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A-MCAC: An Adaptive Mobility- and Connectivity-Aware Clustering Framework for Stable and Efficient Internet of Vehicles Communications

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Abstract

The Internet of Vehicles (IoV) enables intelligent transportation services through real-time communication between vehicles and infrastructure. However, high mobility and frequent topology changes often reduce cluster stability and communication reliability. Traditional clustering approaches commonly rely on static decision criteria and periodic maintenance mechanisms, leading to frequent reclustering operations and increased communication overhead. This paper proposes an Adaptive Mobility- and Connectivity-Aware Clustering (A-MCAC) framework for IoV environments. The proposed approach combines predictive mobility analysis, link lifetime estimation, adaptive weight optimization, and event-driven cluster maintenance to improve Cluster Head (CH) selection and cluster stability. By dynamically adapting clustering decisions according to network conditions, A-MCAC aims to reduce reclustering operations and enhance communication efficiency. The proposed framework is evaluated through simulations and compared with CARAC, MetaLearn, and CPB using cluster lifetime, CH lifetime, reclustering rate, link stability, clustering overhead, packet delivery ratio, end-to-end delay, and throughput. Results demonstrate that A-MCAC improves cluster stability, increases communication reliability, maintains a favorable overhead-performance trade-off, and achieves better network performance across varying vehicle densities. These findings demonstrate that A-MCAC improves both clustering stability and communication efficiency in highly dynamic IoV environments.

Keywords: internet of vehicles; vehicular ad hoc networks; adaptive clustering; cluster head selection; mobility prediction; link lifetime estimation; event-driven maintenance



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1. Introduction

The rapid advancement of Intelligent Transportation Systems (ITS) has accelerated the evolution of Vehicular Ad Hoc Networks (VANETs) toward the broader paradigm of the Internet of Vehicles (IoV) [1,2]. By enabling seamless communication among vehicles, road-side infrastructure, edge servers, and cloud platforms, IoV environments support a wide range of applications, including traffic management, road safety enhancement, autonomous driving, and intelligent transportation services [3–5]. Through Vehicle-to-Vehicle (V2V),

Vehicle-to-Infrastructure (V2I), and Vehicle-to-Everything (V2X) communications, IoV networks facilitate real-time information exchange and improve the efficiency of modern transportation systems [6–8].

Despite these advantages, the dynamic nature of vehicular environments introduces several challenges that significantly affect network performance. High vehicle mobility, rapidly changing network topologies, varying traffic densities, and intermittent wireless connectivity often lead to unstable communication links and frequent route disruptions [9–12]. These issues become particularly critical in dense urban environments where maintaining reliable and scalable communications remains a major concern.

To address these challenges, clustering has emerged as an effective network management technique in VANET and IoV environments. By organizing vehicles into logical groups and electing Cluster Heads (CHs) to coordinate communications, clustering mechanisms improve network scalability, reduce routing overhead, and facilitate information dissemination [13–15]. However, the effectiveness of clustering largely depends on the stability of cluster structures and the reliability of Cluster Head selection decisions. Conventional clustering approaches typically rely on static metrics such as distance, node degree, or instantaneous mobility information, which may lead to frequent cluster reconfiguration and increased communication overhead in highly dynamic vehicular scenarios.

Recent studies have introduced adaptive clustering frameworks that incorporate optimization techniques, machine learning algorithms, and multi-criteria decision mechanisms to improve cluster stability and communication efficiency [16–18]. While these approaches have demonstrated promising results, many existing solutions still suffer from several limitations. Some rely on computationally intensive optimization procedures, whereas others require learning processes or periodic maintenance operations that may increase processing complexity and control overhead. Furthermore, predictive mobility estimation and adaptive clustering decisions remain insufficiently explored in many existing clustering frameworks.

Recent survey studies have highlighted several open challenges in IoV environments, particularly the need for more adaptive and mobility-aware clustering mechanisms to improve communication stability under highly dynamic vehicular conditions [2].

Motivated by the limitations of existing clustering approaches, this work proposes an Adaptive Mobility- and Connectivity-Aware Clustering (A-MCAC) framework for Internet of Vehicles environments. Unlike conventional clustering methods that rely on fixed decision criteria or static maintenance strategies [19–21], the proposed framework dynamically adapts Cluster Head selection according to mobility, connectivity, and link stability. By combining adaptive multi-criteria decision making with predictive mobility estimation and localized cluster maintenance, A-MCAC aims to improve cluster stability and communication efficiency while preserving low computational complexity under dynamic vehicular network conditions.

The main contributions of this work are summarized as follows:

1. A lightweight adaptive clustering framework is introduced that dynamically adjusts Cluster Head selection according to mobility, connectivity, and communication conditions, improving cluster stability in highly dynamic IoV environments.
2. A predictive link lifetime estimation mechanism improves communication reliability by identifying stable vehicle associations before Cluster Head selection.
3. An adaptive multi-criteria Cluster Head selection strategy enhances clustering robustness by dynamically balancing mobility, connectivity, link stability, local density, and communication quality according to network conditions.
4. A localized event-driven maintenance strategy reduces unnecessary reclustering operations and communication overhead while preserving stable cluster structures.

5. Extensive NS-3 simulations demonstrate that A-MCAC consistently improves cluster lifetime, Cluster Head lifetime, link stability, packet delivery ratio, throughput, and communication efficiency compared with representative recent clustering approaches.

The remainder of this paper is organized as follows. Section 2 reviews the related work and identifies the research gap motivating the proposed framework. Section 3 describes the system model and adaptive IoV network architecture. Section 4 details the proposed A-MCAC clustering mechanism. Section 5 presents the simulation setup, performance evaluation, and comparative analysis. Finally, Section 6 concludes the paper and outlines future research directions.

2. Related Work

This section reviews representative clustering approaches proposed for Vehicular Ad Hoc Networks and Internet of Vehicles environments. First, conventional clustering techniques are discussed to highlight their design principles and inherent limitations. Next, recent adaptive and intelligent clustering approaches are reviewed, with particular emphasis on mobility awareness, link stability, and multi-criteria Cluster Head selection. Finally, a comparative analysis is presented to identify the existing research gap and motivate the proposed Adaptive Mobility- and Connectivity-Aware Clustering framework.

2.1. Conventional Clustering Approaches in VANETs and IoV

Clustering has been widely adopted as an effective mechanism for improving network scalability, communication efficiency, and routing performance in Vehicular Ad Hoc Networks and Internet of Vehicles environments. By organizing vehicles into clusters and electing Cluster Heads to coordinate communications, clustering techniques reduce routing overhead and facilitate network management in highly dynamic vehicular scenarios.

Early clustering approaches mainly relied on simple network characteristics for cluster formation and Cluster Head selection. Distance-Based Clustering (DBC) methods group vehicles according to their geographical proximity, aiming to maintain communication links among neighboring nodes [12]. While these approaches are simple to implement and require limited computational resources, their performance often degrades in highly dynamic traffic environments where frequent topology changes lead to unstable cluster structures.

To improve cluster stability, Mobility-Based Clustering (MBC) approaches incorporate mobility-related information such as vehicle speed, direction, and relative movement patterns [13]. Vehicles exhibiting similar mobility characteristics are grouped together in order to reduce cluster fragmentation and prolong cluster lifetime. Although mobility-aware schemes generally achieve better stability than purely distance-based approaches, they may still experience performance degradation when communication quality and network connectivity are not adequately considered.

To address the limitations of single-criterion clustering mechanisms, Weighted Clustering Algorithms (WCAs) have been introduced [15,22]. These approaches combine multiple metrics, including node degree, mobility characteristics, connectivity, and communication quality, into a unified Cluster Head selection process. By considering several network parameters simultaneously, WCAs improve clustering effectiveness and network performance. However, most existing weighted approaches employ fixed weighting coefficients that remain unchanged regardless of traffic density, mobility patterns, or network conditions, limiting their adaptability in dynamic vehicular environments.

More recently, multi-criteria clustering techniques have been proposed to enhance Cluster Head selection and cluster maintenance decisions. These methods jointly evaluate several mobility and communication-related factors to improve cluster stability and reduce

routing overhead. Despite their improved performance, many conventional clustering solutions still rely on static decision mechanisms and periodic reclustering procedures, which may generate excessive control overhead and reduce efficiency under rapidly changing traffic conditions.

Consequently, the limitations of traditional clustering approaches have motivated the development of adaptive and intelligent clustering mechanisms capable of dynamically adjusting their behavior according to real-time network conditions. These recent advances are reviewed in the following subsection.

2.2. Adaptive and Intelligent Clustering Approaches

Recent research has increasingly focused on the development of adaptive and intelligent clustering mechanisms capable of coping with the highly dynamic characteristics of VANET and IoV environments. Unlike conventional clustering approaches that rely on static clustering criteria, these schemes exploit optimization techniques, learning mechanisms, or adaptive decision strategies to improve cluster stability, communication reliability, and routing performance [23].

Zhao et al. [15] proposed an adaptive vehicle clustering algorithm based on power minimization for vehicular ad hoc networks. The proposed approach dynamically adjusts cluster formation decisions according to communication conditions while reducing transmission power consumption. Although the algorithm improves network connectivity and energy efficiency, its cluster management strategy does not explicitly incorporate predictive mobility information or future link behavior during Cluster Head selection.

Sajithabegam and Menakadevi [20] introduced an enhanced clustering and routing framework for software-defined vehicular networks. By combining adaptive routing with clustering optimization, the proposed framework improves communication efficiency and network resource utilization. However, the integration of additional control functionalities may increase management complexity, particularly in large-scale vehicular deployments.

Jalooli and Marefat [24] proposed a stability-oriented clustering mechanism for heterogeneous vehicular environments. Their approach emphasizes cluster stability during route establishment and maintenance. While the reported results demonstrate improvements in communication reliability, the optimization process introduces additional computational overhead that may limit scalability under dense traffic conditions.

Ali et al. [19] developed a secure clustering framework based on Arithmetic Optimization Algorithms (AOA). The proposed method combines clustering decisions with security considerations to improve network robustness. Nevertheless, optimization-based clustering schemes generally require iterative computations and parameter tuning procedures that may increase processing complexity and response time.

Ajmani et al. [21] presented an Ant Colony Optimization (ACO)-based clustering framework for Internet of Vehicles environments. Their solution utilizes metaheuristic optimization to improve Cluster Head selection and cluster organization. Although effective in enhancing communication performance, the iterative nature of ACO may generate additional computational costs, especially in highly dynamic vehicular scenarios.

More recently, learning-assisted clustering approaches have attracted considerable attention. MetaLearn employs learning-based mechanisms to optimize clustering and communication decisions according to network conditions [25]. By leveraging historical observations and adaptive learning processes, the framework improves cluster organization and communication efficiency. However, learning-based approaches often introduce additional training overhead and computational complexity, which may affect their applicability in real-time vehicular environments.

CPB adopts a cluster-based communication strategy designed to improve network organization and routing performance in dynamic vehicular scenarios [26]. The framework utilizes clustering information to support communication management and reduce network fragmentation. Nevertheless, the absence of predictive mobility estimation and adaptive weighting mechanisms may limit cluster stability when traffic conditions change rapidly.

CARAC represents a more advanced adaptive clustering and routing framework that combines cluster management with communication optimization techniques [27]. By considering mobility characteristics and communication conditions, CARAC improves network organization and routing efficiency. Despite these advantages, cluster maintenance remains largely dependent on periodic operations and does not fully exploit predictive mobility estimation or event-driven adaptation mechanisms.

Although recent adaptive clustering approaches have significantly improved network performance, several challenges remain. Most existing solutions rely on optimization procedures, learning mechanisms, or periodic maintenance strategies that may increase computational complexity and communication overhead. Furthermore, predictive mobility estimation, adaptive metric weighting, and localized event-driven maintenance are rarely integrated within a unified clustering framework. These limitations motivate the development of more lightweight and adaptive clustering solutions for highly dynamic IoV environments.

2.3. Comparative Analysis and Research Gap

To better understand the strengths and limitations of existing clustering approaches, Table 1 summarizes the key characteristics of representative schemes commonly used in VANET and IoV environments. The comparison focuses on features that directly affect cluster stability, communication efficiency, and adaptability under dynamic vehicular conditions.

Table 1. Comparative analysis of representative clustering approaches in VANET and IoV environments.

Scheme	Mobility Prediction	Link Stability Awareness	Multi-Criteria CH Selection	Adaptive Weighting	Event-Driven Maintenance	Complexity
MetaLearn [25]	✓	✗	✓	Learning-Based	✗	High
CPB [26]	✗	✗	✓	✗	✗	Moderate
CARAC [27]	Partial	✓	Partial	✗	✗	Moderate
A-MCAC	✓	✓	✓	✓	✓	Low

As shown in Table 1, recent clustering approaches have introduced various mechanisms to improve cluster organization and communication performance in vehicular networks. MetaLearn employs learning-based techniques to enhance clustering decisions, while CARAC integrates cluster-aware communication management to improve routing efficiency and network stability. Similarly, CPB utilizes cluster-based communication structures to support network organization and information dissemination in dynamic vehicular scenarios.

Despite these advancements, several challenges remain unresolved. First, predictive mobility estimation is either partially considered or completely absent in many existing approaches, limiting their ability to anticipate topology changes before they occur. Second, adaptive weighting mechanisms are rarely incorporated into the Cluster Head selection process, causing clustering decisions to rely on fixed or partially adaptive parameters that may not accurately reflect changing traffic conditions. Third, most existing schemes rely on periodic cluster maintenance procedures, which can generate unnecessary control overhead and frequent cluster reconfiguration in highly dynamic environments.

Furthermore, although some approaches consider mobility, connectivity, or communication-related metrics, the joint integration of mobility prediction, link stability estimation, adaptive weighting, and event-driven maintenance remains limited. Consequently, maintaining stable cluster structures while simultaneously reducing communication overhead continues to be a significant challenge in dense and rapidly changing IoV environments.

To address these limitations, this work proposes the Adaptive Mobility- and Connectivity-Aware Clustering. The proposed approach combines predictive mobility analysis, link lifetime estimation, adaptive weight optimization, multi-criteria Cluster Head selection, and event-driven cluster maintenance within a unified clustering architecture. By dynamically adapting clustering decisions according to current network conditions, A-MCAC aims to improve cluster stability, reduce reclustering operations, and enhance communication performance while maintaining low computational complexity.

3. System Model and Adaptive IoV Network Architecture

The Internet of Vehicles is characterized by highly dynamic network topologies, heterogeneous communication environments, and continuously changing traffic conditions. These characteristics make the design of stable and efficient clustering mechanisms particularly challenging, as traditional clustering approaches often rely on static decision criteria and periodic maintenance strategies that are unable to adapt effectively to rapid topology variations.

To address these challenges, this work proposes an Adaptive Mobility- and Connectivity-Aware Clustering that combines predictive mobility analysis, adaptive Cluster Head selection, and event-driven cluster maintenance within a unified architectural model. The proposed framework aims to improve cluster stability, reduce unnecessary reclustering operations, and enhance communication efficiency under varying vehicular traffic conditions.

As illustrated in Figure 1, the proposed architecture adopts a multi-layer design composed of four interconnected layers: the Vehicular Layer, Communication Layer, Edge Intelligence Layer, and Adaptive Intelligence Layer. These layers collaboratively support information collection, communication management, adaptive clustering decisions, and network optimization. While the clustering mechanism operates in a fully distributed manner using locally available information, the architecture also incorporates optional infrastructure support components to facilitate future extensions involving edge-assisted intelligence and large-scale IoV services.

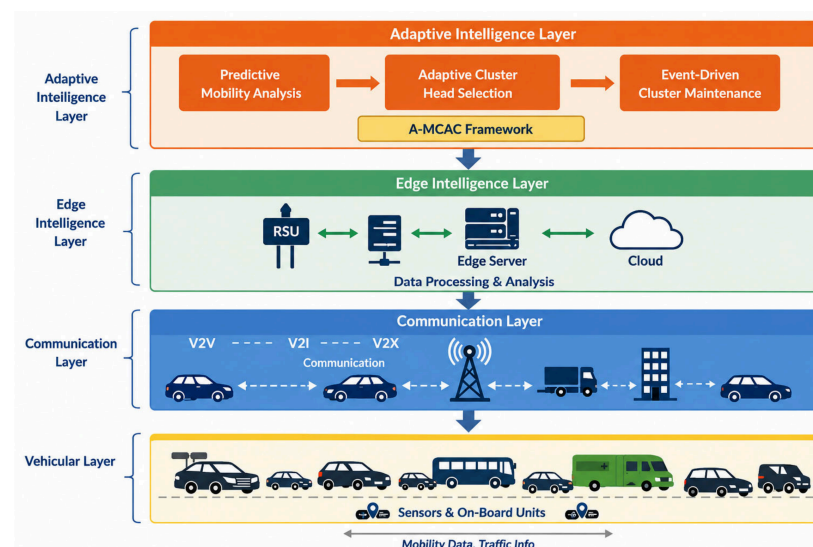


Figure 1. Proposed A-MCAC multi-layer architecture for adaptive clustering in Internet of Vehicles.

The following subsections present the design principles of the proposed framework, describe the functionality of each architectural layer, and explain the operational workflow of the A-MCAC clustering mechanism.

3.1. Design Principles

The design of the proposed Adaptive Mobility- and Connectivity-Aware Clustering framework is guided by three fundamental principles that address the dynamic and highly mobile nature of Internet of Vehicles environments. These principles aim to improve clustering stability, reduce maintenance overhead, and support efficient communication under varying traffic conditions.

3.1.1. Mobility Awareness

Vehicle mobility has a significant impact on network topology and communication reliability in IoV environments. Frequent changes in vehicle speed, direction, and position may lead to unstable communication links and repeated cluster reconfigurations. To address this challenge, the proposed framework incorporates mobility-aware mechanisms that continuously evaluate vehicle movement characteristics and predict future network conditions. By considering mobility stability and estimated predicted link lifetime during the clustering process, the framework can identify vehicles that are more likely to maintain stable connectivity over time.

3.1.2. Dynamic Adaptation

The heterogeneous and rapidly changing nature of vehicular networks requires clustering decisions that adapt to current network conditions. Fixed clustering strategies may perform well under specific traffic scenarios but often fail to maintain efficiency when vehicle density or mobility patterns change. Therefore, the proposed framework adopts an adaptive decision-making strategy in which the importance of clustering metrics is dynamically adjusted according to the observed network state. This adaptive behavior enables the clustering mechanism to respond effectively to different traffic conditions while maintaining cluster stability.

3.1.3. Lightweight Operation

Clustering decisions in vehicular networks must be executed in real time without introducing excessive computational or communication overhead. For this reason, the proposed framework emphasizes lightweight operation based on locally available information obtained through periodic beacon exchanges. All clustering computations are performed using neighborhood information without requiring centralized control or complex optimization procedures. This design choice reduces processing complexity while preserving the responsiveness required in highly dynamic IoV environments.

3.2. Multi-Layer Architecture

To support adaptive clustering and efficient communication in highly dynamic vehicular environments, the proposed A-MCAC framework adopts a multi-layer architecture composed of four interconnected layers, as illustrated in Figure 1. The architecture integrates vehicular communications, adaptive clustering intelligence, and optional infrastructure support components to improve cluster stability and communication efficiency.

3.2.1. Vehicular Layer

The Vehicular Layer represents the physical entities participating in the network, including vehicles equipped with onboard communication and processing capabilities. Vehicles periodically exchange beacon messages containing information such as position,

speed, direction, and connectivity status. This layer serves as the primary source of mobility and communication data used by the clustering process.

In the proposed framework, vehicles are responsible for local information collection, neighborhood monitoring, and participation in cluster formation and maintenance procedures. The dynamic nature of vehicle mobility makes this layer a critical component for achieving stable clustering decisions.

3.2.2. Communication Layer

The Communication Layer enables information exchange among neighboring vehicles through Vehicle-to-Vehicle communications. It supports the dissemination of beacon messages, cluster management information, and data packets required for network operation.

This layer provides the communication infrastructure necessary for neighbor discovery, connectivity evaluation, and Cluster Head coordination. The quality and stability of communication links directly influence clustering performance and routing efficiency.

3.2.3. Edge Intelligence Layer

The Edge Intelligence Layer represents optional infrastructure support components, such as Roadside Units (RSUs) and edge servers, that may assist vehicular applications by providing additional computational and storage resources [28,29].

In the proposed framework, this layer is considered part of the deployment environment and may support future extensions involving large-scale traffic monitoring, distributed analytics, and edge-assisted decision-making. However, the clustering mechanism itself operates independently and does not require continuous infrastructure support.

3.2.4. Adaptive Intelligence Layer

The Adaptive Intelligence Layer constitutes the decision-making component of the proposed A-MCAC framework. It is responsible for processing mobility and connectivity information collected from the lower layers and executing the adaptive clustering functions.

This layer incorporates predictive mobility analysis, link lifetime estimation, adaptive weighting, Cluster Head selection, and event-driven cluster maintenance [30]. By continuously analyzing network conditions, the Adaptive Intelligence Layer enables the framework to dynamically adjust clustering decisions and maintain stable cluster structures under varying traffic scenarios.

It should be noted that the Edge Intelligence Layer and Adaptive Intelligence Layer provide the conceptual architectural context of the proposed framework. While these components illustrate how the clustering mechanism can be integrated within future IoV ecosystems, the experimental evaluation presented in this work focuses exclusively on the Adaptive Mobility- and Connectivity-Aware Clustering mechanism operating within the vehicular communication environment.

3.3. System Operation

The operation of the proposed A-MCAC framework is based on a distributed and adaptive clustering process designed to cope with the dynamic characteristics of Internet of Vehicles environments. The framework continuously monitors local network conditions and performs clustering decisions using information exchanged among neighboring vehicles.

As illustrated in Figure 1, the clustering process consists of six main operational phases: neighbor discovery, mobility estimation, connectivity evaluation, adaptive score computation, Cluster Head selection, and cluster maintenance. These phases are executed periodically using locally available information obtained through beacon exchanges.

3.3.1. Neighbor Discovery

The clustering process begins with periodic beacon exchanges among neighboring vehicles. Each beacon contains relevant information, including vehicle position, speed, direction, and communication status. Using these beacon messages, every vehicle maintains an updated neighbor table and continuously monitors its local environment.

3.3.2. Mobility and Connectivity Evaluation

Based on the collected neighborhood information, vehicles estimate mobility stability and communication reliability. The framework evaluates vehicle movement characteristics and predicts future link behavior by considering relative mobility patterns and expected communication durations. These estimations provide the basis for identifying stable clustering candidates.

3.3.3. Adaptive Score Computation

The collected mobility and connectivity information is processed through the adaptive multi-criteria evaluation mechanism. The importance of the clustering metrics is dynamically adjusted according to current network conditions, enabling the framework to adapt its decisions to different traffic densities and mobility scenarios.

3.3.4. Cluster Head Selection Process

After computing the adaptive scores, vehicles with the highest suitability values are selected as Cluster Heads. The selection process considers multiple factors, including connectivity, link stability, mobility stability, local density, and communication quality. This multi-criteria strategy aims to identify vehicles capable of maintaining stable cluster structures for extended periods.

3.3.5. Cluster Formation

Once Cluster Heads are elected, neighboring vehicles join the most suitable cluster according to the established selection criteria. The cluster formation procedure organizes vehicles into stable communication groups, facilitating efficient coordination and information exchange.

3.3.6. Cluster Maintenance

To preserve cluster stability under changing traffic conditions, the framework continuously monitors cluster status and triggers maintenance operations only when necessary. Event-driven maintenance mechanisms are employed to reduce unnecessary reclustering operations and minimize control overhead. As a result, the clustering structure can adapt to topology variations while maintaining communication efficiency.

The detailed mathematical formulation and algorithmic implementation of these operational phases are presented in Section 4.

4. Adaptive Mobility- and Connectivity-Aware Clustering (A-MCAC)

This section presents the proposed Adaptive Mobility- and Connectivity-Aware Clustering (A-MCAC) mechanism designed to improve cluster stability and communication efficiency in highly dynamic Internet of Vehicles environments. Unlike conventional clustering approaches that rely on static clustering parameters or simplified mobility estimation, the proposed framework integrates predictive mobility analysis, adaptive multi-criteria cluster head selection, and dynamic weight optimization in order to provide robust and stable clustering behavior under varying vehicular conditions.

The proposed clustering framework aims to maximize cluster stability and communication reliability while minimizing communication overhead and frequent cluster reconfiguration. To achieve this objective, the proposed A-MCAC mechanism combines predictive mobility stability, link lifetime estimation, connectivity awareness, local density information, and communication quality within a unified adaptive clustering framework.

4.1. Problem Formulation

Vehicular ad hoc networks are characterized by high node mobility, rapidly changing topology, unstable communication links, and varying traffic density conditions. These characteristics significantly affect cluster stability and communication efficiency in Internet of Vehicles environments.

The vehicular network is modeled as an undirected graph: $G(V, E)$, where:

- $(V = \{V_1, V_2, \dots, V_n\})$ represents the set of vehicles;
- (E) denotes the set of communication links between neighboring vehicles.

A communication link exists between two vehicles (V_i) and (V_j) if the Euclidean distance between them satisfies $d_{ij}(t) \leq R$.

where

- $(d_{ij}(t))$ denotes the distance between vehicles (V_i) and (V_j) at time (t) ;
- (R) represents the communication range.

Each vehicle periodically broadcasts beacon messages containing local mobility information. Therefore, each vehicle can be represented as

$$V_i = (x_i(t), y_i(t), s_i(t), \theta_i(t), a_i(t)) \quad (1)$$

where

- $(x_i(t), y_i(t))$ denotes the vehicle position;
- $(s_i(t))$ represents the instantaneous speed;
- $(\theta_i(t))$ denotes the moving direction;
- $(a_i(t))$ represents the acceleration magnitude.

The objective of the proposed clustering framework is to maximize cluster stability and communication efficiency while minimizing cluster reconfiguration overhead.

The clustering optimization objective can therefore be expressed as: $\max(S, L, C)$, while minimizing $\min(R, O, H)$.

where

- (S) denotes cluster stability;
- (L) represents average link lifetime;
- (C) denotes network connectivity;
- (R) represents the reclustering rate;
- (O) denotes communication overhead;
- (H) represents cluster head switching frequency.

To address these challenges, the proposed A-MCAC framework introduces predictive mobility estimation and adaptive multi-criteria cluster-head selection in order to improve clustering robustness under dynamic vehicular conditions.

4.2. Predictive Mobility Stability Model

Vehicle mobility plays a critical role in clustering stability. Vehicles with unstable movement behavior are more likely to trigger topology fragmentation and frequent cluster reconfiguration [13,24].

Unlike conventional mobility-aware clustering approaches that only consider instantaneous vehicle speed, the proposed framework evaluates mobility stability using speed variation, direction variation, and acceleration variation.

The mobility stability metric of vehicle (V_i) is defined as

$$M_i = \frac{1}{1 + \omega_s \sigma_s + \omega_\theta \sigma_\theta + \omega_a \sigma_a} \quad (2)$$

where

(σ_s) represents speed variation;

(σ_θ) denotes direction variation;

(σ_a) represents acceleration variation;

(ω_s), (ω_θ), and (ω_a) are normalization coefficients controlling the relative influence of each mobility parameter.

Higher values of M_i indicate more stable mobility patterns and a lower probability of future topology disruption.

Vehicles with more stable mobility behavior obtain higher mobility stability scores and are therefore considered more suitable candidates for cluster head selection.

To further improve clustering robustness, the proposed framework introduces predictive mobility estimation. The predicted future position of vehicle (V_i) is estimated as

$$\hat{P}_i(t + \Delta t) = P_i(t) + \vec{v}_i(t)\Delta t + \frac{1}{2}a_i(t)(\Delta t)^2 \quad (3)$$

where

- ($P_i(t)$) represents the current position vector;
- ($\vec{v}_i(t)$) denotes the velocity vector;
- ($a_i(t)$) denotes the instantaneous acceleration magnitude used in the mobility prediction model;
- (Δt) denotes the prediction interval.

This predictive estimation allows the clustering mechanism to proactively estimate future topology evolution and improve cluster stability by selecting vehicles with more stable future trajectories.

To incorporate predictive mobility information into link stability estimation, the future inter-vehicle distance between neighboring vehicles V_i and V_j is estimated as

$$\hat{d}_{ij}(t + \Delta t) = \|\hat{P}_i(t + \Delta t) - \hat{P}_j(t + \Delta t)\| \quad (4)$$

where

- $\hat{P}_i(t + \Delta t)$ and $\hat{P}_j(t + \Delta t)$ denote the predicted future positions of vehicles V_i and V_j , respectively;
- $\hat{d}_{ij}(t + \Delta t)$ represents the predicted inter-vehicle distance.

4.3. Predictive Link Lifetime Estimation

Stable communication links are essential for maintaining robust cluster structures in dynamic vehicular environments. Traditional clustering approaches often estimate link stability using only relative speed difference, which may not accurately reflect future communication reliability [15,27].

In the proposed framework, predictive link lifetime estimation is introduced in order to evaluate the expected duration of communication links between neighboring vehicles.

The relative velocity vector between vehicles (V_i) and (V_j) is defined as

$$\Delta \vec{v}_{ij} = \vec{v}_i - \vec{v}_j \quad (5)$$

where

- $\vec{v}_i$ and $\vec{v}_j$ denote the velocity vectors of vehicles V_i and V_j , respectively;
- $\Delta \vec{v}_{ij}$ represents the relative velocity vector between the two vehicles.

The magnitude of the relative velocity reflects the mobility difference between neighboring vehicles. Lower relative velocity values indicate more similar movement patterns and consequently longer communication link durations.

The estimated predicted link lifetime between vehicles (V_i) and (V_j) is estimated as

$$LLT_{ij} = \frac{\max(0, R - \hat{d}_{ij}(t + \Delta t))}{|\Delta \vec{v}_{ij}| + \varepsilon} \quad (6)$$

where

- (R) denotes the communication range;
- $\hat{d}_{ij}(t + \Delta t)$ represents the predicted inter-vehicle distance;
- $|\Delta \vec{v}_{ij}|$ denotes the magnitude of the relative velocity vector;
- (ε) is a small positive constant introduced to avoid division by zero.

The operator $\max(0, R - \hat{d}_{ij}(t + \Delta t))$ ensures that the estimated link lifetime remains non-negative and prevents invalid lifetime values when neighboring vehicles move beyond the communication range.

Higher link lifetime values indicate more stable communication links and improved clustering reliability.

The average link stability score of vehicle (V_i) is calculated as

$$LS_i = \frac{1}{|N_i|} \sum_{v_j \in N_i} LLT_{ij} \quad (7)$$

where

- $|N_i|$ represents the number of neighboring vehicles.

The average predictive link lifetime is used as the link stability score. The proposed predictive link lifetime estimation allows the clustering framework to proactively avoid unstable communication links and reduce frequent cluster reconfiguration operations.

4.4. Adaptive Multi-Criteria Cluster Head Selection

The selection of stable and reliable cluster heads is a critical challenge in highly dynamic vehicular environments. In conventional clustering approaches, cluster head selection is often based on a single parameter such as connectivity, distance, or mobility. However, relying on isolated parameters may lead to unstable cluster formation and frequent cluster reconfiguration under varying traffic conditions [19–21].

To address these limitations, the proposed A-MCAC framework introduces an adaptive multi-criteria cluster head selection mechanism that combines mobility stability, predictive link lifetime, node connectivity, local density awareness, and communication quality within a unified fitness model.

4.4.1. Node Connectivity Metric

Node connectivity represents the number of neighboring vehicles located within the communication range of vehicle (V_i). Vehicles with higher connectivity can maintain communication with a larger number of neighboring vehicles and are therefore considered more suitable candidates for cluster head selection.

The connectivity metric is defined as

$$C_i = |N_i| \quad (8)$$

where

- (N_i) denotes the neighboring vehicle set of (V_i).

Higher connectivity values indicate improved local communication capability and better cluster coordination potential.

4.4.2. Local Density Metric

Vehicular density significantly affects cluster organization and communication stability. In dense traffic conditions, vehicles located in highly connected regions are more suitable for stable cluster formation.

The local density metric of vehicle (V_i) is calculated as

$$D_i = \frac{|N_i|}{\pi R^2} \quad (9)$$

where

- (R) denotes the communication range.

Higher density values indicate that the vehicle is located in a well-connected local region with improved communication robustness.

4.4.3. Communication Quality Metric

In dynamic vehicular environments, communication quality directly affects link reliability and cluster stability. To improve communication robustness, the proposed framework incorporates a communication quality metric based on received signal strength measurements.

The communication quality metric is defined as

$$Q_i = \frac{1}{|N_i|} \sum_{v_j \in N_i} RSSI_{ij} \quad (10)$$

where

($RSSI_{ij}$) denotes the received signal strength indicator between vehicles (V_i) and (V_j).

Higher communication quality values indicate more reliable communication links and improved clustering stability.

4.4.4. Multi-Criteria Fitness Function

To combine the different clustering metrics, the proposed A-MCAC framework introduces a unified adaptive fitness function for cluster-head selection.

All clustering metrics are first normalized within the interval $[0, 1]$ using min-max normalization:

$$X_i^{norm} = \frac{X_i - X_{min}}{X_{max} - X_{min} + \varepsilon} \quad (11)$$

where

- (X_i) represents the original metric value;

- (X_{min}) and (X_{max}) denote the minimum and maximum values of the considered metric;
- (ϵ) is a small positive constant used to avoid division by zero.

Since all metrics are normalized within $[0, 1]$, they can be combined linearly without introducing scale imbalance.

The cluster head fitness score is then computed as

$$F_i = \alpha C_i^{norm} + \beta LS_i^{norm} + \gamma M_i^{norm} + \delta D_i^{norm} + \eta Q_i^{norm} \quad (12)$$

where

- (C_i^{norm}) denotes normalized node connectivity;
- (LS_i^{norm}) represents normalized predictive link stability;
- (M_i^{norm}) denotes normalized mobility stability;
- (D_i^{norm}) represents normalized local density;
- (Q_i^{norm}) denotes normalized communication quality;
- $(\alpha, \beta, \gamma, \delta, \eta)$ represent weighting coefficients used during cluster head evaluation.

The normalization process prevents metric dominance and ensures balanced cluster-head selection under heterogeneous vehicular conditions.

Vehicles with higher fitness scores are considered more stable and reliable candidates for cluster head selection.

The vehicle with the highest fitness score within a local neighborhood is elected as the cluster head.

The proposed multi-criteria fitness model improves cluster robustness by jointly considering mobility behavior, communication reliability, and local topology characteristics instead of relying on isolated clustering parameters.

4.4.5. Adaptive Weight Optimization

Unlike conventional clustering approaches that rely on fixed weighting parameters, the proposed A-MCAC framework dynamically adjusts the influence of clustering metrics according to real-time vehicular network conditions.

Let

- (ρ) denote average network density;
- (μ) represent average network mobility;
- (λ) denote average link stability.

The parameters ρ , μ , and λ are periodically estimated from local network observations, representing the average vehicle density, average mobility variation, and average link stability measured within the communication neighborhood.

It should be noted that the local density metric D_i and the average network density parameter ρ serve different purposes in the proposed adaptive weighting model. The metric D_i evaluates the local neighborhood density of an individual vehicle and contributes directly to the cluster head fitness score through Equation (12). In contrast, ρ characterizes the overall traffic density observed within the local network and is used solely to dynamically adjust the adaptive weighting coefficients according to current network conditions. Therefore, ρ does not introduce an additional density metric into the fitness function but instead regulates the relative importance assigned to the different clustering criteria under varying traffic densities.

The adaptive weighting coefficients α , β , and γ are dynamically adjusted according to the average network density (ρ), average mobility (μ), and average link stability (λ), respectively.

$$\alpha = \frac{(1 - \delta - \eta)\rho}{\rho + \mu + \lambda} \quad (13)$$

$$\beta = \frac{(1 - \delta - \eta)\lambda}{\rho + \mu + \lambda} \quad (14)$$

$$\gamma = \frac{(1 - \delta - \eta)\mu}{\rho + \mu + \lambda} \quad (15)$$

The adaptive weighting coefficients α , β , and γ dynamically reflect connectivity conditions, link stability, and mobility characteristics, respectively. The coefficients δ and η are predefined design parameters associated with local density and communication quality.

To preserve the contribution of all clustering metrics while ensuring proper normalization, the adaptive coefficients α , β , and γ are computed within the remaining weight budget after allocating fixed weights to δ and η . Consequently, all weighting coefficients satisfy the following:

$$\alpha + \beta + \gamma + \delta + \eta = 1 \quad (16)$$

The coefficients δ and η are fixed design parameters, while α , β , and γ are dynamically normalized within the remaining weight budget.

This adaptive optimization mechanism allows the clustering framework to automatically prioritize connectivity in dense environments, mobility stability in highly dynamic scenarios, and link reliability under unstable communication conditions.

As a result, the proposed A-MCAC framework improves clustering stability and reduces frequent cluster reconfiguration under varying vehicular traffic conditions.

4.5. Event-Driven Cluster Maintenance and Re-Clustering Strategy

Frequent cluster reconfiguration is one of the main challenges in highly dynamic vehicular networks. Due to rapid topology variations and unstable communication links, conventional clustering approaches often perform periodic re-clustering operations that generate excessive communication overhead and reduce cluster stability [26,27].

To address these limitations, the proposed A-MCAC framework introduces an event-driven cluster maintenance mechanism that dynamically triggers re-clustering operations only when significant topology instability is detected. This strategy reduces unnecessary control message exchanges and improves clustering robustness under varying vehicular conditions.

4.5.1. Cluster Maintenance Principle

In the proposed framework, cluster maintenance is continuously monitored using predictive link stability and mobility behavior. Instead of performing full periodic re-clustering, cluster updates are triggered only when predefined instability conditions occur.

For each cluster member vehicle (V_i), the clustering framework continuously evaluates:

- predictive link lifetime;
- mobility stability;
- communication quality;
- connectivity variation.

A cluster maintenance operation is triggered when at least one of the following conditions is satisfied:

- The estimated predicted link lifetime falls below a predefined threshold;
- The cluster head loses connectivity with neighboring vehicles;
- The mobility stability score becomes unstable;
- The communication quality degrades significantly.

This event-driven strategy reduces unnecessary re-clustering operations and improves topology stability in dynamic vehicular environments.

4.5.2. Link Stability Threshold

A minimum predictive link lifetime threshold T_{LLT} is defined to determine whether a communication link is expected to remain stable for a sufficient period. Links whose estimated predictive lifetime falls below this threshold are considered unreliable and may trigger localized cluster maintenance.

Let: $LLT_{ij} < T_{LLT}$

where

- (LLT_{ij}) denotes the estimated predicted link lifetime;
- (T_{LLT}) represents the minimum acceptable link stability threshold.

When the estimated predicted link lifetime between a cluster member and its cluster head falls below the threshold value, the communication link is considered unstable, and a local re-clustering operation is initiated.

4.5.3. Mobility Instability Detection

To detect unstable mobility behavior, the proposed framework evaluates the temporal variation in vehicle mobility stability.

The mobility instability indicator of vehicle (V_i) is defined as

$$\Delta M_i = |M_i(t) - M_i(t - \Delta t)| \quad (17)$$

where

- ($M_i(t)$) denotes the current mobility stability score;
- ($M_i(t - \Delta t)$) represents the previous mobility stability score;
- (ΔM_i) measures the temporal variation in mobility stability.

Higher values of (ΔM_i) indicate significant temporal changes in vehicle mobility and may lead to cluster instability.

To determine whether the observed mobility variation is significant, a predefined mobility instability threshold T_M is introduced. The threshold T_M represents the maximum acceptable temporal variation in the mobility stability score before triggering local re-clustering operations.

If: $\Delta M_i > T_M$ the vehicle is considered highly unstable and reclustering procedures may be triggered.

4.5.4. Cluster Head Stability Monitoring

The proposed framework continuously evaluates the stability of the selected cluster head in order to avoid unnecessary cluster head switching operations.

The cluster head stability score is computed as

$$CHS_i = \omega_1 LS_i + \omega_2 M_i + \omega_3 Q_i \quad (18)$$

where

- (LS_i) denotes predictive link stability;
- (M_i) represents mobility stability;
- (Q_i) denotes communication quality;
- ($\omega_1, \omega_2, \omega_3$) are weighting coefficients associated with predictive link stability, mobility stability, and communication quality, respectively.

To ensure balanced contribution of the cluster head evaluation metrics, the weighting coefficients satisfy

$$\omega_1 + \omega_2 + \omega_3 = 1 \quad (19)$$

This normalization constraint prevents metric dominance and ensures a balanced assessment of cluster head stability under varying vehicular network conditions.

To determine whether the current Cluster Head remains suitable for maintaining cluster stability, a predefined Cluster Head stability threshold T_{CH} is introduced. This threshold represents the minimum acceptable Cluster Head Stability Score required to preserve reliable cluster management. When the stability score falls below this threshold, the Cluster Head is considered insufficiently stable, and a new Cluster Head election is initiated.

If the cluster head stability score decreases below a predefined threshold: $CHS_i < T_{CH}$ a new cluster head reselection process is initiated locally inside the affected cluster.

4.5.5. Local Re-Clustering Strategy

Unlike conventional clustering approaches that perform global re-clustering operations, the proposed A-MCAC framework applies localized re-clustering in order to minimize communication overhead and improve scalability.

When instability is detected, only the affected cluster region performs re-clustering operations, while stable clusters continue normal communication without interruption.

This localized maintenance strategy significantly reduces:

- control packet generation;
- cluster head switching frequency;
- communication overhead;
- network fragmentation.

4.5.6. Re-Clustering Rate Estimation

To evaluate clustering robustness, the re-clustering rate is defined as

$$RR = \frac{N_{RC}}{T_{sim}} \quad (20)$$

where

- (N_{RC}) denotes the total number of re-clustering operations;
- (T_{sim}) represents the simulation duration.

Lower reclustering rate values indicate improved clustering stability and more robust topology management.

The proposed event-driven maintenance mechanism improves clustering stability by proactively detecting unstable communication conditions while avoiding unnecessary global cluster reconstruction operations. As a result, the proposed A-MCAC framework significantly reduces communication overhead and improves topology robustness in highly dynamic vehicular environments.

4.6. Proposed A-MCAC Clustering Algorithm

The proposed A-MCAC framework performs clustering through adaptive multi-criteria cluster head selection combined with predictive topology management and event-driven cluster maintenance.

The clustering process operates continuously in a distributed manner using local beacon exchange and predictive mobility analysis. Each vehicle periodically exchanges mobility and communication information with neighboring vehicles in order to support adaptive clustering decisions.

The operation of the proposed framework consists of the following main phases:

1. Neighbor discovery and local information exchange;
2. Predictive mobility estimation;

3. Link lifetime estimation;
4. Adaptive multi-criteria fitness computation;
5. Cluster head selection;
6. Cluster formation;
7. Event-driven cluster maintenance.

4.6.1. Neighbor Discovery Phase

Each vehicle periodically broadcasts beacon messages containing:

- vehicle identifier;
- current position;
- speed;
- moving direction;
- acceleration;
- communication quality information.

Based on the received beacon messages, each vehicle constructs its local neighboring vehicle set within the communication range.

4.6.2. Predictive Metric Computation

After neighbor discovery, each vehicle computes:

- mobility stability;
- predictive link lifetime;
- node connectivity;
- local density;
- communication quality.

The predictive mobility model is then used to estimate future vehicle positions and anticipate topology evolution.

4.6.3. Adaptive Fitness Evaluation

The computed clustering metrics are normalized and combined using the adaptive multi-criteria fitness function.

For each vehicle (V_i), the clustering fitness score is computed according to the adaptive multi-criteria fitness function defined in Equation (12). The adaptive weighting parameters are then updated dynamically according to the observed vehicular network conditions.

The adaptive weighting parameters are dynamically adjusted according to real-time vehicular network conditions.

4.6.4. Cluster Head Selection

Within each local neighborhood, the vehicle with the highest fitness score is selected as the cluster head.

The cluster head periodically broadcasts cluster advertisement messages, allowing neighboring vehicles to join the cluster.

Vehicles join the cluster head that satisfies:

- highest fitness stability;
- strongest communication quality;
- longest estimated predicted link lifetime.

4.6.5. Event-Driven Cluster Maintenance

Unlike conventional clustering approaches that periodically reconstruct the entire network topology, the proposed framework applies localized event-driven maintenance.

Cluster maintenance procedures are triggered only when instability conditions are detected, including:

- link lifetime degradation;
- communication quality degradation;
- cluster head instability;
- significant mobility variation.

Localized re-clustering operations are then performed only inside unstable cluster regions.

4.6.6. Algorithm Description

The complete operation of the proposed A-MCAC framework is summarized in Algorithm 1.

Algorithm 1. Adaptive Mobility- and Connectivity-Aware Clustering (A-MCAC)

Input:

- Vehicular network ($G(V,E)$),
- Communication range (R)

Output:

- Stable cluster formation and adaptive cluster head selection
1. Initialize vehicular network
 2. Vehicles periodically broadcast beacon messages
 3. For each vehicle (V_i) do
 4. Discover neighboring vehicles within communication range
 5. Compute node connectivity (C_i)
 6. Compute local density (D_i)
 7. Estimate mobility stability (M_i)
 8. Predict future vehicle positions
 9. Compute predicted inter-vehicle distances
 10. Compute relative velocity vectors
 11. Estimate predictive link lifetime (LLT_{ij})
 12. Compute average link stability (LS_i)
 13. Evaluate communication quality (Q_i)
 14. Update adaptive weighting parameters
 15. Compute fitness score (F_i)
 16. Select vehicle with highest fitness score as Cluster Head
 17. Form clusters using local neighborhood association
 18. Continuously monitor:
 - link lifetime,
 - mobility variation,
 - communication quality,
 - cluster head stability
 19. If instability detected then
 20. Trigger localized reclustering
 21. Update affected cluster region
 22. End If
 23. Repeat until simulation termination
-

The proposed algorithm improves cluster stability by combining predictive mobility estimation, adaptive fitness optimization, and event-driven cluster maintenance. This adap-

tive behavior allows the framework to maintain stable communication structures while reducing unnecessary control message exchanges in highly dynamic vehicular environments.

4.7. Complexity Analysis

The computational complexity of the proposed A-MCAC framework mainly depends on neighbor discovery, predictive metric computation, adaptive fitness evaluation, and localized cluster maintenance operations.

Let

- (N) denotes the total number of vehicles in the network;
- (k) represents the average number of neighboring vehicles within the communication range.

4.7.1. Neighbor Discovery Complexity

During the beacon exchange phase, each vehicle periodically discovers neighboring vehicles located within its communication range. The neighbor discovery process requires local distance evaluation between neighboring nodes.

The computational complexity of neighbor discovery is approximately: $O(Nk)$

In practical vehicular environments, the average number of neighboring vehicles k is significantly smaller than the total number of vehicles N due to the limited communication range of V2V communications.

4.7.2. Predictive Mobility and Link Lifetime Estimation Complexity

The predictive mobility estimation and link lifetime computation are performed locally using neighboring vehicle information.

For each neighboring vehicle pair, the framework computes:

- relative velocity;
- predictive future position;
- estimated link lifetime.

The corresponding computational complexity is $O(Nk)$, since each vehicle only evaluates neighboring vehicles within its local communication region.

4.7.3. Adaptive Fitness Evaluation Complexity

The proposed multi-criteria fitness computation combines:

- connectivity;
- mobility stability;
- predictive link lifetime;
- local density;
- communication quality.

Since the clustering metrics are locally computed and normalized, the fitness evaluation complexity remains $O(Nk)$.

This lightweight distributed computation avoids expensive global optimization procedures commonly used in AI-based clustering approaches.

Since $k \ll N$ in practical vehicular environments, the proposed framework maintains near-linear scalability suitable for dense IoV scenarios.

4.7.4. Cluster Maintenance Complexity

Unlike conventional clustering approaches that periodically reconstruct the entire network topology, the proposed A-MCAC framework performs localized event-driven maintenance operations.

Only unstable cluster regions trigger reclustering operations. Therefore, the reclustering complexity depends on the size of the affected local cluster region rather than the entire network.

The localized maintenance complexity can therefore be approximated as $O(k^2)$, where

- (k) denotes the local cluster size.

This localized strategy significantly reduces communication overhead and improves scalability under dense vehicular conditions.

4.7.5. Communication Overhead Complexity

The communication overhead of the proposed framework mainly results from:

- beacon message exchange;
- cluster advertisement messages;
- cluster joining operations;
- localized cluster maintenance messages.

Since the proposed framework avoids unnecessary global reclustering operations, the communication overhead remains significantly lower compared with conventional periodic clustering approaches.

The communication overhead complexity is therefore estimated as: $O(Nk)$.

4.7.6. Overall Computational Complexity

The computational complexity of the proposed A-MCAC framework is dominated by local neighboring vehicle processing and adaptive fitness computation.

Therefore, the total computational complexity of the proposed clustering framework can be approximated as: $O(Nk)$.

Compared with optimization-based and learning-based clustering approaches that may require iterative global optimization or intensive training procedures, the proposed A-MCAC framework maintains lightweight distributed clustering behavior suitable for real-time vehicular communication environments.

Table 2 provides a qualitative comparison between the proposed A-MCAC framework and the considered clustering approaches from a computational perspective. Although A-MCAC incorporates predictive mobility estimation, adaptive weighting, and multi-criteria Cluster Head selection, its computational complexity remains $O(Nk)$ because all computations are performed locally using neighboring vehicle information. In contrast, learning-based approaches may introduce additional training overhead, while periodic clustering schemes often generate higher maintenance costs under dense vehicular conditions.

The low complexity classification of A-MCAC is attributed to its distributed operation and localized event-driven maintenance, which avoids iterative optimization procedures and centralized processing requirements.

The proposed predictive adaptive clustering mechanism therefore provides an effective trade-off between clustering stability, communication efficiency, and computational complexity under highly dynamic Internet of Vehicles conditions.

The event-driven maintenance mechanism contributes to clustering convergence by limiting topology reconstruction only to unstable local regions, thereby preventing excessive oscillatory cluster formation.

Unlike iterative optimization or learning-based approaches, A-MCAC does not rely on centralized training procedures or repeated optimization cycles requiring formal convergence guarantees. Instead, clustering decisions are performed through localized heuristic

evaluations based on predictive mobility estimation, connectivity assessment, and link-lifetime analysis. Consequently, cluster stability is achieved through adaptive decision-making and event-driven maintenance mechanisms rather than mathematical convergence processes. The effectiveness of this strategy is demonstrated through the experimental results presented in Section 5.

Although execution time measurements may provide additional implementation-specific information, the computational efficiency of the proposed framework is evaluated through asymptotic complexity analysis, which offers a hardware-independent assessment of its scalability and facilitates objective comparison with existing clustering approaches.

Table 2. Complexity comparison of clustering approaches.

Scheme	Mobility Prediction	Multi-Criteria CH Selection	Adaptive Weighting	Maintenance Strategy	Complexity Level
CARAC	Partial	Partial	No	Periodic	Moderate
MetaLearn	Yes	Yes	Learning-Based	Periodic	High
CPB	No	Yes	No	Periodic	Moderate
A-MCAC	Yes	Yes	Yes	Event-Driven Localized	Low

5. Performance Evaluation and Discussion

5.1. Simulation Environment

To evaluate the effectiveness of the proposed Adaptive Mobility- and Connectivity-Aware Clustering, extensive simulations were conducted using the NS-3 network simulator. The proposed framework was compared with three representative cluster-based vehicular communication schemes, namely CARAC, MetaLearn, and CPB. These approaches were selected because they employ clustering mechanisms designed to improve network organization and communication efficiency in highly dynamic vehicular environments.

To ensure a fair and objective comparison, all evaluated schemes were implemented under the same simulation settings adopted from the CARAC framework. The simulation environment was configured using the IEEE 802.11p communication standard and the Manhattan Grid mobility model, which reproduces realistic urban traffic conditions characterized by frequent intersections, varying vehicle densities, and continuous topology changes [6].

Wireless communication behavior, including packet propagation, medium access, and interference among concurrent transmissions, follows the built-in PHY/MAC mechanisms provided by the simulator. These mechanisms provide a realistic communication environment for evaluating the proposed clustering framework under dynamic vehicular-network conditions. The performance evaluation, therefore, relies on the standard communication models provided by NS-3 to ensure a consistent and reproducible simulation environment.

The simulation area covers a region of 1000 m $\times$ 1000 m populated by vehicles moving at speeds ranging from 20 m/s to 35 m/s. The number of vehicles varied from 50 to 250 in order to evaluate the scalability and robustness of the clustering mechanisms under different traffic densities. Four Road Side Units (RSUs) were included in the simulation environment to represent the underlying IoV infrastructure. However, they did not participate in the proposed clustering process and were not involved in Cluster Head selection, cluster maintenance, or adaptive decision-making. Their presence was limited to representing the underlying IoV infrastructure and did not influence the implementation or performance evaluation of the compared clustering algorithms. The fixed coefficients δ and η were set to 0.15 and 0.10, respectively, based on preliminary simulation tuning. The

selected values provided the best balance between cluster stability and communication performance during preliminary experiments and were therefore kept constant throughout all simulation scenarios.

Each vehicle was configured with a communication range of 300 m, while RSUs were assigned a transmission range of 700 m. The packet size was fixed at 512 bytes, and the transmission power was set to 7.5 dBm. Each simulation was executed for 200 s, and all reported results correspond to the average values obtained from multiple simulation runs to ensure statistical reliability. Each scenario was repeated 10 times using different random seeds, and the reported results correspond to the average values obtained from these runs.

The proposed A-MCAC framework was implemented in NS-3 as a clustering layer operating over IEEE 802.11p communications. Vehicles periodically exchange beacon messages containing position, speed, movement direction, and neighborhood information. These beacon messages enable vehicles to compute the clustering metrics defined in Section 4 and perform cluster formation, Cluster Head selection, and cluster maintenance operations.

To support data forwarding and end-to-end communication, the Ad hoc On Demand Distance Vector (AODV) routing protocol was integrated with the proposed A-MCAC clustering framework. This integration enables the evaluation of both clustering performance and network communication efficiency under realistic vehicular networking conditions. AODV was selected because it is a well-established reactive routing protocol widely adopted as a benchmark in MANET and VANET studies. The routing configuration remained identical throughout all experiments, while only the clustering mechanism varied. Consequently, any observed performance differences can be primarily attributed to the effectiveness of the underlying clustering framework rather than routing-specific optimizations.

Although CARAC was originally proposed as a cluster-based routing protocol, the present study focuses on evaluating and comparing the clustering mechanisms employed by the considered approaches under a unified routing environment. This strategy enables a fair assessment of cluster formation efficiency, cluster maintenance capability, and their impact on network performance.

Unlike conventional clustering approaches that primarily rely on mobility similarity or geographical proximity, the proposed A-MCAC framework employs a predictive multi-criteria Cluster Head selection mechanism based on connectivity, link stability, mobility consistency, local density, and communication quality. Furthermore, predictive link lifetime estimation and adaptive weighting optimization are incorporated to enhance cluster stability and reduce unnecessary reclustering operations.

The performance evaluation includes both clustering-oriented and network-oriented metrics. Cluster Lifetime (CL), Cluster Head Lifetime (CHL), Reclustering Rate (RR), Average Link Stability (ALS), and Clustering Overhead (CO) are used to assess clustering effectiveness and stability. In addition, Packet Delivery Ratio (PDR), End-to-End Delay, and Throughput are evaluated to investigate the impact of clustering quality on communication performance.

Table 3 summarizes the simulation parameters used throughout the experiments.

The threshold values and weighting coefficients were determined through preliminary tuning experiments and kept constant throughout all simulation scenarios.

Table 3. Simulation parameters.

Parameter	Value
Network Simulator	NS-3
MAC Protocol	IEEE 802.11p
Routing Protocol	AODV
Simulation Area	1000 m × 1000 m
Simulation Time	200 s
Mobility Model	Manhattan Grid
Number of Vehicles	50–250
Vehicle Speed	20–35 m/s
Optional RSUs	4
Vehicle Transmission Range	300 m
RSU Transmission Range	700 m
Packet Size	512 Bytes
Transmission Power	7.5 dBm
Beacon Interval	100 ms
Link Lifetime Threshold (T_{LLT})	2 s
Mobility Stability Threshold (T_M)	0.20
Cluster Head Stability Threshold (T_{CH})	0.60
CH Stability Weights ($\omega_1, \omega_2, \omega_3$)	(0.4, 0.35, 0.25)
Fixed Weight Coefficients (δ, η)	(0.15, 0.10)
Compared Schemes	A-MCAC, CARAC, MetaLearn, CPB
Evaluation Metrics	CL, CHL, RR, ALS, CO, PDR, Delay, Throughput

5.2. Cluster Lifetime Analysis

Cluster Lifetime is one of the most representative indicators of clustering stability in vehicular networks. A longer cluster lifetime generally reflects the ability of a clustering framework to maintain stable cluster structures despite continuous topology changes.

The average Cluster Lifetime is computed as

$$CL = \frac{\sum_{i=1}^{N_c} T_i}{N_c} \quad (21)$$

where (T_i) denotes the lifetime of cluster (i), and (N_c) represents the total number of clusters formed during the simulation.

To evaluate the impact of vehicle density on cluster stability, the number of vehicles was varied from 50 to 250 while maintaining the simulation parameters presented in Section 5.1. Each scenario was executed multiple times using different random seeds. The reported values correspond to the average results obtained from these runs, while the error bars shown in Figure 2 represent the standard deviation.

Figure 2 presents the average Cluster Lifetime achieved by A-MCAC, CARAC, MetaLearn, and CPB under different vehicle densities. It can be observed that the Cluster Lifetime decreases for all compared approaches as the number of vehicles increases. This behavior is expected because higher vehicle densities lead to more frequent topology changes and increased communication dynamics.

However, the proposed A-MCAC consistently achieves the highest Cluster Lifetime in all evaluated scenarios. For example, when the network contains 50 vehicles, A-MCAC achieves a Cluster Lifetime of approximately 85 s, compared with 74 s, 66 s, and 61 s for CARAC, MetaLearn, and CPB, respectively. Similarly, under dense traffic conditions with 250 vehicles, A-MCAC maintains a Cluster Lifetime of about 61 s, whereas CARAC, MetaLearn, and CPB achieve 53 s, 47 s, and 42 s, respectively.

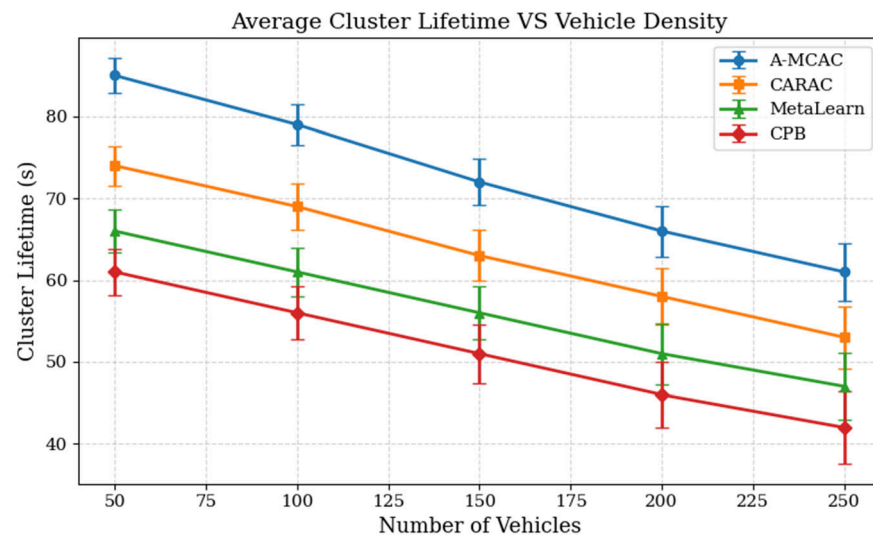


Figure 2. Average cluster lifetime vs. vehicle density.

The obtained results indicate that the proposed clustering framework generates more stable cluster structures than the compared approaches. This improvement is mainly attributed to the proposed mobility-aware clustering strategy and the multi-criteria Cluster Head selection process. By considering future vehicle positions and predicted link stability, A-MCAC is able to select more suitable Cluster Heads and reduce unnecessary cluster reconfigurations.

In addition, the adaptive weighting mechanism enables the clustering process to dynamically adapt to changes in network conditions. As a result, clusters remain stable for longer periods, which contributes to improved network organization and reduced maintenance operations.

From these results, A-MCAC provides superior cluster stability compared with CARAC, MetaLearn, and CPB across all evaluated traffic densities. The longer Cluster Lifetime achieved by the proposed framework provides a stronger foundation for reliable vehicular communications and subsequent routing operations.

5.3. Cluster Head Lifetime Analysis

The stability of Cluster Heads plays a crucial role in maintaining efficient cluster management in vehicular networks. Frequent Cluster Head replacements may generate additional control overhead, increase cluster maintenance operations, and negatively affect communication continuity. Therefore, evaluating Cluster Head Lifetime provides valuable insight into the effectiveness of the Cluster Head selection strategy.

The average Cluster Head Lifetime is calculated as

$$CHL = \frac{\sum_{i=1}^{N_{CH}} T_{CH_i}}{N_{CH}} \quad (22)$$

where (T_{CH_i}) denotes the lifetime of Cluster Head (i) , and (N_{CH}) represents the total number of Cluster Heads observed during the simulation.

Figure 3 illustrates the variation in Cluster Head Lifetime under different vehicle densities. The reported values correspond to the average results obtained from multiple simulation runs, while the error bars represent the standard deviation.

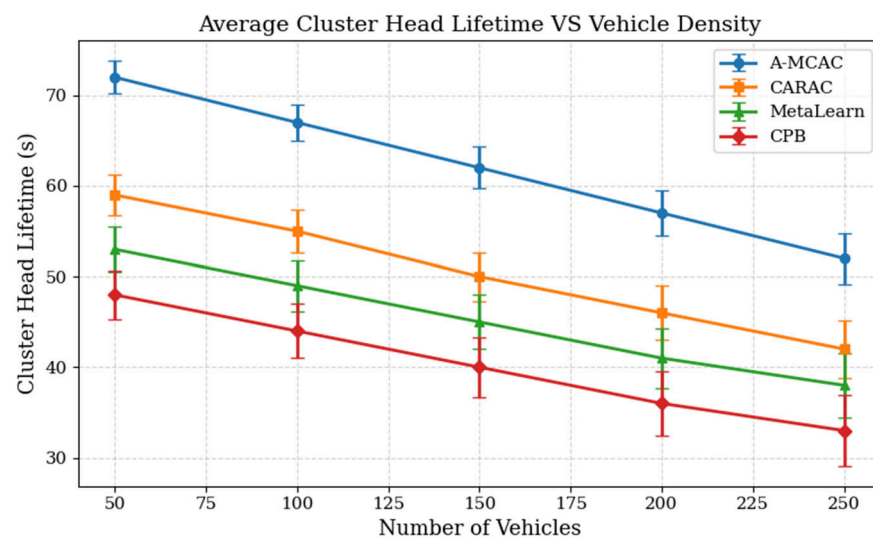


Figure 3. Average cluster head lifetime vs. vehicle density.

As vehicle density increases, Cluster Head Lifetime decreases for all evaluated schemes. This trend is expected because dense vehicular environments experience more frequent topology changes, making it more difficult for a selected Cluster Head to preserve stable relationships with its neighboring vehicles over extended periods.

However, the proposed A-MCAC framework consistently maintains longer Cluster Head durations than the compared approaches. At a density of 50 vehicles, the average Cluster Head Lifetime reaches approximately 72 s, whereas CARAC, MetaLearn, and CPB achieve 59 s, 53 s, and 48 s, respectively. Even under dense traffic conditions with 250 vehicles, A-MCAC preserves a Cluster Head Lifetime of about 52 s, compared with 42 s, 38 s, and 33 s for CARAC, MetaLearn, and CPB.

The observed improvement is closely related to the adaptive Cluster Head selection process introduced in Section 4. Rather than relying on a single clustering parameter, A-MCAC evaluates candidate vehicles using mobility stability, predictive link stability, connectivity, local density, and communication quality. As a result, vehicles selected as Cluster Heads are more likely to remain suitable for longer periods despite changes in network topology.

Another important observation is that the longer Cluster Head Lifetime achieved by A-MCAC contributes directly to reducing cluster maintenance operations. Since Cluster Head replacements occur less frequently, cluster members can maintain stable associations for longer durations, improving cluster organization and communication efficiency.

These results confirm that the proposed multi-criteria selection strategy is capable of identifying more reliable Cluster Heads than CARAC, MetaLearn, and CPB, leading to improved cluster stability under both sparse and dense vehicular traffic conditions.

5.4. Reclustering Rate Analysis

Frequent re-clustering operations are generally a direct consequence of unstable Cluster Heads and short cluster lifetimes. In highly dynamic vehicular environments, excessive re-clustering may increase control traffic, consume network resources, and reduce the efficiency of cluster management. Therefore, minimizing the frequency of re-clustering operations is an important objective for any clustering framework.

The Re-clustering Rate (RR) is evaluated using the formulation introduced in Equation (20), where N_{RC} denotes the total number of reclustering operations and T_{sim} is the simulation duration.

Figure 4 presents the Reclustering Rate obtained by A-MCAC, CARAC, MetaLearn, and CPB under different vehicle densities. The reported values correspond to the average results obtained from multiple simulation runs, while the error bars represent the standard deviation.

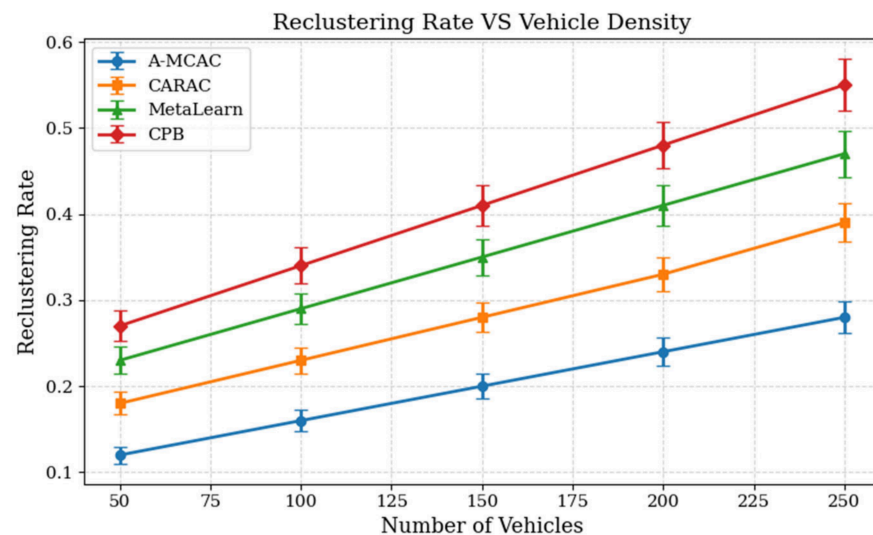


Figure 4. Reclustering rate vs. vehicle density.

As expected, the Reclustering Rate increases with vehicle density for all evaluated approaches. The increase in the number of vehicles generates more frequent topology changes, resulting in a higher probability of cluster fragmentation, Cluster Head replacement, and cluster reorganization.

Despite these challenges, A-MCAC consistently achieves the lowest Reclustering Rate across all simulation scenarios. For instance, at a density of 50 vehicles, the proposed framework records a Reclustering Rate of approximately 0.12, whereas CARAC, MetaLearn, and CPB achieve 0.18, 0.23, and 0.27, respectively. When the network density reaches 250 vehicles, the Reclustering Rate remains limited to 0.28 for A-MCAC, compared with 0.39, 0.47, and 0.55 for CARAC, MetaLearn, and CPB.

This behavior can be explained by the proactive clustering decisions incorporated into the proposed framework. By estimating future vehicle positions and link lifetimes, A-MCAC is able to anticipate topology variations and avoid unnecessary cluster reconfigurations. Furthermore, the adaptive Cluster Head selection process favors vehicles with higher stability characteristics, which contributes to maintaining stable cluster structures over longer periods.

The results also confirm the relationship between Cluster Head Lifetime and Reclustering Rate. As shown in the previous subsection, A-MCAC maintains Cluster Heads for longer durations, which naturally reduces the frequency of cluster reorganization events. Consequently, fewer maintenance operations are required throughout the simulation process.

The obtained results demonstrate that A-MCAC significantly improves cluster stability by reducing the need for frequent reclustering operations, thereby contributing to more efficient and reliable vehicular network management.

5.5. Average Link Stability Analysis

Since the proposed A-MCAC framework relies on predictive mobility analysis and link lifetime estimation, the evaluation of link stability provides direct insight into the effectiveness of the proposed clustering mechanism. In vehicular networks, stable communication links are essential for maintaining reliable cluster structures and reducing the frequency of topology-related disruptions.

Average Link Stability is used to evaluate the reliability of communication links established between neighboring vehicles. Higher ALS values indicate that links remain connected for longer periods, which contributes to improved cluster stability and more efficient communication.

The Average Link Stability is calculated as

$$ALS = \frac{1}{N} \sum_{i=1}^N LS_i \quad (23)$$

where (LS_i) represents the stability of link (i) , and (N) denotes the total number of evaluated links during the simulation.

Figure 5 presents the Average Link Stability achieved by A-MCAC, CARAC, MetaLearn, and CPB under different vehicle densities. The reported values correspond to the average results obtained from multiple simulation runs, while the error bars represent the standard deviation.

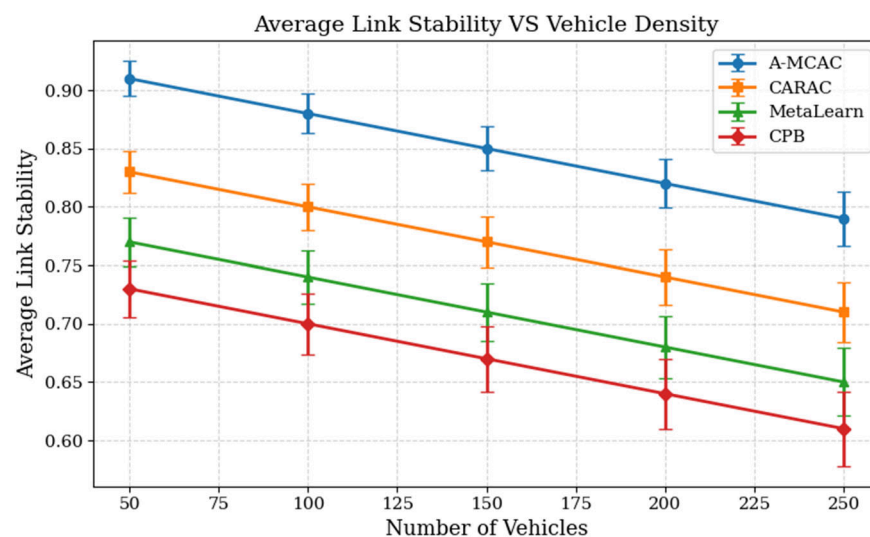


Figure 5. Average link stability vs. vehicle density.

The results show that link stability gradually decreases as vehicle density increases. In dense traffic conditions, vehicles experience more frequent speed variations and topology changes, which increases the probability of link disruptions. Consequently, maintaining stable communication links becomes more challenging for all evaluated approaches.

Despite these conditions, A-MCAC consistently achieves the highest Average Link Stability across all simulation scenarios. For example, when the network contains 50 vehicles, A-MCAC achieves an ALS value of 0.91, whereas CARAC, MetaLearn, and CPB achieve 0.83, 0.77, and 0.73, respectively. At a density of 250 vehicles, the ALS value remains at 0.79 for A-MCAC, compared with 0.71, 0.65, and 0.61 for CARAC, MetaLearn, and CPB.

The observed improvement can be attributed to the link-aware and mobility-aware clustering mechanisms introduced in Section 4. Unlike conventional clustering schemes that mainly rely on current vehicle information, A-MCAC estimates future vehicle posi-

tions and predicts link lifetime before cluster formation decisions are made. This enables the framework to favor communication links that are expected to remain stable over longer durations.

Another important observation is that the higher link stability achieved by A-MCAC explains the improvements observed in Cluster Lifetime and Cluster Head Lifetime. Stable communication links reduce the probability of cluster fragmentation and allow cluster members to maintain their associations with Cluster Heads for longer periods.

The results demonstrate that the predictive mobility and link lifetime estimation mechanisms significantly enhance communication reliability, providing a strong foundation for the clustering stability improvements observed throughout the previous subsections.

5.6. Clustering Overhead Analysis

While clustering stability is an important objective in vehicular networks, it should not be achieved at the expense of excessive control traffic. Therefore, evaluating Clustering Overhead is necessary to assess the cost associated with maintaining cluster structures and supporting the proposed clustering mechanisms.

Clustering Overhead represents the total amount of control information exchanged during cluster formation, Cluster Head election, cluster maintenance, and re-clustering operations. It is calculated as

$$CO = \sum_{i=1}^{N_c} CP_i \quad (24)$$

where (CP_i) denotes the number of control packets exchanged during a clustering operation, and (N_c) represents the total number of clustering-related events observed during the simulation.

Figure 6 illustrates the Clustering Overhead generated by A-MCAC, CARAC, MetaLearn, and CPB under different vehicle densities. As expected, the overhead increases for all evaluated approaches as the number of vehicles grows. Larger networks require additional control messages to maintain cluster organization and manage interactions among participating vehicles.

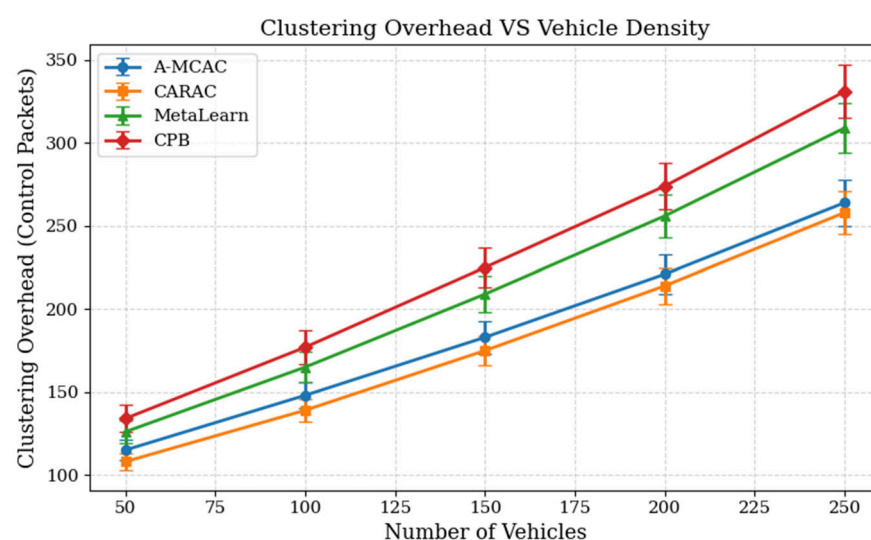


Figure 6. Clustering overhead vs. vehicle density.

The results show that A-MCAC generates slightly higher overhead than CARAC in most simulation scenarios. For example, when the network contains 50 vehicles, A-MCAC produces approximately 115 control packets compared with 108 packets for CARAC. At a density of 250 vehicles, the overhead increases to 264 packets for A-MCAC and 258 packets for CARAC. This additional cost is mainly associated with the predictive mo-

bility analysis, link lifetime estimation, and adaptive weighting mechanisms incorporated into the proposed framework.

However, despite this moderate increase, A-MCAC consistently generates lower overhead than MetaLearn and CPB across all evaluated traffic densities. More importantly, the additional control cost remains limited when compared with the improvements achieved in Cluster Lifetime, Cluster Head Lifetime, Average Link Stability, and Reclustering Rate.

An important observation is that the overhead increase introduced by A-MCAC does not originate from frequent cluster reconfigurations. On the contrary, the proposed framework significantly reduces reclustering operations by maintaining more stable cluster structures. The observed overhead is primarily associated with the additional clustering intelligence incorporated into the proposed framework rather than instability-induced maintenance procedures.

These findings indicate that A-MCAC achieves a favorable balance between clustering cost and clustering performance. Although a moderate increase in control overhead is introduced compared with CARAC, the resulting gains in cluster stability and communication reliability largely compensate for this additional cost.

5.7. Packet Delivery Ratio Analysis

From a communication perspective, the reliability of packet delivery strongly depends on the stability of the underlying network topology. Frequent cluster reconfigurations, unstable communication links, and repeated route failures may significantly reduce the probability of successful packet transmission. Therefore, Packet Delivery Ratio is used to evaluate the effectiveness of the proposed clustering framework from a network performance perspective.

The Packet Delivery Ratio is calculated as

$$PDR = \frac{N_{received}}{N_{sent}} \times 100 \quad (25)$$

where ($N_{received}$) denotes the number of successfully received packets, and (N_{sent}) represents the total number of transmitted packets.

Figure 7 presents the Packet Delivery Ratio achieved by A-MCAC, CARAC, MetaLearn, and CPB under different vehicle densities. The reported values correspond to the average results obtained from multiple simulation runs, while the error bars represent the standard deviation.

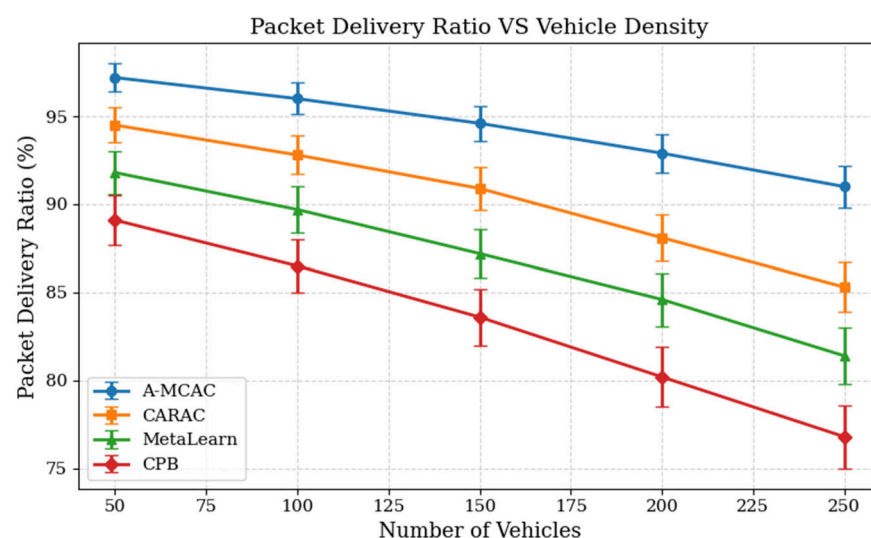


Figure 7. Packet delivery ratio vs. vehicle density.

As vehicle density increases, the Packet Delivery Ratio gradually decreases for all evaluated approaches. This behavior is mainly caused by increased channel contention, packet collisions, and more frequent topology variations in dense vehicular environments.

Nevertheless, the proposed A-MCAC framework consistently achieves the highest PDR values across all simulation scenarios. At a density of 50 vehicles, the proposed framework achieves a Packet Delivery Ratio of approximately 97.2%, while CARAC, MetaLearn, and CPB achieve 94.5%, 91.8%, and 89.1%, respectively. Even when the number of vehicles reaches 250, A-MCAC + AODV maintains a PDR of about 91.0%, compared with 85.3%, 81.4%, and 76.8% for CARAC, MetaLearn, and CPB.

The improvement in packet delivery performance can be directly associated with the clustering stability achieved by A-MCAC. As demonstrated in the previous subsections, the proposed framework provides higher Average Link Stability, longer Cluster Lifetime, and lower Re-clustering Rate. These characteristics reduce route disruptions and improve the continuity of communication paths used during packet forwarding.

Furthermore, the predictive mobility and link-lifetime estimation mechanisms allow the clustering process to proactively avoid unstable communication links. Consequently, packet losses caused by link breakages are reduced, leading to more reliable end-to-end data delivery.

In general, the results clearly indicate that the proposed A-MCAC framework improves communication reliability under both sparse and dense traffic conditions. This confirms that the clustering improvements achieved by A-MCAC translate directly into enhanced network-level performance.

5.8. End-to-End Delay Analysis

Communication latency is highly influenced by route disruptions and packet retransmissions in dynamic vehicular environments. When communication links become unstable, routing protocols must frequently rediscover routes and recover broken communication paths, which increases packet delivery time. Therefore, End-to-End Delay is an important metric for evaluating the impact of clustering quality on communication efficiency.

The average End-to-End Delay is calculated as

$$Delay = \frac{\sum_{i=1}^{N_r} (t_{receive_i} - t_{send_i})}{N_r} \quad (26)$$

where (t_{send_i}) and $(t_{receive_i})$ denote the transmission and reception times of packet (i) , respectively, and (N_r) represents the total number of successfully received packets.

Figure 8 presents the average End-to-End Delay achieved by A-MCAC, CARAC, MetaLearn, and CPB under different vehicle densities. The reported values correspond to the average results obtained from multiple simulation runs, while the error bars represent the standard deviation.

The results show that communication delay increases progressively as the number of vehicles grows. This trend is expected because dense vehicular environments generate higher channel contention, increased packet retransmissions, and more frequent route recovery procedures.

Despite these challenging conditions, A-MCAC consistently achieves the lowest delay among all evaluated approaches. For example, when the network contains 50 vehicles, the proposed framework achieves an average delay of approximately 18 ms, whereas CARAC, MetaLearn, and CPB achieve 22 ms, 27 ms, and 31 ms, respectively. At a density of 250 vehicles, the delay remains limited to 31 ms for A-MCAC, compared with 38 ms, 46 ms, and 53 ms for CARAC, MetaLearn, and CPB.

The reduced delay observed for A-MCAC can be explained by the improved cluster stability achieved throughout the clustering process. Stable Cluster Heads and reliable communication links reduce the occurrence of route interruptions, allowing data packets to follow more consistent forwarding paths toward their destinations.

In addition, the lower Re-clustering Rate achieved by A-MCAC reduces the temporary communication disruptions commonly associated with cluster maintenance operations. As a result, routing decisions remain valid for longer periods, reducing route rediscovery delays and minimizing packet buffering time.

The obtained results demonstrate that the proposed A-MCAC framework improves communication responsiveness and reduces transmission latency under both sparse and dense vehicular traffic conditions. These improvements confirm the positive impact of stable clustering structures on end-to-end communication performance.

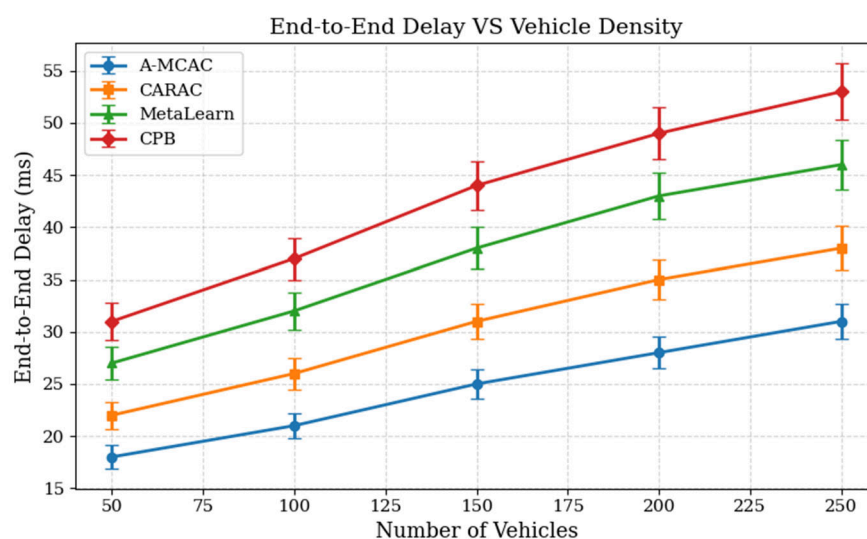


Figure 8. End-to-end delay vs. vehicle density.

5.9. Throughput Analysis

Throughput reflects the efficiency of the network in utilizing available communication resources. Unlike the previous metrics, which evaluate specific aspects of clustering stability or communication reliability, Throughput provides a global indication of how effectively data packets are delivered across the network. Higher Throughput values indicate that a larger amount of useful information successfully reaches its destination within a given period of time.

The average Throughput is calculated as

$$Throughput = \frac{\sum_{i=1}^{N_r} PacketSize_i}{T_{sim}} \quad (27)$$

where $(PacketSize_i)$ represents the size of the successfully received packet (i) , and (T_{sim}) denotes the simulation time.

Figure 9 presents the Throughput obtained by A-MCAC, CARAC, MetaLearn, and CPB under different vehicle densities. The reported values correspond to the average results obtained from multiple simulation runs, while the error bars represent the standard deviation.

As vehicle density increases, the Throughput decreases for all evaluated approaches. This behavior is mainly caused by higher channel contention, packet collisions, and communication interruptions that reduce the amount of successfully delivered data.

Despite these challenges, the proposed A-MCAC framework consistently achieves the highest Throughput across all simulation scenarios. At a density of 50 vehicles, A-MCAC achieves approximately 920 kbps, while CARAC, MetaLearn, and CPB achieve 870 kbps, 820 kbps, and 780 kbps, respectively. When the number of vehicles increases to 250, the Throughput remains at about 770 kbps for A-MCAC, compared with 700 kbps, 645 kbps, and 590 kbps for CARAC, MetaLearn, and CPB.

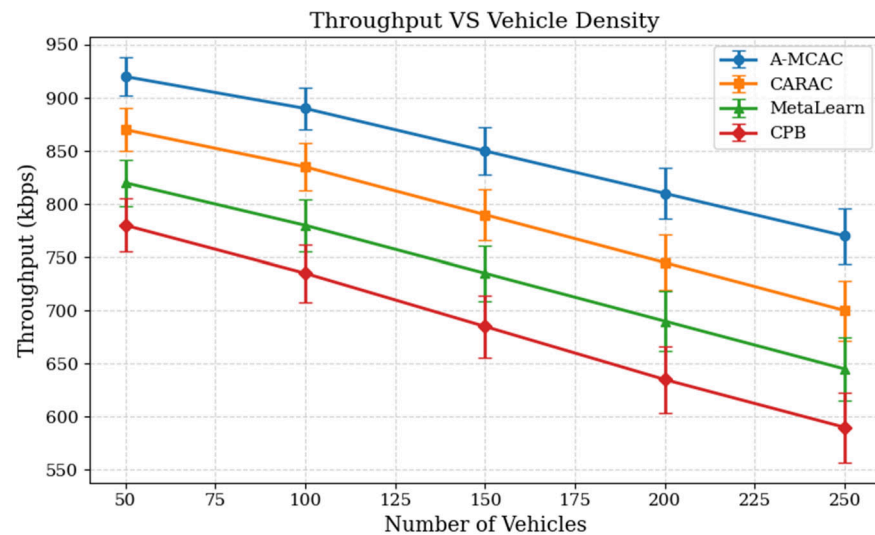


Figure 9. Throughput vs. vehicle density.

The superior Throughput achieved by A-MCAC is closely related to the improvements observed in the previous performance metrics. The higher Packet Delivery Ratio allows a larger number of packets to successfully reach their destinations, while the lower End-to-End Delay reduces transmission inefficiencies associated with route recovery and packet retransmissions. In addition, the improved link and cluster stability help maintain reliable communication paths during data forwarding operations.

These observations indicate that the benefits of the proposed clustering framework are not limited to cluster organization alone. Instead, the stability improvements introduced by A-MCAC directly contribute to enhancing the efficiency of network communications.

These observations confirm that the proposed A-MCAC framework provides superior data transmission efficiency compared with CARAC, MetaLearn, and CPB under all evaluated traffic densities, making it a suitable solution for highly dynamic Internet of Vehicles environments.

5.10. Discussion and Comparative Analysis

The simulation results presented in the previous sections demonstrate the effectiveness of the proposed A-MCAC framework under different vehicular densities. The obtained results show that A-MCAC consistently outperforms CARAC, MetaLearn, and CPB in most of the evaluated performance metrics [25–27].

From the clustering perspective, A-MCAC achieves longer Cluster Lifetime and Cluster Head Lifetime while maintaining a lower Re-clustering Rate. In addition, the proposed framework provides higher Average Link Stability, indicating that the predictive mobility model and the link lifetime estimation mechanism are effective in identifying stable communication links and selecting suitable Cluster Heads.

The improvement in link stability directly contributes to the formation of more stable clusters. As a result, cluster maintenance operations occur less frequently, reducing unnecessary re-clustering events and improving network organization. These observations

confirm the effectiveness of the adaptive multi-criteria Cluster Head selection strategy proposed in Section 4.

The network-level results also demonstrate the benefits of the proposed clustering framework. The higher Packet Delivery Ratio and Throughput achieved by A-MCAC indicate that stable cluster structures provide more reliable communication paths for packet forwarding. Similarly, the lower End-to-End Delay shows that the proposed framework is able to reduce route disruptions and improve communication efficiency even under dense traffic conditions.

Although A-MCAC introduces a slightly higher Clustering Overhead than CARAC, this additional cost remains moderate and is mainly associated with the predictive mobility analysis, link lifetime estimation, and adaptive weighting mechanisms. However, the resulting improvements in Cluster Lifetime, Cluster Head Lifetime, Link Stability, Packet Delivery Ratio, Delay, and Throughput largely compensate for this additional overhead.

Taken together, the obtained results indicate that the proposed A-MCAC framework achieves a favorable balance between clustering stability and communication performance under the considered simulation conditions. The proposed clustering strategy enables the framework to maintain reliable cluster structures while supporting efficient data transmission in highly dynamic vehicular environments.

These results indicate that A-MCAC can provide improved clustering stability and communication performance under the evaluated NS-3 urban vehicular scenarios characterized by high mobility and frequent topology changes.

Although the proposed adaptive weighting mechanism demonstrated consistent performance across the evaluated scenarios, a comprehensive sensitivity analysis of the weighting parameters is left for future work and constitutes an interesting direction for further investigation.

In practical IoV deployments, maintaining a balance between clustering stability and communication overhead remains a critical challenge. The obtained results indicate that the moderate increase in control overhead introduced by A-MCAC is compensated by significant improvements in cluster stability, packet delivery performance, and communication reliability. This trade-off becomes particularly beneficial in dense urban environments where frequent topology changes can severely affect network performance.

6. Conclusions and Future Work

This paper presented A-MCAC, an Adaptive Mobility- and Connectivity-Aware Clustering framework designed to improve cluster stability and communication performance in Internet of Vehicles environments. The proposed framework addresses the limitations of existing clustering approaches by combining predictive mobility analysis, link lifetime estimation, adaptive weighting, and multi-criteria Cluster Head selection.

Unlike conventional clustering schemes that rely mainly on current mobility information, A-MCAC incorporates future vehicle positions and predicted link stability into the clustering process. In addition, the proposed fitness function considers multiple factors, including connectivity, link stability, mobility consistency, local density, and communication quality, to select more suitable Cluster Heads and improve cluster maintenance efficiency.

Extensive simulations were conducted using NS-3 under different vehicle densities and realistic urban mobility conditions. The obtained results demonstrated that A-MCAC achieves longer Cluster Lifetime and Cluster Head Lifetime, higher Average Link Stability, and lower Re-clustering Rate compared with CARAC, MetaLearn, and CPB. Furthermore, the proposed A-MCAC framework improved Packet Delivery Ratio and Throughput while reducing End-to-End Delay. Although a slight increase in Clustering Overhead was

observed compared with CARAC, the gains in clustering stability and communication performance significantly outweighed this additional cost.

The results obtained under the adopted NS-3 simulation environment indicate that integrating predictive mobility information with adaptive clustering mechanisms can enhance the reliability and efficiency of vehicular communications. The proposed framework demonstrates the potential of predictive and adaptive clustering mechanisms for improving communication performance in highly dynamic IoV environments.

Future research will investigate comprehensive sensitivity analyses of the adaptive weighting parameters, more extensive statistical validation of the obtained results, and the integration of edge-assisted intelligence, adaptive parameter learning, and traffic-aware decision-support mechanisms to further improve the scalability and robustness of the proposed framework in large-scale IoV deployments.

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