Improving Vehicular Ad-Hoc Network Stability Using Meta-Heuristic Algorithms

M. Fathian*[,1] , A.R. Jafarian-Moghaddam[2] , M. Yaghini [3]

1. Professor, 2. Ph.D. Student, School of Industrial Engineering, Iran University of Science and Technology, Tehran, Iran 3.Associate professor, School of Railway Engineering Iran University of Science and Technology, Tehran, Iran

*fathian@iust.ac.ir

Abstract

Vehicular Ad-hoc Network (VANET) is an important component of intelligent transportation systems, in which vehicles are equipped with on-board communication devices which enable vehicle-to-vehicle communication. Consequently, with regard to larger communication due to the greater number of vehicles, stability of connectivity will be a challenging problem.Clustering technique as one of the most important data mining techniques is a possible method that can improve the stability of connectivity in VANET. Therefore, this paper presentes two novel clustering algorithms based on Ant Colony System (ACS) and Artifitial Immun System (AIS) as meta-heuristic algorithms. The aim of proposed algorithms is to provide the fast clustering algorithms with high accuracy and improve the stability of VANET. A comparative study is presented to analogize the results of the proposed algorithms with six VANET clustering algorithms in the literature which are taken as benchmarks. Results reveal improvement in stability and overhead on VANET.

Keywords: *Network Management, Vehicular Ad-Hoc Network (VANET), Artificial Immune System (AIS), Ant Colony System (ACS), Clustering Analysis, Meta-Heuristic Algorithms.*

1. Introduction

Vehicular Ad-hoc Network (VANET), the outcome of the traditional Mobile Ad-Hoc Networks (MANETs), is a network of vehicles which communicate with each other by wireless technologies in their own transmission range. VANET is an appropriate network to enhance driver safety (1). Maximum and minimum transmission ranges are 1000 m and 100 m according to the dedicated short range communication (DSRC) standard for inter-vehicle communication (IVC) and vehicle-to-roadside communication (VRC), respectively. Each node (vehicle) in a VANET requires maintaining its own connectivity with other nodes in the network. So, with a large number of nodes, communication management and creating a stable network in VANET are the most challenging tasks due to the greater number of vehicles and rapid variation in network.

Clustering technique is a possible solution for overcoming these shortcomings. Also, clustering is vital for efficient resource consumption and load balancing in large-scale networks (2), because it can facilitate the reuse of resources and hence improve the VANET capacity.

The goal of clustering analysis is to group similar objects. This similarity is defined in terms of the closest distance, farthest distance rules, etc. Clustering analysis has taken several categories like hierarchical clustering, partition-based clustering, density-based clustering, and artificial intelligence-based clustering. In clustering, vehicles are located inside clusters; each cluster has one cluster-head (CH) and one or more members. Vehicles that form a cluster are coordinated by the relevant cluster-head (CH). Vehicles in one cluster directly communicate with each other; but, vehicles that are located in two different clusters can communicate via cluster-heads. Each cluster-head communicates with two different frequencies. One frequency is used to communicate among cluster-heads and another frequency is allocated to communicate between each cluster-head and its members (3). Figure 1 provides an example of the organization of five vehicles into two clusters.

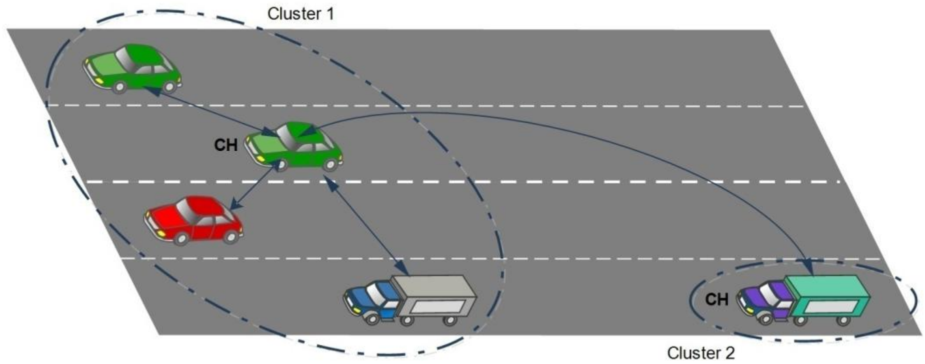

Fig1. Two clusters in VANET network

Although a significant body of studies (4-6) has focused on clustering nodes in Mobile Ad-Hoc Networks (MANETs), clustering in VANET is a new technique which opens new horizons for further studies. VANET enjoys a higher dynamic nature in comparison to MANET because of its quick and permanent change in the speed and position of vehicles. When a vehicle moves out of its cluster, VANET firstly checks whether it is a member of other clusters or not. If so, it separates itself from the current cluster and joins the new one. In addition to supporting the dynamic nature of the VANET environment, the following notices are important characteristics of a VANET clustering algorithm: being fast (fast in run), observing the time limit (real time), precision and accuracy, improving stability (reducing CH changes), improving connectivity (the number of vehicles in a cluster: vehicles have a transmission range and thus cluster size is limited.), and improving the overhead (change of the cluster members is called overhead). Therefore, a good VANET clustering algorithm reduces the number of cluster swaps and increases the network stability.

In this paper, Ant Colony System (ACS) and Artifitial Immun System (AIS) as famous and useful meta-heuristics are used to achieve appropriate clustering algorithms for VANET and at the same time take the above-mentioned characteristics into consideration. Ant system-based clustering algorithm (ACS-BASED) and AIS based clustering algorithm can be appropriate for VANET dynamic environment and improve the stability and overhead of clusters.

The rest of this paper is organized as follows: Related works are reviewed in Section 2. In Section 3, some basic concepts of ACS and AIS, and the proposed clustering algorithms are presented. Section 4 offers the evaluation results and examines the performance of the proposed algorithms through a comparative study. Finally, some conclusions are drawn in the last section.

2. Related Work

A good VANET clustering algorithm should reduce the number of cluster swaps and increase the network stability (7). Clustering algorithms for VANET are categorized into two classes of identifier-based clustering and connectivity-based clustering. In identifier-based clustering algorithms, a node functions as the CH if it has the Lowest/Highest ID among its neighborhoods (8, 9). However, the Connectivity-based clustering chooses a node as the CH provided that it has the most neighboring nodes in its transmission range. Nevertheless, Gerla and Tsai (8) suggested that the identifier-based clustering would be a better choice when compared with the connectivity-based clustering. They also presented CBRP algorithm as a variation of the Lowest-ID algorithm.

Lin and Gerla (10) and Gerla and Tsai (8) proposed the Highest-Degree heuristic algorithm and Lin and Gerla (10) and Baker and Ephremides (11) specified Lowest-ID heuristic algorithm in order to identify CHs in MANET. Highest-Degree and Lowest-ID which are presently used in VANET are the most important clustering algorithms for MANET. Nevertheless, most of the clustering algorithms developed for MANET are not appropriate for VANET because of its high dynamic mobility of vehicles and high change of network topology. Some researchers have attempted to improve the MANET algorithms for use in VANET environment. As an example Chatterjee et al. (12) proposed the weighted clustering algorithm (WCA) by using identifier characteristics such as the degree of a vehicle and also average speed and distance. WCA has high re-affiliation frequency when the network changes very fast which functions as a drawback for it. In (13), two D-HD and D-LID methods have been suggested to improve the stability of the Highest-Degree and

Lowest-ID algorithms for VANET. Blum et al. (14) suggested inter-vehicle communication networks clustering algorithm (COIN) in which instead of ID or relative mobility in classic clustering methods, the selection of the CH is based on vehicular dynamics and driver behavior. Stability in COIN is improved against the Lowest-ID.

Santos et al. (15) presented a reactive location-based routing algorithm called location-based routing algorithm with cluster-based flooding (LORA-CBF). However, high routing overhead and routing load are its drawbacks. Fan et al. (16) introduced a weighted utility function taken the degree, position, velocity and acceleration of vehicles into consideration. They also proposed a realistic micro simulation model to contribute to clustering research in VANETs, and demonstrated how clustering algorithms work in it in order to correlate well with realistic modeling of vehicle mobility in a real deployment. Their algorithm improved the stability in VANETs. Fan et al. (17) analyzed a distributed Directional Stability-based Clustering Algorithm (DISCA) designed for VANETs, which took direction, mobility features, and leadership duration into consideration. They showed that the overhead incurred by DISCA is bound to a constant per node per time step, avoiding expensive re-clustering chain reactions. Almalag and Weigle (18) presented a new clustering algorithm that its objective is to extend the lifetime of a CH. They have claimed that their method of selecting the CH is the key to achieve a more stable cluster.

Ramakrishnan et al. (19) by taking the Simple Highway Vehicular model concept into consideration suggested a mobility model titled simple highway mobility model (SHWM). SHWM is a connectivity-based clustering algorithm that focuses on the development of a clustering framework for communication among the VANET nodes. Daeinabi and et al. (20) proposed three new algorithms for VANET. Their first algorithm is vehicular clustering based on the weighted clustering algorithm (VWCA) that takes the number of neighbors into consideration based on the dynamic transmission range, the direction of vehicles, the entropy, and the distrust value parameters. They also suggested an adaptive allocation of transmission range (AATR) technique for gaining a changeable transmission range mechanism in their algorithms. In AATR technique, the traffic density around the vehicles is used to adaptively adjust the transmission range. Moreover, they introduced monitoring of malicious vehicle (MMV) algorithm to determine a distrust value for each vehicle used in the VWCA by paying attention to the driver behavior.

Meta-heuristics algorithms have high potential to present an appropriate stable clustering for VANET; moreover, they can support high stability / connectivity and low re-affiliation frequency with the fastest possible run time. Consequently, we propose a new clustering meta-heuristics algorithms based on well- known Ant Colony System (ACS) algorithm.

Ant Colony System (ACS) which was introduced by Colorni et al. (21) is based on the results presented in (22). It has widened the scope of application of this algorithm and has been recently used to solve various problems such as clustering. Although limited studies have been done by using ACS for data clustering, the results have provided proofs of the accuracy and speed of ACS-based algorithms. Tsai et al. (23) proposed an algorithm that was named ant colony optimization with different favor (ACODF). ACODF algorithm uses favorable ants in different manners to solve the clustering problem and adopts simulated annealing (SA) concept for ants to decreasingly visit the amount of cities. Besides, it utilizes tournament selection strategy to choose a path rapidly. In this algorithm, the closer nodes have higher trail intensity and the farther nodes have a lower one. Therefore, ants will favor to visit the closer nodes and reinforce the trail with their own pheromone. Finally, the clusters will be built by dividing the pheromone that was laid on the edge between the data points. Yang et al. (24) introduced a clustering algorithm based on the ACS which treats the data (objects or elements) as the ants. Kuo et al. (25) proposed Ant K-means algorithm (AK) and the Ant System-based clustering algorithm (ASCA) (26) to solve the problem of clustering analysis. Kuo et al. (27) combined two algorithms presented in (25) and (26) as a two stage clustering method. The first stage employs the ant system-based clustering algorithm (ASCA) and the ant K-means (AK) to cluster the database while in the second stage the ant colony system-based association rules mining algorithm is applied to discover the useful rules for each group. In this algorithm, updating pheromone is according to total within cluster variance (TWCV). Sahoo et al. (28) used ant colony routing technique based on trust and proposed clustering algorithm by considering direction, position and relative speed of the vehicle for managing the scalability of VANET and also they have proposed an algorithm for selecting the appropriate cluster head (CH) by considering the real time updated position and trust value of vehicles. Their research shows that proposed algorithm has outperformed the Mobility-aware Ant Colony Optimization Routing algorithm in terms of routing overhead. Balaji et al. (29) introduced a combined approach of clustering architecture and Ant Colony Optimization (ACO) routing procedures for performing routing operation in VANET. The proposed method is convenient to urban VANET. They have claimed that making use of Ant Colony optimization Procedures in Cluster architecture is more suitable for VANET.

So, the literature review indicates that although Artifitial Immun System (AIS) has high potential to present an appropriate stable clustering for VANET, but it has not been considered so far. Therefore, this paper uses AIS to achieve an appropriate clustering algorithm for VANET.

Consequently, the algorithms introduced in this paper are new algorithms based on meta-heuristics. Results show that the proposed clustering algorithms are appropriate for VANET dynamic environment and improve the cluster stability and overhead.

3. Proposed Vanet Clustering Algorithm

In this section, we introduce our proposed algorithm based on AIS and describe how it acts and maintains stable clusters dynamically. To read more about the AIS algorithm please refer to (31). Although AIS is able to properly configure the search space but the clusters determination directly using its output is very difficult. Accordingly, this section proposes the two-phase algorithm. First, the search and configuration space is determined by using of AIS algorithm, and then in phase 2, clusters are specified using hierarchical clustering algorithm. Required terms and notations are described throughout the algorithm:

Phase 1:

Step 1.1: Set all the existing data in the database as antigens (N: number of antigens or Ag).

In the proposed algorithm, each vehicle is an Ag.

Step 1.2: Generate a random number of antibodies (N1: number of antibodies or Ab)

Step 1.3: Run the following steps to reach the stopping criteria.

Step 1.3.1: For each Agj (j=1, …, N).

Step 1.3.1.1: Determine affinity (fij) between Agj and Abi (i=1, …, N1)

fij=1/Dij where Dij is Euclidean distance between Agj and Abi.

Step 1.3.2: Sort the Abs in a descending order according to fij

Step 1.3.1.3: Choose a random number of the antibodies with the highest fij {Ab(n)}.

Step 1.3.1.4: Specify the number of prolife rating cells for each of the selected Abs as:

$$N_c = \sum_{i=1}^{n} round\,(N - D_{ij}.N) \tag{1}$$

Number of amplification depends on affinity. Greater affinity will lead to further proliferation.

Step 1.3.1.5: Create a set C from amplified Abs.

Step 1.3.1.6: Do the mutation acting on set C as follows and create a new set C*.

$$C_k^* = C_k + rand\,(0,1) \times D_{kj}.mi\left(Ag_j - C_k\right) \tag{2}$$

mi is the learning rate and is an input parameter and k (k=1, …, K) is the number of C's members.

Step 1.3.1.7: Calculate affinity between C*'s members and Agj.

Step 1.3.1.8: Select the qi percent of the best C*'s members, depending on affinity.

Step 1.3.1.9: Create Mj set from the selected members (cells).

Step 1.3.1.10: Delete those Mj's members that have bigger than tp distance from Agj. tp is a prune threshold and an input parameter.

In this step, those antibodies stay that have the highest similarity to the Agj. Step 1.3.1.11: Calculate affinity between Mj's members and delete those members with the distance of smaller than ts.

ts is suppression threshold and is an input parameter.

In this step, antibodies close to each other are removed; therefore, the network is formed between the antibodies.

Step 1.3.1.12: Create set Mj* from Abs and the existing members in set Mj.

Step 1.3.2.: Calculate affinity between Mj*'s members and delete the members with the distance of smaller than ts.

As a result, the separated networks of antibodies will create the clusters.

Step 1.3.3: Generate a new random number of Abs.

Step 1.3.4: gen=gen+1

Step 1.3.5: Match the new Abs and Mj*'s members as Abs.

Step 1.4: Evaluate the stopping criteria as: (gen <= Maxgen) and (the best fij> 0.01)

Step 1.5: Set M * as the output of the algorithm.

Members of M* are associated with antigens (vehicles). Therefore, M* determines the configuration of VANET network. In the second phase, the clusters are specified.

Phase 2:
Step 2.1: Calculate affinity between Mj*'s members
Step 2.2: Determine 0<cut<1
Step 2.3: Apply hierarchical clustering algorithm
Step 2.4: Select a vehicle from each clusters as CH if the distance of center of cluster and vehicle is lowest.

4. Ant Colony System (ACS) and Proposed Algorithm (ACS-BASED)

In the real world, ants communicate with others by a trail of chemicals called ‘‘pheromones’’ which are deposited by ants when they search for food. Then, the other ants encounter the previously laid pheromones and determine how many probabilities they will follow. As more and more ants pass by the same path, the pheromones on the shorter path would increase, but the pheromones would be evaporated on the other paths, as illustrated in Figure 2 (27).

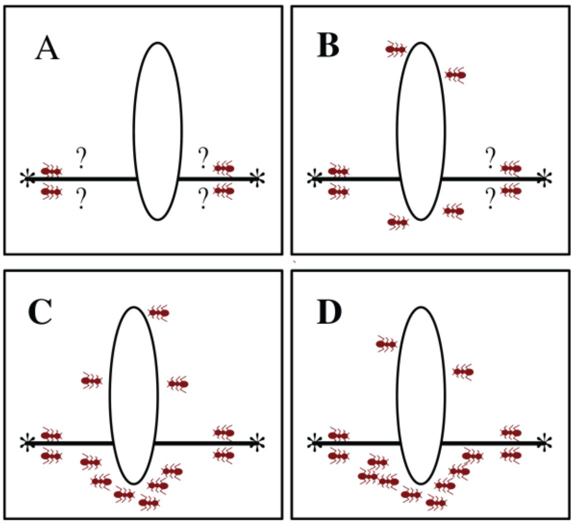

Fig2. The behavior of real ants.

develop mechanisms of cooperation and learn from experiences. ACS is a population-based heuristics that enables the exploration of the positive feedback among agents (27). This robust and versatile algorithm has expanded the scope of application and it has been recently used to solve various problems such as clustering.

Accordingly in this section, we introduce our proposed algorithm and describe how it acts and maintains stable clusters dynamically. In this algorithm, it is assumed that each vehicle is an ant. The following terms and notations are used throughout this study:

Vi, aci = Velocity and Acceleration of each vehicle respectively (i=1, …,m).

E = {O1, O2, …, Om}: a set of m data or objects, where O is the position of vehicles (ants) in two dimensional space. Thus, each object has k=2 attributes including Coordinate of axes X and Y.

α: The relative importance of the trail, $\alpha > 0$.

β: The relative importance of the visibility, $\beta > 0$.

ρ: The pheromone decay parameter, $0 < \rho < 1$.

Q: A constant.

m: Number of ants (vehicles=objects).

nc: Number of clusters.

T: A set of used objects. The maximal number recorded by T array will be m, i.e. T = {Oa, Ob, …, Ot}, where a, b, …, t are the points that an ant has been in it.

Tm: The set T is performed by ant m.

D mean(Tm): The Mean distance between all objects of an ant m and its center of cluster.

TR: Transmission range. Also, maximum range (TR max) is 1000m and minimum range (TRmin) is 100m.

O center (T): The object which is the center of all objects in T, i.e.,

$$O_{center}(T) = \frac{1}{n_T} \sum_{O_i \in T} O_i \qquad (3)$$

Where nT is the number of vehicles in T.

TWCV: Total within cluster variance, i.e.,

$$TWCV = \sum_{k=1}^{nc} \sum_{i \in k} \left(O_i, O_{center}\left(T_K\right)\right)^2 \quad (4)$$

SC: Silhouette Coefficient between two clusters [35], i.e.,

$$if \quad (a < b) \quad : \quad SC = \frac{a}{b} - 1$$

$$if \quad (a > b) \quad : \quad SC = 1 - \frac{a}{b} \quad (5,6)$$

Where a is the average distance between object i and other objects in the same cluster and b is the average distance between object i and other objects in the other clusters. SC is in the interval [0, 1]. SC closer to 1 shows more separation among clusters.

The proposed algorithm includes five sub-procedures that are Divide, Agglomerate_obj, Agglomerate, Remove and CH_selector. Figure 3 shows the procedures of the algorithm.

At the beginning, it initializes the parameters and groups all the objects as a cluster, and then the sub-procedure Divide will divide the cluster into several sub-clusters and some objects which do not belong to any sub-clusters through the consistency of the pheromone and some criterion.

Procedure *ACS-BASED* algorithm

Initialize the parameters
Group all objects as a cluster
Do
Divide for all ant *m*.
Agglomerate_obj for all ant *m*.
Agglomerate for all ant *m*.
Agglomerate_obj for all ant *m*.
Remove for all ant *m*.
Determine the non-clustered objects as outlier objects
Calculating *TWCV*
While (*TWCV* is not change)
Determine clusters by visited objects (vehicles) by each ant *m* (*nc*).
CH_selector for all clusters.

Procedure *Divide*

Lay pheromone on the path by η_{ij} for all *i* and *j*, $i \neq j$
Updating pheromone
Select *m* object from sorted *i*.
Each ant *m* collects object *j* if $\tau_{ij} \geq \bar{\tau}$.

Procedure *Agglomerate_obj*

Let $C = \phi$.
If O_j satisfied with the following equation:

$$D(O_{center}(T_m), O_j) < D_{mean}(T_m)$$

Add O_j to *C*
If (*C*<2) Assign O_j to T_m
Else Assign O_j to T_m if the distance of $O_{center}(T_m)$ and O_j is minimum.

Procedure *Agglomerate*

If T_m satisfied with the following equation:

$$SC(T_{m_i}, T_{m_j}) \leq \alpha$$

Agglomerate T_{mi} and T_{mj} as a cluster.

Procedure *Remove*

Remove object *j* from Ant *m* if $D(O_{center}(T_m), O_j) > D_{mean}(T_m)$.
where $j \in T_m$

Procedure *CH_selector*

Select O_j from T_m as *CH* of cluster T_m if the distance of $O_{center}(T_m)$ and O_j is lowest.
If O_j is an outlier data (a cluster without any members):
Select O_j as *CH* of its cluster

Fig3. The procedure of ACS-BASED Algorithm

Firstly; in this procedure, pheromones stand on the arcs and the average of them is calculated. Secondly, the pheromone on the arcs is updated by $\overline{\tau}$. Ants will be on a point that has the highest average amount of pheromone. After Divide, the Agglomerate_obj is the next step in this algorithm in order to agglomerate the vehicles into the suitable sub-cluster. Then, the distance between a datum (vehicle) and the center of the set Tm is calculated. If this distance is smaller than Dmean(Tm), then the data is assigned to set C. However, If C has more than two members and then the data with the lowest distance from the center of Tm (Dmean(Tm)) is added to the set Tm.

Thirdly, Agglomerate is the sub-procedure to merge the similar two sub-clusters into one cluster. In this procedure GA between two sets Tmi and Tmj is computed if GA is smaller than the predefined amount α (α-cut). Fourthly the two sets Tmi and Tmj are agglomerated as one cluster.

And then Agglomerate_obj is run again. As the next step, after agglomerating the similar objects into the suitable sub-cluster, the Remove subprocedure tries to remove the dissimilarity from the sub-cluster. If the distance between a data (vehicle) from set Tm is bigger than Dmean(Tm), then it is removed from set Tm. The proposed algorithm calculates the total within cluster variance (TWCV).

If TWCV does not change, it stops the procedure. Otherwise, it repeats the sub-procedure Divide, Agglomerate_obj, Agglomerate, Agglomerate_obj and Remove until TWCV does not change.

Moreover, the clusters and their members are determined and data (vehicles) which do not belong to any base-clusters are known as outlier. Finally, CHs are specified at the end of the algorithm. For each set Tm, the data (vehicle) with minimum distance from Dmean(Tm) is selected as CH for that cluster.

5. Comparative Study

In this section, the proposed algorithms are evaluated and assessed through a comparative study. For this purpose, we have used from the data presented by Fan et al. (13). Fan et al. (13) proposed a utility function for clustering in VANET. The aim of their algorithm was to evaluate the number of cluster changes and the cluster size for the simple combinations of the Highest-Degree and Lowest-ID algorithms with the Position and Closest Velocity to Average methods. They have compared six algorithms Lowest-ID, Highest-Degree, Lowest-ID augmented with Position (ID and Pos), Lowest-ID augmented with Closest Velocity to Average (ID and Avg Velocity), Highest-Degree augmented with Position (Deg and Pos), Highest-Degree augmented with Closest Velocity to Average (Deg and Avg Velocity) through two metrics that were identified as (i) the average cluster head change per step and (ii) the average cluster size/ the average cluster head change per step. Accordingly, we have compared the proposed algorithms with six algorithms through these two metrics.

For this purpose, Traffic Simulation 4 (32) is used to generate the data. The stability of the cluster is tested by counting the number of CH changes. Before each new step begins, the proposed algorithm is used to choose the CH and observe if the CH changes for the majority of traffic after the new step. The cluster formation will be processed every 20 seconds quite the same as what Fan et al. (13) did. The experiments carried out show that the best values for the parameters of the AIS based clustering algorithm are as follows: tp=1; ts=[0.2, 0.4]; qi=[0.1, 0.5]; Maxgen=[30, 40].

We assess the proposed algorithms across various wireless transmission range values (0-300 meters) and maximum vehicle speed (40-140 kilometers/hour). Figure 4 summarizes the variation of the average number of CH changes versus the transmission range. An algorithm is more stable if it has the lowest average number of CH changes compared with other algorithms. Whereas speed in proposed algorithms is assumed quite variable, it’s fixed in other six algorithms. Results show that the three Lowest-ID algorithms clearly perform better than the three Highest-Degree algorithms and also, the three Lowest-ID algorithms show very similar performance. Based on the Figure 4, ACS based algorithm (ACS-BASED) performs very similar to the three Lowest-ID algorithms and better than three Highest-Degree algorithms. Results show that our proposed algorithm based on AIS performs very similar to the Highest-Degree algorithm.

Figure 5 displays the performance of all algorithms over various transmission ranges. Higher curves indicate better overall performance. Clustering ratio metric is obtained by dividing the average cluster size by the average cluster head changes. Larger cluster size provides less re- affiliations and on the other hand, less change in CH leads to stable network. Consequently, the best VANET algorithm has the lowest CH changes and the largest cluster size simultaneously and therefore, it has the largest clustering ratio.

As shown in Figure 5, performance of the ACS-BASED is worse than the Lowest-ID algorithms but is better than the Highest-Degree algorithms. This is because our proposed algorithm combines the Lowest-ID and Highest-Degree characteristics. Nevertheless these results show the potential for improvement of ACS-BASED for using in VANET environments to have a good clustering algorithm with lowest CH changes and re-affiliations. Also, performance of the proposed AIS based clustering algorithm is similar to the Highest-Degree.

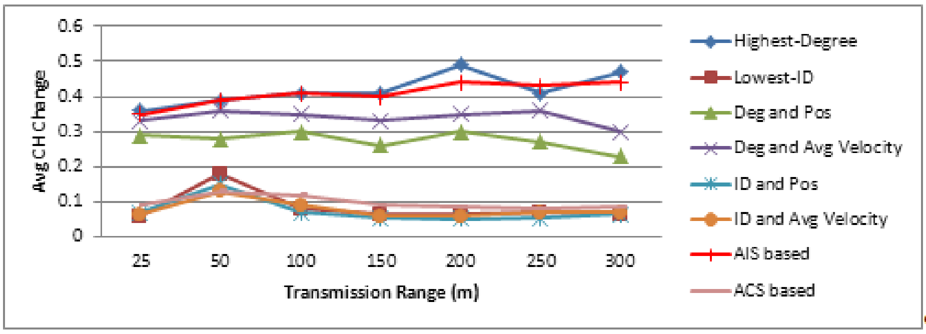

Fig4. CH Changes vs. Transmission Range

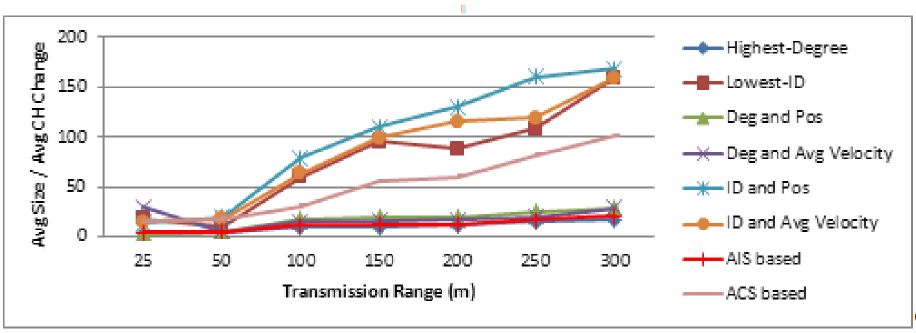

Fig5. Clustering Ratio vs. Transmission Range

6. Conclusion

This paper introduced ant system-based clustering algorithm (ACS-BASED) and AIS based clustering algorithm in order to provide fast clusters with high accuracy and improve the stability of VANET. For the first time, this paper proposes new VANET clustering algorithm based on AIS. ACS-BASED is a robust clustering algorithm that can be appropriate for highly dynamic nature of VANET environments.

To evaluate the algorithms, a comparative study was presented to analogize the results of the proposed algorithms and compare them with six VANET clustering algorithms from the literature. Results showed that the ACS-BASED algorithm and AIS based clustering algorithm performed the same as the Lowest-ID algorithms and Highest-Degree algorithms, respectively. ACS-BASED performance was better than the Highest-Degree and AIS based algorithms.

It should be noted that, these results for AIS algorithm are preliminary and basic results and research is ongoing to develop a more stable VANET network based on AIS. The better performance of the ACS-BASED algorithm could be attributed to the CH selection mechanism that led to a more stable cluster algorithm. For the Lowest-ID algorithms, the transmission range did not have any impact on the selection of CH. In other words, the Highest-Degree and its algorithms performed differently when the transmission range changed. Transmission range affected the number of nodes that were connected to the CH and both of these algorithms used one degree of connectivity when they chose a CH. But, the proposed algorithms combined the Lowest-ID and Highest-Degree characteristics. So, these algorithms utilized the benefits of the Lowest-ID algorithms and reduced the Highest-Degree drawbacks. Because of this property, the overhead associated with the ACS-BASED clustering scheme was considerably reduced. Nevertheless, the results demonstrated that these algorithms could be improved under minimum CH changes and re-affiliations.

References

[1]. Nadeem, T., and P. Shankar. A comparative study of data dissemination models for VANETs, IEEE Mobile and Ubiquitous Systems: Networking & Services, 2006, pp.1-10.

[2]. Liu, X., Zh. Fan, and L. Shi. Securing vehicular ad hoc networks, In Proceedings of the second conference on international pervasive computing and applications, Birmingham, 2007, pp. 424-429.

[3]. Garg, M., and R. K. Shyamasundar. A distributed, clustering framework in mobile Ad Hoc networks, In Proceedings of the International Conference on Wireless Networks (ICWN'04), Las Vegas, 2004, pp. 32-38.

[4]. Sivavakeesar, S., and G. Pavlou. A Prediction-based clustering algorithm to achieve quality of service in multihop Ad Hoc networks, In Proceeding of the London communications symposium (LCS), London, 2002, pp. 17-20.

[5]. Basagni, S., I. Chlamtac, and A. Farago. A Generalized clustering algorithm for Peer-to-Peer networks, In Workshop on Algorithmic Aspects of Communication, Bologna, Italy, 1997.

[6]. Basagni, S. Distributed clustering for Ad Hoc networks, In Proceedings of Fourth International Symposium on Parallel Architectures, Algorithms and Networks (I-SPAN '99), Australia, 1999, pp. 310-315.

[7]. Fan, P., A. Mohamadian, P. Nelson, J. Haran, and J. Dillenburg. A novel direction-based clustering algorithm in vehicular ad hoc networks, In Proceedings of the transportation research board 86th annual meeting, Washington DC, United States, 2007.

[8]. Gerla, M., and J. Tsai. Multicluster, mobile, multimedia radio network, Wireless Networks, Vol. 1, 1995, pp. 255-265.

[9]. Steenstrupt, M. Cluster-based networks, chapter 4, Addison-Wesley, 2001.

[10]. Lin, C. R., and M. Gerla. Adaptive Clustering for Mobile Networks, IEEE Journal on Selected Areas in Communications, Vol. 15, 1997, pp. 1265-1275.

[11]. Baker, D. J., and A. A. Ephremides. Distributed algorithm for organizing mobile radio telecommunication networks, In Proceedings of the second international conference on distributed computer systems, 1981, pp. 476-483.

[12]. Chatterjee, M., S. K. Das, and D. Turgut. WCA: a weighted clustering algorithm for mobile ad hoc networks, Journal of Cluster Computing, Vol. 5, 2002, pp. 193-204.

[13]. Fan, P., G. J. Harran, J. Dillenburg, and P. C. Nelson. Cluster-based framework in vehicular ad- hoc networks, ADHOC-NOW 2005, LNCS 3738, Springer, 2005, pp. 32-42.

[14]. Blum, J., A. Eskandarian, and L. Hoffman. Mobility management in IVC networks, In Proceedings of the IEEE intelligent vehicles symposium, 2003, pp. 150-155.

[15]. Santos, R. A., A. Edwards, R. Edwards, and L. Seed. Performance evaluation of routing protocols in vehicular ad hoc networks, The International Journal of Ad Hoc and Ubiquitous Computing, Vol. 1, 2005, pp. 80-91.

[16]. Fan, P., P. Nelson, J. Haran, and J. Dillenburg. An improved compound clustering algorithm in vehicular ad-hoc networks, In Proceedings of the ninth international conference on applications of advanced technology in transportation (AATT06), Chicago, IL, USA, 2006, pp. 424-430.

[17]. Fan, P., P. Sistla, and P. Nelson. Theoretical Analysis of a Directional Stability-based Clustering Algorithm for VANETs, VANET'08, San Francisco, California, USA, 2008, pp. 80-81.

[18]. Almalag, M. S., and M. C. Weigle. Using Traffic Flow for Cluster Formation in Vehicular Ad-hoc Networks, The 35th Annual IEEE Conference on Local Computer Networks, Denver, Colorado, USA, IEEE, 2010, pp. 631-636.

[19]. Ramakrishnan, B., R. S. Rajesh, and R. S. Shaji. CBVANET: A Cluster Based Vehicular Adhoc Network Model for Simple Highway Communication, Int. J. Advanced Networking and Applications, Vol. 2, 2010, pp. 755-761.

[20]. Daeinabi, A., A. GhaffarPour Rahbar, and A. Khademzadeh. VWCA: An efficient clustering algorithm in vehicular ad hoc networks, Journal of Network and Computer Applications, Vol. 34, 2001, pp. 207-222.

[21]. Colorni, A., M. Dorigo, and V. Maniezzo. Distributed Optimization by Ant Colonies, In Proceeding of European conference on Artificial Life (ECAL91), Paris, France, Elsevier Publishing, 1991, pp. 134-142.

[22]. Deneubourg, J. L., S. Aron, S. Goss, and J.M. Pasteels. The self-organizing exploratory pattern of the Argentine ant, Journal of Insect Behavior, Vol. 3, 1990, pp. 159-168.

[23]. Tsai, C. F., H. C. Wu, and C. W. Tsai. A new clustering approach for data mining in large databases, In Proceedings of the international

[24]. symposium on parallel architectures, algorithms and networks (ISPAN'02), IEEE Computer Society, 2002, pp. 1087-4089.

[25]. Yang, X. B., J. G. Sun, and D. Huang. A new clustering method based on ant colony algorithm, In Proceedings of the 4th world congress on intelligent control and automation, 2002, pp. 2222-2226.

[26]. Kuo, R. J., H. S. Wang, T. L. Hu, and S. H. Chou. Application of Ant K-Means on Clustering Analysis, Computers and Mathematics with Applications, Vol. 50, 2005, pp. 1709-1724.

[27]. Kuo, R. J., and C. W. Shih. Association rule mining through the ant colony system for National Health Insurance Research Database in Taiwan, Computers and Mathematics with Applications, Vol. 54, 2007, pp. 1303-1318.

[28]. Kuo, R. J, S. Y. Lin, and C. W. Shih. Mining association rules through integration of clustering analysis and ant colony system for health insurance database in Taiwan, Expert Systems with Applications, Vol. 33, 2007, pp. 794-808.

[29]. Sahoo, R. R., R. Panda, D.K. Behera, and M. K. Naskar. A trust based clustering with Ant Colony Routing in VANET, Computing Communication & Networking Technologies (ICCCNT), 2012 Third International Conference on, Vol. 1, 2012, pp. 26-28.

[30]. Balaji, S., S. Sureshkumar, and G. Saravanan. Cluster Based Ant Colony Optimization Routing For Vehicular Ad Hoc Networks, International Journal of Scientific & Engineering Research, Vol. 4, 2013, pp. 26-30.

[31]. Tan, P. N., M. Steinbach, and V. Kumar. Introduction to Data Mining, Addison-Wesley (2005).