User-oriented Fuzzy Logic-based Clustering Scheme for Vehicular Ad-hoc Networks

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***Abstract*—Vehicular ad-hoc networks (VANETs) are considered to have an enormous potential in enhancing road traffic safety and traffic efficiency. Socio-economic challenges, network scalability and stability are identified among the main challenges in VANETs. In response to these challenges, this paper proposes a novel user-oriented Fuzzy Logic-based k-hop distributed clustering scheme for VANETs that takes into consideration the vehicle passenger preferences. The novelty element introduced is the employment of Fuzzy Logic as a prominent player in the clustering scheme. To the best knowledge of the authors, there are no Fuzzy Logic-based clustering algorithms designed for VANETs. Simulation-based testing demonstrate how the proposed solution increases the stability of vehicular networks, lifetime and stability of cluster heads compared to both the classic LowestID algorithm and an utility function-based clustering scheme previously proposed by the same authors.**

Keywords-component; vehicular, ad-hoc networks, fuzzy logic, clustering algorithm

I. Introduction - Towards The Next Generation of In-Car Infotainment Systems

Vehicular ad-hoc networks (VANETs) are considered to have an enormous potential in enhancing road traffic safety and traffic efficiency. Therefore various governments have launched programs dedicated to the development and consolidation of vehicular communications and networking [1] and both industrial and academic researchers are addressing many related challenges, including socio-economic ones, which are among the most important [2].

Socio-economic challenges include the cost of the infrastructure needed for the deployment of VANET solutions and the market penetration of vehicle-to-vehicle (V2V) and vehicle-to-infrastructure(V2I) communication technologies. Two solutions were proposed for the latter problem that either enforce a regulative order, or deploy attractive applications in order to advertise the added value of the technology [1].While it appears credible that in the future the governments will impose the adoption of the V2V and V2I communication technologies for new vehicles through regulation, there will be long periods of time during which the penetration rate of these technologies will be very low (e.g. in USA alone it will take more than 10 years to acquire 100% penetration rate if a new technology will start to be deployed on vehicles now) [1].

In this context, the deployment of attractive applications based on V2V and V2I communication technologies, such as VANET-based in-car infotainment applications, appears to be the best solution to fasten the market penetration of these technologies. Several steps towards this new generation of in-car infotainment solutions have already been made. Examples include a VANET-based decentralized mechanism for free parking place discovery [3], green vehicular routing solutions [4], [5] and video streaming solutions over VANETs [6], [7]. Based on the consideration that smart applications that provide personalized content to vehicle passengers according to their interests are most attractive in-car applications, we proposed a user-oriented solution for multimedia content delivery over VANETs in [8]. This solution supports various value added services in the vehicles, e.g. touristic video guide, news, entertainment. For instance, a group of friends driving around a touristic area can have their car on-board unit act as a live touristic guide, playing video previews of the attractions in that area. Specific to our solution proposed in [8] is an utility function-based k-hop clustering scheme that groups vehicles around cluster heads (CH) selected to have their position, velocity and interest in the most popular content closest to most vehicles in the k-hop same direction neighborhood.

Making use of an utility function is not the best approach to handle linguistic knowledge like “closest position” or “closest velocity” to those of other vehicles. This observation lead to the proposal of the **novel user-oriented k-hop clustering scheme for VANETs based on Fuzzy Logic**, presented in this paper. Fuzzy Logic is unique in that it is able to handle both numerical data and linguistic knowledge [9]. In addition, Fuzzy Logic approaches in real-time systems have been demonstrated to be very efficient [9] (e.g. Fuzzy Logic cruise-controllers deployed in Nissan and Subaru vehicles [10]). To the best knowledge of the authors the employment of Fuzzy Logic as a major player in the clustering scheme for VANETs is highly novel. Complex simulation-based testing show the proposed solution increases network stability in comparison with Lowest ID [11], a state-of-the-art clustering solution, and the utility function-based clustering solution proposed in [8].

This paper is structured as follows. Section II discusses related works and section III presents in details the proposed Fuzzy Logic-based clustering scheme. Section IV presents testing results and conclusions are drawn in the last section.

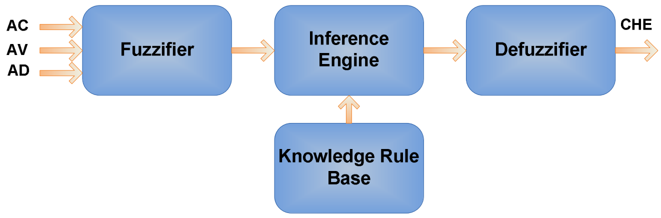

Figure 1. FLC structure

II. Related Works

In the literature, there is a considerable number of clustering solutions designed for VANETs. Lowest ID is a state-of-the-art clustering algorithm in ad-hoc networks and was borrowed in VANETs from the area of Mobile Ad-hoc Networks (MANETs) [11]. Although its principle is very simple, it is a very efficient algorithm, more efficient than other clustering schemes (e.g. Highest-Degree [11]) that take into consideration more parameters [12]. Lately, new clustering schemes that consider more VANETs-specific characteristics were proposed. Many of them are utility function-based [8], [12], [15] or weight-based [12], [13], [14], while others are employing concepts like Euclidean distance [16], affinity propagation [17] or similarity in the mobility patterns [18]. To date, **there are no Fuzzy Logic-based clustering schemes designed for VANETs**, which make use of VANET-specific characteristics. Fuzzy Logic was employed in the design of a learning mechanism for predicting future vehicle speed and position in a VANET specific cluster-based MAC protocol [13]. However, Fuzzy Logic does not play the main role in clustering, the solution subscribing to the weight-based clustering solutions. Also, there are few Fuzzy Logic-based clustering schemes proposed in MANETs [19], [20], [21]. Although VANETs represent an instantiation of MANETs, they have unique features such as unlimited transmission power, higher computational capability and higher mobility, but predictable due to the road infrastructure. These features make the MANET solutions mentioned [19], [20] unsuitable for VANETs as they are focused on the transmission power conservation, a very delicate issue in MANETs, but not an issue of importance in VANETs. In addition these works do not take into consideration important characteristics of VANETs that subscribe to the predictability of the mobility, such as direction of travel.

The proposed user-oriented Fuzzy Logic-based k-hop distributed clustering scheme takes into consideration passengers' interest in a certain information/content, location, velocity and direction of travel. It represents a response to both problems mentioned in the socio-economic challenges in VANETs. Clustering and especially multi-hop clustering increases the transmission distance between road-side units (RSUs) and the vehicles. This leads to a cost-effective infrastructure as less RSUs need to be deployed.

In addition, other main challenges in VANETs such as network stability and scalability [2] are addressed. Unlike most ad-hoc networks that usually assume a limited network size, VANETs can be extended on the entire road network which involves a potentially great number of vehicle-nodes. In addition, the high mobility of the vehicles imposes stability issues in VANETs. Clustering addresses these issues as it provides good system performance, a good management and stability of the networks in the presence of mobility and large number of nodes [11].

III. User-orientedFuzzy Logic-based K-hop Distributed Clustering Scheme

A. Overview

The proposed user-oriented Fuzzy Logic-based distributed clustering scheme organizes the vehicles into k-hop clusters according to vehicle location, direction of travel and velocity and passenger interests in certain information/content. Vehicles organize themselves into clusters around the CH vehicle in the k-hop same-direction neighborhood. The eligibility of a vehicle for the CH role, *CHE* (CH eligibility) score, is computed by each vehicle and then advertised in "hello" messages exchanged by vehicles in the k-hop same direction neighborhood. The vehicle with the largest *CHE* is the CH in the cluster. The *CHE* score for each vehicle is computed by the proposed novel Fuzzy Logic Controller (FLC) deployed in each vehicle. Additionally, each vehicle has a location-aware component (e.g. GPS-based) and a context-aware user model. The location-aware component provides information about vehicle's location, speed and direction. The context-aware user model manages the interests of vehicle passengers in certain content and stores a vector of interests. The vector of interests of vehicle *i* has the following format: $[p_{i1}, p_{i2},\dots,p_{ij}, \dots p_{in}]$, where p_{ij} represents the percentage of interest in topic *j*. Location, speed, direction and vector of interests are further used in computing the FLC inputs. These inputs are average compatibility (AC), average distance (AD) and average velocity (AV). The rules employed in the computation of the crisp values for AC, AD and AV are similar to those used in [8] and are presented in equations (3), (4) and (5).

Each vehicle periodically broadcasts a message containing its unique id, vector of interests, location and speed. Based on these messages, each vehicle *i* establishes its neighbors traveling in the same direction, and computes and stores in a list (N_i) neighbor-related information. The list N_i is described in equation (1).

$$N_i = \{(j, v_j, (x_j y_j), [p_{i1}, p_{i2},\dots,p_{ij}, \dots p_{in}], IC_{ij}) \mid j \in V_i\} \quad (1)$$

Where V_i is the set of id-s of same-direction k-hop neighbors of vehicle *i*; v_j is the velocity of vehicle *j*; (x_j, y_j) are the coordinates of the positions of vehicle *j* and IC_{ij} is the interest compatibility between vehicle *i* and vehicle *j*. IC_{ij} is measured by applying cosine similarity between the two vector of interests associated with vehicle *i* and vehicle *j* as presented in equation (2).

$$IC_{i,j} = \Phi(i,j) = \frac{\sum_{k=1}^{n} p_{ik} p_{jk}}{\sqrt{\sum_{k=1}^{n} p_{ik}^2 \sum_{m=1}^{n} p_{jm}^2}} \quad (2)$$

AD_i is defined as the average absolute distance between vehicle *i* and its neighbors from N_i and is described in equation (3).

$$AD_i = \frac{\sum_j \sqrt{(x_j - x_i)^2 + (y_j - y_i)^2}}{|N_i|} \quad (3)$$

where (x_i, y_i), (x_j, y_j) are the coordinates of the positions of vehicles *i* and *j*, respectively.

AV_i is defined as the average of the differences between the velocity of the vehicle *i* and those of its neighbors from N_i.

$$AV_i = \frac{\sum_j |v_i - v_j|}{|N_i|} \quad (4)$$

In equation (4), v_i, v_j represent the velocity of vehicle *i*, and vehicle *j*, respectively.

AC_i is defined as the average of the interest compatibilities computed for vehicle *i* and each of its neighbors from N_i.

$$AC_i = \frac{\sum_j IC_{ij}}{|N_i|} \quad (5)$$

In equations (2), (3), (4) and (5), *j* takes the values of all ids from N_i, and $|N_i|$ is the cardinality of N_i.

B. Fuzzy Logic ControllerDescription

This section presents a detailed description of the FLC specific to our proposed solution. The structure of the FLC, presented in Figure 1. , includes a *Fuzzifier*, an *Inference Engine*, a *Defuzzifier* and a *Knowledge Rule Base* and is typical for a Fuzzy Logic controller. The design of the presented FLC is a trade-off between accuracy and reduced computation complexity and follows design principles from [9] and [22]. Next paragraphs summarize the design of each of the FLC components.

Fuzzifier takes the crisp values of *AC*, *AD* and *AV* as inputs and gives as output their corresponding Fuzzy degree of membership based on the defined membership functions. The membership functions of *AC*, *AD* and *AV* are trapezoidal and they are described in equations (6), (7), (8) and (9), while the membership function of *CHE* is triangular and is described in equations (10) and (11). Trapezoidal and triangular membership functions were used for the input/output parameters due to their suitability to real-time systems as they have reduced computation complexity (in special in the case of triangular membership functions) [9].

$$\mu_{trapezoidal} = \begin{cases} \frac{x-a}{b-a}, & a \le x \le b \\ 1, & b \le x \le c \\ \frac{d-x}{d-c}, & c \le x \le d \\ 0, & otherwise \end{cases} \quad (6)$$

μ(AC) = {(a, b, c, d)| a, b, c, d are the coefficients for $\mathcal{F}_{\mathcal{AC}}^{\mathcal{L}}, \mathcal{F}_{\mathcal{AC}}^{\mathcal{M}}, \mathcal{F}_{\mathcal{AC}}^{\mathcal{H}}$*} = {(-∞, 0, 0.2, 0.4), (0.2, 0.4, 0.6, 0.8), (0.6, 0.8,1, ∞)}* (7)

μ(AV) = {(a, b, c, d)| a, b, c, d are the coefficients for $\mathcal{F}_{\mathcal{AV}}^{\mathcal{L}}, \mathcal{F}_{\mathcal{AV}}^{\mathcal{M}}, \mathcal{F}_{\mathcal{AV}}^{\mathcal{H}}$ *} = {(-∞, 0, 0.2*v_{max}*, 0.4*v_{max}*), (0, 0.2*v_{max}*, 0.8*v_{max}*,* v_{max}*), (0.6* v_{max}*, 0.8* v_{max}*,*v_{max}*, ∞)}* (8)

μ(AD) = {(a, b, c, d)| a, b, c, d are the coefficients for $\mathcal{F}_{\mathcal{AD}}^{\mathcal{L}}, \mathcal{F}_{\mathcal{AD}}^{\mathcal{M}}, \mathcal{F}_{\mathcal{AD}}^{\mathcal{H}}$ *} = {(-∞, 0, 0.2*d_{max}*, 0.4*d_{max}*), (0, 0.2*d_{max}*, 0.8*d_{max}*,* d_{max}*), (0.6*d_{max}*, 0.8* d_{max}*,* d_{max}*, ∞)}* (9)

$$\mu_{triangular} = \begin{cases} \frac{x-a}{m-a}, & a < x \le m \\ \frac{b-x}{b-m}, & m < x < b \\ 0, & otherwise \end{cases} \quad (10)$$

μ(CHE) = {(a, b, c)| a, b, c are the coefficients for $\mathcal{F}_{\mathcal{CHE}}^{\mathcal{VL}}, \mathcal{F}_{\mathcal{CHE}}^{\mathcal{L}}, \mathcal{F}_{\mathcal{CHE}}^{\mathcal{M}}, \mathcal{F}_{\mathcal{CHE}}^{\mathcal{H}}, \mathcal{F}_{\mathcal{CHE}}^{\mathcal{VH}}$ *} = {(-∞, 0, 0.25), (0, 0.25, 0.5), (0.25, 0.5, 0.75), (0.5, 0.75,1), (0.75, 1, ∞)}* (11)

Inference Engine maps the input fuzzified values to the output Fuzzy set described by the output membership function. The mapping is done based on the "IF-THEN" rules contained in the ***Knowledge Rule Base*** and described in equation (12).

$\mathcal{R}^{(\ell)}$ *:* ***IF*** *AC is* $\mathcal{F}_{\mathcal{AC}}^{\ell}$ ***AND*** *AD is* $\mathcal{F}_{\mathcal{AS}}^{\ell}$ ***AND*** *AV is* $\mathcal{F}_{\mathcal{AV}}^{\ell}$ ***THEN*** *CHE is* $\mathcal{F}_{\mathcal{CHE}}^{\ell}$ (12)

where $\mathcal{R}^{(\ell)}$ is the index of the rule in the *Knowledge Rule Base* and $\mathcal{F}_{\mathcal{AC}}^{\ell}$, $\mathcal{F}_{\mathcal{AS}}^{\ell}$, $\mathcal{F}_{\mathcal{AV}}^{\ell}$, $\mathcal{F}_{\mathcal{CD}}^{\ell}$ and $\mathcal{G}^{\ell}$ are the corresponding Fuzzy sets of *AC*, *AV*, *AD* and *CHE*, respectively (Figure 2.).

Defuzzifier takes the Fuzzy set given as output by the inference process and transforms it in the crisp value of *CHE*. The defuzzification is performed based on the centroid method which is used in the Mamdani Fuzzy Logic controllers [23].

Linguistic Variables		Fuzzy Sets
Input linguistic variables	Average Compatibility (*AC*)	{Low ($\mathcal{F}_{\mathcal{AC}}^{\mathcal{L}}$), Medium ($\mathcal{F}_{\mathcal{AC}}^{\mathcal{M}}$), High ($\mathcal{F}_{\mathcal{AC}}^{\mathcal{H}}$)}
	Average Velocity (*AV*)	{Low ($\mathcal{F}_{\mathcal{AV}}^{\mathcal{L}}$), Medium ($\mathcal{F}_{\mathcal{AV}}^{\mathcal{M}}$), High ($\mathcal{F}_{\mathcal{AV}}^{\mathcal{H}}$)}
	Average Distance (*AD*)	{Low ($\mathcal{F}_{\mathcal{AD}}^{\mathcal{L}}$), Medium ($\mathcal{F}_{\mathcal{AD}}^{\mathcal{M}}$) , High ($\mathcal{F}_{\mathcal{AD}}^{\mathcal{H}}$)}
Output linguistic variable	CH Eligibility (*CHE*)	{Very Low ($\mathcal{F}_{\mathcal{CHE}}^{\mathcal{VL}}$), Low($\mathcal{F}_{\mathcal{CHE}}^{\mathcal{L}}$), Medium($\mathcal{F}_{\mathcal{CHE}}^{\mathcal{M}}$), High($\mathcal{F}_{\mathcal{CHE}}^{\mathcal{H}}$), Very High($\mathcal{F}_{\mathcal{CHE}}^{\mathcal{VH}}$)}

Figure 2. Input/Output Linguistic Variables

IV. TESTING RESULTS

The proposed Fuzzy Logic-based clustering scheme was tested through simulation. For this purpose, a new simulation platform was designed by coupling iTETRIS [24], an open-source simulation platform used in vehicular networks, and Octave [25], an open source tool that has support for Fuzzy Logic.

A. Performance Metrics

To evaluate the performance of the proposed clustering scheme, three performance metrics were used.

The first performance metric used is the Mean CH Lifetime (MCHL) which is a very popular metric employed in the evaluation of the CH-based clustering algorithms performance [17]. The importance of CHs lifetime is crucial as usually CH is the main controller and content forwarder in the CH-based clustered networks.

The second performance metric used is the Mean CH Stability (MCHS) that is defined by the equation (13).

$$MCHS = \frac{Ts}{\sum_{i=1}^{n} ci} \quad (13)$$

In (13), n is the number of clusters formed during the simulation period Ts and c_i represents the number of changes of CH in cluster i. MCHS is an indicator of both CH and network stability.

The third performance metric is the Mean Number of Clusters, a common metric that is a measure of network stability [17]. When there are fewer clusters, better network stability is obtained.

B. Comparison-based Performance Assessment

The performance of the proposed Fuzzy Logic-based clustering scheme is compared to the performance of other two CH-based clustering schemes. One is the state of the art clustering algorithm, Lowest ID [11], which is probably the best known in the area of ad-hoc networks. Its principle is very simple. The nodes have assigned a unique fixed id which is broadcasted periodically in the network. The clusters are formed around the node with the lowest id among them which is chosen as CH. The other clustering scheme used for comparison is the Utility Function-based clustering solution that the authors proposed in [8].

C. Simulation Setup and Results

The values of the main parameters used in the simulation are summarized in TABLE I.

TABLE I. THE VALUES OF SIMULATION PARAMETERS

Parameters	**Values**
Network topology	Grid
Number of hops	2
Transmission range (d_{max})	250m
Vehicle's maximum speed (v_{max})	[30km/h – 70km/h]
Drivers imperfection(sigma)	0.5
Number of bi-directional lanes	{2, 4}
MAC protocol	IEEE 802.11p
Vehicle information message	800 bits
Simulation time	300s

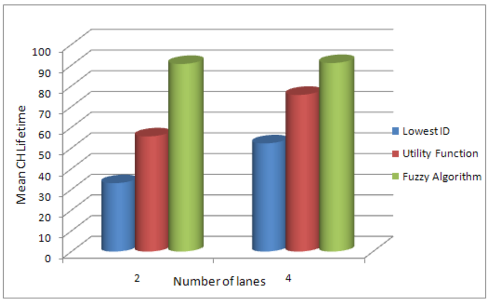

Figure 3. Mean CH Lifetime vs number of lanes

The first set of simulation results are focused on the analysis of the performance metrics versus the number of lanes. The maximum speed of the vehicles considered was 50 km/h and the number of lanes is varied between 2 and 4. The results of the simulation tests (Figure 3. , Figure 4. , Figure 5.) demonstrate that the performance of the proposed Fuzzy Logic-based clustering scheme overcomes the performance of the two algorithms it is compared against. For example, it can be seen how MCHL is 37.3% longer in the Fuzzy Logic-based solution than that of the Utility Function-based scheme and 72.75% longer than that of the Lowest ID solution for 2 lanes. For 4 lanes, the benefits are 19.2% and 40.4%, respectively.

The results in terms of the MCHS metric for 2 lanes shows that the CHs selected by the Fuzzy Logic-based algorithm is with 29.3% more stable than the CHs selected by the Utility Function-based algorithm and with 29% more stable than the CHs selected by the Lowest ID. For 4 lanes, the benefits are 56% and 70%, respectively.

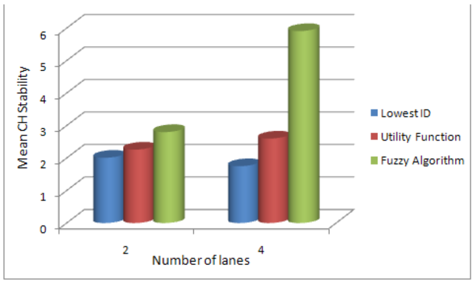

Figure 4. Mean CH Stability vs number of lanes

The results considering the Mean Number of Clusters illustrate that the number of clusters decreased by using the proposed Fuzzy Logic-based algorithm.

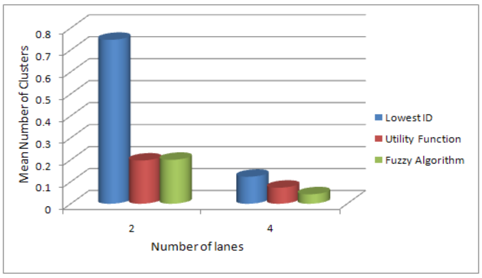

Figure 5. Mean Number of Clusters vs number of lanes

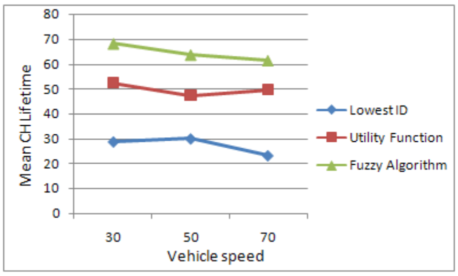

Figure 6. Mean CH Lifetime vs vehicle speed

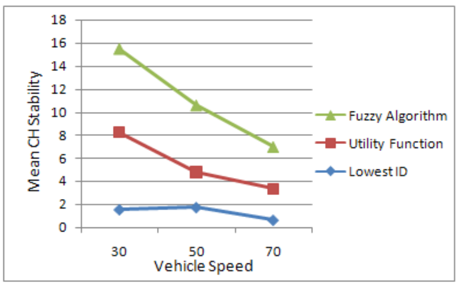

Figure 7. Mean CH Stability vs vehicle speed

The second set of simulations is focused on the analysis of the performance metrics versus the vehicles' speed. In this case, the number of lanes has a fixed value (2 lanes) and the speed varies in the [30-70km/h] interval. The results of this set of simulations (Figure 6. , Figure 7. , Figure 8.) demonstrate better performance of the Fuzzy Logic-based clustering scheme in comparison to both Lowest ID and Utility Function-based clustering schemes. For example, it can be seen how MCHL is 10.7% longer in the Fuzzy Logic-based solution than that of the Utility Function-based scheme and 37.7% longer than that of the Lowest ID solution when the speed is equal to 70km/h. For 30 km/h, the benefits are 16.9% and 39.5%, respectively, while for 50km/h the benefits are 14.4% and 33%, respectively.

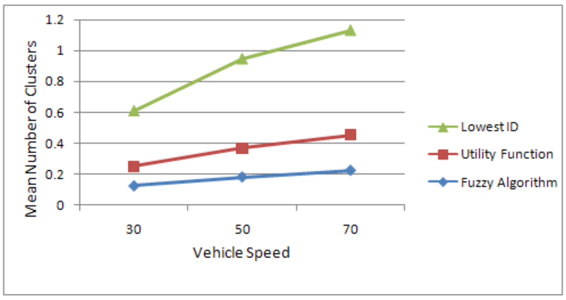

Figure 8. Mean Number of Clusters vs vehicle speed

D. Overhead Analysis

Compared to the Lowest ID algorithm, the proposed Fuzzy Logic clustering scheme introduces additional messages which are translated into overhead. However, it is assumed that the clustering-specific messages are exchanged via the control channel (IEEE 802.11p) and this does not affect the dissemination of data. The additional complexity and energy consumption is not an important issue in VANETs. The Utility Function-based algorithm and the proposed Fuzzy Logic-based algorithm have the same number of clustering messages.

V. Conclusions and Future Work

This paper has proposed a novel user-oriented Fuzzy Logic-based k-hop distributed clustering scheme for VANETs. This clustering scheme considers the preferences of vehicle passengers that are going to be delivered with content of their interest. The resulted clustered network deals better with the scalability and stability issues of VANETs. Simulation tests demonstrate that the proposed Fuzzy Logic-based clustering scheme achieves better network stability and increased cluster head lifetime than the state-of-the-art algorithm, Lowest ID, and the user-oriented Utility Function-based clustering scheme proposed by the authors in [8].

Future works include a deeper analysis of the overhead and new performance tests that also involve data delivery.

VI. Acknowledgements

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