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A Novel Approach for Dynamic Stable Clustering in VANET Using Deep Learning (LSTM) Model

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ABSTRACT- Clustering in VANETs, which dynamically evolve into wireless networks, is difficult due to the networks' frequent disconnection and fast changing topology. The stability of the cluster head (CH) has a huge impact on the network's robustness and scalability. The overhead is decreased. The stable CH assures that intra- and inter-cluster communication is minimal. Because of these difficulties, the authors seek a CH selection technique based on a weighted combination of four variables: community neighborhood, quirkiness, befit factor, and trust. The stability of CH is influenced by the vehicle's speed, distance, velocity, and change in acceleration. These are considered for in the befit factor. Also, when changing the model, the precise location of the vehicle is critical. Thus, the predicted location is used to evaluate CH stability with the help of the Kalman filter. The results showed that the befit factor performed better than the latest developments. Because of the high speed of the vehicle, dynamic changes and frequent communication link breaks are unavoidable. In order to fully perceive issue, a graphing approach employed to assess the eccentricity then the communal neighborhood. Using Eigen gap heuristic, the link dependability is determined. Trust is the final important parameter that has not yet been taken into account in the weighted method. The trust levels are specifically being evaluated for the primary users using an adaptive spectrum sensing. Long short-term memory (LSTM), a deep recurrent learning network, used to train the likelihood of detection under diverse signal and noise situations. By using LSTM model, significantly decreased the false rate. The cluster head stability has improved for high traffic density, significantly improved according to the comparative analysis with the weighted and individual metrics. The efficiency of the network has also greatly increased in terms of throughput, packet delay, packet delay ratio, and energy consumption.

Keywords: VANET, Deep Learning, Clustering.

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1. INTRODUCTION

A VANET, which has mobile nodes regarded as moving automobiles on road [1]. Applications for ITS have increased as a result of the development of VANET technology. This can be roughly categorized as safety-oriented apps designed to improve security and lower the number of fatal traffic accidents. The other is non safety, which attempts to give passengers extra services like traffic control and information exchange [2]. The on-board units (OBUs) are used to communicate between vehicles. Since V2I communications are cheap and widely accessible, they are vital for the majority of ITS applications. Road-Side Units (RSUs) allow vehicles to communicate with established infrastructure. The system design model for VANET communication is depicted in *figure 1*. V2V communication protocol typically uses two methods of data dissemination: flooding and relaying. When flooding happens, each node sends the data packet it has just received to its neighbors. To get to the data packet's source, the procedure is repeated. In a flat, dense network, using this method will cause floods [3]. When relaying, the message is first broadcast to every vehicle nearby before being sent to a select group of targets. The relaying strategy increases the likelihood that data transfer will be successful, albeit at a considerable cost and delay. One of the common solutions to this problem is clustering on VANET. A VANET can be designed to collect, aggregate, and disseminate data through clustering.

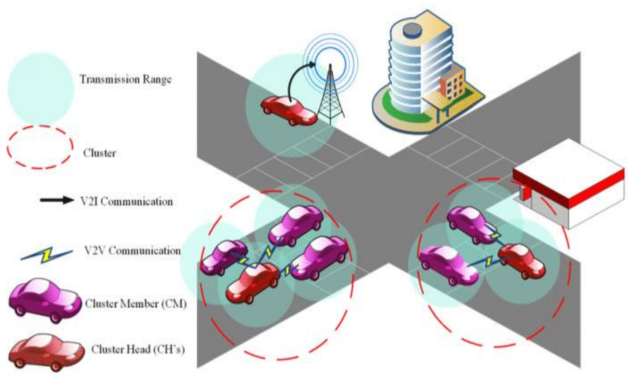

Figure 1: VANET System

Objects moving in VANET are clustered into manageable groups through clustering. In dynamic clustering, the vehicles are grouped on-the-spot because they do not have any physical connection and they are all moving. The clustering strategy has various advantages, including effective bandwidth, proper resource distribution, and scalability [4]. In VANETs, a variety of techniques are used for clustering [5] The routing and forwarding capabilities of vehicles alter with their position on urban highways because their positions frequently shift and are unevenly distributed. These issues cause the network to become unstable, necessitating the usage of a cluster model offers excellent stability for a dynamically changing VANET [6]. According to this investigation, most stability-related schemes are developed under the impact of a stability parameter. This method also taken into account variables like link time, acceleration, and speed. These techniques don't take into account the kind of vehicle that is actually in the traffic situation. Additionally, the neighbor's connectivity is not investigated [7]. They are designed for usage on highways where a vehicle's excessive speed results in a dynamic shift in the static cluster formation that compromises the stability of the cluster head [8]. The authors created a weighted cluster head selection based on several characteristics using all of these literature evaluations. A fit factor is introduced, along with a neighborhood in the community, eccentricity, and a trust value. The following are some of the contributions made by the authors to this article:

(i) Authors proposed a befit factor is based on T_l, or how long it takes a vehicle to finish the final section of a lane. Utilizing the vehicle's speed, this is calculated. Knowing the precise speed is crucial for cluster head stability because the speed of any vehicle can change. This research addresses this issue; the present positions of each vehicle were anticipated by the authors, and the befit factor was computed using these positions. The comparison results used by the authors serve to demonstrate validity.

(ii) The use of a supplementary facility known as RSU was another attempt by the authors to improve the performance of the VANET (RSUs). By taking into consideration the angle suspended by the lanes, the trade-off between the high installation and maintenance costs and the number of RSUs for enhanced coverage is resolved in this study. The effect of intersections is also taken into account to prevent confusion regarding the lane's direction.

(iii) Authors developed a recurrent neural network-based sensing strategy using the LSTM, and they presented spectrum sensing as a classification task. The signal's power spectrum is fed into the LSTM, which then trains the network with various signal noise data types. The choice is determined in accordance with the noise class's confidence. The deep learning foundation of the proposed method allows the network to automatically pick up new parameters and adapt to varying levels of noise. By granting the Primary users use of the network bandwidth, the stability of the VANET is increased.

(iv) A VANET's architecture is dynamic, with quick vehicle arrivals and irregular vehicle spacing. To form a stable cluster, they must be changing.

To accomplish this, the authors created graph model, which specifies the parameters for clustering and its performance.

The article remaining sections are as: *Section 2* presents network model, Kalman filter location prediction, and RSU placement. *Section 3* discusses the multimeric selection of weighted CH technique and all of its metrics. The simulation work is presented in *section 4* along with a comparison of the suggested scheme to the current state of the art. The authors wrap up their work with the work's prospects in the final part.

2. PREDICTION OF NETWORK MODEL INCLUDING RSU

The suggested strategy focuses on the terrain around roadways. This variant is primarily intended for vehicles equipped with a GPS that records location data and an IEEE 802.11p-compliant radio transceiver that facilitates communication with other vehicles and the RSU. For efficient traffic control and organization, &e automobiles often communicate distinct geographic proximity information. With the same requirements in accordance, weighted, dynamic, adaptive, and fuzzy clustering algorithms were developed. Depending on how close they are to the RSU, which is positioned close to the roads, the vehicles are grouped together in this location. Fit, trust, communal neighborhood, and eccentricity are the four elements that cross to choose which cluster head (CH) will lead the group. The others are people in the cluster (CM). The participants communicate with one another using V2V (vehicle-to-vehicle). Examples include the variables position, distance covered, location, acceleration, and others that are stored in the each CM. CH fulfils its responsibility by disseminating significant information to the CM and RSU within range.

2.1 Network Model

Figure 2(a) depicts the network model under consideration and un-clustered depicts the nodes in the VANET. The nodes under each cluster head in *figure 2(b)* are now in constant contact with the RSU. The following is taken into account by the network model:

1. For the study, a real-time road map is used.
2. The analysis takes into account the vehicle's mobility for a predetermined amount of time.
3. Every vehicle has a distinct ID and is regarded as a node that changes over time.
4. RSUs are strategically positioned in each lane using accurate road analysis and a consistent communication range.
5. For real-time data collection and synchronization, a GPS device and buffer memory are installed in each vehicle and the RSU.
6. Communication between the CM and CH-CM is made possible via V2V.
7. The Kalman filter calculates the position of each vehicle and provides the RSU with information about the range of vehicles while ensuring smooth transitions between RSU and uninterrupted communication.
8. The maxing hop is the distance in hops between the cluster head and its core node.
9. A 64-bit data packet is utilized.

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2.2 RSU Deployment
The vehicles need an additional facility like RSU to improve network performance due to overhead delay and fewer storage facilities. There is always a trade-off between providing adequate RSU coverage across all of the locations while also keeping installation and maintenance costs to a minimal.

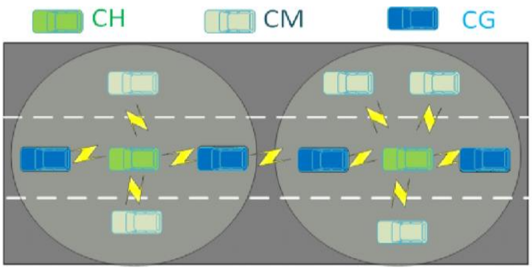

Figure 2(a): Un-clustered approach

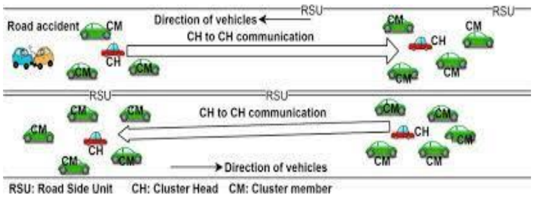

Figure 2(b): VANET Clustering approach

This prompts a search for the best places where the RSU can keep a cost-effective communication route open. The environment has an impact on communication since any empty space will result in a loss of packets sent between the vehicle and RSU. The lane coordinates used in this deployment come from the SUMO simulation. It is believed that each RSU has a defined circular transmission range RSU_t^{L-ID}. On both sides of the highways, there are. Each lane has sufficient coverage without any empty areas, and &is assures there is no interference within the RSU's coverage range. The geometric methodology is used to determine the deployment locations based on the specific lane direction. An RSU is positioned at the start of each lane to obtain the following location's lane curvature, cos(α), which is employed. Any point's location on the path can be represented as [i,j], and the following location is determined as:

$$i_{next} = i_{old} + RSU_t^{L+ID^*} \cos(\alpha)$$

$$j_{next} = j_{old} + RSU_t^{L+ID^*} \sin(\alpha)$$

Thus, the RSU transmission range is explained. The cross lane won't be sufficient to create these conditions once the angle component has been introduced. There aren't many checkpoints that can guarantee that the cross-lane can be used to position RSU continually. *Figure 3* depicts the RSU's deployment.

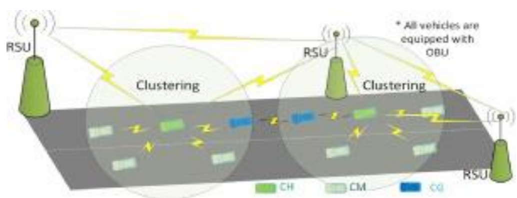

Figure 3: VANET with RSU deployment

2.3 Location Prediction
Using Kalman's technique, which predicts the location of the vehicle using geographical routing, in this project. The direction and velocity have an impact on where the vehicle will be. It has also been demonstrated that the angle of the vehicle, which changes over time, is crucial in determining the position. Using the Kalman filter, the prediction is made. To estimate its position, speed, and direction, every vehicle makes use of a Kalman filter prediction. At the next moment, each parameter's values are at the subsequent instant are and position vector at time t is:

$$i(t) = \left[i^\wedge(t), j^\wedge(t), V_v^\wedge(t), \alpha^\wedge(t) \right]^\wedge T$$

$$j(t) = \left[i^\wedge(t), j^\wedge(t), V_v^\wedge(t), \alpha^\wedge(t) \right]^\wedge T$$

$$i(t+1) = [i^\wedge(t) + V_v^\wedge(t) X \cos(\alpha(t) X \Delta T]$$

$$j(t+1) = [j^\wedge(t) + V_v^\wedge(t) X \sin(\alpha(t) X \Delta T]$$

Every RSU searches for moving objects within its field of view, and new anticipated positions are subsequently calculated using the judgement equation below. With knowledge of the angle suspended by the lane, the difference between the historical and forecast positions is used to calculate the current update value.

3. DYNAMIC WEIGHTED CH STABILITY ALGORITHM
The two primary parts of the clustering model that was designed are cluster construction and CH selection. The cluster head is selected after the vehicles are separated into smaller groups for cluster creation using befit factor (BF), community neighbourhood (CN), eccentricity (Ecc), along with trust (T). Additionally, these variables ensure the cluster head's long-term stability. To prevent the overriding effect, each of these indicators has been standardised.

3.1 Cluster Formation
Cluster's establishment is supervised by the RSU. In the cluster formation shown by *Algorithm 1*,

#Algorithm 1. Formation of Cluster

Input: Velocity V_v and location [i,j]; the number of the lanes in amap; time
Output: Cluster(C), N No. of clusters
For t = 1:time
For x = 1: no lane
  if any vehicle detected in RSU
    D: RSU location and Vehicle location
    V_v: speed of the vehicle
    If $D < \triangle D_t \| V_v < \triangle V_t$
      RSU ← Id
    Endif
      C ← RSU, ∀ Id
    Endif
End
N ← ∀C; C≠ Null

For the initial timestamp transmission, each vehicle moves into the lane and interacts with each RSU that is in range of it. A stable cluster can only form for timestamp with distance D and the relative variation in vehicle's speed V_v are both observed for

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that timestamp. The RSU and that vehicle are separated by a calculated distance. The vehicle is momentarily connected to that RSU if the distance is less than a threshold D_t. All nearby vehicles that are travelling in the same direction must go through this process. Each vehicle's speed level may differ in the real-time scenario, and this variance may have a significant impact on how a cluster forms. The vehicle is permitted to permanently attach to an RSU if the change in relative speed is less than a certain threshold (V_t), stable cluster development is also seen, and this is the case. Now that the vehicle's ID has been stored, the RSU enters the cluster (CM).

3.2 Cluster Head

Choosing the cluster head—a VANET node that oversees or controls the cluster—comes next. It takes charge of the routing path's broadcasting, discovery, and upkeep. It is in charge of broadcasting, discovering, and maintaining the routeing path. The RSU is still in charge of sustainably maintaining the intra- and intercommunication channels. Any clustering technique must take the stability of cluster head in the VANET into account first. Due to the high dynamic mobility of the vehicles, the cluster stability may eventually diminish as a result of frequent re-clustering. This research proposes a weighted combination of four parameters as the methodology for the cluster head selection. All of these factors point in the direction of finding a stable CH. The following discusses all of these factors and how they combine to help you choose a good CH.

3.2.1 Befit Factor (BF)

It aims to maximise the cluster structure's stability. Elected CH is required to maintain lengthier connections with all cluster members in order to guarantee this. As a result, the three measures created in are used to calculate the BF.

$$BF = w1xT_1 + w2x\Phi_v + w3xn_h$$

Where w1, w2, and w3 are the weights that vary between [0, 1], satisfy the requirement that (w1 + w2 + w3=1), and it can be changed by local vehicle having authority depending on the state of the roads and the behavior of cluster members. The first statistic is T_l, or "time to leave," which measures how long it takes a vehicle to cross a lane. The first statistic is called T_l, or "time to leave," and it measures how long it takes a vehicle to travel the final stretch of a lane. This function makes sure that a CH is chosen with adequate time to finish the lane without having for heading for long duration. Then, it is computed using L, the lane length, D, the length of time it takes a car to travel that D portion of lane, and t, the time it takes a car to travel that D portion of lane.

$$T_1 = \frac{L-D}{t}$$

The second parameter Φ_v , which stands for average relative speed, measures how closely a vehicle's velocity resembles that of its surroundings. The long-term velocity of vehicles is considered while designing a reward function. Each vehicle's speed (V_v) is measured. As a result, their speed receives an absolute value (ð) that is either rewarded or penalized, and as a result, the average relative speed is either raised or lowered, as illustrated in

$$\Phi_v(t+1) = \Phi_v(t) + \partial; |v_v - v_a| \le s_t$$
$$\Phi_v(t+1) = \Phi_v(t) - \partial; |v_v - v_a| \ge s_t$$

Where S_t Factor makes sure a vehicle travelling at velocity V_v is nearly driving at the same speed as its nearby neighbors. Utilizing the TraCI parameters, the initial value of ϕ_v is determined and set to 0.01.

3.2.2 Eccentricity

It is due to the rapid speed of the vehicles, communication links fail more frequently in real time. An evolving cluster model is necessary for maintaining the relationship. Usually, re-clustering will be required as soon as the CH resigns or ceases to be qualified to serve in that capacity. The idea of eccentricity is introduced to assure stability. Here, spectral clustering is used to create a dynamic graph-based model. A vehicular graph topology is defined as $G(N,L,L_r)$, In order to depict the graph topology with dimensions N X N, the affinity matrix is built. The Laplacian graph is the method used for spectral clustering. The affinity matrix's Laplacian graph is calculated:

$$A = \begin{cases} l_{xy,} if\,(D_x, D_y) \in L \\ 0, if x = y \\ \infty, Otherwise \end{cases} \quad A = \begin{bmatrix} l_{11} & \dots & l_{1N} \\ \dots & l_{22} & \dots \\ l_{N1} & \dots & l_{NN} \end{bmatrix}$$

The original dataset is used to derive the eigenvectors of a similarity/affinity matrix in spectral clustering. Mobile vehicle dimensionality reduction will be modelled after the graph's Eigen decomposition. The eigenvalue of the Laplacian graph is used to determine the ideal number of clusters. The eigenvalues are sorted in ascending order using the Eigen map heuristic, from which k is selected to represent the clusters at that timestamp.

$$L_g = M_d - A\,,\; d_{xy} = \sum A_{xy}$$

Once the cluster count is known, the k eigenvectors of a matrix with dimensions N k are then obtained. Ecc's maximum value makes sure that the expanding graph-based cluster head selection is steady.

$$Ecc_i = \frac{1}{|N_i|} \sum_{\gamma_i \in N_i} \gamma_i$$

3.2.3 Community Neighborhood (CN)

Information about neighbours is also provided by the growing Laplacian graph. The importance of the neighbour ensures that the CH will remain stable because the cluster member won't change until a certain timestamp, forming a reliable link between them. When the following conditions are met, the transmission factor (TF), which is utilised in the design of the CN, denotes the dependability of the connection between two vehicles:

$$TF(L_{xy}) = \begin{cases} 0, if l_{xy} \prec TR \\ \dfrac{TR^2 - l_{xy}}{TR^2}, if\, 0 \prec l_{xy} \prec 1 \end{cases}$$

Where TF denotes the vehicle's maximum transmission range and l_{xy} denotes the separation between the two vehicles at the timestamp t. Following the definition of the neighbour nodes as being those vehicles that satisfy the criteria TF (l_{xy}) > 0, the neighbour connection centrality is then counted.

$$NC = \sum_{l_{xy} \in NL} TF(l_{xy})$$

The final step is to compute CN, weighted average of NC over timestamp t. $CN = w_i x NC$

3.2.4 Trust (T)
Cluster stability is also greatly influenced by the type of vehicle, so using this method to deal with hostile and compromised nodes is very effective. Spectrum sensing, a technique for effectively utilising the spectrum. Here, the spectrum sensing issue is categorised using LSTM, to train network, many signal and noise data types are used. Recurrent neural networks are used in this method, which enables it to recognise the energy characteristics and adapt to unwanted data in a dynamic and real-world context. It makes the possibility of determining which primary users (PU), such as ambulances, police vehicles, or any other civic service, should use spectrum first in an emergency. The others are regarded as secondary users (SU).

LSTM Model Design
Update, forget, and output gates are the three primary gates that make up an LSTM cell. The following is a description of each gate's function:

1. Select the appropriate time to update the current cell state using the update gate (u).
2. Forget gate (f): Ignore the operation of the present cell
3. Delivering the output through an output gate (0)

Using each gate's unique bias and sigmoid function, all three gates are updated.

$$\rho_u = \sigma(w_u[a^{\langle t-1\rangle}, j^{\langle t\rangle}] + b_u)$$
$$\rho_f = \sigma(w_f[a^{\langle t-1\rangle}, j^{\langle t\rangle}] + b_f)$$
$$\rho_o = \sigma(w_o[a^{\langle t-1\rangle}, j^{\langle t\rangle}] + b_o)$$

Where the weight matrices are w_u, w_f, and w_o. The symbols b_u, b_f, and b_o stand for bias terms.

Because binary bases are not employed, the architecture used for this study includes a two-bit layer every 100 nodes, a fully linked layer, and a SoftMax layer. Each batch contains 500 data points since the network is trained over 500 iterations at a training data of 0.01.

3.3 The Designed Complete Algorithm's Computational Complexity
This section investigates the dynamic weighted algorithm's computational complexity. As a result, the algorithm's overall time complexity is represented by

$$o_t = o_{cf} + o_{ch}$$

Where O_{cf} refers for the CH selection and O_{ch} for the cluster formation time complexity. In the worst-case scenario, the maximum allowed number of vehicles was incorrect. The absolute maximum time complexity for this is

$$o_{cf} = o(\log M^2)$$

Four parameters are taken into account while choosing a cluster head. The cluster head selection's overall time complexity is

$$o_{ch} = o_b + o_{Ecc} + o_{CN} + O_T$$

All parameters have been determined as part of the linear equation that represents the complexity of BF. Only the constant values that must be computed and fetched are the departure time and the relative average speed.

4. RESULTS AND DISCUSSION
4.1 Simulation Environment
The Simulation of Urban Mobility software Tool (SUMO 0.25.0), the TraCI, and MATLAB (R2020a) are used for all simulation studies. MATLAB is used to assess network performance metrics.

4.2 Evaluation of Network Performance
The four network performance measures covered in the following are used to gauge the significance of the suggested strategy. In this scenario, the packet transfer is started through any arbitrarily selected source that the CH receives, CH then transfers the packet to the target. *Table 1* contains the parameters of the communication network.

The ++ following settings for the simulation environment are used to test the proposed scheme:

1. Varying vehicle densities
2. The Kalman filter estimates the vehicle's position inside a cluster depending on its present Location.

Table 1: Simulation Parameters

Channel	Wireless
Propagation	m=3
MAC	802.11
Data rate	4,8,12Mbps
Range	350mts
Packet size	64bytes
Packet Interval	200msec

Energy (E): Each node's energy consumption for communication is given in Joules. The distance between each hop directly affects how much energy is used.

$$E = \alpha_1 + \alpha_2 + \alpha_3$$

PDR stands for packet delivery ratio and measures the proportion of packets that are successfully delivered from a

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source vehicle to a destination vehicle on average. The PDR decreases with increasing data speeds.

$$PDR = \frac{\sum_{x=1}^{N} Packetreceivedx(datarat\exp acketsize)}{packetgeneratedatsourcex(datarat\exp acketsize)}$$

Packet delay (PD) is the length of time it takes for a packet to travel from its source to its destination vehicle through a transmission medium. The length of each hop as well as network noise and congestion all affect packet delivery time.

$$PD = \frac{\sum_{x=1}^{N} Packettransmittedx(datarat\exp acketsize) - packetreceivedx(datarat\exp acketsize)}{t}$$

Throughput It is the amount of information efficiently transferred from a source vehicle to a destination vehicle in a certain time period (kbps). Having a more stable network and fewer hops can increase throughput.

$$Throughput = \frac{\sum_{x=1}^{N} Packetreceivedx(datarat\exp acketsize)}{t}$$

The frequency with which the same vehicle can be used as the CH over the course of the full solution is known as **cluster head stability**.

$$C_s = \mathrm{mod}\, e(\sum_{x=1}^{t} Id)$$

The results are displayed in *figure 4* at a certain point in the whole simulation duration. From this, we can see that the suggested scheme's CH selection is higher than the individual one created by the various artistic states. The same platform was used for every simulation. Numerous network metrics are also investigated for the suggested architecture on the 750 vehicular densities. A cluster member sends a data packet to the cluster head, which then sends it to the target cluster member.

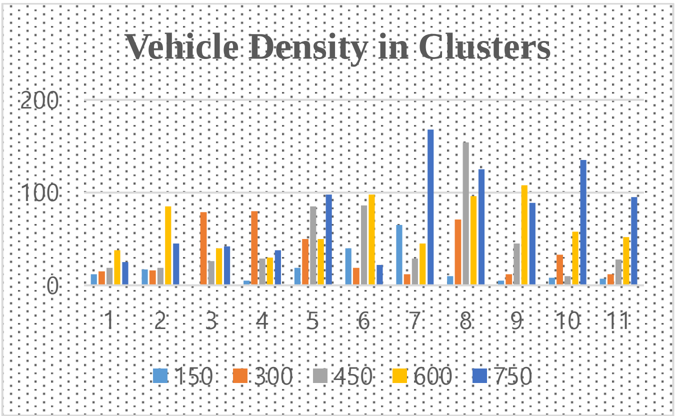

Figure 4: Vehicle Density in Clusters

The typical energy consumption in a cluster for with different data speeds is depicted in *figure 5*. For particular clusters at each data rate, consumption is seen to fall or remain constant; this could be because the cluster topology or CH have remained unchanged.

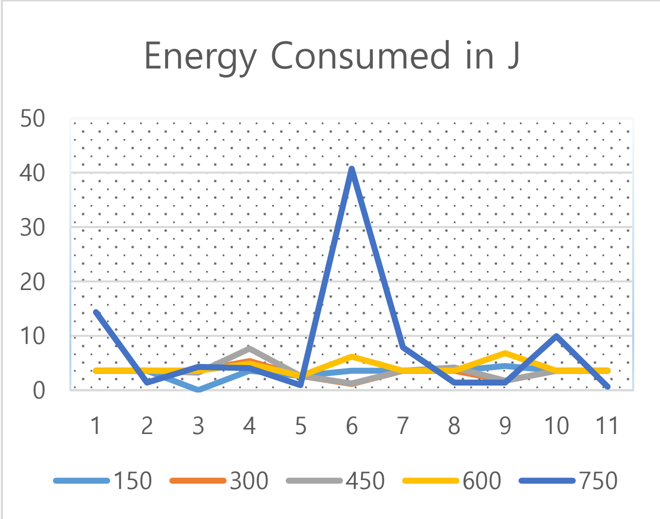

Figure 5: Energy Consumed in Various Clusters

The PDR and PD are depicted in *figures 6 and 7*, respectively. Additionally, the throughput is examined, as seen in *figure 8.*

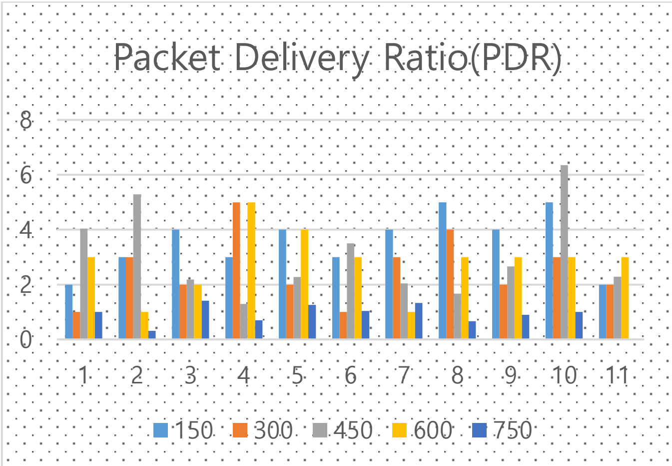

Figure 6: PDR in Clusters

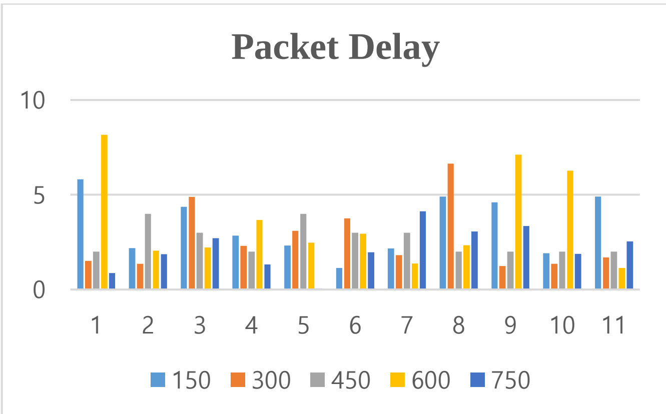

Figure 7: Packet Delay

The efficiency of the network as it was intended is measured by the throughput. A high throughput value is indicative of improved performance and improved coordination among cluster members.

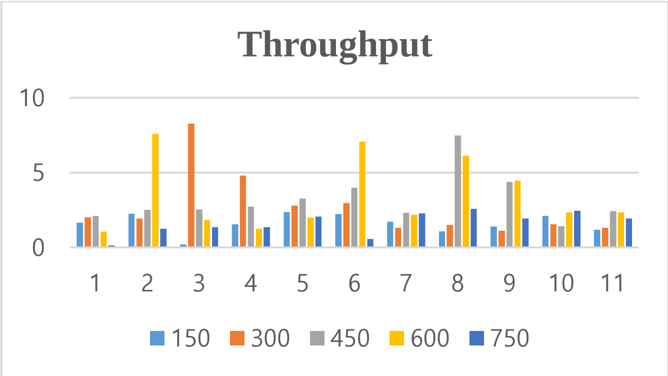

Figure 8: Throughput for Vehicle with different densities in various clusters PDR in Clusters

5. CONCLUSION

This research presents a novel weighted approach-based strategy to identify stable cluster head. The four distinct metrics are combined into this formulation such as fit factor, eccentricity, community neighbourhood, and trust to choose a stable cluster head. Because they become hidden in the network, among other things, the trust value for the primary users is listed last.

To ascertain the energy of the key users, a deep learning LSTM is trained for a variety of signals and noises. With a misclassification rate of about 14 percent, accuracy is about 80%. The frequency with which a vehicle is chosen as the CH is recorded, and this frequency is used to evaluate the stability of a cluster head. The outcomes demonstrate the superiority of the weighted technique over cluster head stability attained using a single metric. The results of the throughput, PD, energy, and PDR tests have shown that the suggested technique is superior at different data speeds.

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