if distance is Low and speed is Slow, then suitability is High)
  Defuzzify fuzzy output and compute final score (priority): $w_j = d'_j + s'_j$
Select vehicle $v_{CH} \leftarrow \arg\min_{v_j \in C_i}(w_j)$
return v_{CH}

Step 3: Apply Min-Max Normalization

Normalize distances and speeds within cluster C_i as:

$$d'_j = \frac{d_j}{\max_{v_k \in C_i} d_k}, \quad s'_j = \frac{s_j}{\max_{v_k \in C_i} s_k} \tag{3.3}$$

Here, k is an index variable iterating over all vehicles in cluster C_i to compute the maximum distance and speed values used for normalization. The index j represents the current vehicle being normalized.

Example 7 *Here,* $\max d_j = 2.83$*,* $\max s_j = 40$*; normalized values are:*

Vehicle	d_j	d'_j	s_j	s'_j
v_1	*2.83*	*1.00*	*20*	*0.50*
v_2	*2.00*	*0.71*	*30*	*0.75*
v_3	*2.00*	*0.71*	*40*	*1.00*

Step 4: Applying Fuzzy Logic for Cluster Head Selection

Fuzzy logic is used to evaluate distance and speed as input variables to determine the Cluster Head Priority. The fuzzy inference system assigns each vehicle a priority based on predefined fuzzy rules, as shown in Table 3.1.

The fuzzy inference process involves the following steps:

Distance	**Speed**	**Cluster Head Priority**
Low	Slow	High
Low	Moderate	High
Low	Fast	Medium
Medium	Slow	High
Medium	Moderate	Medium
Medium	Fast	Low
High	Slow	Medium
High	Moderate	Low
High	Fast	Low

Table 3.1: Fuzzy Rules for Cluster Head Selection

1. **Fuzzification:** The normalized values of distance and speed are mapped into fuzzy sets (Low, Medium, or High).
2. **Rule Evaluation:** The fuzzy rules (Table 3.1) are applied to determine the Cluster Head Priority for each vehicle.
3. **Defuzzification:** The priority values are aggregated and converted into a crisp output, selecting the vehicle with the highest priority as the cluster head.

Example 8 *For normalized values:*

Vehicle	d'_j	*Fuzzy Distance*	s'_j	*Fuzzy Speed*
v_1	*1.00*	*High*	*0.50*	*Moderate*
v_2	*0.71*	*Medium*	*0.75*	*Fast*
v_3	*0.71*	*Medium*	*1.00*	*Fast*

Using Table 3.1: - v_1: (High, Moderate) → Low priority - v_2: (Medium, Fast) → Low priority - v_3: (Medium, Fast) → Low priority

Step 5: Compute Weight for Cluster Head Selection

To quantify the fuzzy logic output, a weighted score is computed for each vehicle:

$$w_j = d'_j + s'_j \tag{3.4}$$

A lower weight indicates a more suitable cluster head candidate.

Example 9

Vehicle	d'_j	s'_j	w_j
v_1	*1.00*	*0.50*	*1.50*
v_2	*0.71*	*0.75*	*1.46*
v_3	*0.71*	*1.00*	*1.71*

Step 6: Final selection of the cluster head

The vehicle with the lowest weight w_j is selected as the cluster head. If no suitable vehicle meets the criteria, the centroid of the cluster is chosen as the cluster head to maintain network stability.

Example 10 *Vehicle v_2 has the lowest weight 1.46, so it is chosen as the cluster head for cluster C_1 at $ts = 1$*

Algorithm 3 outlines the structured approach for selecting cluster heads using fuzzy logic.

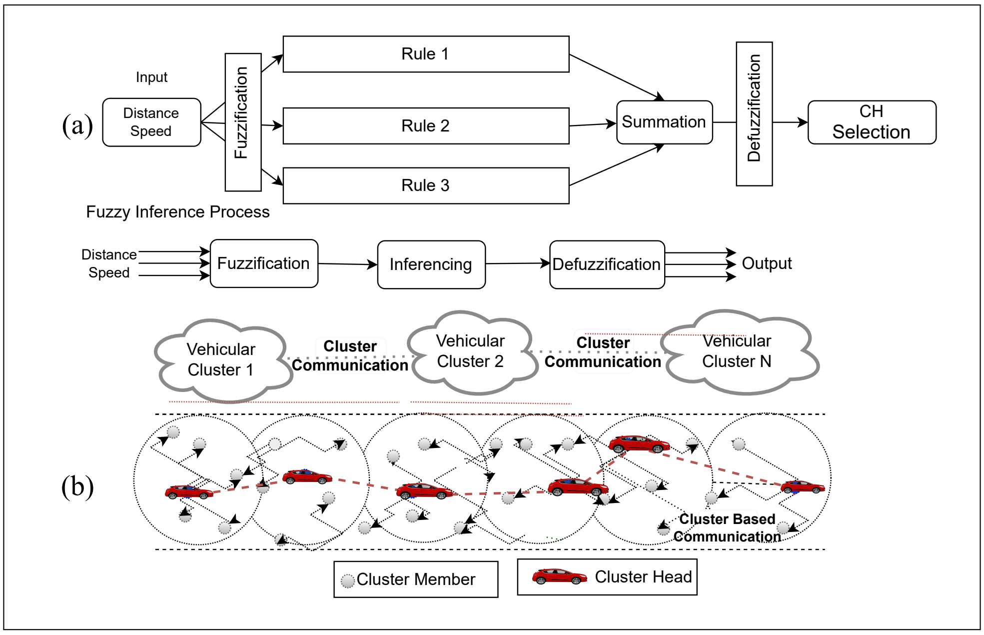


Figure 3.1: The proposed framework integrating fuzzy logic for cluster communication

3.3 Intra-Cluster and Inter-Cluster Communication

Once cluster heads (CHs) are selected using the fuzzy logic-based approach, the next step is establishing efficient communication within and between clusters. Effective data exchange is essential for maintaining network stability, reducing congestion, and ensuring seamless information flow in vehicular networks. **Intra-cluster communication** enables vehicles within the same cluster to communicate with their designated CH, which acts as a central coordinator, managing data aggregation and transmission. Meanwhile, **Inter-cluster communication** facilitates information exchange between CHs, ensuring network-wide connectivity. CHs collaborate with neighboring clusters to relay critical updates, adapt to dynamic traffic conditions, and optimize data dissemination.

Fig. 3.1 illustrates the proposed framework integrating fuzzy logic for cluster communication among AVs. Vehicles moving along the road are dynamically grouped into MVC-formed clusters to facilitate efficient data exchange. Within each cluster, fuzzy logic is applied to select the most suitable cluster head (CH) based on multiple factors, ensuring stable communication and optimized packet transmission. The Fuzzy Inference Process evaluates vehicle attributes such as speed, direction, and connectivity, transforming them into fuzzy sets through fuzzification. These inputs are processed using predefined fuzzy rules, leading to defuzzification, where the most suitable vehicle is assigned as the CH. By implementing this MVC-based clustering strategy with fuzzy logic-driven CH selection, the network achieves higher packet delivery ratios, lower latency, and improved overall communication efficiency.

Chapter 4

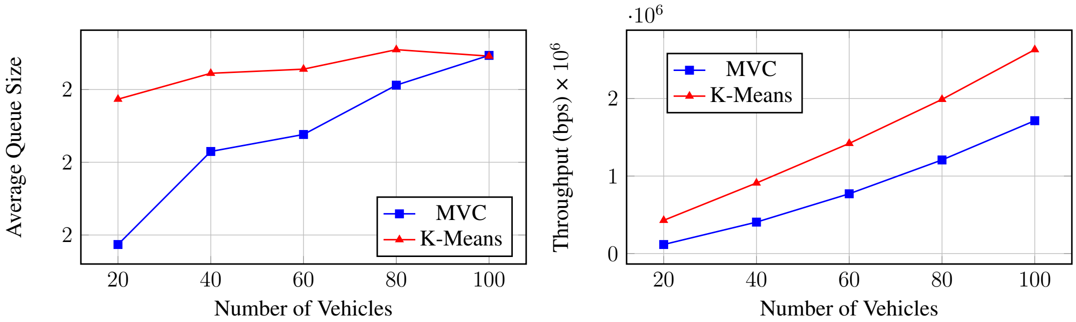
Simulation Environment and Results

The simulation was conducted using the NS-3 [19] network simulator to evaluate the performance of K-Means and MVC clustering algorithms in an infrastructure-less vehicular communication scenario. Simulation for Urban Mobility (SUMO) [20] was used to model realistic vehicle movements, enabling an analysis of network performance under different traffic densities based on key communication metrics. The simulation environment was implemented in C++ on an Ubuntu 24.04 system, running on an Intel Core i7-1065G7×8 processor with 16 GB of RAM to ensure efficient execution. The scenario models a highly dynamic three-lane highway, with 20 to 100 vehicles moving at varying speeds, allowing us to assess how clustering mechanisms adapt to changing network conditions while minimizing packet loss. The detailed simulation settings are provided in Table 4.1.

Parameter	**Value**
Simulator	NS-3
Mobility Model	SUMO
Clustering Algorithms	K-means, MVC
Network Size	20-100 vehicles
Performance Metrics	Queue Size, Packet Transmission, Packet - Delivery Ratio, Throughput, Average Delay,

Table 4.1: Simulation parameters and values

The queue size represents the average number of packets waiting to be processed in the system. As shown in Fig.4.1 (a), the queue size remains relatively stable across different vehicle densities for both MVC and K-Means clustering methods. However, K-Means exhibit slightly higher queue sizes than MVC. This indicates that MVC is more efficient in managing network congestion, as it forms clusters dynamically based on vehicle density, reducing packet accumulation in the queue. In contrast, K-Means relies on predefined cluster sizes, which may not adapt well to changing traffic conditions, leading to slightly increased queue sizes.
Throughput measures the rate of successful data transmission across the network. As shown in Fig.4.1 (b), MVC consistently achieves higher throughput than K-Means across varying vehicle densities. While K-Means experience a decline in throughput



(a) Queue Comparision (b) Throughput Comparison

Figure 4.1: The comparison of Queue and Throughput of MVC and K-Means in Vehicular Network

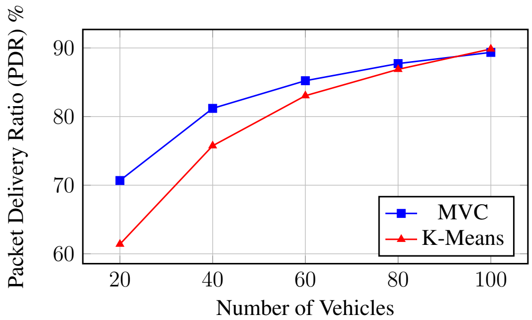
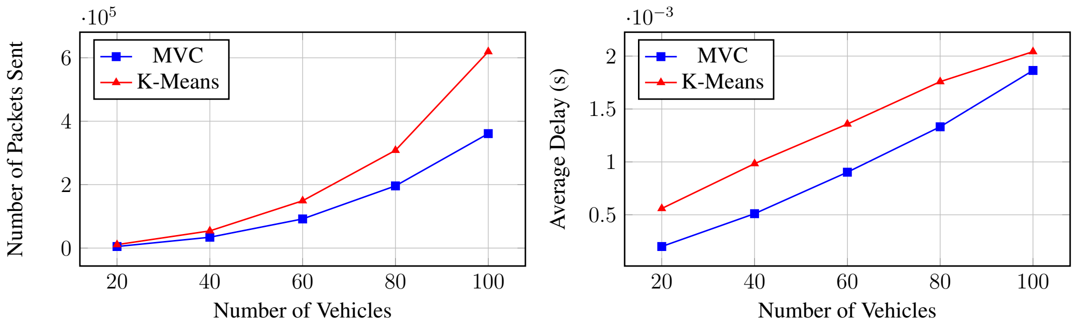


Figure 4.2: Packet Delivery Ratio Comparison

as the number of vehicles increases, MVC maintains a stable and higher transmission rate. This highlights MVC's ability to adapt dynamically to changing network conditions, making it a more suitable choice for infrastructure-less vehicular networks that require efficient and scalable data dissemination
Packet Delivery Ratio (PDR) represents the percentage of successfully received packets out of the total packets sent. As illustrated in Fig.4.2, MVC consistently outperforms K-Means across various vehicle densities. While both algorithms maintain relatively high PDR values, MVC achieves a delivery ratio close to 90%, whereas K-Means fluctuate between 65% and 80%. The superior PDR of MVC highlights its ability to form adaptive and robust clusters, ensuring more reliable data transmission. In contrast, K-Means struggle in highly dynamic environments with frequent changes in vehicle density, leading to increased packet loss and reduced transmission efficiency.

The number of packets transmitted is a key metric for assessing network efficiency. As shown in Fig. 4.3 (a), MVC consistently enables more packet transmissions than K-Means. This indicates that MVC facilitates a more efficient communication framework, allowing vehicles to exchange information more effectively while minimizing packet loss. The higher transmission rates in MVC can be attributed to its adaptive clustering approach, which dynamically adjusts to changing network conditions. This flexibility leads to better resource utilization and fewer retransmissions, enhancing overall network performance.

The average delay metric measures a packet's time to reach its destination. As illustrated in Fig. 4.3 (b), MVC consistently maintains lower delay values than K-Means, especially as the number of vehicles increases. This suggests that MVC enables



(a) Packet Transmission

(b) Average Delay

Figure 4.3: The comparison of packet transmission and average delay of MVC and K-Means in Vehicular Network

faster packet transmission by dynamically forming clusters based on real-time vehicle density, resulting in shorter and more efficient communication paths. In contrast, K-Means' rigid clustering structure struggles to adapt to fluctuating traffic conditions, often leading to additional transmission delays. This issue becomes more pronounced in high-density scenarios, where frequent re-clustering is required, further increasing network latency.

Chapter 5

Conclusion and Future Work

This thesis presented a communication framework for autonomous vehicles (AVs) that do not rely on infrastructure like roadside units. The proposed method uses MVC, a density-based clustering algorithm, and fuzzy logic to select cluster heads (CHs). Unlike K-Means, which needs a fixed number of clusters and performs poorly with outliers, MVC can create clusters based on how vehicles are spread out in real time. This makes it better suited for environments where vehicle density and movement change frequently.

This framework uses fuzzy logic to choose the best vehicle to act as a cluster head. It considers factors like speed, distance, and how well a vehicle is connected to others. This approach helps reduce the number of messages exchanged, lowers communication delays, and improves the network's stability.

We tested the proposed method using the NS-3 network simulator. The results showed that the MVC and fuzzy logic framework performed better than the traditional K-Means method. It had better performance in terms of smaller queue sizes, higher packet delivery ratios, lower delays, more packet transmissions, and higher data throughput. These improvements are important for making sure that AVs can communicate quickly and reliably without depending on external infrastructure.

Future Work

While the proposed framework has demonstrated encouraging results, several opportunities exist for further enhancement and refinement. One important direction is the incorporation of diverse mobility models, as vehicle behavior can differ greatly across environments such as highways, city streets, and intersections. Understanding how these varying mobility patterns influence clustering efficiency and communication stability will make the framework more adaptable to real-world scenarios. Building on this, the current fuzzy logic-based cluster head (CH) selection method can be improved by integrating additional parameters such as vehicle energy levels, signal strength, link quality, and real-time traffic load. This would enable more intelligent and reliable CH decisions that contribute to longer-lasting and more stable clusters. To further support real-time responsiveness, the framework can be integrated with 5G networks and edge computing, allowing vehicles to offload processing tasks to nearby edge servers, thereby reducing latency and improving communication efficiency. In addition, addressing resource optimization is essential; employing predictive models or reinforcement learning could help minimize unnecessary data transmissions, leading to more efficient use of bandwidth, energy, and processing power. Another area of improvement involves accounting for heterogeneous vehicles, as real-world traffic includes a mix of cars, trucks, and motorcycles with different capabilities. Including this diversity in simulations will provide a more comprehensive evaluation of the framework's robustness. Furthermore, conducting large-scale and dense network simulations—such as city-wide deployments—will help test the framework's scalability and identify potential performance bottlenecks. Lastly, considering environmental factors such as buildings, foliage, and adverse weather conditions in the simulation setup will enhance the realism of the results and prepare the framework for practical implementation. Altogether, exploring these directions will significantly strengthen the proposed approach and bring it closer to deployment in real-world autonomous vehicular networks, especially in infrastructure-less environments.

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