http://dx.doi.org/10.5755/j01.eee.21.1.7729 ELEKTRONIKA IR ELEKTROTECHNIKA, ISSN 1392-1215, VOL. 21, NO. 1, 2015

Rough Set Based Fuzzy Scheme for Clustering and Cluster Head Selection in VANET

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***Abstract*—In Vehicular Ad hoc Network (VANET), clustering helps vehicles to communicate with other vehicles and to the nearby Road Side Unit (RSU). Conventional clustering methods follow precise clustering which degrades the stability of cluster formation. To stabilize the formation of clusters, the vehicles in the boundary region of more than one cluster should be uniquely added to the proper cluster. Fuzzy set representation of clusters makes this possible by assigning a membership value to all the vehicles and supports the formation of clusters based on this membership value. Since the cluster lifetime is very minimal in vehicular network, fuzzy based clustering is too descriptive to interpret the clustering results. In this paper, the rough set based fuzzy clustering is employed for formation of clusters in a VANET. Using this scheme, a vehicle in the transmission range of more than one cluster namely, the boundary vehicles are assigned with a membership value. Based on the fuzzy rule base, the vehicles are assigned to the appropriate cluster. Theoretical analysis and experimental results show that rough set based fuzzy scheme obtains 10 % to 20 % more average cluster lifetime and 20 % to 25 % more cluster head lifetime when compared to existing approaches.**

***Index Terms*—Clustering, fuzzy sets, rough sets, vehicular ad hoc network.**

I. INTRODUCTION

Safety and comfort on travel has become an important concern in human life. Wireless innovations help public to access internet services everywhere on travel. The present day vehicles are equipped with certain wireless devices known as On Board Unit (OBU) that enable communication between vehicles and the RSUs deployed for every one kilometer and thereby organizing a network known as Vehicular Ad hoc Network (VANET). Such feature helps the vehicles and RSU to report events like traffic congestion warning to other vehicles and thereby making them to take an alternate path to avoid congestion. Such events when not addressed immediately can lead to a great havoc in the network. To resolve this issue, the safety messages should be securely delivered faster.

Security of the safety messages can be achieved by authentication [1]. To make the process of authentication faster [2], vehicles in the communication range of an RSU can be grouped to be in one cluster and a cluster head is elected to authenticate all the vehicles available in the cluster. Formation of clusters in a dynamic vehicular network and selection of cluster head plays a major role.

Existing research works have proposed the use of hard clustering and fuzzy based approaches for clustering the vehicles. Hard clustering approach [3], [4], clusters the vehicles based on their locations and the vehicles in the boundary region are not precisely allocated to be in the appropriate cluster. This enables the network to reform the clusters within a short period of time thereby degrading the stability. Also, the lifetime of the cluster head is minimal. In fuzzy based approaches [5], [6], all the vehicles are assigned with a membership value and those vehicles with a low membership is assumed to be in the boundary region. Based on criteria like speed and time, the decision is made to include the vehicle in the appropriate cluster.

In fuzzy based approaches, the cluster formation time is time consuming since membership values are computed for all the vehicles and decision is done. In this paper, the concept of rough fuzzy sets [7] is employed in the formation of clusters and cluster head selection. Initial clustering of vehicles is made based on the location and using rough set theory vehicles are categorized to be in the lower and upper approximations. Then, the vehicles in the boundary region are assigned with a membership value based on the speed, direction of travel. Accordingly, they are assigned to the appropriate clusters.

The rest of the paper is organized as follows. Section II discusses the related works. In Section III, the application of rough sets for cluster formation and cluster head selection is discussed in detail. Section IV discusses on the proposed methodology which includes the framework for cluster formation and cluster head selection. Section V discusses the simulation results and analyses the performance of the proposed system. Section VI concludes and proposes the future work that can be carried out.

II. RELATED WORKS

Several works have been carried out in the formation of clusters and selection of cluster heads. Huang *et. al* [3] has proposed a clustering method based on the distance between the neighboring vehicles. Since the factor taken for clustering is only the distance, it leads to certain limitations. In this method, two vehicles travelling in the opposite

Manuscript received August 7, 2014; accepted December 2, 2014.

direction will be clustered based on the distance. Since vehicles move opposite to each other frequent reformation of clusters is required.

Almalag *et. al* [4] proposed a lane-based clustering method where the vehicles are grouped based on their driving direction. Since the clusters are formed based on the traffic flow, stable clusters are maintained and frequent formation of clusters and cluster head can be avoided. This method uses the factors like network connectivity level, average distance level and average velocity level for the formation of clusters and cluster head. However, when there is a discrepancy in speed, frequent reformation of clusters and cluster heads should be done.

Driver's behavior is most prominently based on the moving pattern of the vehicles. This factor combined with speed and direction was taken for cluster formation by Chenn *et. al* [8]. According to this scheme, a grouping indicator is calculated and forwarded within the vehicles in the same transmission range. Based on this value a cluster head is elected. Since the speed of a vehicle may vary on time, this method requires frequent reformation of clusters and cluster heads.

Daeinabi *et. al* [9] has taken into consideration the number of neighbors based on the dynamic transmission range, the direction of vehicles, and entropy and distrust value for cluster formation. However, this paper doesn't discuss any methods for cluster head formation and it focusses on dynamic adaptive transmission range.

In addition to location and direction, Rawshdeh *et. al.* [10] has considered speed in their approach for cluster formation. Vehicles with similar mobility pattern are grouped together into one cluster. In this approach, multi-metric election technique is used for cluster head selection.

Another approach proposed by Kakkasageri *et. al* [11] has considered the relative speed of the vehicle and direction for formation of clusters. In this approach, the cluster head is selected based on the stability metric which is derived from the degree of connectivity, average speed and time to leave the road intersection. The cluster head announces the mobility pattern to all the cluster members. It also predicts the future association of cluster members based on the mobility pattern. All the cluster members with the similar mobility pattern can reconnect each other with the cluster head after passing an interconnection.

Region based clustering proposed by Saleet *et. al* [12] uses geographical coordinates for formation of clusters. This approach minimizes the number of location updates to other vehicles in the network. Even though the scalability of the network is improved, this scheme leads to increased number of packet collisions and delay in transmission.

In approaches provided in [13]–[15], uses the location attribute for clustering the vehicles in the VANET. In [16] Syed *et. al* proposes a clustering method for the formation of stable clusters which too results in crisp clustering and loss of messages.

All these existing methods for cluster formation are crisp clustering methods where vehicles that are uncertain about their clusters are not properly assigned to the appropriate clusters. To improve the performance of these crisp clustering techniques authors in [5], [6], [17] proposed a fuzzy based approach for clustering where membership values are computed for all the vehicles based on the location and speed of travel and the analysis shows that this method performs better in cluster formation, cluster lifetime and cluster head lifetime compared to the hard clustering methods.

However, this scheme incurs more overhead and memory consumption when compared to hard clustering approaches. To summarize, all the existing approaches results in certain limitations which degrades the performance of the system thereby leading to packet loss which results in loss of important safety messages. To overcome the limitations of all the existing approaches, the concept of rough set theory along with fuzzy system [18] is proposed for clustering of the vehicles and cluster head selection.

III. Rough Set Theory

The concept of rough set theory developed by a polish scientist Pawlak [19] is a method for making the decision in case of uncertainty or vagueness in clustering. A data set is represented as an information table I = (U, A) where U represents each row of objects and 'A' represents each column of attributes. Any information system is a decision system if it is of the form I = (U, {A U {d}). Here'd' is a decision attribute. The main idea of rough set theory is to separate discernible objects from indiscernible objects and to assign them to the lower and upper approximations of sets.

The basic properties of rough set theory [20] are defined as,

1. A data object can be a member of at most one lower approximation.
2. A data object which is a member of lower approximation of a cluster is also a member of the upper approximation of the same cluster.
3. A data object that does not belong to any lower approximation is a member of at least two upper approximations.

The rough membership function shown in (1) can be used to define approximations [21] and the boundary region of a set using (2)–(4):

$$\text{«}^{R}_{X = \mathrm{U} \to \langle 0,1 \rangle}, \tag{1}$$

$$R_{*}(X) = \left\{ x \in U : \text{«}^{R}_{X}(x) = 1 \right\}, \tag{2}$$

$$R^{*}(X) = \{ x \in U : \text{«}^{R}_{X}(x) > 0 \}, \tag{3}$$

$$R_{BR}(X) = \{ x \in U : 0 < \text{«}^{R}_{X}(x) < 1 \}. \tag{4}$$

This concept of rough sets was employed for clustering the spatial data in [22], [23] and in this paper we apply the concept of rough fuzzy sets for clustering the vehicles in the vehicular network.

IV. Proposed Methodology

In the proposed method, rough fuzzy sets are employed to categorize the vagueness in the boundary region. Initial clustering is done as shown in Fig. 1 by considering the location attribute and then based on the condition attributes speed and direction the vehicles in the boundary region are clustered. Each vehicle announces its presence to its neighbors by sending a beacon message which includes the pseudo ID, location, timestamp, direction and speed.

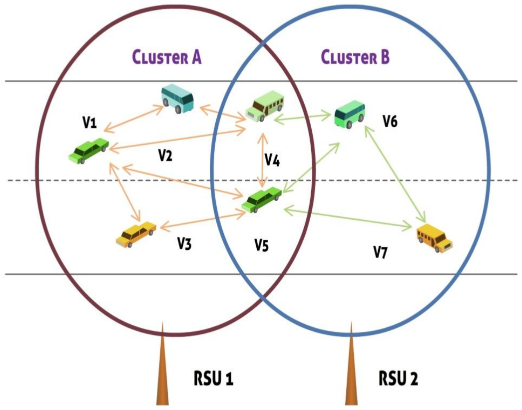

Fig. 1. Initial cluster formation

Each vehicle computes the distance between itself and its neighbors and computes a distance matrix. From the matrix, all the values starting from the maximum value is compared with the specified distance. If the distance computed is less than a specified distance, the concerned vehicle is assumed to be in the lower approximation of the cluster. Else, if the distance computed is greater than the specified distance, it is assumed to be in the upper approximation of a cluster.

A. System Framework

Clustering in VANET requires all vehicles to be exactly added to one cluster. Existing hard clustering approaches adds vehicles to one cluster irrespective of their attributes. However, the fuzzy clustering scheme computes membership values for all the vehicles and adds them to their appropriate cluster. These non-rough clustering schemes don't exactly consider the vehicles in the boundary region available in both the clusters. Considering the limitations of the existing clustering schemes, the proposed system framework uses rough fuzzy scheme for clustering the boundary region vehicles precisely. Figure 2 shows the framework of the proposed model.

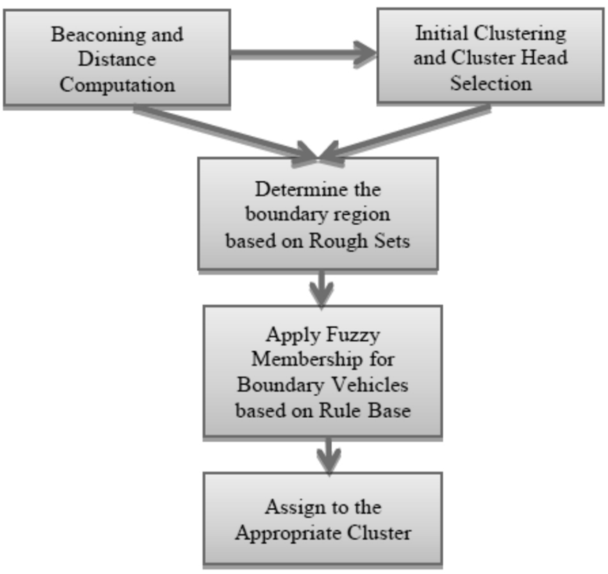

Fig. 2. Framework of the proposed model.

Each vehicle announces its presence to its neighbors by sending a beacon message, which includes the pseudo ID, location, direction and speed. Based on the location information, each vehicle computes the distance between itself and its neighbors and computes a distance matrix for the sample data as shown in Table I.The RSU broadcasts the centroid location to all the vehicles in its communication range.

TABLE I. DISTANCE MATRIX FOR CLUSTER 1 VEHICLES.

	1	2	3	4	5
1	0.0	156.20	121.60	329.84	340.58
2	156.20	0.0	100.0	223.60	260
3	121.60	101.98	0.0	208.80	220
4	329.84	223.60	208.80	0.0	63.24
5	340.58	260	220	63.24	0.0

Based on the computed distance values, the vehicles associated with the maximum distance are retrieved and their corresponding location is compared with the specified location. If it is less than the specified location, it is added to the current cluster else it is moved to the next cluster. Table II shows the initial clustering done based on the distance matrix. After initial clustering, it can be seen that vehicles {4 and 5} belongs to both clusters A and B.

TABLE II. INITIAL CLUSTERING TABLE.

Vehicle ID	Location (x, y)	Speed (km/hr)	Direction	Cluster
1	<100, 100>	40	0	1
2	<200, 220>	30	1	1
3	<220, 120>	30	1	1
4	<420, 180>	35	1,0	1,2
5	<440, 120>	15	0,1	1,2
6	<560, 200>	30	0	2
7	<720, 130>	40	1	2

After initial clustering is done, the cluster head is selected for each cluster. The distance between the vehicles current location and the centroid location are computed and the vehicle with the minimum distance is elected as the cluster head. The pseudo code for the proposed Rough Fuzzy Cluster Head (RFCH) is shown in algorithm 1.

Algorithm 1: Pseudo Code for Cluster Head Selection

Input : Location
Output : Cluster Head

Initialize
L = $\{(x_1,y_1),(x_2,y_2),\ldots(x_n,y_n)\}$ // Location of vehicles
CL = (p,q) // Center location
begin
minD = ∞
  for i = 1 to n **do**
  Compute D^2_i = Sqrt((p-x_i)2 – (q-y_i)2)
  if (D_i <= minD)
  minD = D_i
  minInd = i
  end if
  end for
end

Initial clustering clusters vehicles based on their locations irrespective of their travelling direction. Not all neighbors can be clustered together. The difference in speed among the neighbors is the key factor for constructing a stable cluster. So, it is well to decide the stable and non-stable cluster members.

Based on rough fuzzy set theory [24], [25], the vehicles are clustered. If the location of the vehicle is less than the computed specified location and the relative speed of the vehicle is less than$\pm\Delta_V$, then such vehicles are assigned to the lower approximation of the cluster as given in (2) and are assigned with a membership value 1. If the neighboring vehicles are greater than the specified location and the relative speed is greater than $\pm\Delta_V$, then such vehicles are assigned to the upper approximation of the cluster by using (3) and (4). When the same set of vehicles belongs to two or more clusters, they are assumed to be in the boundary region of the clusters. The membership value of all the vehicles in the boundary region are computed by using Gaussian membership function as shown in (5) for the attributes speed and direction

$$\text{«}(x)=e^{-(x-c)^2/2\pm^2}. \tag{5}$$

The pseudo code of the proposed Rough set based Fuzzy Clustering (RFCF) is shown in algorithm 2. The RSU broadcasts the centroid location and each vehicle computes the specified distance and the distance matrix. Vehicles in boundary region are identified and Gaussian membership function in (6) is used to compute the membership value of vehicles.

RFCF
Algorithm 2: Pseudo Code for Rough Fuzzy Cluster Formation

Initialize
V = {v_1, v_2,…, v_n} // Vehicle IDs;
L = {(x_1,y_1), (x_2,y_2),…, (x_n,y_n)} // Location
S = {s_1, s_2,…, s_n} // Speed;
D = {d_1 d_2,...,d_n} // Distance;
CL = (p, q) // Center location
DD = (α, β) // Driving direction as a unit vector;
specD // Specified distance
begin
for i = 1 to n **do**
if (D_i >= specD)
  if (DD = α && S >θ)
  μ(i) = f(~,S,D) //varies from 0.6 to 1
  else
  μ(i) = f(β,S,D) //varies from 0.1 to 0.5
  else
  μ(i) = 1; //lower approximation
  end if
end if
end for
end

Table III shows the assignment of membership values to the vehicles for formation of clusters. The membership values are computed for the vehicles in the boundary region based on the rule set. The rule base for assigning fuzzy membership includes location, speed and direction attributes. The speed and direction attributes are termed as conditional attributes. The rule set is constructed as follows:

1. IF (Location is very far) AND (Speed is low) AND (Direction is forward)
   THEN Cluster is cc
2. IF (Location is very far) AND (Speed is low) AND (Direction is reverse)
   THEN Cluster is cc
3. IF (Location is very far) AND (Speed is medium) AND (Direction is forward)
   THEN Cluster is cc
4. IF (Location is very far) AND (Speed is medium) AND (Direction is reverse)
   THEN Cluster is nc
5. IF (Location is very far) AND (Speed is high) AND (Direction is forward)
   THEN Cluster is cc
6. IF (Location is very far) AND (Speed is high) AND (Direction is reverse) THEN Cluster is nc

TABLE III. MEMBERSHIP TABLE FOR CLUSTER 1.

Vehicle ID	Location	Speed	Direction	Cluster	« Value
1	<100, 100>	40	0	1	1.0
2	<200, 220>	30	1	1	1.0
3	<220, 120>	30	1	1	1.0
4	<420, 180>	35	1,0	1,2	0.8
5	<440, 120>	20	0,1	1,2	0.3
6	<560, 200>	30	0	2	0.0
7	<720, 130>	40	1	2	0.0

TABLE IV. LINGUISTIC VARIABLES.

	Linguistic Variables	Fuzzy Set
Input	Location (L)	{Very Near, Near, Far, Very Far}
	Speed (S)	{Low, Medium, High}
	Direction (D)	{Forward, Reverse}
Output	Cluster (C)	{Current Cluster, Next Cluster}

The categorical value for location includes {very near, near, far, and very far}, the categorical values for speed include {low, medium, high} and the categorical values for direction include {forward, reverse}. The decision attribute cluster has two categorical values that include {cc (current cluster), nc (next cluster)}.

Decision to include vehicles in the appropriate clusters is made based on the fuzzy rules and based on the computed membership values vehicles are added.

V. Simulation And Performance Evaluation

A. *Scenario Characteristics*

The traffic simulator SUMO is used to generate the mobility of vehicles. This is provided as an input to OMNET++. The scenario includes the creation of a vehicular network which varies from 10 to 100 nodes. The acceleration is taken as 10 % of the maximum velocity. The minimum velocity V_{min} is fixed to 20 km/hr and the maximum velocity is varied from 20 km/hr to 100 km/hr. The road structure is created with 6 junctions. The radio model used in the simulation is LAN 802.11p which provides a transmission rate of 2 Mbps and a transmission range of 1000 m. The update interval for safety messages is fixed to 300 milliseconds. The total simulation time is

1000 s.

B. Evaluation Criteria

The performance of the proposed clustering scheme is analysed based on three important metrics and the comparisons are made with the existing hard clustering and fuzzy based clustering methods.

C. Average Cluster Lifetime

The lifetime of a cluster determines the stability of the network which in turn helps the vehicles to be connected to its current cluster for a maximum time. This is a key metric that shows the performance of clustering in a vehicular ad hoc network. Figure 3 shows the cluster lifetime and the average cluster lifetime produced by the proposed rough fuzzy method compared with the existing hard clustering and fuzzy based methods. The lifetime of a cluster is computed using (6). Here, CL represents the cluster lifetime, SL_{v_i} represents the starting location of vehicles, EL_{v_i} represents the ending location of the vehicles and SD_{v_i} represents the speed of the vehicles

$$CL = \frac{\left(SL_{v_i} - EL_{v_i}\right)}{SD_{v_i}}. \tag{6}$$

From Fig. 3, it is evident that the speed of the vehicles is varied from 20 km/hr to 100 km/hr and the lifetime of the cluster is validated.

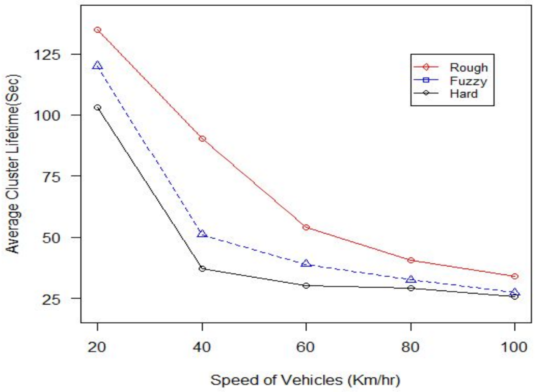

Fig. 3. Average cluster lifetime.

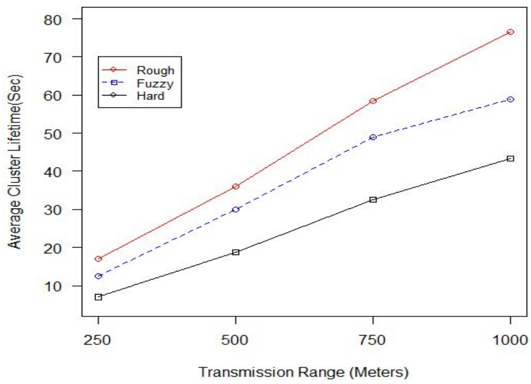

Fig. 4. Average cluster lifetime vs transmission range.

Here, the transmission range of each cluster is fixed to 1000 m. Evaluation shows that the cluster lifetime for the proposed rough fuzzy method is increased by 10 % to 20 % when compared to the existing hard clustering and fuzzy approaches.

Figure 4 shows the average lifetime of a cluster when the transmission range is varied from 250 m to 1000 m. It is evident that, the average cluster lifetime of rough fuzzy method has an increased average cluster lifetime of 10 % to 20 % when compared to hard and fuzzy clustering approaches. It is also evident that, when the transmission range is 1000 m the average lifetime of the cluster is better in all the approaches. So, the ideal transmission range can be fixed to 1000 m.

D. Average Cluster Head Lifetime

The meantime by which a node in a cluster remains a cluster head shows the stability of the system. Longer the duration of the cluster head, more is the stability of the network. Equation (7) is used to compute the average cluster head lifetime. Figure 5 shows the lifetime of the cluster head when the speed is varied from 20 km/hr to 100 km/hr and the transmission range is fixed to 1000 m. In (7), CHL represents the cluster head lifetime; CHL_{v_i} represents the location of the cluster head, CEL_{v_i} represents the ending location of the cluster and SD_{v_i} represents the speed of the vehicle

$$CHL = \frac{\left(CHL_{v_i} - CEL_{v_i}\right)}{SD_{v_i}}. \tag{7}$$

It is evident from Fig. 5 that the lifetime of the cluster head is 20 % to 25 % more than the fuzzy and hard clustering approaches.

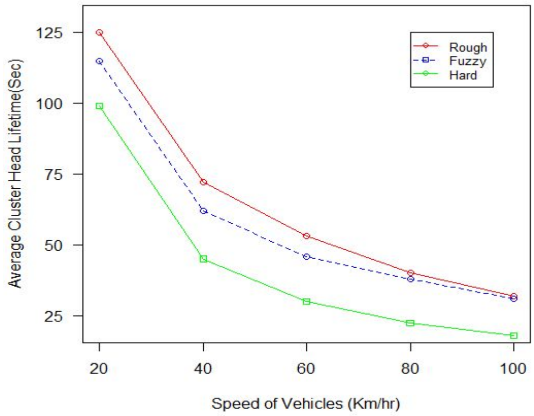

Fig. 5. Average cluster head lifetime.

E. Memory Consumption

The memory space in the processing unit of the vehicles is limited and should be used effectively to increase the performance of the system. Table V shows the list of attributes and their size measured in bytes. In the case of hard clustering as shown in Table V the vehicle ID, location, direction and speed attributes for all the vehicles in the cluster are stored in the database. The database size is represented as 'N'.

In the case of fuzzy clustering, membership values are computed for all the vehicles and stored in the database along with the other attributes as shown in Table VI and its size is given by 'N+1'. In case of rough fuzzy clustering, the membership value is computed for those vehicles in the boundary region and the database size is computed as N (B) +1.

TABLE V. ATTRIBUTES.

Pseudo ID	Location	Speed	Direction
2 bytes	4 bytes	4 bytes	1 byte

TABLE VI. ATTRIBUTES FOR FUZZY AND ROUGH FUZZY.

Pseudo ID	Location	Speed	Direction	« Value
2 bytes	4 bytes	4 bytes	1 byte	2 bytes

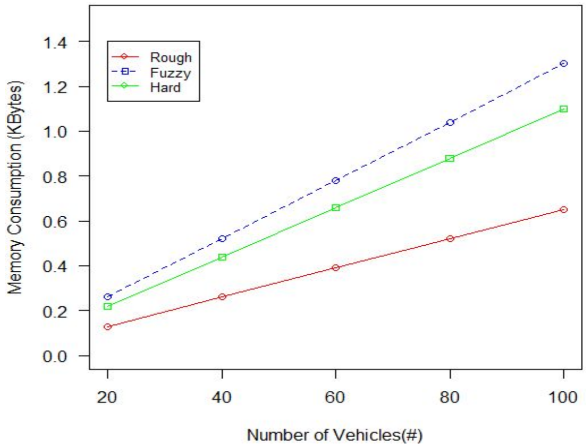

Fig. 6. Memory Consumption.

Figure 6 shows the comparison of memory consumption by hard, fuzzy and rough fuzzy approaches. Analysis shows that fuzzy method of clustering incurs more memory when compared to hard and rough fuzzy clustering. Since in rough fuzzy method, membership value is computed for boundary region vehicles, the size of memory occupied is less when compared to the existing approaches.

VI. CONCLUSIONS

In this paper, the rough set based fuzzy scheme is adopted for cluster formation. To the best of our knowledge, this scheme performs precise clustering thereby resulting in better average cluster lifetime, average cluster head lifetime and memory consumed when compared to the existing hard and fuzzy clustering approaches. This model supports stable cluster formation and cluster head selection. In future, signature generation by the cluster head and signature verification will also be added to improve the safety message communication in vehicular ad hoc network.

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