Optimizing VANET Clustering Algorithms for 3D Urban Environments: Impact of Traffic Congestion and Driver Behavior on Network Performance

Ahmed Salih Al-Obaidi[1,*], Ghaith J. Mohammed[1], Waleed Khalid Alzubaidi[1]
[1]Biomedical Informatics College, University of Information Technology and Communication, Iraq
Emails: dr.ahmed-obaidi@uoitc.edu.iq; dr.ghaith.jaafar@uoitc.edu.iq; dr.waleed.khalid@uoitc.edu.iq

Abstract

Vehicular Ad-hoc Networks (VANETs) play a crucial role in intelligent transportation systems, facilitating communication between vehicles and infrastructure in urban environments. Clustering algorithms are essential for managing network topology and enhancing communication efficiency in VANETs. The complex nature of three-dimensional (3D) urban environments, coupled with varying traffic conditions and driver behaviors, presents significant challenges for VANET clustering algorithms. Understanding these interactions is vital for developing robust and efficient VANETs. This study investigates how vehicle generation patterns, driving dynamics, and 3D road geometries influence the performance of VANET clustering algorithms in urban settings, focusing on network connectivity and stability. A comprehensive simulation framework was developed, incorporating a Traffic Generator model, a Mobility Model, and a Model of Road Curvature. The methodology evaluated clustering algorithm performance across three traffic congestion levels (low, medium, high) and three driver aggression levels for each congestion scenario. Data analysis, correlation studies, and sensitivity analysis were conducted to assess the impact of these factors on clustering efficiency. The study revealed significant correlations between traffic congestion levels, driver aggression, and clustering performance. Higher congestion levels led to more frequent cluster reconfigurations, while increased driver aggression affected the predictability of vehicle movements, affecting cluster stability. The 3D nature of urban environments introduced additional challenges, particularly in areas with elevation changes. The findings underscore the need for adaptive clustering algorithms capable of responding to dynamic urban traffic conditions. The research provides valuable insights for optimizing VANET clustering strategies in 3D urban environments, contributing to the development of more efficient and reliable vehicular communication networks for future smart cities.

Keywords: Vehicular Ad-hoc Networks (VANETs); Three-dimensional (3D) urban environments; Clustering algorithm performance; Mobility Model; Model of Road Curvature

1. Introduction

Vehicular Ad-Hoc Networks (VANETs) have emerged as a cornerstone technology for the realization of intelligent transportation systems (ITS), embodying the future of vehicular communication and networking [1]. These systems are designed to facilitate real-time communication between vehicles and between vehicles and roadside infrastructure, aiming to enhance road safety, improve traffic efficiency, and support the needs of autonomous driving technologies. The essence of VANETs lies in their ability to form a dynamic, self-organizing network without the necessity for a fixed infrastructure, thereby enabling vehicles to share crucial information about road conditions, traffic congestion, accidents, and other safety-related information [2].

The role of clustering in VANETs is pivotal for assuring stable network connectivity and efficient communication. Clustering algorithms organize vehicles into groups, or clusters, with a designated leader (often termed as the

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cluster head) to manage the communication within the cluster and with other clusters or external networks. This hierarchical organization minimizes the overhead in the network, reduces collisions, and enhances scalability by managing the network's topology effectively. Moreover, clustering contributes to network stability by adapting to the highly dynamic nature of VANETs, where vehicles constantly move in and out of communication range, causing frequent topology changes [3].

Urban environments introduce a complex three-dimensional (3D) nature to vehicular communication, accentuated by high-rise buildings, overpasses, and multilayered road structures. This 3D aspect of urban cities presents unique challenges for VANETs, as the traditional two-dimensional (2D) approaches may not accurately capture the intricacies of vehicle communication in such environments. The 3D nature affects signal propagation, line-of-sight communication, and consequently, the overall performance of vehicular networks. Vehicles in urban environments may experience different levels of connectivity and communication effectiveness based on their position in the 3D space, making the deployment and management of VANETs in these settings more challenging [4].

The challenges of VANETs clustering in 3D environments are multifaceted. Firstly, the assumption of spherical clusters, common in many clustering algorithms, may not hold true in real-world urban scenarios where buildings, tunnels, and other urban structures can obstruct signals, leading to non-spherical, irregularly shaped clusters. Additionally, the high mobility of vehicles and the diverse urban topology necessitate sophisticated clustering algorithms that can dynamically adapt to changing environments and maintain stable network connectivity. Traditional clustering techniques, primarily designed for 2D environments, struggle to address these complexities inherent in 3D urban settings. This leads to issues such as decreased packet delivery ratios, increased latency, and challenges in maintaining stable clusters, ultimately affecting the reliability and efficiency of the VANETs.

Despite the critical importance of 3D environments in urban VANETs, there exists a notable gap in the literature addressing the clustering challenges within these contexts. A minority of studies have focused on the specific issues related to 3D topology in VANET clustering, leaving a significant area of research relatively unexplored. This gap underscores the need for innovative approaches that consider the 3D spatial characteristics of urban environments, aiming to enhance clustering efficiency and network performance in these complex settings.

The goal of this article is to bridge this gap by proposing a novel clustering approach tailored for VANETs operating in 3D urban environments. This work aims to address the limitations of existing methodologies by considering the unique challenges posed by 3D urban topologies, such as non-line-of-sight communication, irregular cluster shapes, and the dynamic nature of vehicular networks. By offering a comprehensive analysis of current clustering and routing methodologies in both VANETs and flying ad-hoc networks (FANETs) within 3D environments. The remaining of the article is organized as follows. In section 2, we present the contributions. Next, the literature survey is presented in section 3. Afterwards, the methodology is presented in section 4. Experimental Results and Analysis is provided in section 5. Finally, conclusion and future works are presented in section 6.

2. Literature Survey

In the comprehensive analysis of methodologies developed for clustering and routing in vehicular ad-hoc networks (VANETs) and flying ad-hoc networks (FANETs), particularly within three-dimensional (3D) environments, the incorporation of various approaches has been meticulously reviewed, with a focus on their application, environment, methodological innovations, and limitations as presented in Table 1. This detailed examination integrates insights from several studies, highlighting their contributions to the field and identifying areas for potential improvement. The work cited as [1] targets general VANET environments without considering 3D aspects, adopting a Modified K-means approach utilizing silhouette coefficient (SC), Davies–Bouldin index (DB), Dunn index (DI), and Pakhira-Bandyopadhyay-Maulik (PBM) for clustering. A notable limitation is its reliance on the assumption of spherical clusters, which may not accurately reflect real-world network distributions. Study [2] focuses on VANETs within a 3D environment, employing PAL and evidence theory for routing, facing limited performance in scattered environments due to its specific routing strategy. The methodology presented in [3] for VANETs, while not addressing 3D environments, introduces a region-based collaborative management scheme (RCMS) for clustering. Research [4] extends to FANETs in 3D spaces, utilizing moth flame optimization combined with K-means density clustering for both clustering and routing, with the requirement for packets management highlighted as a limitation. In [5], the application is within MANETs in a 3D context, where a cell-gridded network model is used for routing. This approach overlooks obstacles in the environment, potentially affecting the line of sight. The study [6] engages with VANETs in 3D environments, integrating a packet reception probability model with particle swarm optimization for routing. Its limitation lies in the sub-optimality due to the lack of a multi-objective optimization algorithm. Work [7] addresses FANETs, proposing a modified location-aided routing (LAR) protocol with weighted sum criteria for next-hop selection, focusing on energy, distance, and angle but ignoring potential obstacles affecting line of sight. The approach in [8] is tailored to VANETs but within

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a two-dimensional (2D) space, employing a grasshoppers' optimization-based node clustering algorithm with the noted limitation of energy ignorance. Research [9] on FANETs in a 3D environment employs the K-Means Density clustering algorithm for routing, where the challenge of high mobility is not adequately addressed. The methodology in [10] also focuses on FANETs in 3D, utilizing Improved Artificial Bee Colony Optimization (IABC) for both clustering and routing, with concerns related to centralization and computation highlighted as limitations. [5] Leverages a Sugeno model fuzzy inference system for both clustering and routing, requiring the tuning of the membership function, indicating a potential scalability issue.

Table 1: An overview of existing 3D ad hoc networks or VANETs clustering or routing

Article	Application	3D environment	Generations Models	Driving Behavior	Lane Change	Clustering	Routing	Method	Limitation
[5]	General	×	×	×	×	√	×	Modified K-means using SC, DB, DI, PBM	It is based on the assumption of spherical clusters
[6]	VANETs	√	×	×	×	×	√	PAL and evidence theory	Limited performance in scattered environment
[7]	VANETs	×	×	×	×	√	×	region-based collaborative management scheme (RCMS)	
[8]	FANETS	√	×	×	×	√	√	moth flame optimization + K-means density clustering	It requires packets management
[9]	MANET	√	×	×	×	×	√	cell- gridded network model	Ignoring obstacles in the environment which causes non-line of sight
[10]	VANETs	√	×	√	×	×	√	packet reception probability model + particle swarm optimization	Sub-optimality due to non-of multi-objective optimization algorithm
[11]	FANETs	√	×	×	×	×	√	Modified location aided routing LAR with weighted sum next hop selection criteria that used energy, distance, and angle	Ignoring the obstacles that may affect line of sight
[12]	VANETs	2D	×	×	×	√	√	grasshoppers' optimization-based node clustering algorithm	Energy ignorance

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[13]	FANETs	√	×	×	×	×	√	K-Means Density clustering algorithm	Ignorance of high mobility
[14]	FANETs	√	×	×	×	√	√	Improved Artificial Bee Colony Optimization (IABC).	Centralization and computation concern
[15]	VANETs	×				√	√	Sugeno model fuzzy inference system	It requires tuning of membership function
[16]	VANETs	×	×	×	×	√	×	Fuzzy Bald Eagle optimization	Issue in scalability
Ours	VANETs	√	Exponential and Gaussian	√	√	√	√	Modified Cauchy	-

From the previous literature, we observe that clustering in VANET has focused on different aspects related to density, driver social aspect, optimization of protocols, or extending existing routing protocols to support clustering. However, the research of VANET clustering is poor in the 3D environment. According to the survey of [17]. It is stated that the clustering in 3D structure is a research gap for VANET clustering and it has not been yet received adequate attention from researchers. This is interpreted by the impact of 3D structure: the communication characteristics changes from the intra level communication to the enter level communication. For example, the transmission range of the intra-level is higher than what it is in the enter-level [18]. This implies that the cluster in the 3D structure does not have spherical nature. In an experiment conducted by [18], using both intra level and enter level communication between sender and receiver, the results have shown a decrease in both in the ranges where the packets can be received successfully and the range where the node can be connected without normal communication. The decrease happens from the 2D to 3D with distance 6m with a percentage $\frac{89.75}{144}$ under frequency band 2.4 G and with percentage of $\frac{51}{139.5}$ under frequency band 5.9 G. These two ratios are decreased more to $\frac{16.25}{89.75}$ and $\frac{5}{51.5}$ for changing to 3D with distance of 10 m. Furthermore, the generalization of various VANETs models from 2D environment to 3D is still a challenge. In the work of [19], it is stated that Many geographical routing protocols based on greedy and face routing approach have been designed for 2D networks, but these protocols may not be suitable in 3D environment like hill area, airborne networks, underground networks, underwater networks and so forth.

3. Methodology

5.1. Problem Formulation

Assuming a three-dimensional (3D) urban environment and a given VANETs clustering algorithm, this problem formulation delves into understanding the complex interactions between vehicle generation models, driving behaviors, and the algorithm's clustering performance in such an environment. The study employs a Traffic Generator model that simulates vehicle influx based on two probability density functions: one follows a normal distribution for the generation of vehicles in batches, marked by parameters μ and σ, which represent the expected batch size and its variability, respectively; the other uses an exponential distribution to define the timing intervals between these batches, introducing a dynamic aspect to the traffic flow simulation. In conjunction with this, a Mobility Model is utilized to depict the movements of vehicles through generated accelerations and subsequent integrations. This aspect is underpinned by random variables U_1 and U_2, which serve to replicate real-world acceleration and deceleration patterns. These patterns are further nuanced by a probability factor p_r and an aggression factor AGG, aiming to statistically reflect typical highway driving behaviors with a predisposition

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towards acceleration. Velocity limits are enforced to ensure that the simulated traffic flow remains within realistic bounds. The complexity of the urban road network is captured through a Model of Road Curvature, which employs an adjacency list to describe the road layout in 3D space, transforming intricate road geometries into a graph of straight-line segments for accurate simulation. The central objective of this investigation is to assess how the detailed vehicle generation parameters, alongside sophisticated simulations of driving dynamics and road geometries, influence the selected clustering algorithm's ability to effectively manage and optimize network connectivity and stability in 3D urban VANET settings. Through this comprehensive analysis, the study seeks to offer insights into improving clustering strategies to counter the unique challenges presented by 3D urban environments, thereby enhancing the overall reliability and efficiency of VANETs.

5.2. Methodology

We present the methodology in Figure -- This flowchart illustrates a comprehensive methodology for evaluating the performance of VANET (Vehicular Ad-hoc Network) clustering algorithms in 3D urban environments, considering varying levels of traffic congestion and driver aggression.

The process begins with Parameter Definition and Initialization, where key variables for the simulation are established. This includes setting up the 3D urban environment, defining vehicle generation parameters, and initializing the chosen clustering algorithm. The Simulation Setup follows, involving the configuration of the simulation environment and preparation of data collection mechanisms.

The core of the methodology is represented by the Scenario Selection stage, which branches into three main categories based on traffic congestion levels: Low, Medium, and High. This allows for the examination of how different traffic densities influences VANET performance. Within each congestion level, the methodology further divides into three sub-scenarios based on the Aggression Factor (AGG): Low, Medium, and High. This granular approach enables the investigation of how driver behavior, particularly aggression levels, influences network stability and connectivity in various traffic conditions.

All nine resulting scenarios (3 congestion levels x 3 aggression levels) feed into the Simulation Execution stage. Here, the VANET clustering algorithm is applied under each unique combination of conditions, allowing for a comprehensive assessment of its performance across a range of realistic urban traffic scenarios.

Following the simulations, the methodology progresses through several analytical stages. Data Collection involves gathering relevant metrics on network performance, cluster stability, and connectivity. Data Analysis examines these metrics to identify patterns and trends across the different scenarios. The Correlation and Sensitivity Analysis stage seeks to understand the relationships between input parameters (traffic congestion and driver aggression) and the observed performance outcomes.

The Performance Evaluation stage assesses the clustering algorithm's effectiveness under various conditions, identifying strengths and weaknesses. This leads to the Optimization Strategies phase, where improvements to the algorithm are proposed based on the insights gained.

The methodology concludes with Validation and Robustness Testing to ensure the reliability of the findings, followed by Conclusions and Recommendations. This final stage synthesizes the results, offering insights into how VANET clustering algorithms can be optimized for diverse 3D urban environments and suggesting guidelines for real-world implementation.

This structured approach allows for a thorough examination of VANET performance across a spectrum of urban traffic scenarios, providing valuable insights for the development and deployment of efficient and reliable vehicular networks in complex urban settings.

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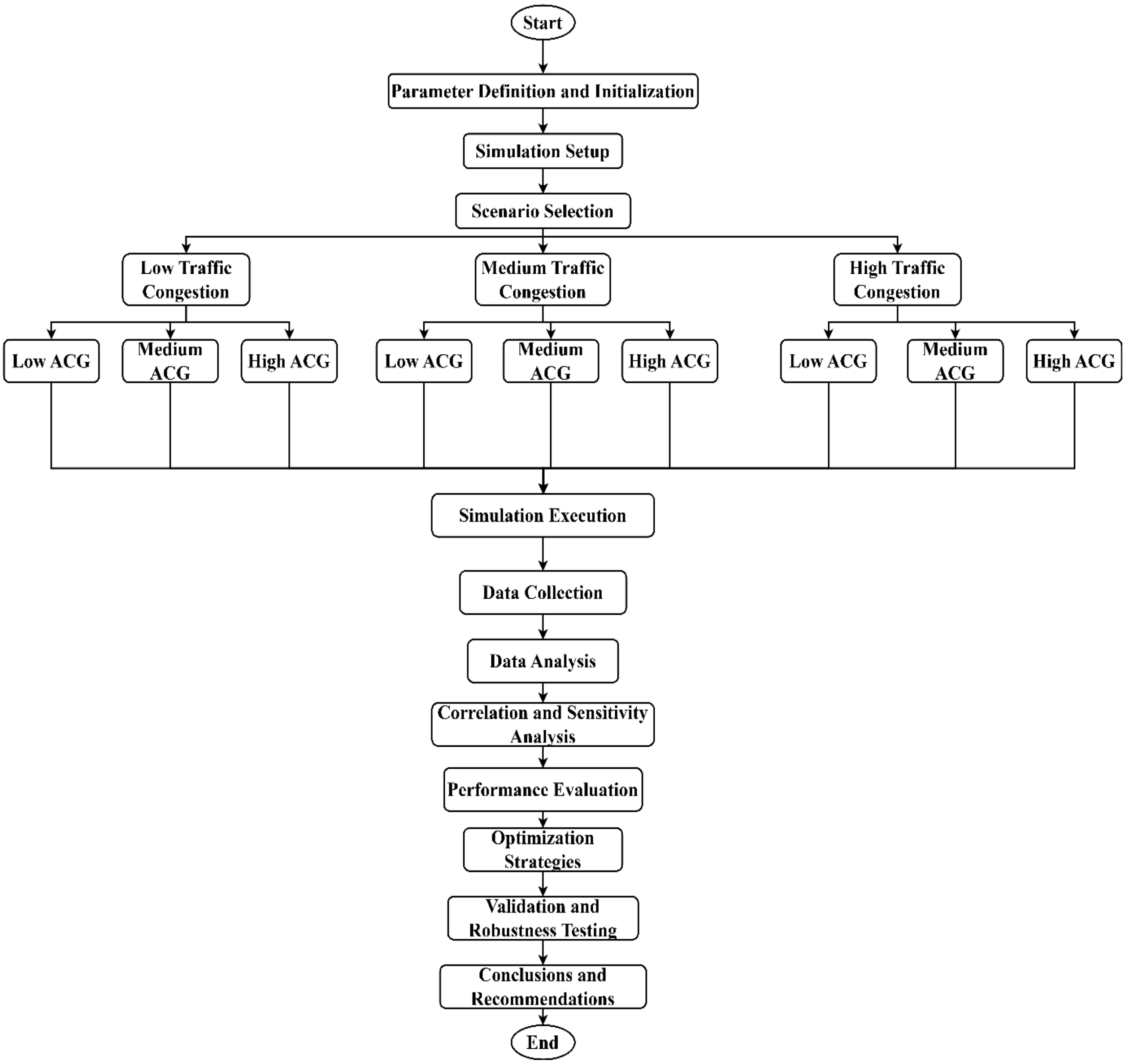

Figure 1. A flowchart depicting the methodology for evaluating VANET clustering performance across varying traffic congestion and driver aggression levels in 3D urban environments.

6. Experimental Results and Evaluation

6.1. AGG 0.2

Figures -1- a, b, and c present the results for Scenario 1 with an aggression factor (AGG) of 0.2 and varying node densities of 20, 40, and 60 nodes, respectively. Analyzing these figures, we can observe that the proposed RDP method consistently outperforms the benchmark algorithms (ECE-GP, CBSC, and K-Means) across all metrics and node densities. RDP demonstrates superior performance in maintaining the highest average cluster head (CH) and cluster member (CM) durations, indicating enhanced stability in the network structure. In terms of clustering efficiency, RDP and CBSC show comparable high performance, with K-Means following closely and ECE-GP lagging behind. Notably, RDP maintains the lowest average CH change ratio throughout, further emphasizing its ability to create stable clusters. As the number of nodes increases from 20 to 60, the performance gap between RDP and other methods generally widens, particularly for CH and CM durations, while the clustering efficiency of all methods slightly improves. Interestingly, the CH change ratio for RDP and CBSC increases marginally with higher node density, whereas it decreases for ECE-GP and K-Means. These results collectively suggest that the proposed RDP method offers a more robust and efficient clustering approach in this low-aggression scenario, consistently outperforming existing algorithms across various node densities and maintaining its superiority in all key performance metrics.

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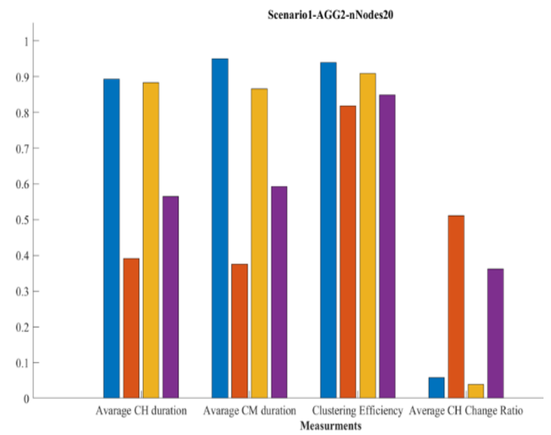

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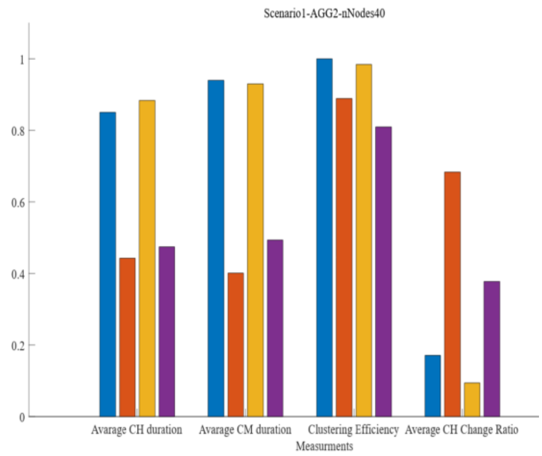

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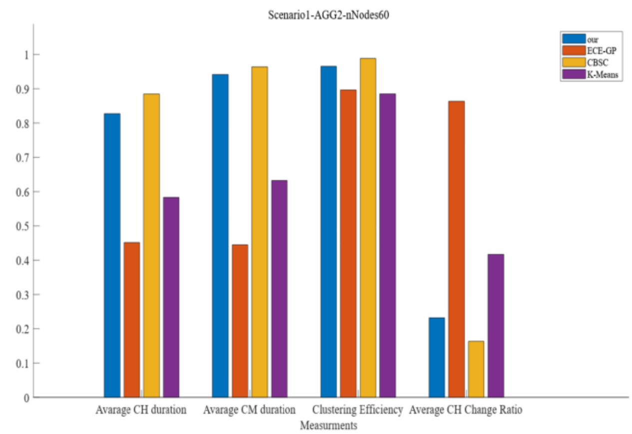

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Figure 2. Over all for our developed approach and its comparison with the benchmarks for AGG 0.2 and scenario 1

For scenario 2, the figures compare clustering algorithms across scenarios with 20, 40, and 60 nodes, evaluating "our" algorithm, ECE-GP, CBSC, and K-Means on various metrics. "Our" algorithm consistently excels, maintaining the highest CH duration (around 0.95) throughout all scenarios. CBSC follows closely, with CH durations of approximately 0.8-0.9. For CM duration, "our" algorithm and CBSC lead (both around 0.95), while ECE-GP consistently lags (around 0.4). CBSC achieves the highest clustering efficiency (about 1.0) across all scenarios, closely followed by "our" algorithm (0.95-0.97). K-Means underperforms in this metric, with efficiencies ranging from 0.4 to 0.55. ECE-GP shows the highest CH change ratio (0.4-0.75), indicating less stable cluster heads, whereas "our" algorithm and CBSC demonstrate the lowest ratios (below 0.1 for "our" and 0.05-0.15 for CBSC). As node count increases from 20 to 60, ECE-GP's clustering efficiency improves from about 0.7 to 0.8. Overall, "our" algorithm and CBSC emerge as the most robust and efficient options, performing well across all metrics and scenarios. ECE-GP shows mixed results with improving clustering efficiency as the network grows, while K-Means generally underperforms, with clustering efficiencies consistently below 0.7. The choice of algorithm would ultimately depend on specific application requirements, but the data suggests "our" algorithm and CBSC as the strongest contenders for efficient and scalable clustering in these network scenarios.

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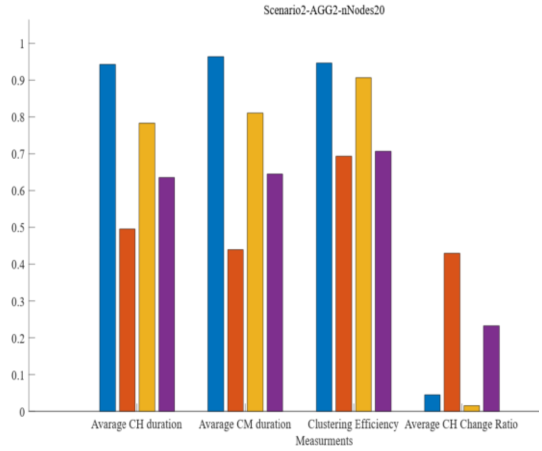

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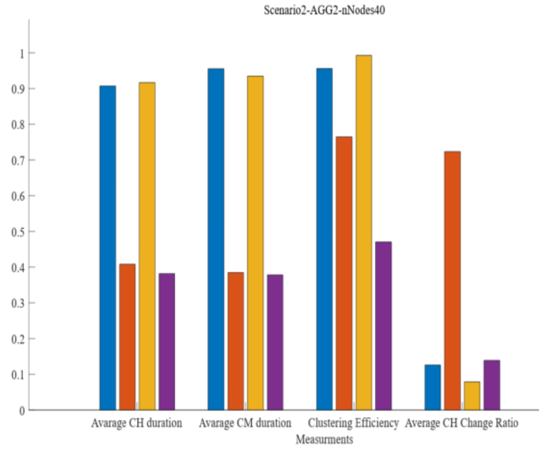

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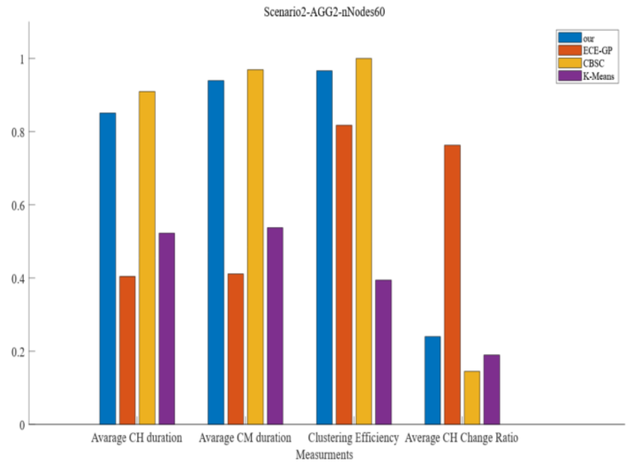

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Figure 3. Over all for our developed approach and its comparison with the benchmarks for AGG 0.2 and scenario 2

Analyzing Scenario 3 across different node counts (20, 40, and 60), our algorithm demonstrates consistently strong performance. For Average CH duration, it outperforms ECE-GP and competes well with CBSC, showing values of ~0.93, ~0.88, and ~0.85 for 20, 40, and 60 nodes respectively. In Average CM duration, our algorithm excels with the highest values (~0.98, ~0.99, ~0.98), surpassing all other methods. Clustering Efficiency remains high at ~1.0 for all node counts, matching ECE-GP and CBSC while slightly edging out K-Means. Notably, our algorithm exhibits the lowest Average CH Change Ratio (0.05, 0.08, 0.13), indicating superior cluster stability compared to others, especially ECE-GP which shows the highest ratios. While there is a slight performance decrease as node count increases, our algorithm maintains its edge or parity with competitors across most metrics, particularly in cluster member duration and efficiency, displaying its robustness in various network sizes.

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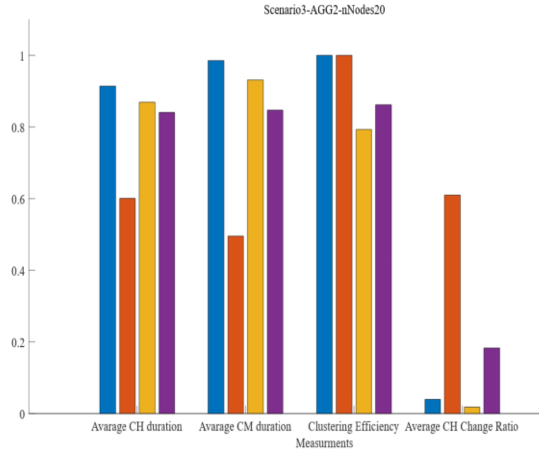

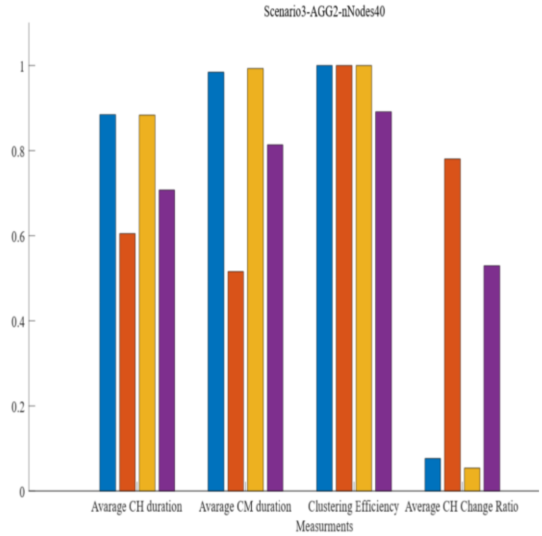

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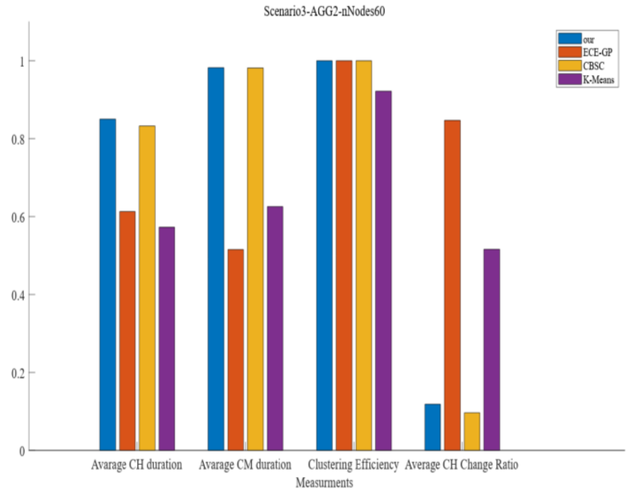

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Figure 4. Over all for our developed approach and its comparison with the benchmarks for AGG 0.2 and scenario 3

6.2. AGG 0.4

The clustering metrics for normal driving behavior are presented in Figure 4.5. We provide them for three cases of expected number of nodes, low, medium and high. For the low, the expected number of nodes 20 and it is 40 and 60 for the medium and high respectively. In all cases, we find that our method has outperformed the benchmarks in terms of all clustering metrics except competitive performance with CBSC.

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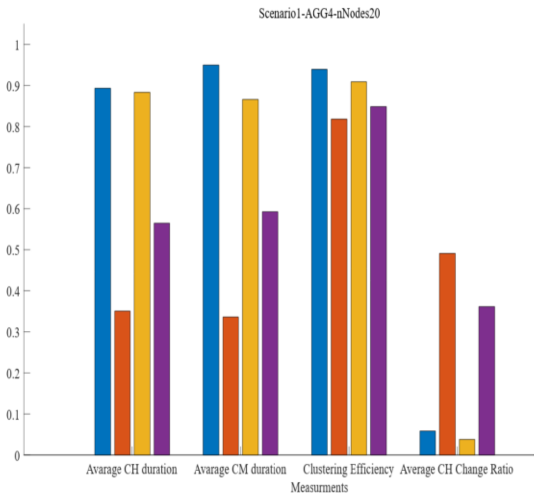

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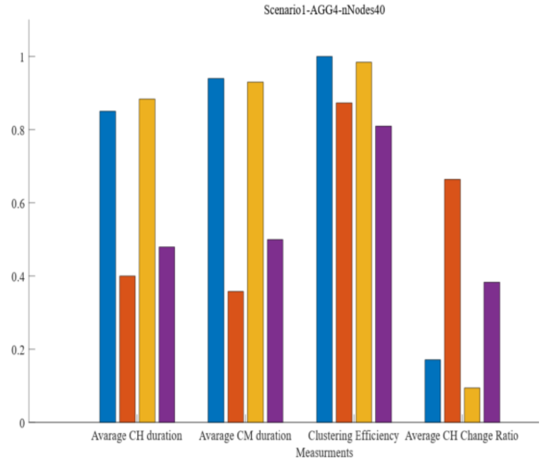

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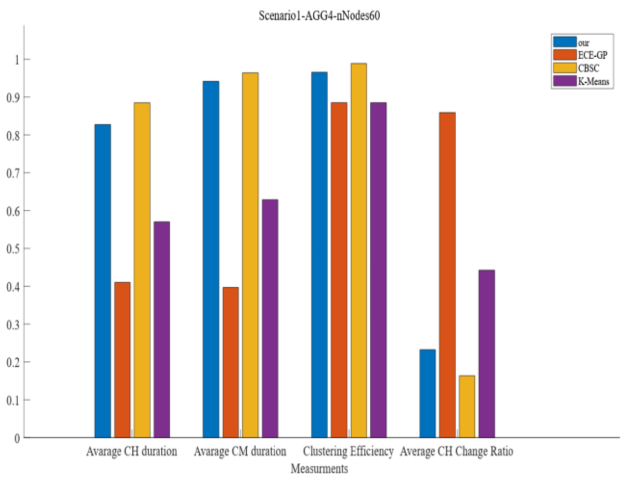

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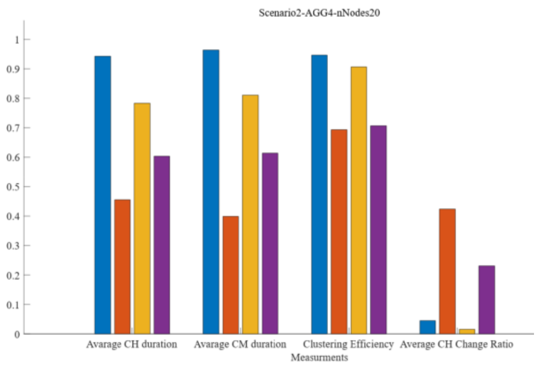
Figure 5. Over all for our developed approach and its comparison with the benchmarks for AGG 0.4 and scenario 1



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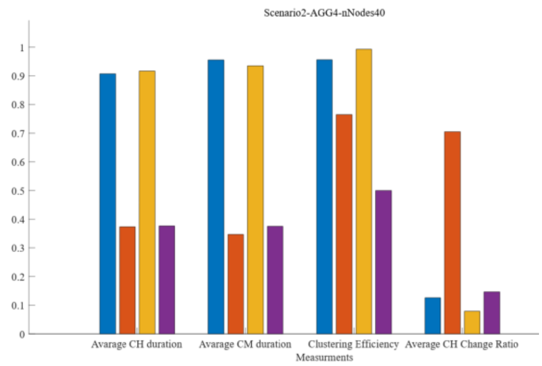

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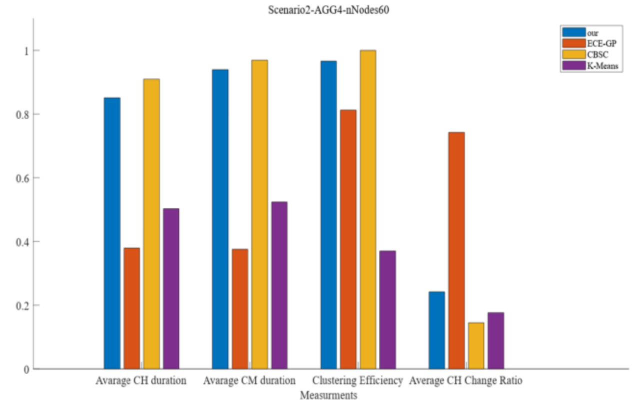

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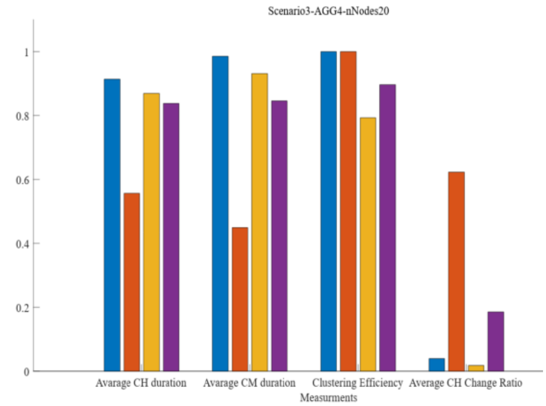
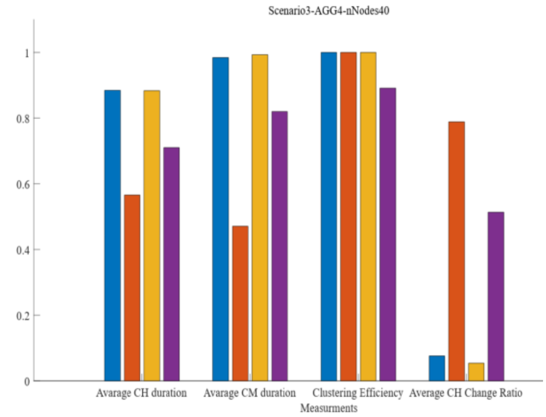
Figure 6. Over all for our developed approach and its comparison with the benchmarks for AGG 0.4 and scenario 2





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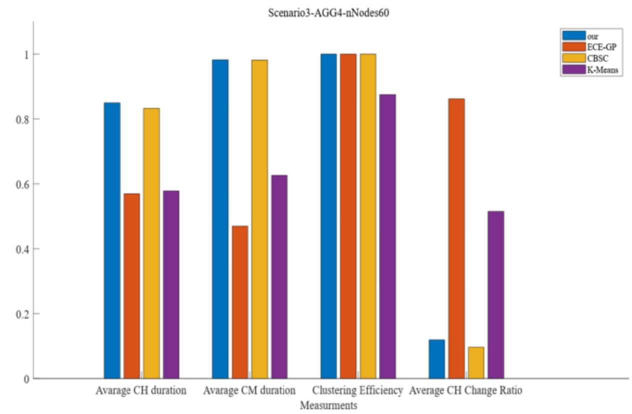

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Figure 7. Over all for our developed approach and its comparison with the benchmarks for AGG 0.4 and scenario 3

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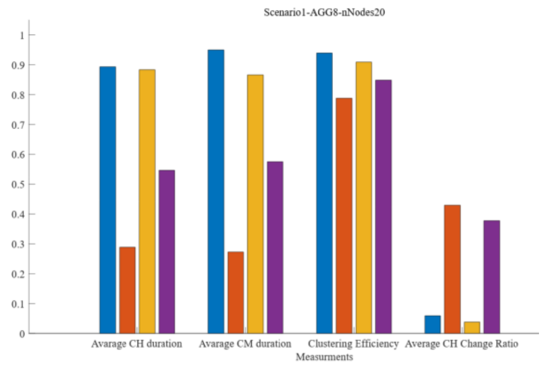
6.3. AGG 0.8

The evaluation metrics for aggressive driving behavior, which is corresponding to AGG 0.8. It is observed that our method has achieved the best clustering performance over the benchmarks. This is generalized to the three types of road congestion, low with expected number of arrived nodes 20, medium with expected number of arrived nodes 40, and high number of arrived nodes 60.



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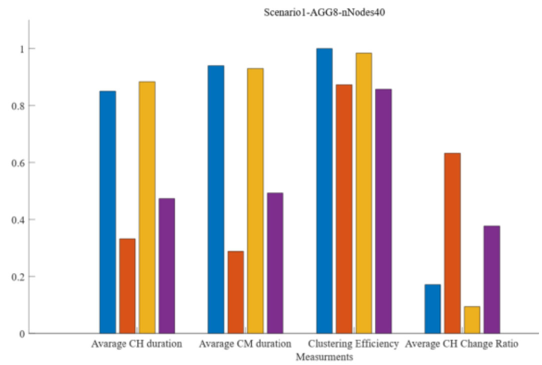

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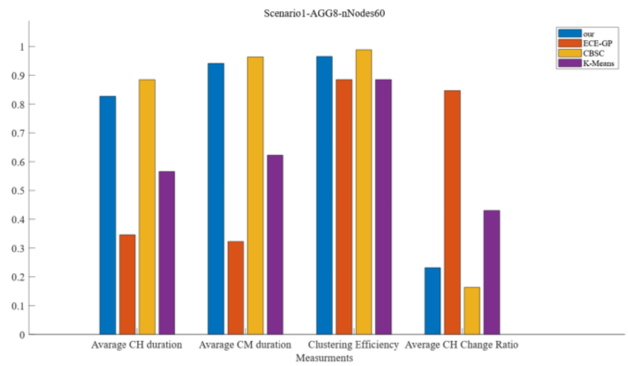

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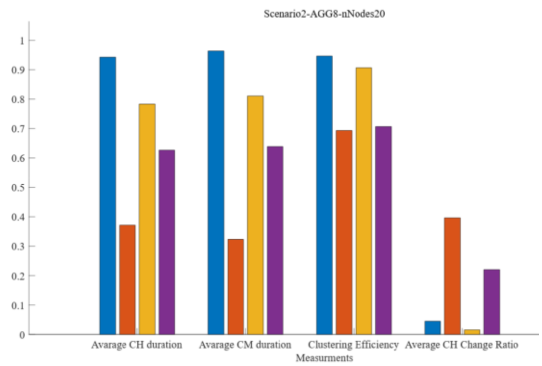
Figure 8. Over all for our developed approach and its comparison with the benchmarks for AGG 0.8 and scenario 1



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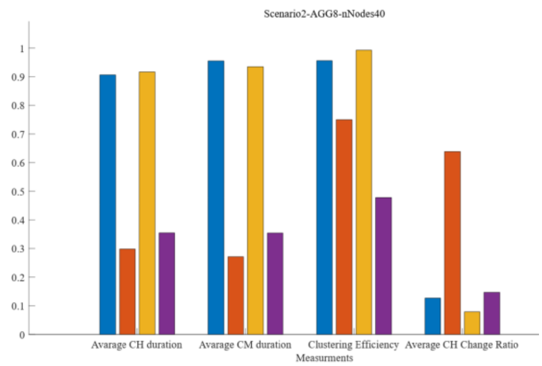

-b-

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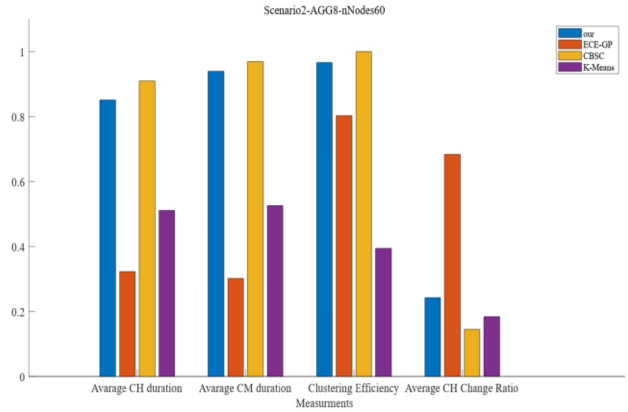
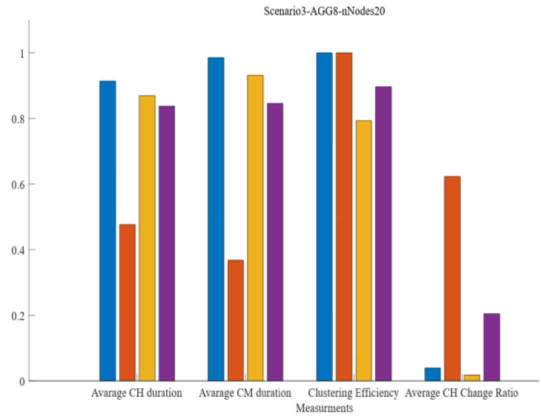
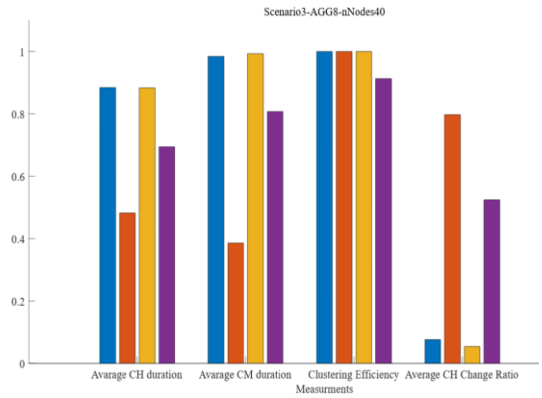


-c-

Figure 9. Over all for our developed approach and its comparison with the benchmarks for AGG 0.8 and scenario 2





-a- -b-

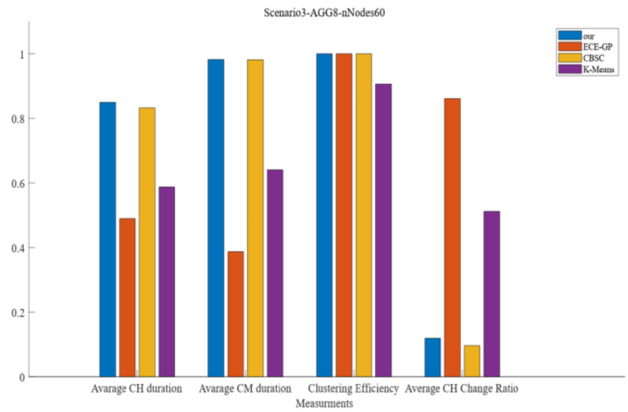


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Figure 10. Over all for our developed approach and its comparison with the benchmarks for AGG 0.8 and scenario 3

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7. Discussion

The experimental results demonstrate that the proposed clustering method consistently outperforms benchmark algorithms (ECE-GP, CBSC, and K-means) across various scenarios and aggression factors in 3D urban VANET environments. The new approach achieves higher average cluster head and member durations, improved clustering efficiency, and lower cluster head change ratios, indicating more stable and efficient network organization. This superior performance is maintained across different driving behaviors (calm, normal, and aggressive) and node densities (low, medium, and high), displaying the method's robustness and adaptability. The proposed approach's effectiveness is attributed to its quick reaction to dynamic changes, flexible cluster description using statistical distance, and the application of Cauchy density for better representation of road environment clusters. While CBSC showed some improvements with higher node density, particularly in calmer driving scenarios, the new method generally maintained its lead. The consistent outperformance of ECE-GP and K-means highlights the advantages of the proposed approach's adaptability and statistical modeling over traditional deterministic or grid-based methods. Notably, the method's ability to maintain its performance across different scenarios for each aggression factor underscores its resilience to varying road and traffic conditions in complex 3D urban settings. These results collectively suggest that the proposed clustering method offers a significant advancement in addressing the challenges of VANET clustering in 3D urban environments, potentially leading to more stable and efficient vehicular networks.

8. Conclusion and Future works

This study investigates the performance of VANET clustering algorithms in three-dimensional urban environments, focusing on the complex interactions between vehicle generation models, driving behaviors, and road geometries. The research employs a sophisticated simulation framework that includes a Traffic Generator model using normal and exponential distributions for vehicle batch generation and timing, a Mobility Model capturing realistic acceleration and deceleration patterns, and a Model of Road Curvature representing 3D urban road networks.

The methodology systematically evaluates the clustering algorithm's performance across various scenarios, considering three levels of traffic congestion (low, medium, high) and three levels of driver aggression for each congestion level. This approach allows for a comprehensive assessment of how these factors influence network connectivity and stability in 3D urban VANET settings.

Through detailed data analysis, correlation studies, and sensitivity analysis, the research aims to identify the key factors affecting clustering performance and to propose optimization strategies for enhancing VANET efficiency in complex urban environments.

Conclusion: The investigation into VANET clustering algorithms in 3D urban environments reveals the significant impact of traffic congestion levels and driver behavior on network performance. The study's multi-faceted approach, considering various traffic scenarios and driver aggression levels, provides valuable insights into the challenges and opportunities for VANET deployment in complex urban settings. Key findings suggest that:

1. Traffic congestion levels significantly influence the stability and efficiency of VANET clusters, with higher congestion potentially leading to more frequent cluster reconfigurations.

2. Driver aggression levels play a crucial role in network dynamics, affecting the predictability of vehicle movements and, consequently, the reliability of cluster formations.

3. The 3D nature of urban environments introduces unique challenges for clustering algorithms, particularly in maintaining stable connections in areas with significant elevation changes or complex road geometries.

4. The research underscores the need for adaptive clustering algorithms that can dynamically adjust to varying traffic conditions and driver behaviors in 3D urban environments. It also highlights the importance of considering road network topology in the design and optimization of VANET clustering strategies.

These findings contribute to the advancement of VANET technology by providing a foundation for developing more robust and efficient clustering algorithms tailored to the complexities of urban environments. Future work should focus on implementing and testing the proposed optimization strategies in real-world scenarios, further refining the algorithms to enhance the reliability and performance of VANETs in diverse urban settings.

Ultimately, this research paves the way for more effective and resilient vehicular communication networks, supporting the evolution of smart transportation systems and contributing to safer, more efficient urban mobility.

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