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VRACE-VANET : FUZZY-BASED RELAIBLE ADAPTIVE CLUSTERING APPROACH FOR CONNECTIVITY ENHANCEMENT

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ABSTRACT

Vehicular Ad Hoc Networks (VANETs) play an important role in ensuring reliable communication in Intelligent Transportation Systems (ITS). This helps to improve efficient transportation services for vehicles. However, several existing clustering methods such as mobility based and weighted clustering algorithms, which face challenges in maintaining stability in clusters. This issue is further pronounced in environments where there is high vehicle mobility and periodic changes in network structure. Therefore, to overcome these drawbacks, this study proposes Vehicular Reliable Adaptive Clustering Environment (VRACE), an adaptive clustering method based on a fuzzy approach. This incorporates queuing theory to improve the cluster stability and communication efficiency of the network. This method selects the cluster heads based on several factors such as relative mobility, direction of vehicles, link quality, travel direction and vehicle speed. Estimating these factors allows the structure to make adaptive decisions suitable for dynamic vehicular environments. This system was evaluated through simulation under different vehicle density scenarios using SUMO and NS2. The proposed method improves overall network performance by showing approximately 14% increase in cluster lifetime, 2.5% higher throughput, 4.3% improvement in packet delivery ratio (PDR) and 22.5% reduction in end-to-end delay. These findings indicate that VRACE can support reliable communication in dense and rapidly changing vehicular networks.

Keywords: *Vehicular Network, Fuzzy Systems, Clustering approach, Connectivity, Vehicle to Vehicle Communication.*

1. Introduction

The VANET (Vehicular adhoc Network) is a field that attracts a lot of researchers because of its ability to communicate with the surrounding urban traffic environment. With the rapid advancement of Intelligent Transportation Systems (ITS), vehicular communication technologies have gained notable attention. Communication standards like Dedicated Short Range Communication (DSRC), WAVE (Wireless Access in Vehicular Environments) and IEEE 802.11p are often adopted for vehicle-to-vehicle (V2V) interactions. In urban traffic environment with high vehicle density, the number of vehicles can exceed 80-120 vehicles per kilometer per lane. At the same time, communication range of on-board units generally varies between 50-300 meters depending upon transmission power and channel conditions. Under such circumstances, the network topology changes continuously. Vehicles frequently enter and leave the communication range causing link interruptions and unstable communication structures. As a result, maintaining reliable connectivity becomes an obstacle in the design of VANET systems. Due to the real time data requirement, VANETs have been regarded as a special class of adhoc networks. The most important consideration when creating a VANET is to setup a stable network and communication due to the high movement nodes with random spatial distribution. In VANET high movement of vehicles leads to frequent deviations in connectivity and coverage among the moving vehicles Varshini et al., (2018) & Aravindkumar & Varalakshmi, (2022). This challenge has motivated the development of connectivity optimization methods Alagumani & Natarajan, (2025) & Naskath & Paramasivan, (2018). Clustering is one of the commonly used techniques for organizing the network, since it can improve system scalability, enhance connectivity and reduce the network connection failure frequency. Although many existing clustering practices face problems in highly dynamic traffic conditions. Expeditious vehicle movement often causes frequent topology variations leading to repeated cluster head (CH) (Aravindkumar & Varalakshmi, 2022) re-elections and cluster fragmentation. In heavy congestion, clusters may also experience excessive load that results in communication delays and packet loss. In addition, several traditional clustering protocols rely on fixed parameters or single metric decision rules. These approaches restrict the capability to adapt to rapidly changing vehicular environments.

Designing link layers for cluster-based vehicular networks is another challenge. Aside from clustering, coverage and connectivity are two performance metrics that are of upmost importance that determine the quality of network communications (Chawhan et al., 2023). To further understand them, researchers study the probability of connectivity between vehicle-to-vehicle (V2V) for both single and multi-way road scenarios. In clustered network, one vehicle in each group is responsible for communication coordination, which is called a head of cluster (CH). The members (CM) are the other nodes of the cluster. They directly or indirectly communicate with CH through other CMs. In A survey by Ayyub et al., (2022) & Karne & Sreeja, (2022), different clustering algorithms for adhoc networks are discussed. For example, Mobility clustering algorithm, these use vehicle mobility information to form stable clusters. Lowest Identifier (LID) a simple approach in which the node with lowermost id is selected as head of cluster. Next direction based clustering approach, it chooses approach clustering nodes travelling in the same direction to improve cluster stability. But, due to their inherent characteristics such as high mobility and variable channel conditions, conventional algorithms are not usable to simulate VANET Senouci et al (2020). However, various fuzzy based and mobility aware clustering strategies have been proposed, many of them mainly emphasize mobility characteristics during cluster head selection. Factors such as service capacity and communication load of the cluster head are repeatedly overlooked during cluster formation and handover processes. Consequently, even stable nodes can become overloaded when large numbers of vehicles join the cluster. This condition can negatively affect the communication reliability and global network performance. Therefore, an effective clustering strategy is required that considers both mobility stability and communication service capacity in order to maintain reliable connectivity in dense VANET environments.

Therefore, researchers have proposed specific clustering algorithms that suit the required properties for VANETS (Chen et al., 2021). Hence, these algorithms are designed to suit the specific needs of the dynamic environment application. In order to enhance network connectivity, this research proposes a fuzzy based clustering algorithm. To overcome these limitations, this study introduces Vehicular Reliable Adaptive Clustering Environment (VRACE), an adaptive clustering structure based on fuzzy rule evaluation. This model aims to enhance connectivity in VANET environments. This system incorporates mobility-aware fuzzy decision rules with queuing theory-based estimation of service capacity. Through this method, heads are picked not only accordance with their mobility stability but also on their ability to effectively manage communication traffic (Latif et al., 2023). Combining of mobility factors like travel direction, vehicle speed and relative movement with queue-based service capacity analysis, the VRACE framework attempts to reduce cluster instability. This is followed by avoiding of cluster head overload and supporting of reliable V2V communication in dense urban traffic conditions. The research work presented here makes the following distinct contributions:

- An adaptive clustering structure utilizes fuzzy inference to enhance link reliability and communication consistency within vehicular ad hoc networks.
- Encompassing of queuing theory to estimate service capacity of cluster heads during cluster formation and handover operation.
- A mobility-aware cluster maintenance mechanism to decrease cluster reconfiguration in urban traffic congestion.

Performance analysis of the suggested VRACE foundation using SUMO, NS2 and MATLAB under different vehicular traffic scenarios. The remaining paper is organized as follows: After introduction, clustering approaches used to increase connectivity in urban roads have been reviewed. Section III describes the designing and simulation of VRACE model. The final section will talk about the contributions of this work and future research possibilities. The remaining paper is organized as follows: After introduction, clustering approaches used to increase connectivity in urban roads have been reviewed. Section III describes the designing and simulation of VRACE model. The final section will talk about the contributions of this work and future research possibilities.

2. Literature Review:

Stable communication in Vehicular Ad Hoc Networks (VANETs) requires stable clustering mechanisms since vehicles are fast-moving which results in changing topology and resulting in short-duration communication. With these dynamic conditions, sustainable connectivity in urban and highway contexts is in need of smart, adaptive, resource-efficient solutions that will ensure reliable connectivity. Clustering has been found to be a viable solution to counter topology instability as well as enhance the performance of data dissemination. Recent studies combine fuzzy logic with metaheuristic optimization to provide better cluster head (CH) selection, better choices in uncertain conditions, and greater cluster stability, which requires more adaptive and predictive clustering solutions to next-generation vehicular communication networks. The Fuzzy Bald Eagle Search (F-BES) algorithm, where the fuzzy logic is used to control the uncertainties in vehicle mobility and the Bald Eagle Search methodology is used to increase the efficiency of clustering, was proposed by Blessy & Brindha (2024). Their solution improves the reliability of the communication between vehicles and roadside units (RSUs) and has longer connectivity under high-mobility conditions. Another severe problem in clustered VANETs is security because such systems can be attacked by cybercriminals. The hybrid Intrusion Detection System that was proposed by Kalaivani and Santhalakshmi (2025) consists of a combination of Modified Possibility Fuzzy C-Means (MPFCM) clustering with Whale Optimization Algorithm and Deep Neural Networks. Their architecture identifies both zero-day and known attacks enhancing the strength of vehicular communication.

The previous work on the foundations also led to cluster stability. Kaur et al., (2022) suggested a mobility-based clustering algorithm that integrates relative vehicles speed to form a cluster. Their focus on variation of speed and other parameters greatly minimized the clustering reformation and prolonged cluster life than the classical MANET-based methods of clustering. In the analytical view, Xiao et al. (2021) investigated connectivity probability in freeway vehicular scenarios by modeling vehicle distribution and communication links. Their analytical framework demonstrated how traffic density and network topology influence network connectivity and communication reliability in vehicular environments. Of late, researchers have investigated the use of fuzzy-logic-based mobility management systems in VANET communication management. Singh et al., (2024) and Mukhtaruzzaman and Atiquzzaman (2025) suggested adopting fuzzy-based congestion control strategies that dynamically adjust the use of parameters like beacon busy ratio, road topology and vehicle acceleration to enhance the process of message distribution. Nevertheless, the techniques do not support much multi-cluster synchronization and energy efficiency in heavy city traffic. This creates a requirement to ensure multi-cluster fuzzy coordination structures are incorporated with energy-saving communication techniques to promote reliability in large scale VANET implementation.

The methods of clustering are usually grouped based on the CH election criteria. Initially the simple metrics like node identity or connectivity were used. The Lowest-ID algorithm picks the node with the lowest identifier as CH, which is simple but leads to imbalance in the load as the same nodes keep on being the CHs. On the same note, Highest-Degree algorithm chooses nodes with the largest number of neighbors and thus, it covers a lot of space; however, it leads to frequent cluster reconfigurations, given the high mobility of vehicles. To overcome these shortcomings, the Weighted Clustering Algorithm (WCA) synthesizes several parameters and they include node degree, relative speed, transmission power, and battery level (Sandeep & Venugopal, 2025; Shandil, 2023). WCA is fair in CH selection, but the weight coefficients are fixed values (Badole & Thakare, 2024), which are not able to respond to changing traffic conditions. Mobility-aware clustering schemes are solutions to this problem through which vehicles can be predicted to be moving using GPS and sensor data, and the stability of clusters is ensured. MhCA and SDPC were a few of the protocols that estimate future vehicle positions and multi-hop connectivity to minimize cluster reconfiguration. Table 1 represents the summary of the representative clustering algorithms, their main parameters, their main contribution, and limitations. Fuzzy logic is an additional clustering algorithm, which allows making decisions with multi-criteria in the conditions of uncertain networks. Fuzzy systems increase the stability of a cluster and minimize the unnecessary switching of CH by mapping the parameters into linguistic variables using their membership functions. Further models like Intuitionistic Fuzzy Logic use hesitancy factors in order to represent uncertain data more accurately. Nonetheless, there are still issues of complexity of rule-base and non-adaptive membership functions of fuzzy systems which show that adaptive methods of optimization are needed to facilitate highly dynamic vehicular networks.

Table 1 - Comparative Analysis of Clustering Methods in VANETs

Ref (S.No–Author–Year)	**Clustering /Routing Type**	**Algorithm /Technique**	**Key Parameters**	**Simulation Tool / Dataset**	**Key Contribution**	**Limitation**
Ayyub et al., (2022)	ID-based clustering	Lowest-ID clustering	Node ID, connectivity	NS2 simulation	Simple cluster head selection method for VANET nodes	Frequent cluster reformation in high mobility
Zhang et al., (2021)	Degree-based clustering	Highest-Degree algorithm	Neighbor count, connectivity	SUMO + OMNeT++	Improves cluster formation based on neighbor density	Unstable in dynamic vehicular mobility
Sharma et al., (2023)	Weighted clustering	Weighted Clustering Algorithm (WCA)	Speed, node degree, mobility	NS3 simulation	Balanced cluster head selection using weighted metrics	High computational overhead
Kaur & Kakkar (2023)	Mobility-aware clustering	FR-ARO fuzzy clustering	Speed, distance, link stability	MATLAB + SUMO	Improves cluster stability using fuzzy decision rules	Increased processing complexity
Kaur et al., (2023)	AI / Metaheuristic clustering	Fuzzy Bald Eagle Search	Vehicle speed, direction, distance	MATLAB simulation	Optimizes cluster head selection in VANETs	Limited real traffic validation
Xiao et al., (2021)	Connectivity-based clustering	Eigenvalue connectivity model	Link probability, vehicle density	Real highway dataset	Analytical connectivity prediction for vehicular networks	Not adaptive to cluster formation
Yu et al., (2025)	Secure Routing-based clustering	Mobility-aware channel allocation	Channel utilization, mobility	SUMO simulation	Improves message prioritization in vehicular platoons	Focus mainly on MAC layer
Elhoseny et al., (2023)	AI routing + clustering	Grey Wolf Optimization + Fuzzy inference	Cluster size, path lifetime	NS2 simulator	Enhances routing efficiency in clustered VANET	Higher computational cost
Husnain et al., (2023*)*	Routing-based VANET architecture	Adaptive clustering framework	Beacon ratio, traffic density	Veins simulator	Improves cluster lifetime and routing performance	Energy efficiency not considered
Dutta et al., (2024)	Hybrid ITS clustering	Intelligent transportation clustering framework	Traffic density, connectivity	Real vehicular dataset	Comprehensive VANET clustering analysis for ITS	Lacks adaptive fuzzy decision models

Mobility prediction is significant in enhancing stability in clustering of VANETs due to the fact that the topology of the vehicles changes more rapidly than the routing protocols (Syed Rabiya et al., 2023; Evangeline et al., 2025). Predictive models are used to predict parameters like the Link Expiration Time (LET) so that breakage can be predetermined and cluster handovers can be caused beforehand. An example is the clustering method based on connectivity prediction like CP-DC whereby vehicles speed, direction, and distance are utilized in order to preserve consistent cluster structures. Nevertheless, the majority of mobility prediction algorithms are more concentrated on preserving topological stability, including extending the lifetime of cluster heads (CH) whereas they do not pay attention to the service capacity of the CH during cluster transitions (Muthukrishnan & Kannan, 2023). The queuing theory offers a supplementary analytical approach in the sense that it characterizes a CH as a service node processing incoming packets. In the case the CH is already congested with traffic workload, the admission of new members during handover can cause a rise in delay and packet loss. Waiting time and service reliability can be estimated by means of queuing models like the M/M/1 or the M/G/1 (Hosseinzadeh et al., 2025; Feng et al., 2024). Although the fuzzy logic method has been widely used in the choice of CH (Aissa et al., 2022; Zhao et al., 2022; Xiao et al., 2021), the overwhelming majority of clustering models do not consider dynamics of queues and this poses a research gap in this research.

VRACE-VANET is novel approach in that it incorporates fuzzy logic and queuing theory to provide stability to the cluster and the reliability of its services. Fuzzy logic is used as the decision making system in the selection of cluster head (CH), where several mobility and connectivity parameters are considered that include vehicle velocity, direction, degree of node, and quality of links. Membership functions are used to establish the topologically stable nodes which are adequate to become CHs. Nevertheless, topological stability is not sufficient to ensure the capability of managing the network traffic. To overcome this shortcoming, queuing theory analyses the service capability of candidate CHs as a model of each CH as a queue. It approximates queuing time, and the likelihood of packet drop with the entry of new members to the cluster. The selection of a node requires the following conditions to be met: strong topological affinity and sufficient service capacity such that service rate (μ) is higher than the arrival rate (λ) ensuring $\rho = \lambda/\mu < 1$. This has been achieved by avoiding overloaded node in the stable and has provided reliable communication within the dynamic VANET environment.

3. VRACE approach

The main aim of the research will be to come up with a fuzzy logic based clustering algorithm that will effectively cluster vehicles into steady groups and hence improve the stability and flexibility of the VANET. Mobility of the vehicles and network density are two important elements that determine communication performance in VANET setting. The main challenge of guaranteeing reliable and streamlined communication under such dynamic environments is the necessity to consider a number of parameters: vehicle speed, node density, signal strength, and data transmission rate, as well as address the fluctuations in the network conditions, the needs of the applications, and user preferences (Soleymaninasab et al., 2025). The fuzzy-based clustering algorithm as proposed uses relative mobility, speed, direction, and acceleration/deceleration of vehicles as input measures, which are used to create clusters, appoint cluster heads, and stabilize a cluster. The approach is a fuzzy inference system (FIS)-based clustering method used to assess the probability of vehicle connectivity to come up with the best groupings.

3.1 Fuzzy Inference System (FIS) Design

The VRACE clustering mechanism utilizes a Mamdani-type FIS to identify suitable Cluster Heads (CHs) in highly dynamic vehicular networks. This FIS takes various mobility and connectivity metrics as input variables and returns a crisp output to determine the suitability of the vehicles to act as a CHs. The designated inputs for the fuzzy controllers include the following metrics: Relative Speed (S) difference in speed of near by vehicles. Direction Similarity (D) the directional alignment of vehicles travelling in the same traffic flow. Relative Mobility (RM) the variation in the speeds and positions of vehicles. Signal Strength (RSSI) the signal strength between neighboring nodes. Buffer Queue Length (BQL) the packets to be transmitted by the nodes. The input variables are converted into linguistic variables such as Low, Medium, and High and are represented by membership functions such as the triangular and trapezoidal membership functions handle the uncertainty and impreciseness of the mobility data. The fuzzy rule base considers the above mentioned input variables to determine the suitability of the vehicles to act as cluster heads.Some examples of fuzzy rules that can be applied in this case are: IF speed difference is Low AND direction similarity is High AND signal strength is High THEN node suitability is Strong CH candidate. IF mobility variation is High OR buffer queue length is High THEN node suitability is Weak CH candidate. The engine uses the the min–max composition method for evaluating these fuzzy rules, and the output is extracted by applying the Height of Maxima (HoM) defuzzification method, which selects the best candidate for being the cluster head. The fuzzy decision rules used to select cluster heads (CHs), merge clusters, and resign, lead to the higher stability of the clusters and significant cluster lifetime. On the whole, the suggested approach improves the work of VANET keeping the communication between all vehicles strong, adaptive, and context-dependent.

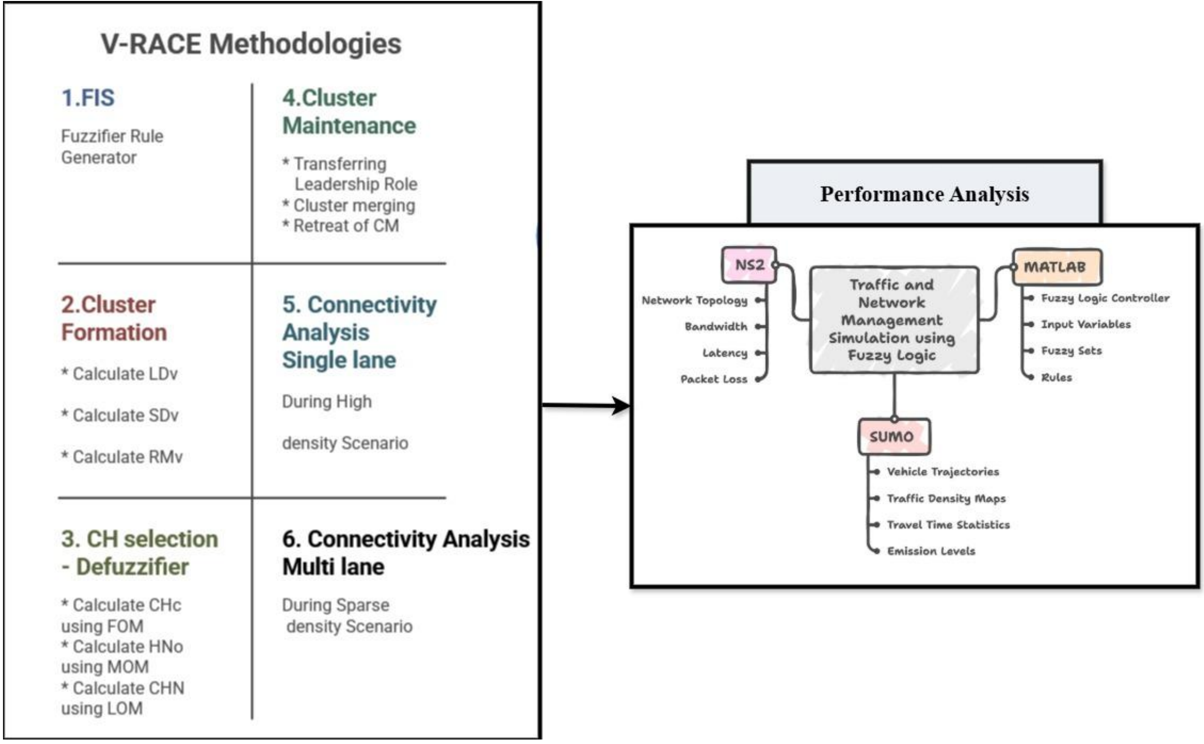

Fig. 1. Architectural Overview of VRACE protocol

3.2 Cluster Formation

Clustering concepts plays a key role in VANETs by structuring vehicles into organized groups thereby progresses the complete connectivity, stability and communication of the network. When a vehicle moves an urban roadway, it is initially identified as a usual node (Naskath et al., 2020 & Naeem et al., 2023). At this point, it transmits beacon messages containing mobility features to its neighboring nodes and currently recives same data from peers. Using the collected information, the vehicle controls whether a Cluster Head (CH) is already available in its communication zone. If a CH is sensed, the vehicle links with in it zone are turn into a Cluster Member (CM).

In this work, the clustering strategy is specifically designed to support two different Vehicle-to-Vehicle (V2V) communication scenarios, ensuring stable connectivity and effective message dissemination in dynamic traffic environments. In V2V clustering scenario, vehicles are taking over the leadership role and make the cluster with its peers using WAVE standard. fig.1 depicts the block diagram of proposed VRACE protocol.

Assume in a V2V communication, the cluster is made using the two moving vehicles x and y, in which each vehicle looks for a CH, which are at most K-hops away. In this clustering model, a network can be partitioned into smaller as well as more stable connected networks in terms of relative mobility RM_V , acceleration (a_n) and direction ($\vec{d}$) etc. A vehicle calculates RM_V with its neighbors based on their speed and location differences. This information is updated using beacon data received. The location differences LD_V between the vehicles L_x & L_y, are calculated as follows,

$$LD_V = \left|L_x - L_y\right| \tag{1}$$

Speed differences (SD_V) between the vehicles in urban roadway scenario is calculated using

$$SD_V = \left|S_x COS\theta - S_y COS\theta\right| \tag{2}$$

where, θ is vector angle between the vehicles. Now, the RM_V value is calculated from Equation (1) and (2). ∂ and ∂' are the weight values of location and speed of the vehicles.

$$RM_V = \partial LD_V + \partial' SD_V \tag{3}$$

In order to provide fair and objective cluster head selection, the parameters used in the fuzzy decision algorithm are mathematically defined. The relative mobility between vehicles vi and vj is given as:$RMij = \sqrt{((vxi - vxj)^2 + (vyi - vyj)^2)}$where the coordinates of the vehicles vi and vj are given as (vxi , vyi) and (vxj , vyj) respectively. The variation in the speeds of the vehicles i and j is gven as $\Delta Sij = |Si - Sj|$. where the speed of the vehicles vi and vj are given as Si and Sj respectively. The similarity in the direction between the vehicles vi and vj is given as $Dij = \cos(\theta i - \theta j)$where the direction is given as θ. The RSSI between the vehicles $RSSI = T - Loss(d)$ where T is transmission power and Loss(d) is the path loss at a given distance d. These parameters collectively determine the stability and communication reliability of potential cluster head nodes.In this proposed methodology, each vehicle travel within its peers' transmission range V_{TR}. The location coordinate of vehicle is denoted as (L_V).

V2V Cluster Formation Algorithm

```
1.  Gather vehicle location differences;$LD_V$ coordinates of vehicles;
2.  Set the range for vehicle transmission;$V_{TR(i,j)}$;
3.  Gather the speed differences $SD_V$ coordinates;
4.  Workout the relative mobility $RM_V(i,j)$;
5.  Make FIR-Fuzzy inference rule ($f(x)$) = ($RM_V$, $\vec{d}$, $a_n$)
6.  Look at the process of FIR$f(x)$;
        If ( $f(x)$==medium) then
            $V_i$ becomes a cluster member as CM;
        Else if ( $f(x)$==high) then
            $V_i$ becomes a CM and suggested as a possible cluster head $CH_{No}$ ;
            And pick cluster head using CH select();
        Else if ( $f(x)$==low) then
            $V_i$ as CM or reject;
        End if
7.  Cluster Head selection();
8.  End cluster formation.
```

The affinity values of each vehicle calculated using a fuzzifier in terms of RM_V, a_n and $\vec{d}$. Now, a vehicle can link in a cluster on account of the affinity values that define the nearness of the V2V cluster. If affinity range of the peer cluster size is more than the actual then the vehicle make a decision to link in to the clusters of the V_{TR} as CM, else it joins in another cluster. If the two neighboring vehicles, travel within the same transmission range with same direction and same a_n those vehicles can form a cluster group on the urban roadway. At the same time, opposite direction based clustering is considered only when d_{act} is low. Hence, this approach is not considered to avoid less cluster life time. The process of creating and picking a cluster head is done through a fuzzy based multi-attribute decision making (MADM) technique.

It helps to make rules for fuzzy logic $f(x)$ and for all changes. In this algorithm (3.2.1), the parameters $\mathrm{RM_V}$, $\vec{\mathrm{d}}$, and $\mathrm{a_n}$ are used as inputs to make fuzzy rules using fuzzy logic. fig.2 & 3 shows the fuzzy membership function (FM) for acceleration $\mathrm{a_n}$ and direction $\vec{\mathrm{d}}$. The e fuzzifier function by translating data in tofuzzy sets.

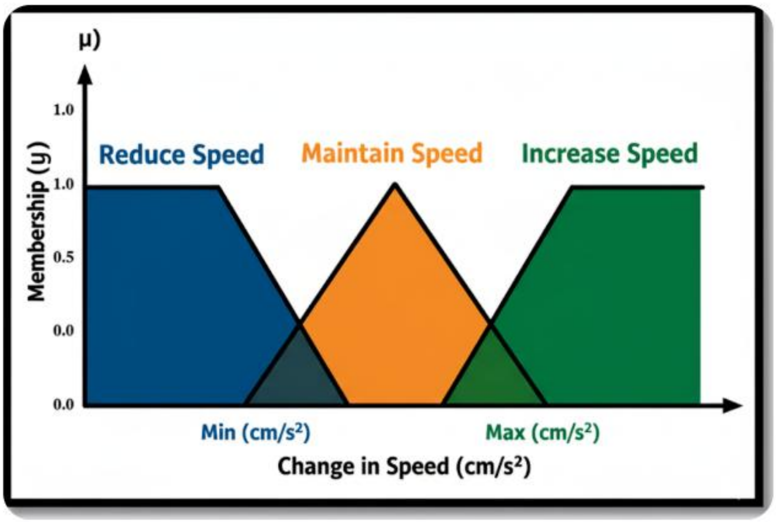

Fig. 2. FM function ($\mathbf{a_n}$)

The input parameters are assigned to the set:
$\mathrm{RM_V} = \{\mathrm{High} = 65\mathrm{Kmph\ to\ }100\mathrm{Kmph}, \mathrm{Medium} = 35\mathrm{Kmph\ to\ }65\mathrm{Kmph}, \mathrm{Low} = 35\mathrm{Kmph}\}$, $\vec{\mathrm{d}} = \{\mathrm{same}, \mathrm{oppposite}\}$
and $\mathrm{a_n} = \{\mathrm{accelerate}, \mathrm{same}, \mathrm{decelerate}\}$.

Triangular and trapezoidal membership functions are applied to derive membership values (μ) based on fuzzy set parameters (Yousif et al., 2025). Using these values, product inference rules are formed according to the given inputs. The subsequent stage involves defuzzification, which is the reverse of fuzzification, and it is used to finalize the Cluster Head (CH) selection process.

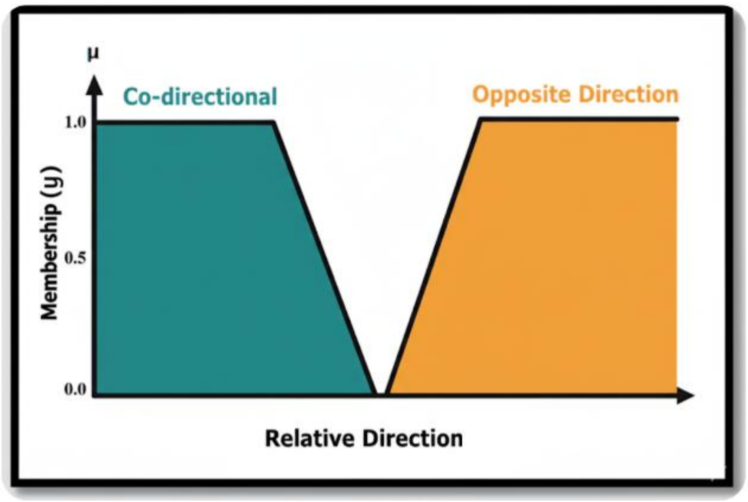

Fig. 3. FM function ($\vec{\mathbf{d}}$)

3.3 Cluster Head Selection

Maintaining cluster stability is a primary goal in clustering, and thus head selection plays a vital part. A stable CH minimizes reorganization overhead, avoids frequent re-elections, and ensures an efficient hierarchical structure (Zhao et al., 2022). In this process, the most suitable nominee is chosen as CH over others. The next stage uses defuzzification in the Fuzzy Inference System (FIS) to identify the current CH , the next CH, and CH nominees. Defuzzification converts aggregated fuzzy rules into crisp outputs through methods like lambda cut, centroid, or maxima. This effort adopts the Height of Maxima method, which relates three schemes as F_OM **:**First of Maxima,next L_OM:Last of Maxima, and last M_OM **:**Mean of Maxima. According to F_OM, the current CH is selected from the nominee set. CH_C is a current cluster head.

$$CH_C = \min\{x \mid f(x) = \max_h f\{w\}\} \quad (4)$$

The Next Head CH_N is nominated based on the L_OM method as,

$$CH_N = \max\{x \mid f(x) = \max_h f\{w\}\} \quad (5)$$

and residual CM of most is reflected as $\mathrm{CH_{No}}$,

$$\mathrm{CH_{No}} = \frac{\sum_{xi \in M} x_i}{|M|} \quad (6)$$

M is defined as $M = \{x_i \mid \mu(x_i) = h(c)\}$ where $|M|$

M is Cardinality set. $\mathrm{Here}, h(c)$ is the altitude of fuzzy set. In this clustering structure, each node collects the data that is $\mathrm{RM_V}$ calculated by each node in the lane, to choose head using F_OM with least $\mathrm{RM_V}$ and direction of moving nodes. The $\mathrm{CH_{No}}$, is calculated using M_OM and when the CH_C exit from the cluster, CH_C is directly elected by CH_N as CH_C. The CH_C and CH_N selection is beaconed among cluster members. The elected CH act as the intermediary between other CMs. Each vehicle communicates with its peers either directly (CM) or CH.

Algorithm for Cluster Head (CH) Selection

```
Initialize cluster head selection with CH_Select().
Read the list of candidate cluster heads.$CH_{No}$
Construct fuzzy inference rules for evaluating candidates.
Defuzzify the fuzzy output.$f(x)$
Compute the First Maximum ($F_OM$) value.$FOM$
Assign the current cluster head based on $F_OM$.$CH_C$
Compute the mean of maxima:$MOM$
Use this to update and maintain the list of nominee cluster heads.$CH_{No}$;
Compute the Last Maximum ($l_OM$) value:$LOM$
Use this to designate the next head in the network.$CH_N$;
End the CH selection process.
```

Queue-Based Cluster Head Service Evaluation: In order to avoid the cluster head overload during cluster formation and handover, VRACE uses queuing theory for evaluating the service provided by candidate cluster heads. Each cluster head is considered as a service node that serves packets received from other members of the cluster. The M/M/1 queue model is considered which assumes that packets are received according to a Poisson distribution and service is exponential distribution. Let λ = data arrival rate, μ = packet service rate, ρ = traffic intensity that is calculated as $\rho = \lambda / \mu$. For a stable cluster head, it is necessary that $\rho < 1$. The typical waiting time in the queue is given by: $q = \lambda / (\mu(\mu - \lambda))$.If the Queue length is expected to exceed a certain threshold, then that node is rejected even though it is mobility stable indicating that it has enough service for handling cluster communication without congestion.

3.4 Cluster Maintenance

In a VANET environment, vehicles may enter or leave the urban roadway at any time, making cluster stability an important objective. To ensure longevity, durable Cluster Heads (CHs) are selected and maintained. Cluster maintenance mainly occurs due to three reasons. First, leadership transfer happens when the current CH is unable to continue or exits the cluster. In this case, the next eligible node assumes the CH role while the former CH switches to a CM, ensuring seamless intra- and inter-cluster communication without reconfiguration. Second, cluster merging takes place when two CHs come within the same transmission range. The vehicle with the higher F_OM remains the leader, and the other CH is assigned the role of the CM, and the new CH sends beacon messages to endure connectivity. Finally, there is CM withdrawal, which is caused by high topology changes or the movement of vehicles. In this case, the CM moves out of range or leaves the laneway. If a node does not receive periodic beacons, it assumes disconnection and removes the member from the list, and sends updated beacon messages to the cluster. If there is an absence of a successor, the CM takes the role of the CH automatically. Over time, this node may revert to CM status or detach from the cluster. Each CM is assigned a nominee value, and comparisons are made with predefined thresholds. When the variation surpasses the edge, a new head is elected. These normalized inputs span from 0.0 to 1.0, where the 0.0–0.2 interval represents lowest priority candidates and values above 0.7 represent stronger contenders. This quantification supports reliable CH selection, and Table 1 illustrates a sample fuzzy rule base with corresponding output values.

Cluster Head Maintenance Procedure

```
Input: Fuzzy ranges of current and next Cluster Head (CH)
Output: Updated Cluster Head
Retrieve the fuzzy values of current $F_{CH_C}$ and next possible cluster head $F_{CH_N}$;
Compare the fuzzy ranges of both head
    If ($F_{CH_N}$ > $F_{CH_C}$) then
Assign next as current cluster head and update current ranges
$CH_C = CH_N$;
Else
Select new cluster head using CH select() ;
End if
End the procedure.
```

Table 2 - Sample Fuzzy Logic Rule Base of VRACE

Rule	Condition (x=RM_V , y=a_n, z=$\overrightarrow{d}$)	Output
1	IF (X is minimal) ⋂ (Y is speed drop) ⋂ (Z is Identical)	0.5
2	IF (X is Moderate) ⋂ (Y is speed drop) ⋂ (Z is Identical)	0.8
3	IF (X is minimal) ⋂ (Y is speed rise) ⋂ (Z is Identical)	1.0
4	IF (X is Moderate) ⋂ (Y is speed drop) ⋂ (Z is Inverse)	0.6
5	IF (X is Elevated) ⋂ (Y is speed rise) ⋂ (Z is Inverse)	0.1
6	IF (X is Elevated) ⋂ (Y is speed rise) ⋂ (Z is Inverse)	0.2

Adaptive Re-Clustering Strategy : The VRACE protocol provides supports for an adaptive re-clustering strategy ,which helps to ensure stability in the network. Re-clustering of nodes occurs based on the following events: Cluster head moves out of transmission range, Cluster head queue load exceeds the threshold, Link stability of nodes within a cluster drops below a threshold level, Topology changes due to vehicle mobility. In case any of these events happen, a new cluster head election process is initiated using the fuzzy decision framework.

3.5 Connectivity Analysis

In this section, connectivity probability measures how likely vehicles can communicate with nearby peers using the minimum number of hops in the dense area.

Assume, the road length is L, d'_{act} be the count of vehicles per meter of lane (l). Let the transmission range of vehicles V_{TR} and, then the cumulative probability distribution function (PDF) is measured as, $f(n, l) = \frac{(d'_{act} l)^n}{n!} e^{-(d'_{act})l}, \text{where } n \geq 0;$ If the distance among peer vehicles denoted as $\ddot{D}G$ smaller than the lane per meter then the PDF is evaluated as ,

$$P\left\{ \ddot{D}G \leq l \right\} = 1 - e^{-d'_{act} l} \tag{7}$$

According to V2V communications approaches, connectivity probability is analyzed using two different scenarios such as single and multilane of heavy traffic roadway scenarios.

Connectivity between Vehicles in a Single-Lane Environment

In this single lane V2V scenario, vehicles act as both CM and CH and travel in the identical or same direction $(\vec{d})$. Here, the inter vehicle distance between two consecutive vehicles is $\ddot{D}G_i$. If $\ddot{D}G_i$ come under the range of V_{TR} then the particular vehicle is joined as CM in this cluster. So the connectivity probability is calculated as,

$$P' = \prod_{i=0}^{N-1} p\left\{ \ddot{D}G_i \leq V_{TR} \right\} \tag{8}$$

V2V based cluster communication scenario is represented in fig.5. In the single lane connectivity scenario two options are possible to make a seamless connectivity, either vehicle can connect with the CM and its probability measure is q or it can directly connect with CH and its probability measure is p. Now, the connectivity probability is described as

$$P_{V1} = \prod_{i}^{N-1} q.P\left\{ \ddot{D}G_i \leq R_{CM}) \right\} + p.P\left\{ \ddot{D}G_i \leq R_{CH}) \right\} \tag{9}$$

R_{CM} and R_{CH} coverage radius of CM and CH vehicles. As per equation 7, the overall communication of V2V in single lane (P_{SV}) is defined as,

$$P_{SV} = \left[q.\left(1 - e^{-d'_{act} R_{CM}}\right) + p.\left(1 - e^{-d'_{act} R_{CH}}\right) \right]^{N-1} \tag{10}$$

Connectivity between Vehicles in a Single-Lane Environment

fig. 5 represents the V2V communication at multilane scenario. In this scenario, the adjacent lanes as well as vehicle moving directions $(\vec{d})$ are considered for connectivity analysis. Whenever the separation exceeds the signal reach the two consecutive vehicles $\ddot{D}G_i$ is greater than its transmission limit V_{TR} ,the link breakages happened so the vehicles can try to make a connectivity with the adjacent lane clusters. During this scenario, the connectivity link of same lane is considered as broken link B_l. So the vehicle can try to connect with adjacent lane cluster's CM or CH. As per the fig.5, the connectivity among vehicles is established using more than one cluster (N). If established connectivity is only formed by CM then the connectivity probability is defined as $q_k.$ $P_{Bl} = \sum_{k=0}^{N-1} \left(1 - e^{-d'_{act} R_{CM}}\right)$, else if it is generated by the CH then connectivity probability is $P_{Bl} = \sum_{k=0}^{N-1} p_k.\left(1 - e^{-d'_{act} R_{CH}}\right)$, else if it is established by both combination of CM and CH then connectivity probability is represented as,

$$P_{Bl} = \left\{ \ddot{D}G > V_{TR} \right\} = \sum_{k=0}^{N-1} q_k.\left(1 - e^{-d'_{act} R_{CM}}\right) + p_k.\left(1 - e^{-d'_{act} R_{CH}}\right) \tag{11}$$

Sometimes the adjacent lane vehicles directly communicated with single cluster via healthy links. This link established either using CM or CH. Thus, utilizing binomial distribution theory the whole connectivity probability $P_T(k)$ is defined using two different link qualities such as broken(Bl) and reliable healthy links(Hl).

$$P_T = \binom{N-1}{k} P_{Bl}{}^{k}(P_{Hl})^{N-1-k} \tag{12}$$

Here, k of N-1 has broken links and P_{Hl} is healthy links in a network.

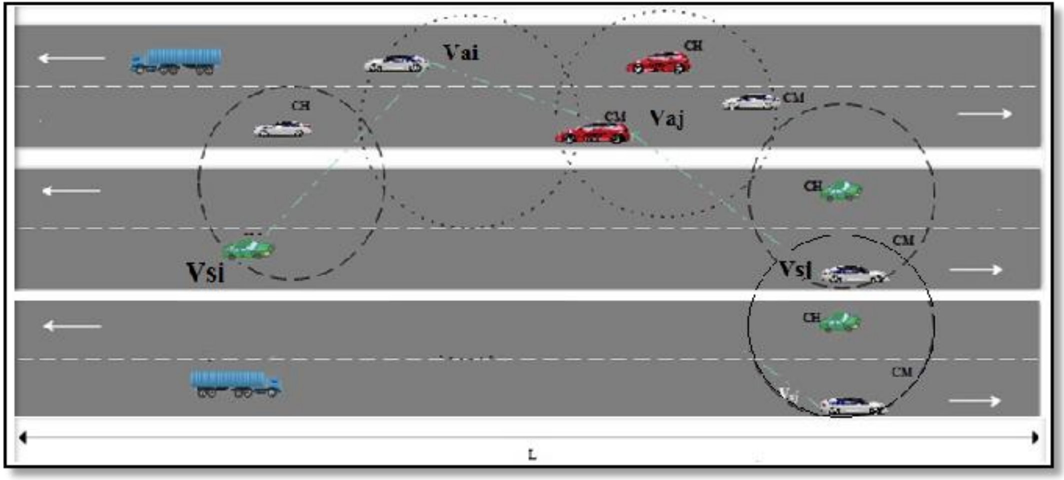

Fig. 4. Cluster based V2V communication scenario

As per the fig. 5, V_{si} and V_{sj} in same lane, and $\ddot{D}G$ is longer than the V_{TR}. Thus they can to communicate with adjacent lane vehicles of V_{ai} and V_{aj}. The probability function of $P_{sa(i)}$ and $P_{sa(j)}$ is ,

$$P_{sa(j)} = P_{sa(i)} = P\{\ddot{D}G \le V_{TR}\} = 1 - e^{-d'_{act}V_{TR}} \tag{13}$$

Thus, connectivity probability among V_{si} and V_{sj} is denoted as, $P_{s(i,j)} = P_{sa(j)} + P_{sa(i)}$. Healthy link communication P_{Hl} is defined as the two adjacent lane vehicles are directly connected with single cluster, either by CM or CH is signified as,

$$P_{Hl} = \{\ddot{D}G \le V_{TR}\} = \sum_{k=0}^{N-1} q_k.\left(1 - e^{-d'_{act}R_{CM}}\right) + p_k.\left(1 - e^{-d'_{act}R_{CH}}\right) \tag{14}$$

$$P_{MV} = \binom{N-1}{k} P_{Bl}{}^{k}(P_{Hl})^{N-1-k} \tag{15}$$

Thus as per Equation 15, the overall connectivity of multilane V2V communication P_{MV} is calculated.

4. Simulation Setup and Performance Assessment

The proposed work is implemented using three simulators (Narendra et al., 2014): SUMO for traffic simulation, NS2 for network simulation, and MATLAB for fuzzy-based experiments. The simulations are conducted by varying vehicle density and speed to evaluate performance. The overall efficacy of the proposed system is analyzed in terms of Packet Delivery Ratio (PDR), Network Throughput, average lifespan of Cluster Heads (CH) and Cluster Members (CM), and network connectivity under different scenarios. Table 2 outlines the variables for the simulations.

4.1 Comparing Quantitative Performance

The performance of the proposed VRACE clustering mechanism was compared to conventional clustering protocols such as mobility and stability-based clustering techniques in order to its efficacy. Packet delivery ratio (PDR), cluster lifetime, control overhead, transmission delay, and throughput are among the assessment metrics. To test the robustness of the proposed method, simulation experiments were carried out in various vehicle density scenarios. To guarantee the results statistical reliability, each experiment was run several times and the average values were considered. The findings show that VRACE improves network performance by combining queue-aware cluster management with fuzzy inference driven cluster head selection. When compared to baseline methods, the suggested approach shows enhanced stability in extremely dynamic vehicular environments.

Table 3 -Simulation parameters of VRACE

Parameters	**values**
Simulation Tool	NS-2 / SUMO
Geographical area considered for simulation	500mX50m
Simulation Duration	200 Seconds
Area of Map	Kovilpatti–Urban roadway
Mobility model	random waypoint mobility model
Vehicles Count	50 -200
Vehicle Speed	35-55 km/h
Simulator used	MATLAB /SUMO/NS2
protocol used for :PHY/MAC	IEEE 802.11p-WAVE standard
OBU Coverage Range (m)	50 /100
Network: Interface/Channel Type	Wireless PHY/Wireless
Traffic Type	CBR / Safety Message Broadcast
Data packet size (bytes)/ data count	512 /100
Antenna type	Omni

The simulation outcomes indicate that the proposed VRACE framework effectively ensures seamless connectivity compared to other related approaches. The performance evaluation metrics are described as follows:

- **Average lifetime of Cluster head and member:** This measure the mean lifetime of the Cluster Head (CH), which manages transmissions within the cluster, and the Cluster Member (CM), responsible for relaying messages inside the cluster. It also includes the average rate of CH changes relative to vehicle density and speed. The connectivity performance of the proposed network is assessed network parameters like packet delivery ratio, Throughput and connectivity probability.

$$L_{CH} = \frac{1}{N_{CH}} \sum_{i=1}^{N_{CH}} (T^{i}_{end} - T^{i}_{start})$$

Where

- L_{CH} = Average lifetime of cluster heads
- N_{CH} = Total number of cluster heads
- T^{i}_{start} = Time when node i becomes cluster head
- T^{i}_{end} = Time when node i stops being cluster head

$$L_{CM} = \frac{1}{N_{CM}} \sum_{j=1}^{N_{CM}} (T^{j}_{leave} - T^{j}_{join})$$

Where

- L_{CM} = Average lifetime of cluster members
- N_{CM} = Total number of cluster members
- T^{j}_{join} = Time when node joins cluster
- T^{j}_{leave} = Time when node leaves cluster

- **Packet Delivery Ratio:** The proportion of successfully delivered packets relative to aggregate count transmitted by the initiating nodes.
- **Network Throughput:** The measurement of the actual data packets successfully forwarded through the network framework.

$$PDR = \frac{R}{S} \times 100$$

Where

- S = Total number of packets sent by source vehicles
- R = Total number of packets successfully received

$$Throughput = \frac{R_{bits}}{T}$$

Where

- R_{bits} = Total number of received data bits
- T = Total simulation time

- **Connectivity Probability:** It defines the likelihood that a vehicle can reach other vehicles to deliver messages with the minimum number of hops.

$$CP = \frac{N_{connected}}{N_{total}}$$

Where

- $N_{connected}$ = Number of vehicles that maintain communication links
- N_{total} = Total number of vehicles in the network

Average lifespan of CH and CM:

fig. 5 illustrates the average cluster head duration, in seconds, for various vehicle velocities with the transmission range fixed at 50 m. As vehicle speed increases, the frequency of CH changes rises, resulting in a shorter average CH lifetime. Notably, the proposed VRACE scheme maintains a comparatively long CH duration of about 52.38s for CH and 57.91s for CM at 35 km/h, and even at 100 km/h it sustains more than 80 s at both levels with higher density. The high-pitched decline in CH stability at higher velocity reflects the increased motion and frequent network structure changes, accentuating the issue of conserving stability of cluster in rapid conditions.

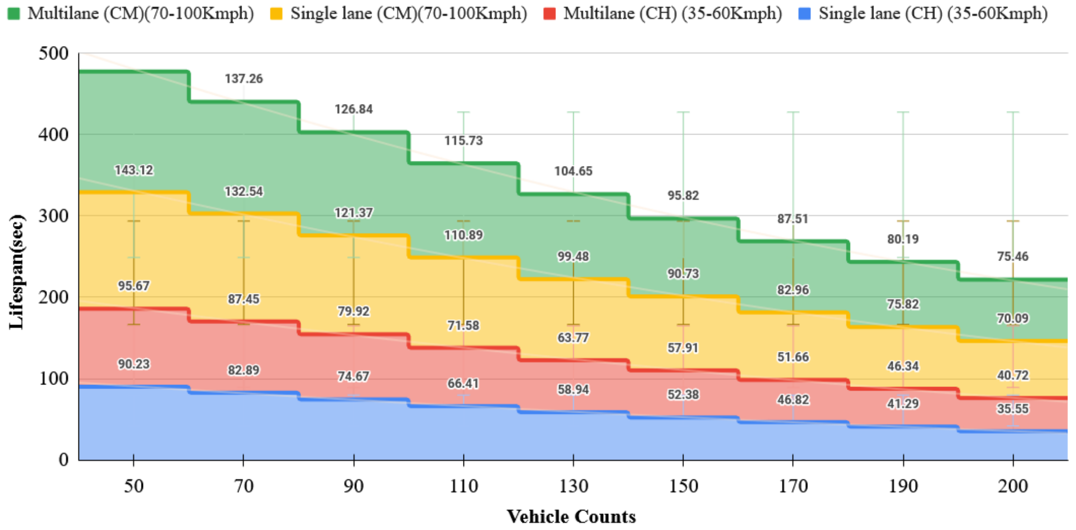

Fig. 5. Variation of CH Lifetime with Vehicle Speed

fig.5 illustrates the Cluster Member life time in seconds under varying vehicle speeds, with transmission range fixed at 50m and 100 vehicles. An increase in velocity leads to more frequent CMH changes. This results in a noticeable reduction in average CM stability. Notable VRACE sustains a long CM of approximately 40 to 42 seconds at 35Kmph. However as speeds increase up to 55kmph, the CM lifespan decreases significantly averaging around 5 in single lane and dropping to about 8 seconds in multilane.

Packet delivery ratio

The PDR of the VRACE schemes is evaluated under varying vehicle densities and speeds. Higher PDR values directly improve the overall network throughput. From 50 vehicles onward, the PDR shows significant improvement. In the dmax=200 scenario, PDR exceeded 70%, with multilane clusters ensuring better delivery than single lane(fig.6).

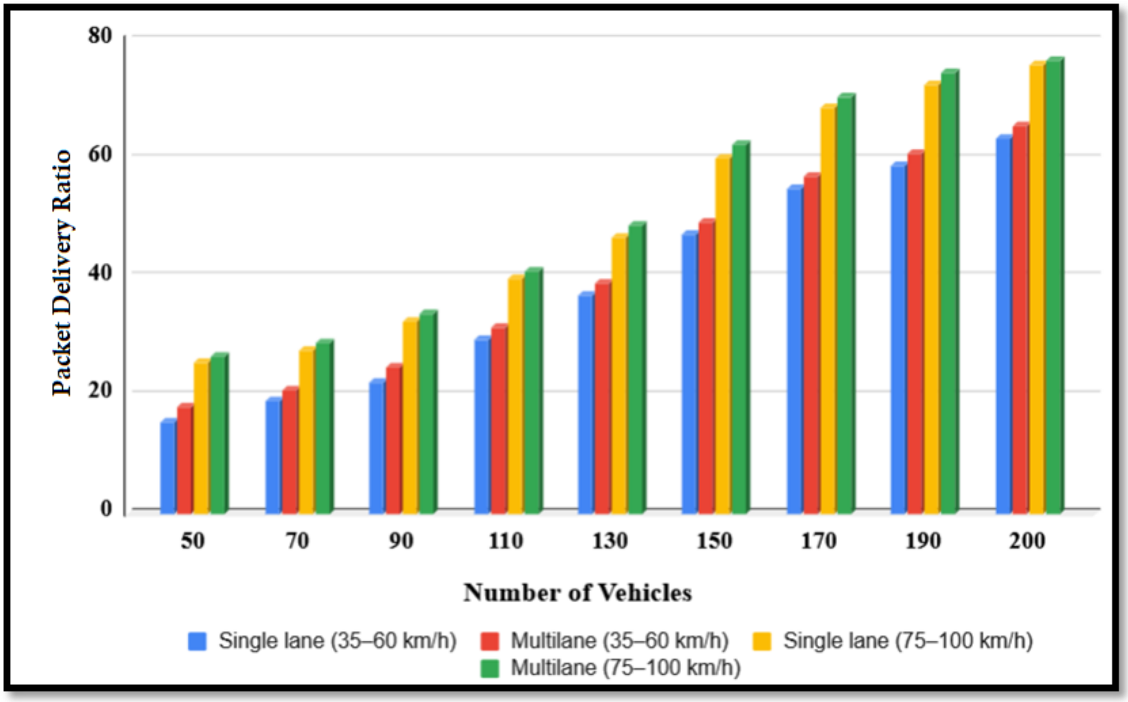

Fig. 6. PDR of VRACE in terms of density of vehicles

Network Throughput

fig.7 presents the network throughput of the system under two traffic scenarios, evaluated for different vehicle densities and speeds. The results show that the VRACE protocol achieves a maximum throughput of 39.194 Kbps at a speed of 85 km/h. On average, VRACE delivers 38.74 Kbps in a multilane environment, which is higher than the 32.3 Kbps recorded in the single-lane setup. Across the speed range of 35 to 100 km/h, reflecting typical urban traffic conditions, VRACE consistently provides about 6% higher throughput than the single-lane scenario.

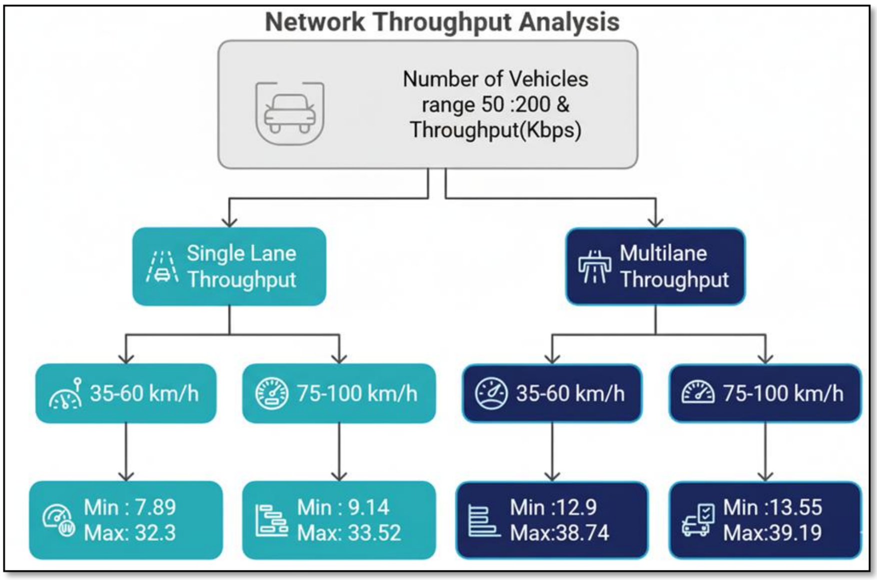

Fig. 7. Network Throughput in terms of density of vehicles

Network Connectivity

The network connectivity analysis was carried out under four different scenarios by varying both vehicle velocity and density. Among these, the V2V multilane model demonstrated the highest efficiency and optimal performance, as reflected in its superior connectivity probability ranges. This model consistently achieves lower latency compared with the single-lane approach. As per equation 10 and 15, enhanced connectivity reduces data loss and supports higher throughput. As illustrated in fig.8, at an approximate speed of 100 km/h, the multilane configuration maintains nearly 40 % connectivity even under low-density conditions, and exceeds 90 % connectivity during high-density operation. The ability to sustain such performance is mainly attributed to stable cluster maintenance and lower cluster-head (CH) change rates, which ensure robust network formation.

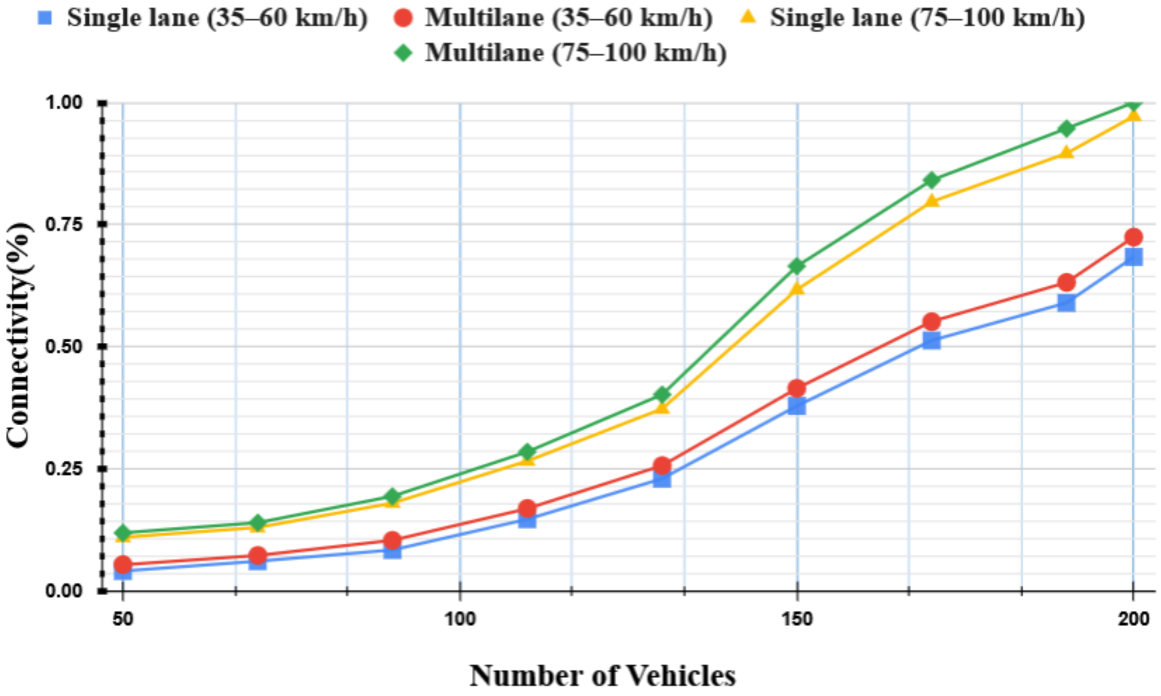

Fig. 8. Vehicle Density and Its Impact on Connectivity Probability

Table 4 - Comparative Performance Analysis of VRACE with Mobility-based Clustering and WCA

Metric/75-100 Kmph/150 vehicles	Mobility Clustering (Single)	WCA (Single)	*VRACE (Single)	Improvement (%)	Mobility Clustering (Multi)	WCA (Multi)	*VRACE (Multi)	Improvement (%)
Packet Delivery Ratio (%)	54.8	57	60.1	4.2↑	56	60.2	62.6	4.5↑
Connectivity Probability (%)	0.45	0.5	0.61	0.135↑	0.5	0.56	0.655	0.125↑
Packet Loss (%)	45.2	43	39.9	4.2↓	44	39.8	37.4	4.5↓
Network Throughput (Kbps)	27.6	29	30.7	2.4↑	29.1	30.5	31.9	2.1↑
Avg CH Lifespan (sec)	30.6	42.5	52.3	15.75↑	34	44.5	57.9	18.65↑
Avg CM Lifespan (sec)	77.2	84.9	90.7	9.65↑	78.5	88.9	95.8	12.1↑
End-to-End Delay (ms)	160	143	127	24.5↓	148	137	122	20.5↓

Table 3 below illustrates the comparative analysis between the VRACE algorithm and the traditional Clustering Algorithm (Yu et al., 2025 & Sharma et al., 2023). The proposed VRACE shown improvements over the baseline clustering techniques. The packet delivery ratio is improved due to the formation of stable clusters, and the lifetime of the clusters is improved through the adaptive selection of the cluster heads based on the mobility and communication parameters. Moreover, improvements are observed in the throughput, and this is due to the reduced congestion through the queue-based management of the clusters. The control overhead is still maintained at a moderate level due to the efficient management techniques used for maintaining the clusters. It can be seen that the fuzzy inference decision-making technique has improved the reliability of the vehicular communication.

VRACE has better performance in dense scenario due to the FIS, which allows for adaptive decision-making based on metrics such as the vehicle mobility and link quality. This ensures more stable cluster head selection. Moreover, the incorporation of queuing theory ensures effective buffering of messages during cluster head change, thus preventing congestion and loss of messages. However, the processing of fuzzy rules may impose computational overhead, hence impacting scalability for large networks. Future work will be directed towards comparing the proposed approach with other clustering techniques based on machine learning and evaluating the framework using real vehicular mobility traces for scalability and practical deployment. The proposed VRACE was assessed for scalability based on the varying node density. The number is increased and communication stability is maintained through adjustments to the selection and cluster maintenance processes of the clusters. The flexibility of this proposed method can be seen in this dense urban environment.

5. Conclusion

This research presents VRACE, a fuzzy inference rule based adaptive clustering framework designed for Vehicular Ad Hoc Networks (VANETs). The primary objective is to improve network connectivity, cluster stability and routing productivity in dense urban traffic environments through intelligent clustering strategy. In many existing VANET clustering techniques, maintaining stable communication remains challenging because of fast topology variations and high vehicle mobility. To vanquish these issues, the presented foundation combines fuzzy logic-based decision making with queuing-theory based stability control. This integration enables adaptive cluster head selection and supports efficient cluster maintenance in highly dynamic vehicular environments. The performance was examined under two communication scenarios that are single lane and multi-lane vehicular networks. Simulation observations indicates that multi-lane traffic conditions conquered better packet transmission efficiency and maintained inflated throughput compared to single line scenarios. Even at a vehicle speed of 100 kmph, VRACE sustained PDR of 78.82%, throughput of 39.1 kbps and loss of 21.3% demonstrating reliable performance at greater velocity. This stability is reflected in the average lifespan of cluster heads and cluster members. Cluster head selection is measured using mobility and communication parameters such as link quality, travel direction and vehicle speed to enhance cluster stability and routing performance. For instance, vehicle speeds between 35 kmph and 60 kmph with 100 vehicles the cluster lifespan reached 60.23 seconds in single lane and 68.67 seconds in multi lane scenarios. When the speed extended between 70 kmph and 100 kmph, the lifespan further extended to 103.12 seconds and 108.34 seconds respectively. These outcomes showcase that VRACE performs beneficially under both low-density and high-density traffic conditions while maintain constant V2V communication. Although the obtained results specify notable improvements, the current analysis is limited to simulation-based experiments. Real word vehicular surroundings may introduce additional challenges like heterogeneous communication constraints and variations in congestion requiring further refinement of framework. Future work will focus on extending VRACE to heterogeneous ITS environments that incorporates V2I communication. Furthermore, machine learning techniques may be prospected to support predictive cluster head selection. Besides, validation using real world vehicular mobility traces can be considered to improve scalability, reliability and security of next generation vehicular communication networks.

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