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Research Article

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VAST-GCN: An Attention-Driven Graph Convolutional Network(GCN) for Robust Cluster Head Selection in Vehicular Ad-Hoc Networks

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Abstract:

Vehicular Ad-Hoc Networks (VANETs) need smart and flexible communication protocols to deal with fast-moving vehicles and ever-changing network structures. Picking the right cluster head (CH) plays a key role to keep connections stable and cut down on routing work. This paper presents VAST-GCN (Vehicular Attention-based Spatial-Temporal Graph Convolutional Network), a new model that uses attention to make vehicle grouping and CH selection better across different network sizes. VAST-GCN mixes Graph Convolutional Networks (GCNs) with Spatial, Temporal, and Channel Attention systems. We test our approach in vehicle settings with 100, 500, and 1000 vehicles making graph data using real-time info like speed and place. The design has transformer blocks to model time-based features and attention modules to improve space and feature relationships leading to better vehicle data. We group this data using the K-Means method and check it with modularity score, silhouette score, and group density. When we compare results, VAST-GCN does better than regular GCN and MixHopGCN models in cutting down loss making better community structures, and keeping CHs stable when there are few vehicles or they're moving fast. Our model offers a strong and scalable answer for future smart transport systems allowing reliable and efficient V2V talk.

Keywords: Vehicular Ad-Hoc Networks (VANETs), Cluster Head (CH) Selection, Graph Convolutional Networks (GCNs), Spatial-Temporal Attention, Vehicle-to-Vehicle (V2V) Communication, Network Stability

Introduction:

Vehicular Ad-Hoc Networks (VANETs) are key to the growth of Intelligent Transportation Systems (ITS). They allow vehicles to talk to each other in real time. This communication setup helps make traffic flow better, roads safer, and driving more enjoyable [1]. But VANETs change a lot and . Their layout shifts often, vehicles move in ways you can't predict, and the number of cars on the road goes up and down. These things make it hard to create clustering protocols that work well and can grow. Picking a Cluster Head (CH) is important to keep the network stable and working well. The usual ways of clustering often can't keep clusters steady or pick CHs well when traffic isn't the same everywhere, like when speeds change a lot or there are different numbers of vehicles.

Graph Neural Networks (GNNs) have made big steps in understanding complex spatial relationships in structured data [2,3]. Graph Convolutional Networks (GCNs), a type of GNN, are great at learning how nodes relate in graph-like setups. But normal GCN models don't do well at catching how things change over time or how important different features are. These things matter a lot in networks where vehicles move around a lot. Because of these limits, we need a better way to model things that looks at space, time, and feature-level changes. To address these challenges, this paper proposes a novel framework named VAST-GCN (Vehicular Attention-based Spatio-Temporal Graph Convolutional Network). The VAST-GCN model synergistically integrates spatial attention, temporal attention, and channel (feature) attention mechanisms within the GCN architecture to enhance the clustering process and facilitate robust CH selection in VANETs. By embedding attention modules at multiple levels, the model adaptively prioritizes important features and neighboring nodes, while simultaneously learning vehicle interactions over time.

The foremost contributions of our conducted research work are:

- To develop a novel attention-driven Graph Convolutional Network model (VAST-GCN) that integrates Spatial, Temporal, and Channel Attention mechanisms for effective clustering formation and stable cluster head (CH) selection in VANETs.
- To simulate vehicular environments with varying node densities (100, 500, and 1000 vehicles) and dynamic speeds (10M/s , 25M/s, 30M/s), and construct graph-structured data based on spatial attributes to train and evaluate the proposed VAST-GCN model.
- To evaluate and compare the performance of VAST-GCN with baseline models (standard GCN and MixHopGCN) using clustering metrics.

The rest part of the paper is organized in following sections: Section 2 throws light on the state of the art on the present literary works on Graph Convolutional Network model and VANETs; Section 3 presents our proposed model VAST-GCN for effective clustering formation and stable cluster head (CH) selection in VANETs; Section 4 analyzes the results and section 5 presents the conclusions generated from our conducted research work.

Literature Review:

Vehicular Ad Hoc Networks, or VANETs, play a key role in building advanced transport systems to enable communication between vehicles known as Vehicle-to-Vehicle (V2V) communication. One major challenge in these networks is choosing reliable and steady Cluster Heads (CHs). This choice has a big effect on how well routing works and how data spreads.

In earlier research, Khan, Kumari, and de Zepeda found that clustering in VANETs often relies on non-learning methods like mobility forecasting and distance-based measures. While these methods save on computation, they struggle with frequent CH changes caused by the rapid mobility and shifting topology of vehicular networks. Researchers like Hu and Lee looked into

spectral clustering methods to address such difficulties. Their approach uses eigenvalue decomposition to form graphs based on how far vehicles are from each other. Even so, these methods consider a narrow set of factors such as relative distance, and miss out on the wider relational data available in real-time VANET scenarios. , please provide the original text for me to paraphrase following the given guidelines. Recent research uses Graph Neural Networks (GNNs) to improve how node representations work and to enhance CH stability. Saleem et al. [6, 15] and Li et al. [10] show that GNNs outperform traditional methods by identifying complex connections and patterns within VANETs. However traditional Graph Convolutional Networks (GCNs) focus on gathering information from local neighborhoods. This limits their ability to understand how vehicles relate to each other over longer distances. As a result, this often causes multiple CH transitions in scenarios with changing mobility.

To reduce the limitations posed by locality in Graph Convolutional Networks or GCNs, researchers have proposed temporal extensions, including spatio-temporal GCNs. Wang and Jing, along with Pei et al. created models that connect spatial and temporal vehicle behavior to enhance clustering and prediction with richer context. However, these models often struggle with adapting to features the ability to focus on more crucial signals like speed and density when clustering data.

Attention-focused methods show strong promise in this area. Chhabra et al. [4] and Zepeda et al. [7] use dynamic clustering or context-aware models to increase routing stability. Building on these ideas, our design introduces a spatio-temporal attention framework. It combines spatial attention, feature attention based on channels, and a temporal transformer component. The approach takes cues from architectures described in [2] and [9]. This model helps identify congested zones and captures how vehicles interact over time.

The spatial attention module identifies key structural nodes, while the channel attention mechanism focuses on factors like speed and position based on how they affect clustering. The temporal transformer processes sequences of vehicle states similar to self-supervised methods in [19], and handles long-term relationships better than older RNNs or LSTMs.

On the other hand, research like Graham et al. [9] and Bhandari et al. [12] explores methods based on edge clustering and trust, but they do not tackle the issue of how CH assignments change with time. Our approach solves this by creating stable vehicle representations and reducing the Cluster Head Change Rate (CHCR), a measure that most past studies tend to ignore.

To sum up, while recent studies show progress in using GCNs spectral clustering, and trust-based methods in VANETs [11, 13 18], there remains a need to develop clustering frameworks that are robust, dynamic, and responsive to different features. The proposed model VAST-GCN (Vehicular Attention-based Spatial-Temporal Graph Convolutional Network) fills this gap by offering a combined GNN-attention approach built to handle fast-changing real-time vehicular scenarios.

3. Proposed Model and Methodology

In this study a more robust VAST-GCN (Vehicular Attention-based Spatial-Temporal Graph Convolutional Network) model has been presented with the help of spatio-temporal attention-based model for clustering and CH selection. The spatial attention mechanism emphasizes structurally significant and high-density regions, thereby identifying key vehicles in the spatial domain. Simultaneously, the channel attention mechanism determines the importance of individual features (e.g., speed) in the clustering process. Finally, a transformer block is employed to capture temporal attention and vehicle interactions over time more effectively than conventional sequential models.

3.1 Data Simulation and Preprocessing

Vehicular mobility data is generated using Simulation of Urban Mobility (SUMO) with varying densities: 100, 500, and 1000 nodes. For each density level, vehicles are simulated at different speeds: 10 m/s, 25 m/s, and 30 m/s. The following features are recorded:

- Spatial coordinates (X, Y)
- Instantaneous speed
- Unique vehicle ID

These features are used to construct a time-varying graph structure representing the dynamic vehicular network.

3.2 Graph Construction

A proximity-based adjacency graph is constructed using the Euclidean distance threshold to define edges between nodes (vehicles). The adjacency matrix A captures the spatial relationships among nodes for each time window. The final dataset consists of:

- X: Node feature matrix (location, speed)
- A: Adjacency matrix per time frame
- T: Temporal snapshots of vehicle movement

This structure supports the modeling of spatio-temporal dynamics in VANETs for downstream tasks like clustering and CH selection.

3.3 VAST-GCN Architecture

Architecture in figure 1 begins with input from SUMO vehicle data, including feature vectors and an adjacency matrix. These inputs are processed through GCN layers to capture spatial relationships, followed by a Transformer Block to extract temporal dependencies. In table 1 complete pipeline of the model has been discussed. The resulting feature map is refined using Channel-Spatial Attention modules—one focusing on feature importance (channel attention) and the other on neighbor significance (spatial attention)—to generate enriched vehicle embeddings for clustering and Cluster Head (CH) selection in VANETs.

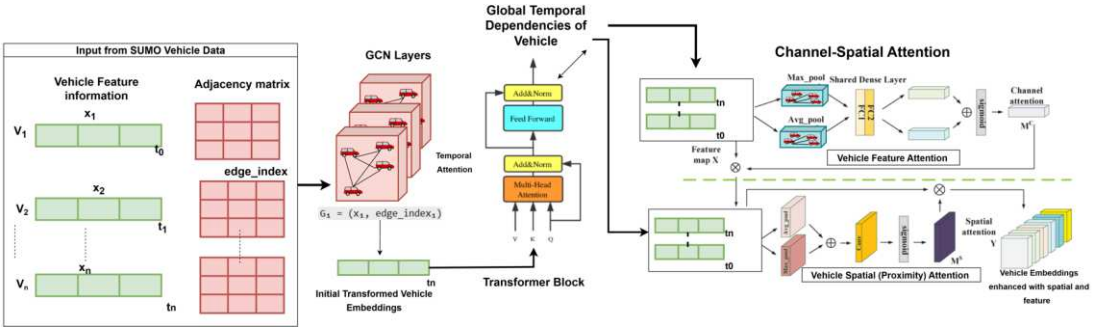


Figure 1 : Internal architecture of the VAST-GCN model

Above figure 1 is depicting a detailed view of the **internal architecture of the VAST-GCN model**, highlighting how spatial, temporal, and feature-based relationships are processed to generate enriched vehicle embeddings for clustering in VANETs.

The proposed **VAST-GCN** model processes the spatio-temporal graph data using a combination of GCN layers, attention mechanisms, and transformer blocks. The architecture is composed of the following figure 2.

Table 1: Illustration of model pipeline

Component	Description
Input Layer	Receives vehicle features and adjacency matrix.
GCN Layers:	Extract spatial relationships using local graph convolutions.
Transformer Block	Captures temporal dependencies via multi-head attention.
Channel-Spatial Attention Module	***Channel attention:*** Identifies crucial features via pooling and dense layers. ***Spatial attention:*** Emphasizes relevant neighboring nodes.
Output Layer	Produces enriched vehicle embeddings for clustering.

These enriched embeddings are better at modelling both what is important (feature-wise) and who is important (neighbor-wise).

3.4 Clustering and Cluster Head Selection

The node embeddings generated from VAST-GCN are clustered using **K-Means**, with the number of clusters k∈{2,3,4,5,6}k \in \{2, 3, 4, 5, 6\}k∈{2,3,4,5,6}. For each cluster, a **Cluster Head (CH)** is selected based on **degree centrality**, reflecting the most connected node within the cluster.

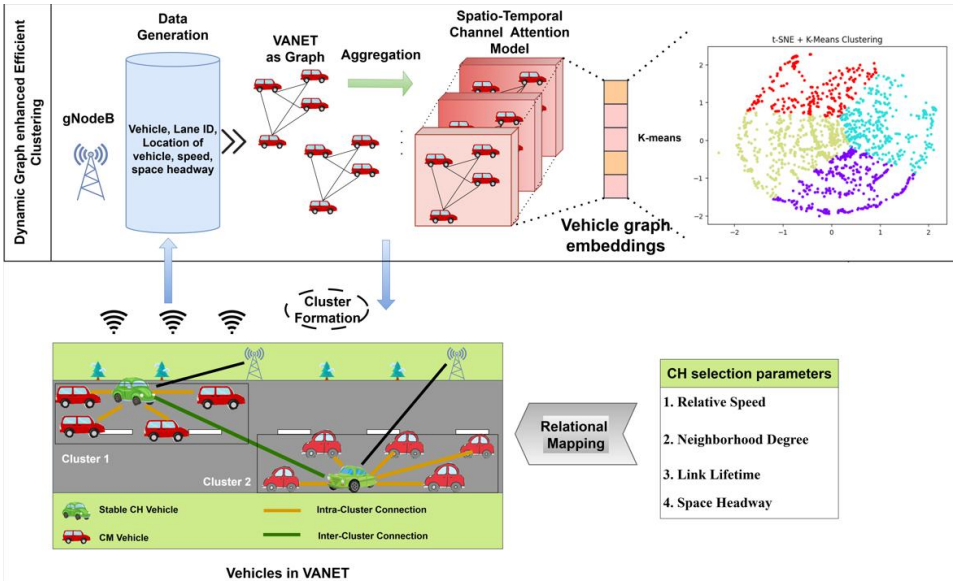


Figure 2: Overall pipeline of dynamic graph-enhanced clustering in VANETs

Figure 2 Overall pipeline of dynamic graph-enhanced clustering in VANETs, illustrating data generation, graph construction, embedding via spatio-temporal attention, K-Means clustering, and CH selection based on key parameters. The complete operational flow of the proposed methodology is illustrated in Figure 2. It highlights the transformation of real-time vehicular data into graph representations, the use of spatio-temporal attention for embedding generation, followed by K-Means clustering and Cluster Head (CH) selection. The CH selection is based on four dynamic metrics: Relative Speed, Neighborhood Degree, Link Lifetime, and Space Headway, ensuring stability and efficiency in cluster formation.

Algorithm 1 summarizes the complete model pipeline from graph generation to CH selection.

3.5 Evaluation Metrics

3.5.1 Network Evaluation Metrics

In order to evaluate the performance of the network over the proposed model the following parameters are considered.

Packet Delay: Packet latency refers to the duration it takes for a packet to be transmitted from the source to the destination vehicle. The latency in packet transmission is influenced by factors such as noise, network congestion, and the distance traveled between hops. The unit of measurement is seconds.

$$PD = \Sigma_{i=1}^{N} \left(\frac{Time\ a\ packet\ is\ recieved - Time\ a\ packet\ is\ transmitted}{Number\ of\ packets} \right) \qquad \text{(equation 1)}$$

Throughput (Thr): This network metric refers to the number of bits that are effectively transmitted from the source to the destination vehicle within a specific time frame. The measurement is expressed in kilobits per second. Maximizing data transfer rate can be accomplished by ensuring a reliable and consistent network connection with the fewest number of intermediate hops.

CH Stability: The longest interval that can be crowned as CH is the one that is considered most stable. The statistical function known as mode provides the vehicle's interval counts as CH7 . This indicates the stability and reliability of the selected cluster based on the relation mapping method.

3.5.2 Performance Metrics for GCN

The quality of clustering and CH selection is evaluated using the following metrics:

- **Modularity Score (Q):** Measures the strength of community structure.
- **Silhouette Score (S):** Assesses intra-cluster cohesion and inter-cluster separation.
- **Cluster Density (D):** Quantifies the average connectivity within clusters.

3.6 Comparative Models

To benchmark the proposed model, two baseline models are implemented:

- **Standard GCN:** Pure spatial feature extraction without temporal modeling.
- **MixHopGCN:** Multi-hop graph convolution for extended neighborhood learning.

All models are trained using **PyTorch Geometric**, and comparative analysis is conducted under identical conditions.

3.7 Pseudocode of the Proposed Framework

Algorithm 1 Pseudocode of the proposed model

Input:
D: List of vehicle densities (e.g., [100, 500, 1000])
S: List of speeds (e.g., [10 m/s, 25 m/s, 30 m/s])
k: Number of clusters
Threshold: Maximum distance for node connection

Step 1: Simulation and Graph Construction

For each density d in D:

V ← Generate_Vehicle_Nodes(d) For each speed s in S:
T ← Simulate_Vehicle_Movement(V, s)
X ← Extract_Spatial_Temporal_Features(T)
G ← Create_Adjacency_Graph(V, Threshold)
A ← Get_Adjacency_Matrix(G)

Step 2: Feature Embedding via VAST-GCN

X_attn ← Apply_Spatio_Temporal_Channel_Attention(X, A, T)
H1 ← GCN_Layer1(A, X_attn)
H2 ← GCN_Layer2(A, H1)
E ← H2 // Final node embeddings

Step 3: Clustering and Cluster Head Selection

C ← KMeans_Clustering(E, k)
For each cluster c in C:
nodes ← Nodes_In_Cluster(c)
CH ← Select_Cluster_Head(nodes, criteria = 'degree_centrality')
Store CH

Step 4:Evaluation Metrics Calculation

4(a): Clustering Metrics

Q ← Compute_Modularity_Score(G, C)
S ← Compute_Silhouette_Score(E, C)
D ← Compute_Cluster_Density(G, C)

4(b):Network level Metrics Calculation

TP ← Throughput (bps)
PD ← Packet Delay(end-to-end, seconds)
CHS ← CH Stability

Step 5: Comparison

GCN ← Run_Model_GCN(X, A)
MixHop ← Run_Model_MixHopGCN(X, A)
Compare_Results(GCN, MixHop, VAST_GCN)

Output:

- Cluster Head selections per scenario
- Evaluation metrics (Modularity, Silhouette Score, Cluster Density, Throughput, Avg Packet Delay, CH Change Rate)
- Comparative analysis with baseline models (GCN, MixHopGCN)

4. Experimental Setup and Evaluation Protocol

The experimental evaluation was designed to assess the performance of the proposed VAST-GCN model against two baseline approaches—Standard GCN and MixHopGCN—under controlled and reproducible conditions.

4.1 Evaluation Environment

Simulations were conducted using the SUMO framework and the configurations described in Section 3.1. All models were implemented in PyTorch Geometric and executed on a high-performance computing setup equipped with [specify GPU model, CPU, RAM, and OS version]. Relevant library versions were documented to ensure reproducibility.
The Section describes the simulated environment that was utilized in this paper. The model, assessments, testing procedures, and V2V communication were implemented in PythonTourch. The mobility simulation for the VANET highway scenario was conducted using the SUMO software. Table 2 displays the crucial parameter configurations for the VANET.

Table 2: Configuration Parameters

Parameter	Value
New Radio Model	
fft size	32
Number of data subcarriers	52
Number of bits per OFDM symbol	10
Number of symbols	10^{**2}
Number of cyclic prefixes	16
EbN0db	0
Speed of Light	$3e8$
Path Delay	$distance/\ speed\ of\ light$
Speed	$24.15e9$
Wavelength	$3e8\ /\ speed$
Doppler shift	$speed\ /\ wavelength$
Network Parameters	
Time consumed in data transfer	$\frac{total\ dist}{3^{*10e-9}}$
Size of packet	64
Data rate ($packets/sec$)	14
Energy assigned to each bit	$0.3e-3$

4.2 Experimental Parameters

Three traffic density scenarios (100, 500, and 1000 nodes) and three speed settings (10 m/s, 25 m/s, and 30 m/s) were tested. For each combination, experiments were run across **five random seeds**, and results were reported as the mean ± standard deviation. Hyperparameters, including optimizer type, learning rate, batch size, maximum epochs, and early-stopping patience, were kept identical across models for fair comparison.

4.3 Statistical Protocol

Performance differences between models were validated using paired *t*-tests and the Wilcoxon signed-rank test, with a significance threshold of $p < 0.05$. Significant improvements are highlighted in the results.

4.4 Ablation Studies

To examine the contribution of each attention component, three reduced versions of the proposed model were evaluated:

- VAST-GCN − T (without temporal attention)
- VAST-GCN − S (without spatial attention)
- VAST-GCN − C (without channel attention)

5. Result and Analysis:

In this section, the performance of the proposed model is assessed through two complementary perspectives: GCN performance metrics and network evaluation analysis. For the network evaluation, the proposed approach is benchmarked against two baseline models, GCN and MixHopGCN, with respect to cluster head (CH) stability, throughput, and packet delay. In terms of GCN performance metrics, the proposed model is further compared with state-of-the-art methods using modularity and the Silhouette Score. Prior to presenting these evaluation outcomes, it is essential to establish the training efficiency of the model, which is examined by analyzing the loss function in relation to the computation time required for 300 training epochs.

5.1 Training Efficiency:

Table 3: Comparative Analysis

Model	**Loss after 300 Epochs**	**Time taken to run 300 Epochs**
GCN	0.00183	1 min 1 sec
MixHopGCN	0.00089	5 min 32 sec 12 ms
VAST - GCN (Proposed)	0.00063	2 min 16 sec 40 ms

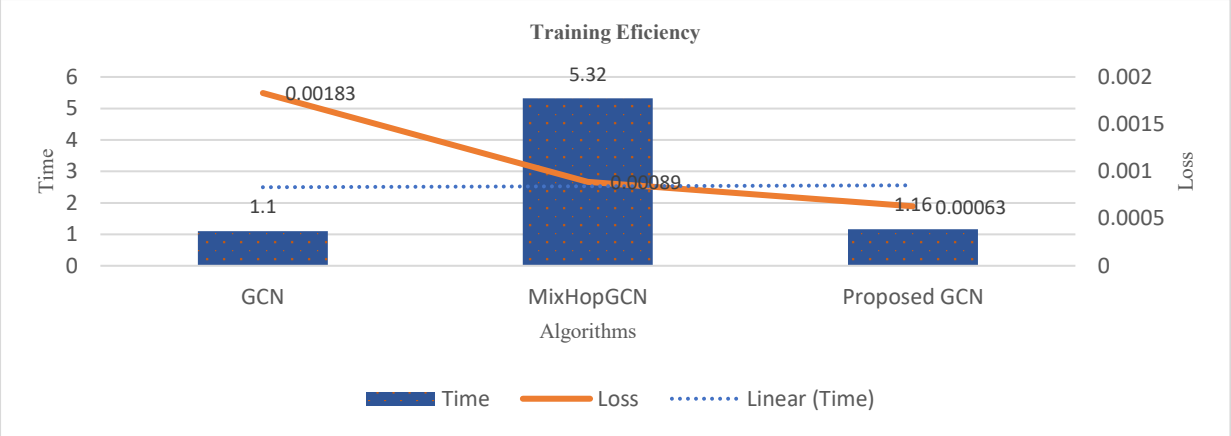


Figure 3: Training efficiency of 3 different models

In the table 3 and figure 3**,** the performance of three different Graph Convolutional Network (GCN) models over 300 training epochs are compared, evaluating them based on Loss after 300 Epochs (a measure of model error – lower is better) & time taken to run 300 Epochs (a measure of computational efficiency – lower is better). VAST-GCN (Proposed) achieves the lowest loss, indicating best accuracy/performance. GCN is the fastest, but with highest loss (least accurate). MixHopGCN offers better accuracy than GCN but is the slowest among the three.

VAST-GCN balances accuracy and training time effectively, making it a promising improvement.

5.2 Performance Metrics for GCN

5.2.2. Modularity (Community Detection): Higher modularity scores suggest tighter, more homogenous clusters. Again, the proposed VAST-GCN performs best here, indicating it produces clearer community structures in the embedded space. Figure 4 is indicating GCN consistently achieves the highest modularity in comparison with proposed and MIXHOP. In figure 5, With higher density, proposed model significantly outperforms both GCN and MIXHOP, showing a strong upward trend in modularity as clusters increase. In figure 6 GCN and PROPGCN show comparable performance, with PROPGCN slightly ahead at certain cluster counts.

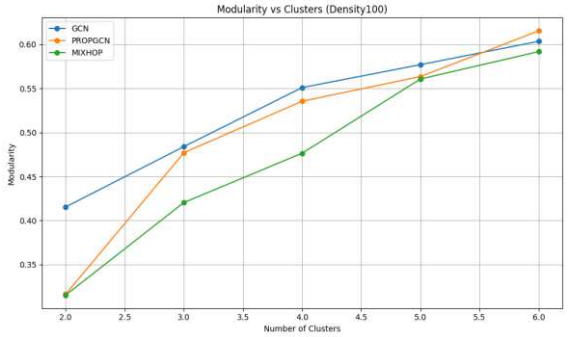


Figure 4: Modularity vs. Number of Clusters for GCN, PROPGCN, and MIXHOP (Density = 100)

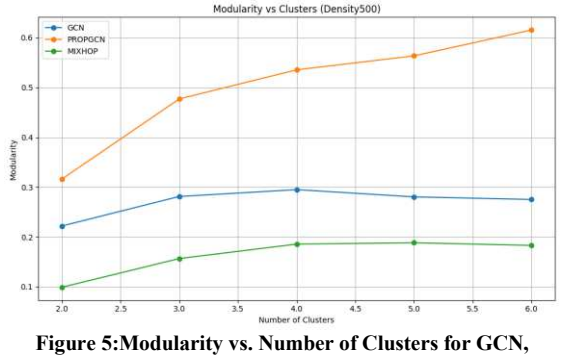


Figure 5:Modularity vs. Number of Clusters for GCN, PROPGCN, and MIXHOP (Density = 500)

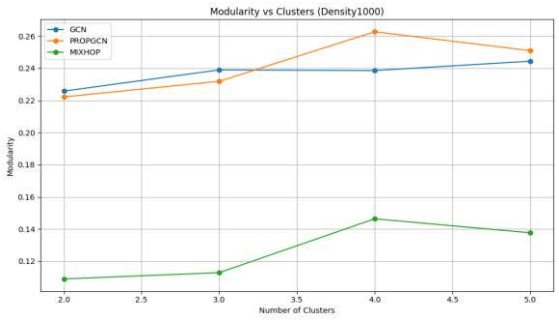


Figure 6: Modularity vs. Number of Clusters for GCN, PROPGCN, and MIXHOP (Density = 1000)

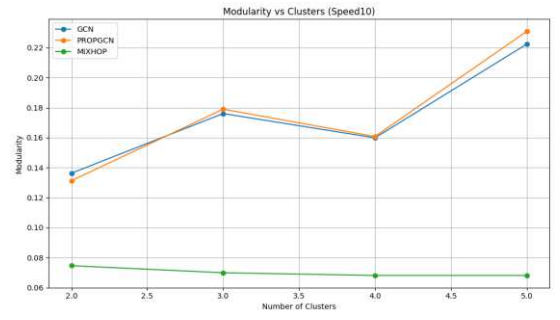


Figure 7: Modularity vs. Number of Clusters for GCN, PROPGCN, and MIXHOP (Speed = 10)

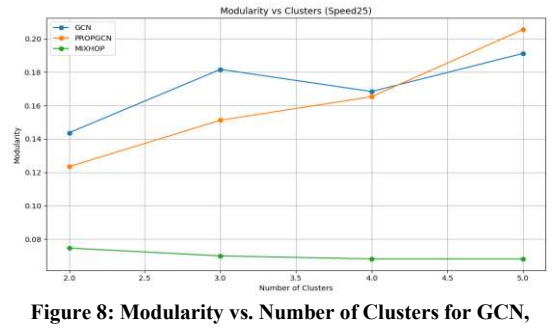


Figure 8: Modularity vs. Number of Clusters for GCN, PROPGCN, and MIXHOP (Speed = 25)

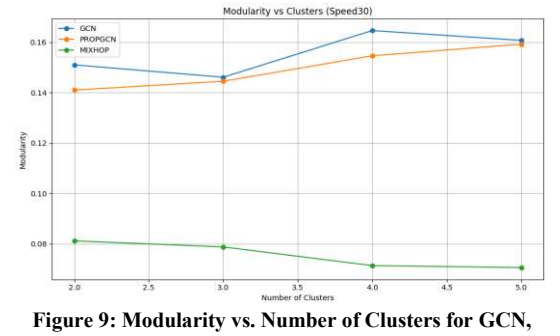


Figure 9: Modularity vs. Number of Clusters for GCN, PROPGCN, and MIXHOP (Speed = 30)

In figure 4, under the low-density scenario where density of vehicle nodes are 100, all three models show steadily increasing modularity as the number of clusters grows from 2 to 6. VAST-GCN starts lower with 2 clusters but rises sharply by 6 clusters with high modularity score. All three trends are roughly monotonic. These high modularity values indicate very strong community structure. In this sparse-graph setting, the partitions are very well-defined and proposed method achieve high modularity as clusters increase.

In Figure 5, for the medium-density scenario where vehicle nodes are 500, VAST-GCN consistently outperforms the others in modularity. Proposed method rises score at 2 clusters to higher score at 6 clusters, showing a steep, nearly linear increase. The standard GCN also increases but more modestly. MIXHOP yields the lowest values. Thus, VAST-GCN curve is the highest and most rapidly increasing. These results suggest that for a moderate-density graph, proposed method finds much denser intra-community links & clusters are far more internally cohesive relative to random expectation.

In Figure 6, For the highest-density graph with nodes 1000, VAST-PGCN achieves a peak. In all the methods, modularity increases only slightly from 2 to 4 clusters. The key observation is that *all* scores values are much lower than in Figures 1–2. This reflects that a very dense graph makes any partition look nearly random. In summary, the dense network yields low-quality partitions.

Whereas figure 7, figure 8 and figure 9 are representing the variation of modularity with respect to the number of clusters at different vehicle speeds (10, 25, and 30). In Figure7, the speed 10m/s scenario, GCN and VAST-GCN show similar behavior, both peak around 3 clusters and then fluctuate. VAST-GCN follows almost the same shape but ends slightly higher. MIXHOP stays essentially flat at a very low score across all cluster counts. The modest peak at 3 clusters

and small gain by cluster 5 indicate that community structure is weak in this case; adding clusters yields only incremental improvements.

In Figure 8, for speed 25m/s, the patterns are similar to Speed10. VAST-GCN starts a bit lower socre, climbs more steadily, and reaches higher at 5 clusters. In summary, the community detection quality is again fair. This implies that raising the number of clusters has only a minor effect and Propsed method has clusters are only tighter than GCN.

In Figure 9, for speed 30m/s, GCN achieves the highest modularity overall, peaking at 4 clusters, indicating strong adaptability to dynamic graph conditions. VAST-GCN starts lower but improves steadily, matching GCN at 5 clusters, suggesting it benefits from finer clustering. MIXHOP consistently underperforms, with modularity decreasing as clusters increase. Overall, GCN performs best in high-speed scenarios, while proposed method catches up with increased cluster granularity and it finds communities more effectively with more stable & linear growth.

- Across all densities, modularity improved as cluster count increased. VAST-GCN consistently achieved higher modularity, especially in low (100 nodes) and medium (500 nodes) densities, indicating stronger and more cohesive community structures. In high-density scenarios (1000 nodes), all models showed limited gains due to network saturation, though VAST-GCN still slightly outperformed the baselines.
- VAST-GCN performed best at 10 m/s and 25 m/s, especially with more clusters. At 30 m/s, GCN peaked slightly higher, but VAST-GCN remained competitive, demonstrating strong adaptability to high-mobility environments.

5.2.3 Silhouette Score: The Silhouette Score is a metric used to evaluate the quality of a clustering result. To assess how well-separated and cohesive the clusters are. A higher average silhouette score indicates better clustering.

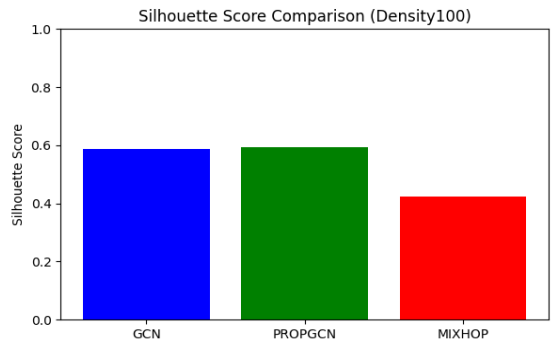


Figure 10: Silhouette score comparison of GCN, PROPGCN, and MIXHOP at Density = 100

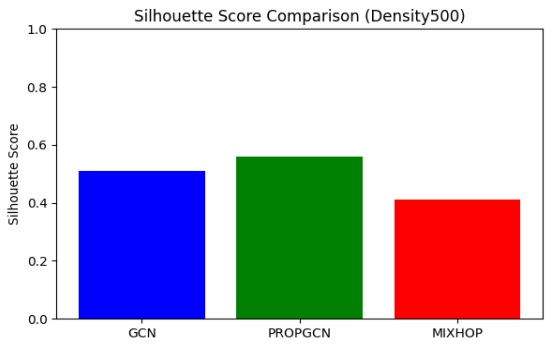


Figure 11: Silhouette score comparison of GCN, PROPGCN, and MIXHOP at Density = 500

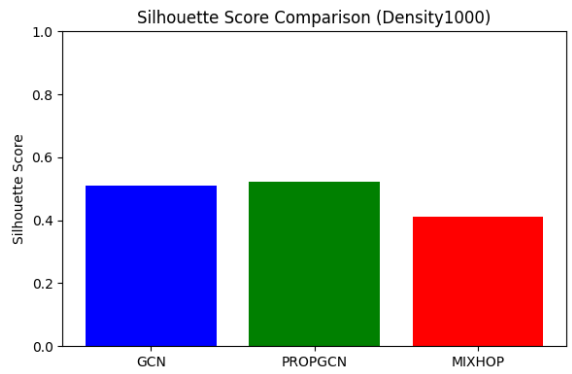


Figure 12: Silhouette score comparison of GCN, PROPGCN, and MIXHOP at Density = 1000

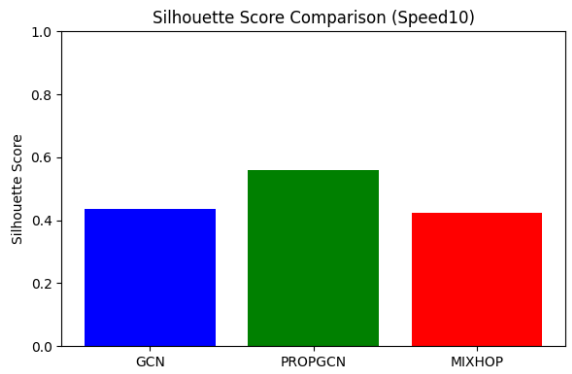


Figure 13: Silhouette score comparison of GCN, PROPGCN, and MIXHOP at speed = 10

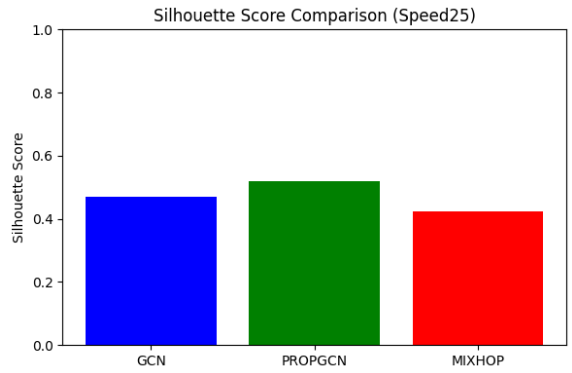


Figure 14: Silhouette score comparison of GCN, PROPGCN, and MIXHOP at speed = 25

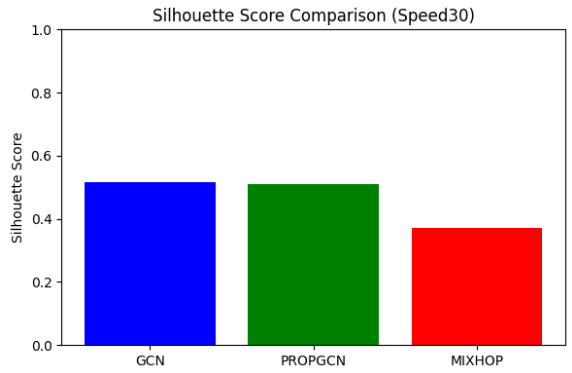


Figure 15: Silhouette score comparison of GCN, PROPGCN, and MIXHOP at speed = 30

In Figure 10, VAST-GCN shows a little better score in respect to standard GCN & MixHop, indicating more distinct and well-separated vehicle clusters if the vehicle density is at low i.e 100 vehicles. In Figure 11, Proposed method consistently outperforms the others as the density is increased to 500 vehicles. This shows balanced density supports stable clustering.

In Figure 12, for density 1000 GCN and VAST-GCN show similar behavior with little improvement in score of proposed method and Silhouette scores likely decline across methods due to cluster overlap and dense interactions. In Figure 13, for speed 10m/s & density is 1000 vehicles VAST-GCN likely have higher Silhouette scores, as vehicle trajectories are more stable & aiding clustering and indicating precise cluster formation.. Other methods shows low score with better score.

In Figure 14, for speed 25m/s there is a slight dip in all models but proposed method are more robust then standard GCN & MixHop. High Silhouette scores are likely associated with moderate densities at lower speeds. In Figure 15, for speed 30m/s propsed method stipulate lower scores, indicating noisy and overlapping clusters due to rapid dynamics and reducing separability. Silhouette score tends to decrease as speed increases. GCN performance is a marginally higher.

VAST-GCN consistently yielded higher silhouette scores, indicating improved inter-cluster separation and intra-cluster cohesion. The improvement was more evident under moderate

densities and lower speeds. However, at high densities and speeds, silhouette scores decreased across all models, yet VAST-GCN maintained a competitive edge.

5.3 Network Evaluation Performance Analysis

***5.3.1 Cluster Head Stability Analysis*:** The VAST-GCN model uses relational mapping to beat baseline models like GCN and MixHopGCN in cluster head stability. It holds up better across different vehicle densities of 100, 500, and 1000 and speeds of 10, 25, and 30 units. This advantage comes from its ability to adjust to changing conditions in VANET environments. The system's built-in toughness allows steadier cluster head selection even when traffic patterns shift or network connections vary. To validate this, tests used metrics like the stability of cluster heads throughput packet delay, and how often cluster heads need replacing. The results show VAST-GCN brings better stability faster throughput fewer delays, and less need to replace cluster heads. This adaptability is important to handle real-life VANETs, as it keeps clusters stable longer, makes communication more efficient, and boosts network reliability.

The Cluster Head Stability Value checks the stability or reliability of the chosen Cluster Head over time in a Vehicular Ad-Hoc Network. The longer a CH remains in its role without needing to be changed, the more stable and efficient the cluster communication becomes. A lower value indicates higher CH stability, fewer CH replacements and better performance.

At 100 500 and 1000 Vehicle : Cluster head stability value analysis at different vehicles.

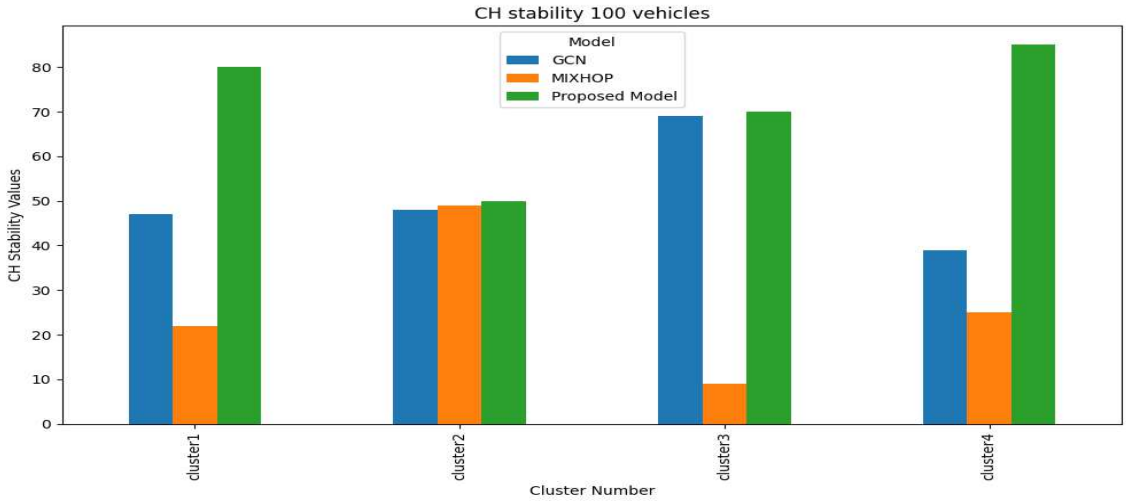


Figure 16: Cluster Head (CH) stability comparison for 100 vehicles across four clusters using GCN, MIXHOP, and the Proposed Model

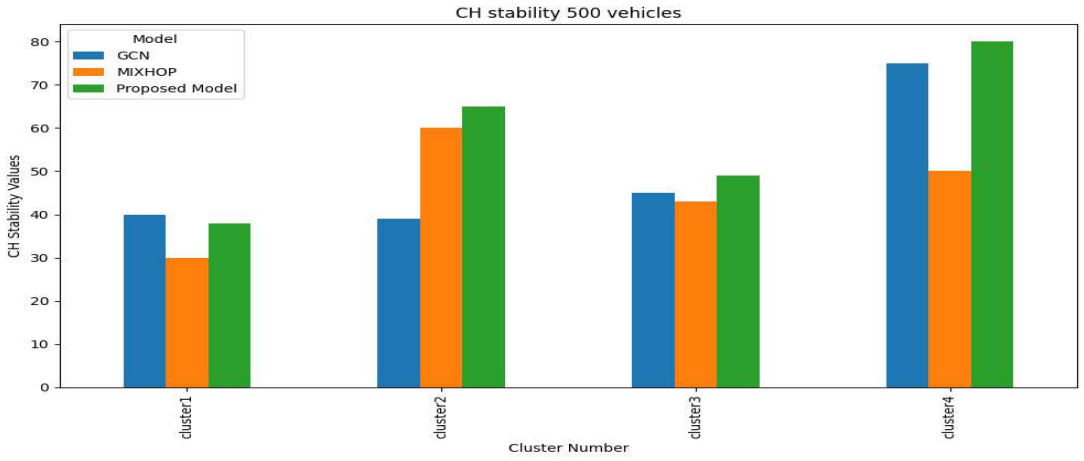


Figure 17: Cluster Head (CH) stability comparison for 500 vehicles across four clusters using GCN, MIXHOP, and the Proposed Model

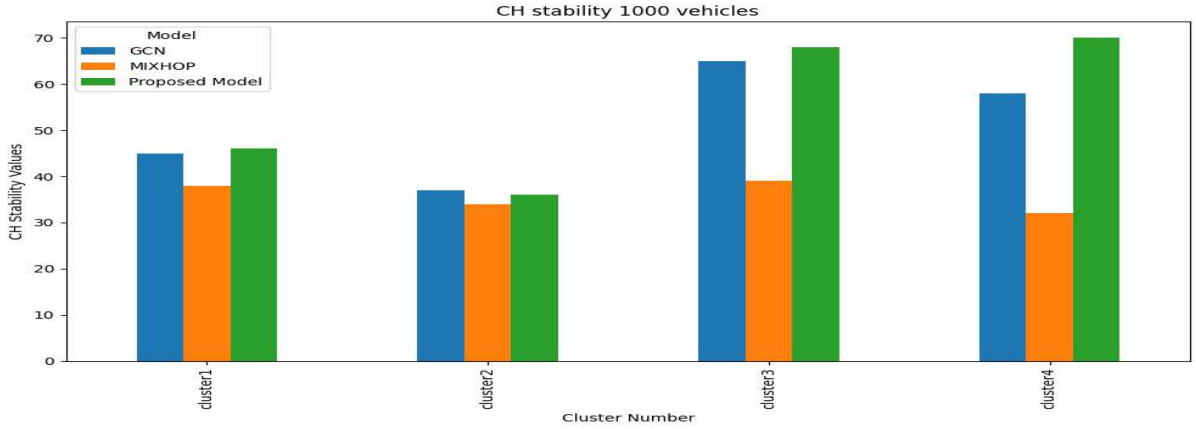


Figure 18: Cluster Head (CH) stability comparison for 1000 vehicles across four clusters using GCN, MIXHOP, and the Proposed Model

In Figure 16 presents a comparative analysis of cluster head (CH) stability values across three vehicular scenarios—100, 500, and 1000 vehicles—using three models: GCN, MIXHOP, and a VAST-GCN. Each scenario evaluates CH stability across four clusters.

In the 100-vehicle scenario, the Proposed Model consistently outperforms both GCN and MIXHOP in three out of four clusters, demonstrating superior CH stability. Notably, in cluster 3, both GCN and the Proposed Model exhibit similarly high stability values, while MIXHOP underperforms across most clusters. In figure 17, 500-vehicle scenario reveals similar trends. The Proposed Model maintains higher stability values in clusters 2, 3, and 4, with MIXHOP achieving its best performance in cluster 2, though still slightly below the Proposed Model. In the 1000-vehicle scenario (figure 18) , although the gap between models narrows in cluster 1 and cluster 2, the Proposed Model again demonstrates dominant performance in clusters 3 and 4, with CH stability values approaching or exceeding 70. GCN maintains relatively consistent performance, while MIXHOP continues to yield the lowest CH stability across most clusters.

Overall, the analysis suggests that the VAST-GCN provides more robust and stable cluster head selections, particularly as vehicular density increases, indicating its effectiveness in highly dynamic vehicular networks.

At 10, 25 and 30 Speed:

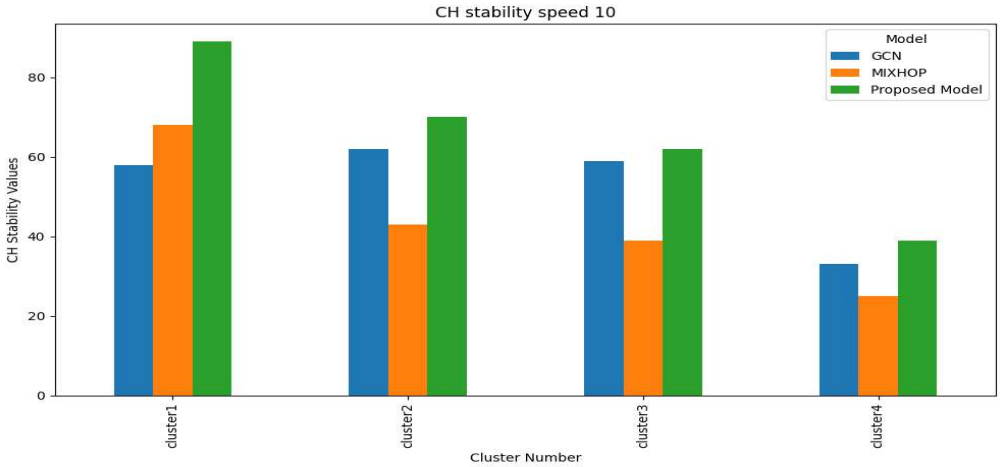


Figure 19: Cluster Head (CH) stability comparison at speed 10 using GCN, MIXHOP, and the Proposed Model

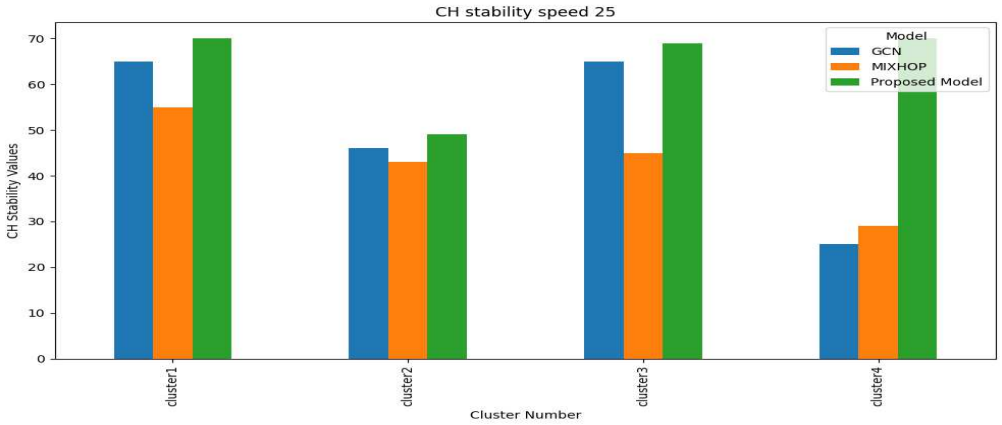


Figure 20: Cluster Head (CH) stability comparison at speed 25 using GCN, MIXHOP, and the Proposed Model

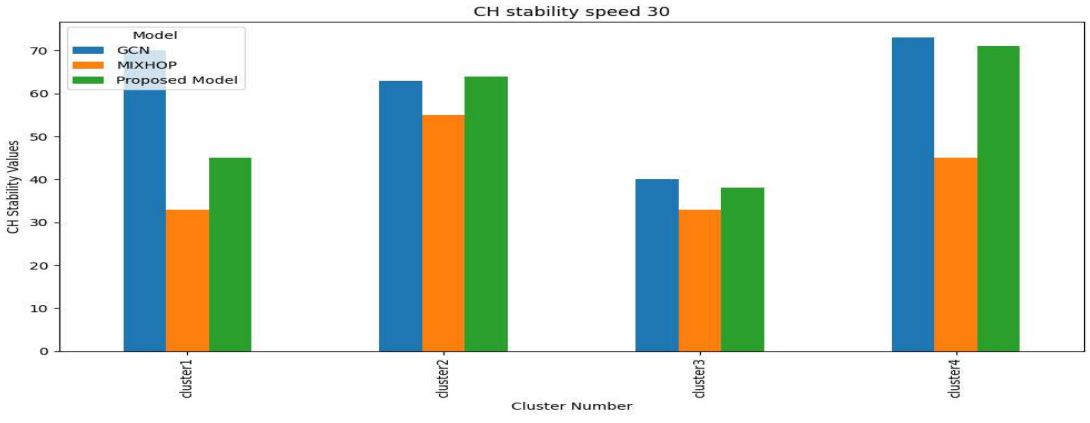


Figure 21: Cluster Head (CH) stability comparison at speed 30 using GCN, MIXHOP, and the Proposed Model

Figure 19, figure 20 and figure 21 illustrates a comparative analysis of Cluster Head (CH) stability values across three vehicular speed scenarios—10, 25, and 30 units—evaluating the performance of three models: GCN, MIXHOP, and a VAST-GCN.

In the 10-speed scenario, the Proposed Model consistently outperforms the other two models in clusters 1 to 3, indicating stronger CH stability. The Proposed Model is better suited for low-speed vehicular environments, likely due to more stable connectivity.

In the 25-speed scenario, the Proposed Model maintains its leading performance across all clusters, with particularly notable improvements in clusters 1, 3, and 4. GCN and MIXHOP exhibit moderate stability values, but the gap between them and the Proposed Model remains evident, underscoring the Proposed Model's robustness as vehicle speed increases. For the 30-speed scenario, the Proposed Model continues to demonstrate high stability in clusters 2 and 4, nearly matching or slightly trailing GCN in cluster 4. However, in cluster 1, GCN significantly outperforms both MIXHOP and the Proposed Model. MIXHOP remains the least stable across all clusters, especially in high-speed conditions.

Overall, the analysis indicates that the VAST-GCN consistently achieves superior CH stability across varying speeds, particularly at moderate levels. GCN performs competitively, especially at higher speeds, while MIXHOP shows the least favorable performance, suggesting limited adaptability to dynamic vehicular conditions. These findings support the Proposed Model's efficacy in maintaining cluster stability under fluctuating mobility scenarios in vehicular ad hoc networks (VANETs).

5.3.2 Throughput : Throughput helps to measure the ability of a chosen cluster head to keep communication dependable in a changing vehicular setting. A stable CH maintains high throughput, indicating consistent and efficient data delivery between cluster members and the CH.

At 100, 500 and 1000:

Figure 22, figure 23 and figure 24 provides a comparative analysis of network throughput performance across three vehicular densities—100, 500, and 1000 vehicles—evaluated using three models: GCN, MIXHOP, and a VAST-GCN. Throughput, measured in Kbps, is analyzed over four cluster groups in each scenario.

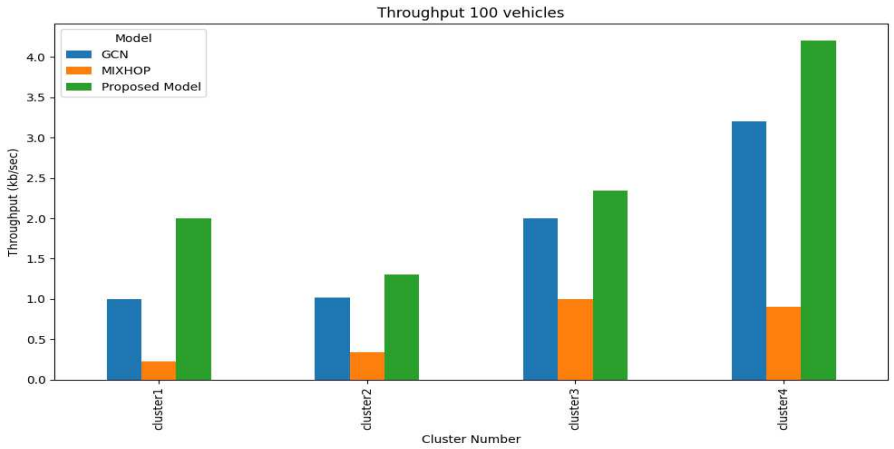


Figure 22: **Throughput comparison for 100 vehicles using GCN, MIXHOP, and the Proposed Model**

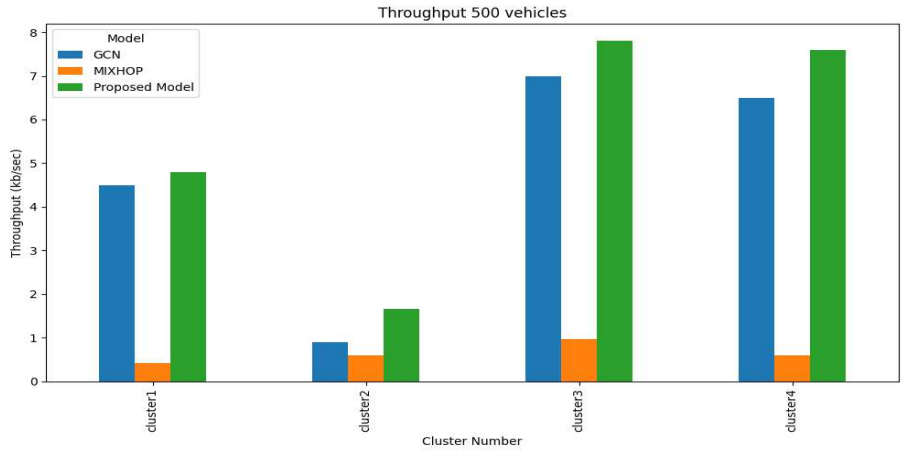


Figure 23: **Throughput comparison for 500 vehicles using GCN, MIXHOP, and the Proposed Model**

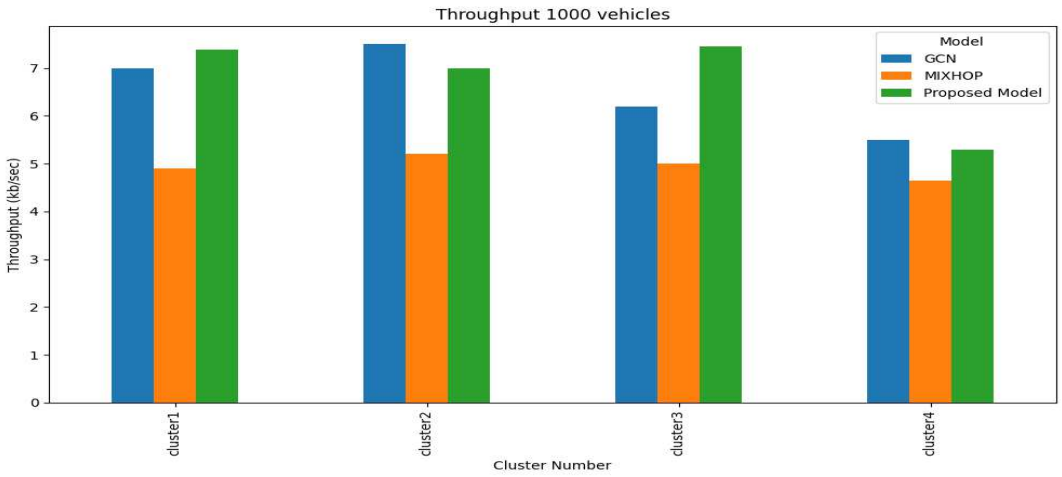


Figure 24: **Throughput comparison for 1000 vehicles using GCN, MIXHOP, and the Proposed Model**

In the **100-vehicle scenario**, the Proposed Model consistently achieves the highest throughput across all clusters. This trend indicates that the VAST-GCN is more effective in maintaining data transmission efficiency even in low-density networks. For the **500-vehicle scenario**, the throughput improves significantly for all models, particularly for the Proposed Model and

GCN. In the **1000-vehicle scenario**, both the Proposed Model and GCN demonstrate strong throughput across all clusters, with the Proposed Model slightly outperforming GCN in clusters 1 and 3. MIXHOP continues to show the weakest performance. The highest throughput values—over 7 Kbps—are achieved by the Proposed Model in clusters 1, 2, and 3, illustrating its robustness under high-density conditions. Overall, the VAST-GCN consistently delivers superior throughput across all vehicular densities, confirming its efficiency and scalability in high-mobility vehicular networks. GCN shows stable performance as network density increases, while MIXHOP underperforms, indicating limited adaptability. These results substantiate the Proposed Model's suitability for throughput-optimized applications in vehicular ad hoc networks (VANETs).

At 10, 25 and 30 Speed:

In figure 25, figure 26 and figure 27, graphs illustrate throughput performance across varying vehicle speeds (10, 25, and 30 units) using three models: GCN, MIXHOP, and a VAST-GCN.

At 10-speed, the Proposed Model and GCN show comparable performance, both achieving high throughput across all clusters. At 25-speed, the Proposed Model exhibits the highest throughput in most clusters, indicating superior adaptability at moderate mobility. GCN follows closely, while MIXHOP again performs the worst. At 30-speed, the Proposed Model clearly outperforms both GCN and MIXHOP. GCN maintains relatively strong performance, though slightly lower than the Proposed Model.

The Proposed Model demonstrates robust and consistent throughput across all speed scenarios, with increasing advantage at higher mobility. GCN remains competitive, while MIXHOP underperforms, especially at higher speeds. This highlights the Proposed Model's effectiveness for dynamic vehicular environments requiring reliable data transmission.

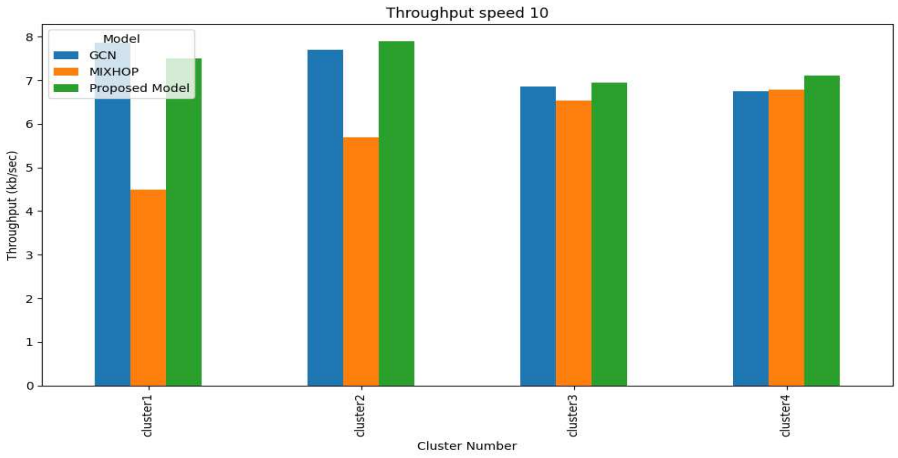


Figure 25: Throughput comparison at speed 10 using GCN, MIXHOP, and the Proposed Model

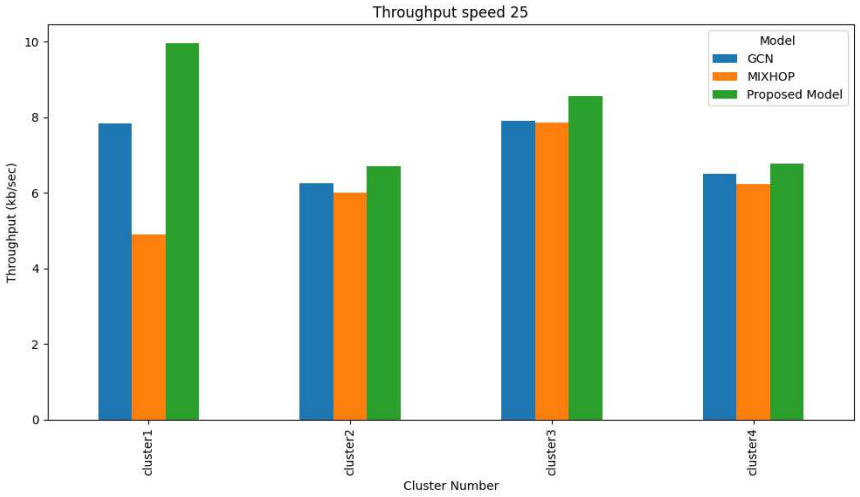


Figure 26: Throughput comparison at speed 25 using GCN, MIXHOP, and the Proposed Model

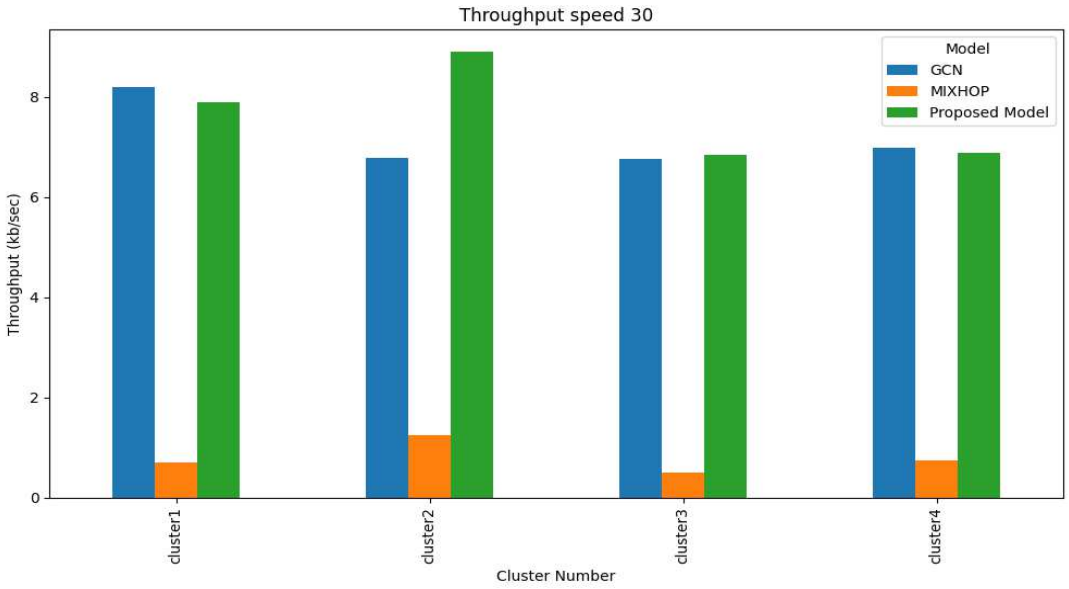


Figure 27: Throughput comparison at speed 30 using GCN, MIXHOP, and the Proposed Model

Throughput is measured in Kbps (kilobits per second) and analyzed across 4 different clusters within each scenario. The **Proposed Model** shows superior throughput performance in almost all 4 **clusters** indicating its strength in smaller networks. **GCN** performs well in cluster 3 but poorly in clusters 1 and 2. **MixHop** shows limited throughput across all clusters in this low-density scenario. **VAST-GCN** adapts better to sparse environments and maintains higher throughput in at least two clusters.

5.3.3 Packet Delay

Packet Delay refers to the total time taken for a data packet to travel from the source vehicle to the destination vehicle in a VANET. In VANETs, especially for safety-critical applications low delay is crucial for effective and timely decision-making. Low packet delay means smoother communication and better performance of real-time services.

At 100, 500 and 1000 Vehicles:

In Figure 28 , figure 29 and figure 30, the graphs compare packet delay performance across three models—GCN, MIXHOP, and the Proposed Model—under varying vehicle densities.

The Proposed Model consistently achieves the lowest packet delay across all cluster sizes and vehicle counts. MIXHOP exhibits the highest delay, especially under high-density conditions (500 and 1000 vehicles), while GCN shows moderate performance.

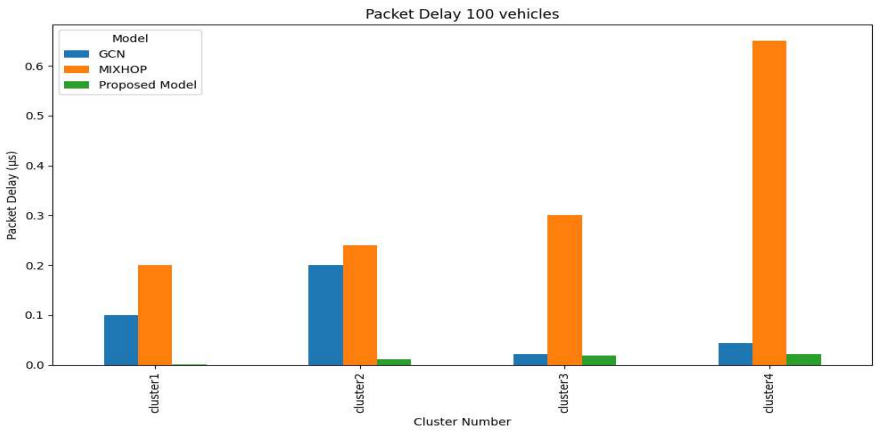


Figure 28: Packet delay comparison for 100 vehicles using GCN, MIXHOP, and the Proposed Model

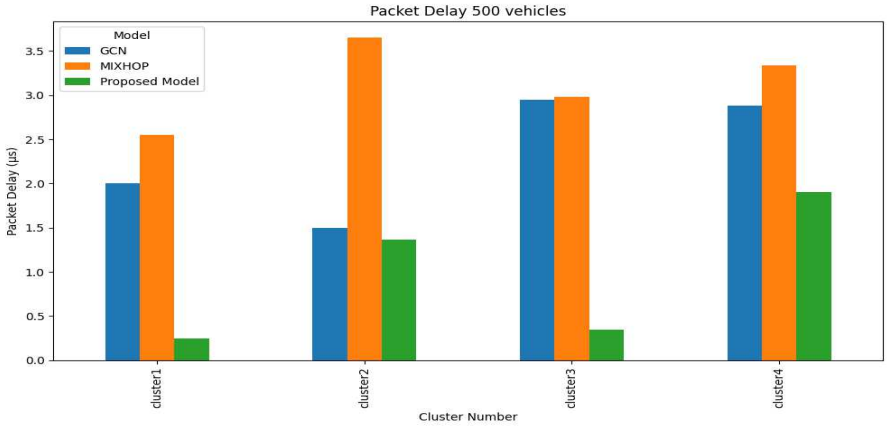


Figure 29: Packet delay comparison for 500 vehicles using GCN, MIXHOP, and the Proposed Model

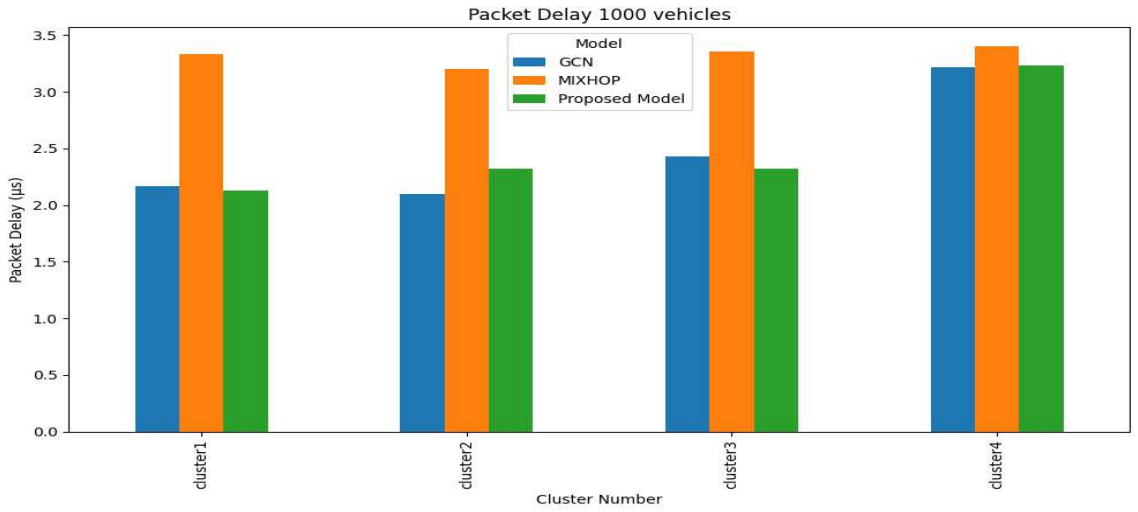


Figure 30: Packet delay comparison for 1000 vehicles using GCN, MIXHOP, and the Proposed Model

At 10, 25 and 30 Speed:

This figure 31, figure 32 and figure 33 compares packet delay across GCN, MIXHOP, and the VAST-GCN at different vehicular speeds.

The Proposed Model consistently achieves the lowest delay, especially at higher speeds (25 and 30), where MIXHOP performs the worst. At speed 10, all models show comparable results, with slight advantage for the Proposed Model.

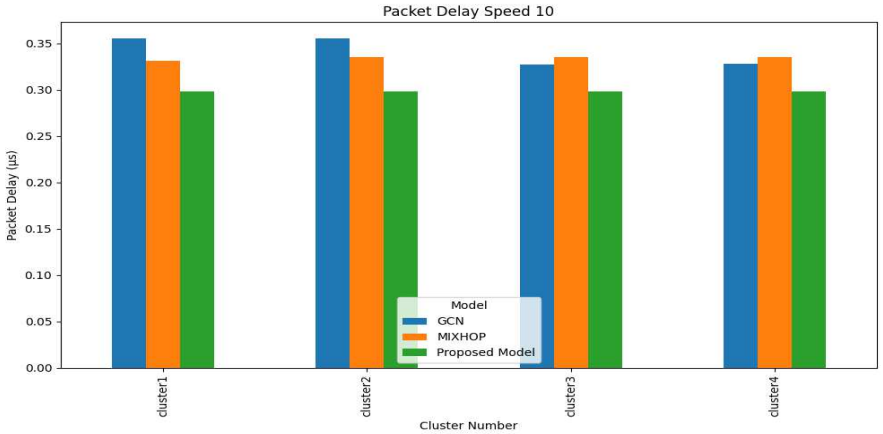


Figure 31: **Packet delay comparison at speed 10 using GCN, MIXHOP, and the Proposed Model**

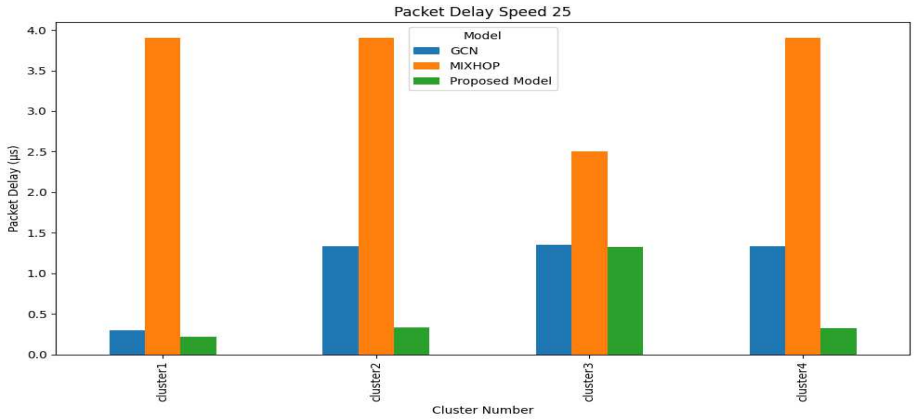


Figure 32: Packet delay comparison at speed 25 using GCN, MIXHOP, and the Proposed Model

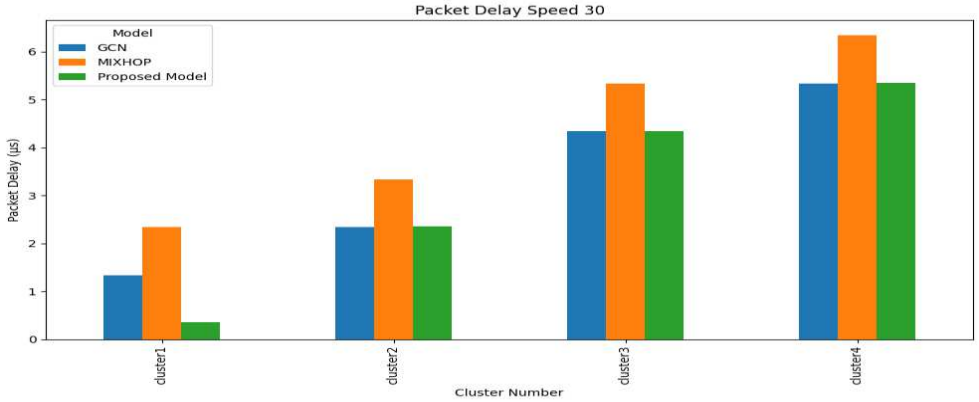


Figure 33: Packet delay comparison at speed 30 using GCN, MIXHOP, and the Proposed Model

The Proposed Model demonstrates superior efficiency in minimizing packet delay, particularly in sparse and dense vehicular networks, making it the most effective for latency-sensitive applications. VAST-GCN maintains low packet delay across all speeds, proving its robustness under mobility variations in vehicular networks.

5.4 Average Cluster head change rate comparison

Average Cluster Head Change Rate Comparison is an essential metric to evaluate cluster stability in VANETs. Frequent changes in cluster heads increase re-clustering overhead, reduce throughput, and introduce packet delays, while lower change rates indicate stronger and more reliable cluster formations. To comprehensively validate the proposed model, the average CH change rate is compared across varying vehicle densities (100, 500, and 1000 nodes) and mobility speeds (10, 25, and 30 m/s).

Table 4: Comparison of Cluster Head (CH) change rates for GCN, MixHop, and VAST-GCN

	GCN	**MixHop**	**VAST-GCN**
Vehicles 100	0.477	0.896	**0.4146**
Vehicles 500	9.820	9.9411	**08.62**

Vehicles 1000	13.560	23.182	**13.618**
Speed 10 m/s	10.332	14.8159	**9.815**
Speed 25 m/s	7.379	12.662	**4.4010**
Speed 30 m/s	5.961	6.9780	**5.972**

Table 4 is showing the comparative analysis of Cluster Head (CH) change rates for GCN, MixHop, and VAST-GCN across varying vehicle densities (100, 500, and 1000) and mobility speeds (10 m/s, 25 m/s, and 30 m/s). Low CH change rate mean less routing overhead and improved data transmission consistency. MixHop records the highest change rates under most conditions, indicating reduced stability, while VAST-GCN demonstrates comparatively lower change rates, highlighting its effectiveness in maintaining stable clusters.

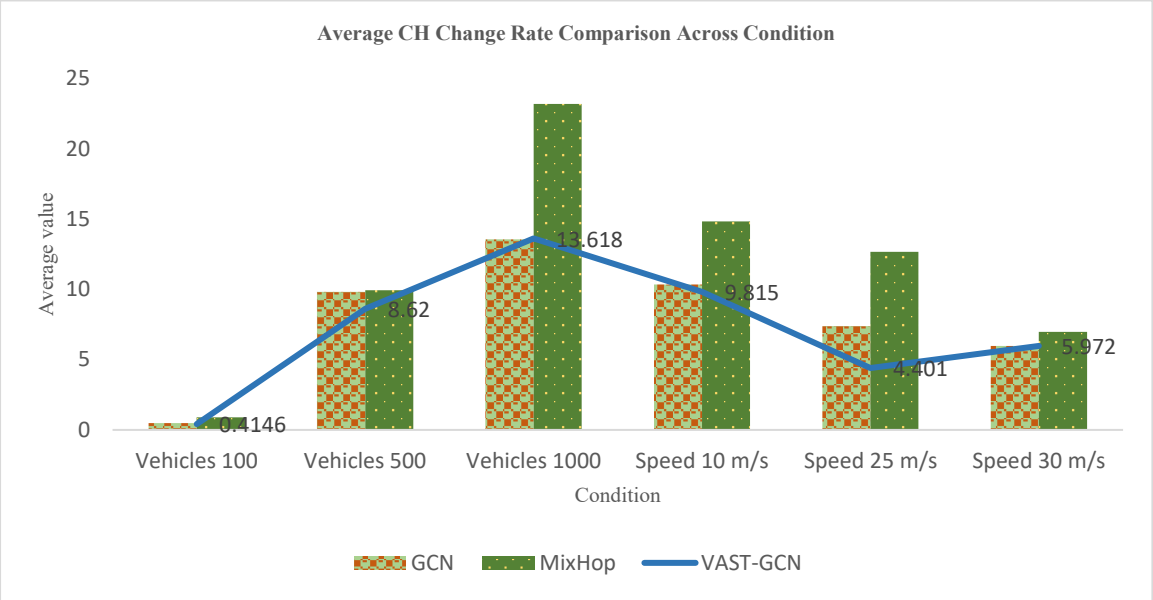


Figure 34: Comparison of Cluster Head (CH) change rates for GCN, MixHop, and VAST-GCN across varying vehicle densities (100, 500, and 1000) and mobility speeds (10 m/s, 25 m/s, and 30 m/s)

The figure 34 compares the average cluster head (CH) change rate for GCN, MIXHOP, and the VAST-GCN under varying vehicle densities (100, 500, 1000) and speeds (10, 25, 30 m/s).

Key Observations:

- The Proposed Model consistently achieves the lowest CH change rate across all conditions, indicating higher stability.
- MIXHOP exhibits the highest volatility, especially under high density (1000 vehicles) and speed (10 m/s), suggesting reduced CH reliability.
- GCN performs moderately but is outperformed by the Proposed Model in every scenario.

The proposed model offers a comprehensive and adaptive clustering approach that overcomes key limitations of traditional and GCN-based methods by incorporating spatial structure, feature salience, and temporal evolution—leading to more stable and efficient V2V communication in VANETs. Particularly in sparse and high-mobility scenarios, our model showed significant improvements in reducing CH transitions and routing overhead. This validates the effectiveness of incorporating spatio-temporal and attention mechanisms in CH selection.

6. Conclusion:

This research introduces **VAST-GCN**, a novel spatio-temporal attention-enhanced Graph Convolutional Network framework designed to address the challenges of clustering and cluster head (CH) selection in dynamic Vehicular Ad-Hoc Networks (VANETs). Through extensive simulation and comparative analysis against baseline models—standard GCN and MixHopGCN—the proposed model demonstrates significant improvements in clustering accuracy, network efficiency, and CH stability.

The experimental results reveal that VAST-GCN consistently outperforms existing models across a range of vehicular densities (100, 500, and 1000 nodes) and mobility conditions (10, 25, and 30 m/s). It achieves superior modularity and silhouette scores, indicating enhanced community structure and cluster cohesion. Furthermore, the model reduces packet delay and increases throughput, showcasing its practical viability for real-time V2V communication. Most notably, VAST-GCN maintains lower cluster head change rates, contributing to reduced routing overhead and more stable network topologies.

By integrating spatial, temporal, and channel attention mechanisms into the GCN architecture, VAST-GCN effectively captures the multifaceted relationships within vehicular networks. This enables the formation of robust and adaptive clusters even under high-mobility and high-density conditions. In conclusion, VAST-GCN represents a significant advancement in intelligent transportation systems, offering a scalable and reliable solution for dynamic CH selection in VANETs. Future work can explore real-world deployment scenarios, scalability to larger urban networks, and further enhancements through federated learning or hybrid communication protocols.

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Funding: No funding sources have been involved in the present investigation.

Data availability: No data is used in the research.

Authors contribution statement:

The corresponding author is responsible for ensuring that the descriptions are accurate and agreed by all authors.

Authors Anish Shandilya have done Conceptualization, Methodology, Software, Validation, analysis, Writing - Original Draft, Varuna Gupta has done Writing - Review & Editing, Bosco Paul Alapatt has done the Visualization and Supervision.

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