Noname manuscript No.
(will be inserted by the editor)

A Fuzzy Logic Approach to Beaconing for Vehicular Ad hoc Networks

Kayhan Zrar Ghafoor · Kamalrulnizam Abu Bakar · Martijn van Eenennaam · Rashid Hafeez Khokhar · Alberto J. Gonzalez

Received: September 29, 2010 / Accepted: January 12,2011

Abstract Vehicular Ad Hoc Network (VANET) is an emerging field of technology that allows vehicles to communicate together in the absence of fixed infrastructure. The basic premise of VANET is that in order for a vehicle detect other vehicles in the vicinity. This cognizance, awareness of other vehicles, can be achieved through beaconing. In the near future, many VANET applications will rely on beaconing to enhance information sharing. Further, the uneven distribution of vehicles, ranging from dense rush hour traffic to sparse late night volumes creates a pressing need for an adaptive beaconing rate control mechanism to enable a compromise between network load and precise awareness between vehicles. To this end, we propose an intelligent Adaptive Beaconing Rate (ABR) approach based on fuzzy logic to control the frequency of beaconing by taking traffic characteristics into consideration. The proposed ABR considers the percentage of vehicles travelling in the same direction, and status of vehicles as inputs of the fuzzy decision making system, in order to tune the beaconing rate according to the vehicular traffic characteristics. To achieve a fair comparison with fixed beaconing schemes, we have implemented ABR approach in JIST/SWANs. Our simulation shows that the proposed ABR approach is able to improve channel load due to beaconing, improve cooperative awareness between vehicles and reduce average packet delay in lossy/lossless urban vehicular scenarios.

Keywords VANET · Beaconing Adaptation · Fuzzy Logic · Cooperative awareness · Vehicular traffic characteristic

K. Zrar Ghafoor · K. Abu Bakar · R. H. Khokhar
Faculty of Computer Science and Information Systems, Universiti Teknologi Malaysia, 81310 UTM Skudai, Johor D. T, Malaysia.
Tel.: +6-017-7193871
E-mail: zgkayhan2@live.utm.my

Martijn van Eenennaam
Department of Telematics, University of Twente, Enschede, Netherlands.

Alberto J. Gonzalez
Department of Telematic Engineering,Technical University of Catalonia/I2cat Foundation, Barcelona, Spain.

1 Introduction

The number of vehicles contending for space in existing transportation systems is growing rapidly. This abrupt growth of vehicles has made driving unsafe and hazardous. Thus, existing transportation infrastructure requires improvements in traffic safety and efficiency. To achieve this requirement, Intelligent Transportation Systems (ITS) have been considered to enable diverse traffic applications such as traffic safety, cooperative traffic monitoring and control of traffic flow. These traffic applications can become realities through emerging VANET because vehicular network is considered as a network environment of ITS. In addition, in the near future more vehicles will be embedded with wireless communication devices such as Wireless Access in Vehicular Environment (WAVE) [1]. When vehicles are equipped with WAVE, they can synchronize and handshake via beacons. In this way, a vehicle exchanges beacon messages periodically, sharing its mobility characteristics with its neighbours, thereby building cooperative awareness.

However, rapid changes in traffic density from sparse to heavy, as well as periodic beaconing between vehicles, can cause the wireless channel between vehicles to promptly become congested, resulting in a high degree of performance degradation of vehicular network [2], [3].

The reason for this channel congestion is that each vehicle periodically broadcasts beacons at a fixed rate. This also leads to high channel overloading and hence packet loss. In short, the higher the frequency of beacon rate, the higher the bandwidth overload in dense traffic conditions [4].

On the other hand, the solution to channel overloading does not involve simply reducing the frequency of beacon generation. As the frequency of beacon generation is reduced, the error will increase between the current physical position and the last reported position. For instance, in geographical routing protocols, reducing beacon rate would lead to the inaccuracy of the exchanged position coordinates between vehicles. This would negatively affect the performance of routing protocols. In short, reducing the beacon rate leads to the exchange of out-of-date information.

From the brief discussion above, it is obvious that there is a pressing need to consider a conditional update approach in which a vehicle adapts its beacon rate when there is considerable variation in its neighbour vehicles mobility/traffic characteristics. Therefore, multiple parameters, like vehicular mobility characteristics and status of vehicle, have been utilized to design an intelligent ABR approach to control beaconing rate. This is because a fixed beacon rate can not tackle both bandwidth consumption and accuracy of vehicle status due to rapid changes in vehicular traffic conditions. Therefore, an intelligent ABR approach in vehicle-to-vehicle communication has been developed to tune the beaconing rate in response to changing vehicular traffic characteristics. The contributions of this study can be summarized as follows:

1. In dense traffic conditions, a low beacon rate is required to reduce overload on the network (with acceptable information awareness) whereas in sparse traffic conditions, a higher beacon rate is required to increase the cooperative awareness (with acceptable beaconing load) between vehicles. Therefore, in contrast to all previous works, we proposed an intelligent ABR approach based on fuzzy logic to tackle the aforementioned issues.
2. We perform simulations to show the effect of traffic density, number of emergency vehicles and shadowing lossy channel on the proposed approach.

In addition, the proposed adaptive approach has been modeled and simulated using JIST/SWANs [5] simulation tool for performance evaluation. Likewise, the fuzzy logic decision making algorithm -which is integrated with the ABR approach- is implemented in java language. Moreover, in this article we use the term vehicle and node interchangeably.

The rest of the paper is organized as follows: Section 2 provides an overview of the current state of the arts. The proposed intelligent ABR approach and the designed fuzzy inference system are discussed in section 3, followed by performance validation and evaluation in section 4, where we highlight the feasibility of our approach by utilizing a real city map, traffic characteristics of vehicles and a realistic wireless channel. Finally, section 5 concludes the paper and discusses future directions.

2 Related Work

The problem of beaconing adaptation has been studied in various prospects in VANET. Transmission power control and beacon rate control are two main examples of adaptation approaches. The authors in [3], [6] and [7] have proposed adaptation approaches to tune transmission power with varying vehicular densities. That is, the purpose is to reduce transmission power in dense vehicular scenarios and hence improve fairness. In addition, adaptation of beaconing can be done by controlling the beacon rate in order to tune it with uneven distribution of vehicles. In this study, we consider the adaptation approach to beacon rate control.

In [8], van Eenennaam et al. proposed an architecture to adapt network and MAC-layer parameters in order to mimic the configuration parameters. This adaptive approach can tune MAC layer configurations and beaconing properties to optimal values in the vehicular scenarios. However, vehicular networks are dynamic, as evidenced by dense rush hours and sparse late night traffic conditions. In designing their model, the aforementioned authors did not take these factors into consideration.

The adaptation of beacon rate is also considered in [9] and [10]. The proposed beacon rate adaptation is based on differences in predicted positions. In their prediction scheme, all vehicles are embedded with modified Kalman estimators to provide continuous estimates of existing positions. This position estimate can be obtained via the last beacon message, enhancing positional accuracy between two sequential beacons. Moreover, the prediction scheme requires that the next beacon message is triggered based on a vehicle's current position and an estimated position. Once the vehicle determines a change in its physical position, it triggers the next beacon message. In this way, vehicles independently estimate the duration of the next beacon message. However, rapid topology changes of vehicles and mobility traffic characteristics were not considered.

In [11], Fukui et al. proposed a beacon adaptation scheme which considers the distance travelled by vehicles. Moreover, vehicles independently determine the number of lanes the current road has, and the higher the number of lanes, the lower is the beacon rate. In addition, another beacon adaptation technique is based on packet loss rate. But, changing beacon rates based on multi lane is unfair because multi lanes do not directly imply higher traffic density. Further, the accuracy of information has not been considered.

The authors in [12] first studied the adaptation of beacon rate in order to compromise between information accuracy and bandwidth consumption. After analysis of the parameters which affect the beacon rate, they proposed a scheme to adapt beacon rate according to the VANET traffic behaviour. In their study, however, intelligently combined traffic parameters like direction, density and status of a vehicle have been neglected. Moreover, their study is based on theoretical analysis.

The different adaptive beaconing approaches mentioned above have their own drawbacks, thus there is an imperative need to design an approach which can fulfill the need for the exchange of information accurately coupled with low bandwidth consumption. To this end, we propose an intelligent ABR approach to dynamically adapt beacon generation frequency according to the traffic density, vehicle direction and status (emergency or non-emergency) of vehicle. More precisely, the proposed ABR is based on the percentage of vehicles moving in the same direction and status of vehicle (the status of a host vehicle or a vehicle itself) on the road. The reasoning behind this parameter selection is demonstrated in sections (3.1.1) and (3.1.2).

3 Proposed Intelligent Adaptive Beaconing Approach

The designed ABR approach is adopted for Vehicle to Vehicle (V2V) communication systems in which vehicles communicate without the presence of infrastructure. The approach is used to tune the frequency of beacon generation with traffic context in VANET. We assume that all vehicles are equipped with wireless radio communication devices in order to facilitate communication with other vehicles. Similar to existing work on VANET, we assume that all vehicles are equipped with a Global Positioning System (GPS) receiver that provides vehicle position information. We also assume that different types of vehicles are deployed in the urban area to account for the presence of both emergency and non-emergency vehicles. Since vehicles on the roads are susceptible to unusual situations, the presence of emergency vehicles is a reasonable assumption.

Instead of simply broadcasting beacons in a fixed time interval, we propose a VANET friendly adaptive approach to control beacon rate. Whenever a vehicle receives a beacon message from its neighbours, the vehicle checks the percentage of directional neighbour vehicles and its emergency status. After collecting this information, it triggers the fuzzy inference system (it is run distributedly by every node upon receiving a periodic beacon message) to calculate the value of the required Beacon Rate (BR_r). The new value of Beacon Rate (BR_n) is then calculated based on the following equation:

$$BR_n = BR_c + \gamma(BR_r - BR_c) \qquad (1)$$

Where BR_n is the new value of beacon rate, BR_c is the current value of beacon rate, BR_r is the required beacon rate which is the output of fuzzy inference system. Further, γ is the weight factor which is used to sustain the value of BR_n. If the value of $\gamma = 0$, $BR_n = BR_c$ i.e. it negates the effect of beacon rate adaptation. On the other hand, $\gamma = 1$ leads to an abrupt increase/decrease of beacon rate. This would cause transient channel congestion/accuracy reduction. In the simulator, through trial and error, we set this value at 0.45. After obtaining the new beacon rate value, we can determine the value of Beacon Interval Time (BIT) (Algorithm 1), enabling the next beacon to be scheduled in BIT seconds. Moreover, the value of required beacon rate depends upon the designed fuzzy inference system. In the next section, the design of the fuzzy inference system is illustrated.

Algorithm 1 Beacon Interval Time Adaptation

```
Initialize BR_c
if Beacon message is received then
    Find percentage of same directional neighbour vehicles
    Find its own emergency status
    Trigger Fuzzy Inference System
    get the value of BR_r
    BR_n = BR_c + γ(BR_r − BR_c)
    BR_c = BR_n
    BIT = 1/BR_c
    Output the value of BIT
end if
```

3.1 Design of Fuzzy Logic Decision Making System

As stated earlier, vehicles can travel at very high speeds, and traffic densities frequently change from sparse to dense and vice versa. Therefore, many criteria can dynamically change the beacon interval.

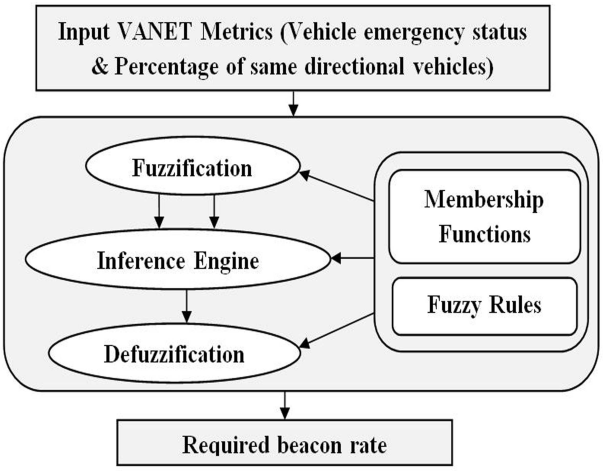

Fig. 1: Fuzzy logic components (fuzzification, inference engine and defuzzification) to generate the required beacon rate (BR_r).

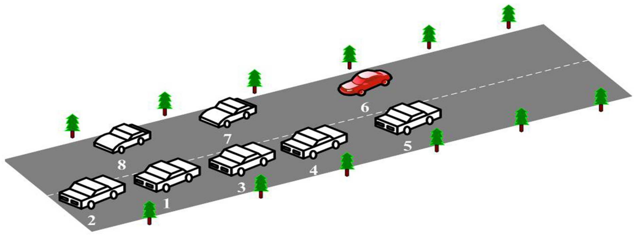

Fig. 2: This vehicular scenario demonstrates the emergency(vehicle number 6)/normal (remaining vehicles) vehicles status and percentage of the same directional vehicles.

Artificial intelligence based decision making systems, such as fuzzy logic, perform well in pattern classification and decision making systems [13]. Accordingly, a fuzzy logic system has been utilized in the proposed intelligent ABR approach. Fuzzy logic is a decision making process based on input membership functions and a group of fuzzy rules. This is similar to the way the human brain operates, which simulates the interpretation of uncertain sensory information [14]. Here it is applied to control the beacon rate based on intelligently combined metrics (percentage of the same directional vehicles and their emergency/nonemergency status). In this case, the vehicle does not know which value of beacon rate is suitable for the current vehicular situation, so fuzzy is a promising solution for this uncertain type of problem.

As demonstrated in Figure 1, the fuzzy inference system consists of fuzzification, inference engine and defuzzification. The first step in designing a fuzzy inference system is to determine input and output variables, and their fuzzy set of membership functions. This is followed by designing fuzzy rules for the system. Furthermore, a group of rules are used to represent inference engine (knowledge base) for articulating the control action in linguistic form. The input parameters of the fuzzy inference system are elaborated in the next sections.

3.1.1 Emergency Status of Vehicles

In a real heterogeneous vehicular environment, different kinds of vehicles, with different kinds of status, are communicating with one another. During unusual traffic conditions, some vehicles may travel on the road with emergency status (e.g. ambulance, fire truck, police car, or it can be any vehicle in an emergency situation such as failing brakes). These vehicles should diffuse their emergency status to their neighbours abruptly, and with a high degree of accuracy. Thus, increased beacon rate is very crucial for these types of vehicles, even under congested traffic conditions. These vehicles need to be able to inform neighbour vehicles to clear the road, with extra cooperative accuracy. On the other hand, normal vehicles follow their usual beaconing rate based on mobility characteristics. Figure 2 shows the common vehicular scenario in which the emergency vehicle is included.

3.1.2 Percentage of Directional Vehicles

In the previous section, we mentioned a vehicle parameter known as emergency status. Beaconing frequency control depends upon the vehicles current status and the traffic condition of neighbour vehicles. This section elaborates the latter (percentage of directional vehicles). Mobility characteristics like direction, velocity, and traffic density are very important parameters to consider when adapting beacon rate in VANET. The reasons of this are summarized as follows. First, vehicles on the road travel in constrained directions, thus vehicle beacon rate adaptation should take both directions into consideration. For instance, in a vehicular scenario with two way traffic, and vehicles moving in one direction have congested traffic conditions, they should reduce beacon rate, whereas vehicles moving in the other direction may vary their own beacon rate. Second, the velocity of vehicles and traffic density are implicitly interrelated to one another. This relationship is clearly known in traffic flow theory as in [15] Kerner states that the vehicles average velocity decreases as a result of increasing vehicular traffic density. Therefore, the percentage of vehicles travelling in the same direction is considered as an input as this parameter implicitly combines direction of vehicles, traffic density and velocity of vehicles.

In Figure 2, vehicles 1,2,3,4 and 5 are moving in the same direction, while 6,7 and 8 are travelling in the opposite direction. If vehicle 1 wants to find the percentage of neighbour vehicles in the same direction, it can perform the following calculation:

$$PDN = \frac{NND}{TNN} \tag{2}$$

where PDN is the percentage of the same direction neighbour nodes, NND determines the number of the same direction neighbour nodes and TNN is the total number of neighbour nodes. Thus, the value of PDN for vehicle one is 0.5715, which means that this percentage of vehicles is moving in the same direction. In this way, this percentage implicitly considers combined direction, traffic density and velocity. Additionally, a vehicle can calculate its relative direction with other vehicles when its own and neighbours direction are known. For example: IF vehicle a is moving in (dx_a, dy_a) direction and vehicle b is moving in (dx_b, dy_b) direction we can calculate the bearing angle (σ) between a vehicle and its neighbour as follows:

$$\cos\sigma = \frac{dx_a \cdot dx_b + dy_a \cdot dy_b}{\sqrt{dx_a^2 + dy_a^2} \cdot \sqrt{dx_b^2 + dy_b^2}} \tag{3}$$

3.1.3 Fuzzification of Inputs and Outputs

The two input parameters to be fuzzified are the Percentage of Directional Neighbour Vehicles (PDN) and Vehicle Status (VS), as illustrated in Figure 3. The membership functions named *Sparse*,*MDense* and *VDen se* are used to represent the *PDN*. The selection of *PDN* membership functions can be derived based on experience as well as trial and error of the application requirement, thus the range begins at (0) and ends at (1). The reasoning behind this range is that a node might not have any same directional neighbour node (0) or all vehicles are moving in the same direction (1). When vehicles are in motion, the value of PDN may vary between its minimum and maximum value. Thus, the value of beacon rate is adapted in response to this percentage variation intelligently combined with the status of vehicles.

In addition, the VS fuzzy variable is represented as sharp/discrete values because status of vehicles is either emergency or non emergency. The discrete value representation of fuzzy variables is possible in fuzzy inference system. In [16], Myllyniemi et al. proposed a fuzzy logic system to tune the data rate, and in their study, discrete value representation has been used as a fuzzy variable. In our fuzzy inference system, we utilize the membership functions *Emerg* and *NEmerg* to represent the emergency/non emergency status of vehicles. As demonstrated in Figure 3, there is no intersection between *Emerg* and *NEmerg* at the x- axes, thus it is a discrete representation of VS fuzzy variable.

Table 1: Knowledge structure based on fuzzy rules

	IF		THEN
Rule	*Perce.ofDirec.*	*VehicleStatus*	BR_r
1	Sparse	Emerg.	VHigh
2	MDense	Emerg.	High
3	VDense	Emerg.	Medium
4	Sparse	NEmerg.	Medium
5	MDense	NEmerg.	Low
6	VDense	NEmerg.	VLow

The output beacon rate is configured to a range between (1 to 10 beacon/second); the greater this value, the lower the duty cycle time for beacon generation. In addition, triangular functions are used as membership functions as they have been extensively used in real-time applications due to their simple formulas and computational efficiency. It is worth mentioning that the wise design of the membership function has a positive impact on the fuzzy decision making process performance.

3.1.4 Fuzzy Inference Engine

The fuzzy inference engine is a group of rules developed using expert knowledge. We have designed the knowledge based rules that connect the inputs and the outputs based on a careful understanding of the philosophy behind vehicular network behaviour. The fuzzy inference system is designed based on 6 rules which are presented in Table 1. In order to demonstrate the correct operation of our designed system, one rule is used to show how the inference engine works and the outputs of each rule are combined for generating the fuzzy decision [14]. Consider a rule If (PDN is Sparse) and (VS is NEmerg) then (BR (beacon/second) is Medium) as an example of calculating output of the specified rule. In our fuzzy inference system, in the case where PDN is 0.206 and VS is 0.532, the beacon rate is 5.22 beacon/second.

In order to calculate beaconing intervals based on Algorithm 1, let us assume that the value of BR_c is 4.7 beacon/second and the output crisp value of fuzzy inference system for BR_r is 5.22 beacon/second. The value of the new beacon rate (BR_n) is equivalent to 4.934 beacon/second. After taking the reciprocal of BR_n, the duty cycle of the new beacon interval becomes 0.2027

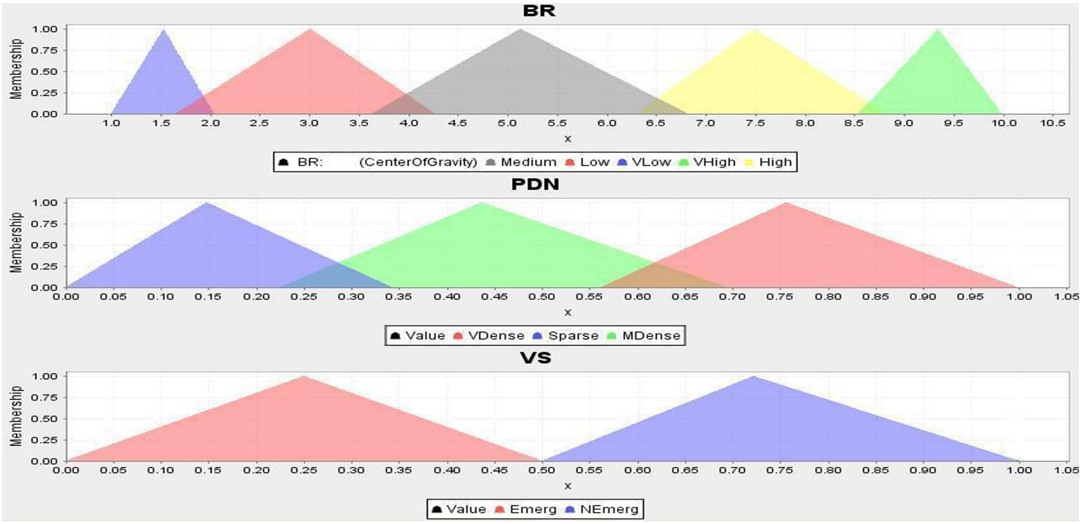

Fig. 3: Fuzzy membership functions for inputs (Vehicle Status (VS) and Percentage of Directional Neighbour vehicles (PDN)) and output (Beacon Rate (BR_r)) variables.

second. The vehicle has this beacon interval because of its non-emergency status and the sparse distribution of neighbour vehicles in the vicinity zone. It means our fuzzy inference system uses a tradeoff decision between parameters (VS and PDN) to adaptively tune the beacon rate. This output is obtained by using Mamdani's fuzzy inference method [14]. Furthermore, Figure 4 depicts the correlation behaviour between input and output variables. The trend shows that the value of output beacon rate increases when the value of PDN is between 0 to 0.2 as well as VS between 0 to 0.5. This is because of the emergency status of the vehicle and the lower percentage of directional neighbour vehicles (upper dark red part). Thus, our fuzzy inference system could increase beacon rate as traffic density decreases (velocity increases) or vice versa.

3.1.5 Defuzzification

Defuzzification refers to the way a crisp value is extracted from a fuzzy set value. In our fuzzy decision making, we take the centroid of area strategy for defuzzification. This defuzzifier method is based on equation 4, as follows:

$$R = \frac{\sum\limits_{AllRules} x_i \times \beta(x_i)}{\sum\limits_{AllRules} \beta(x_i)} \tag{4}$$

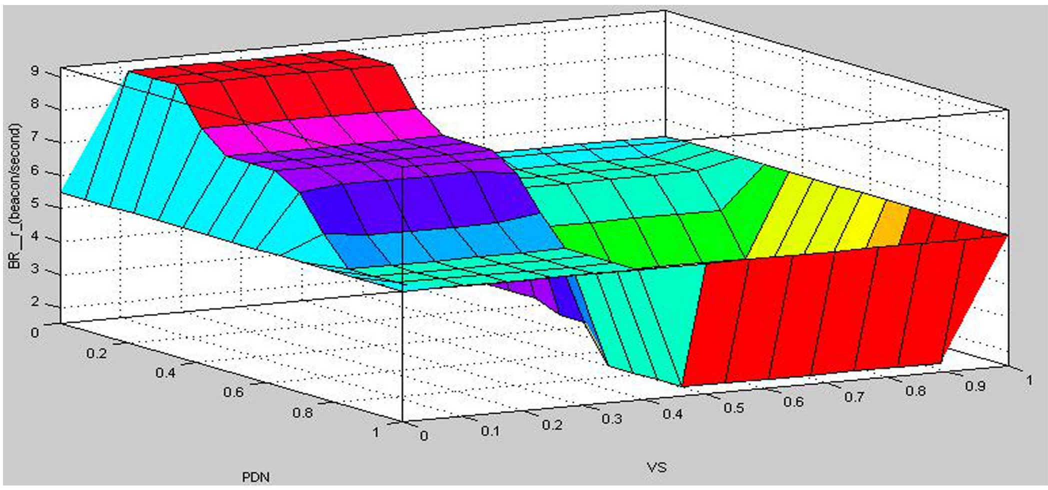

Fig. 4: Correlation between inputs (PDN and VS) and output (BR_r).

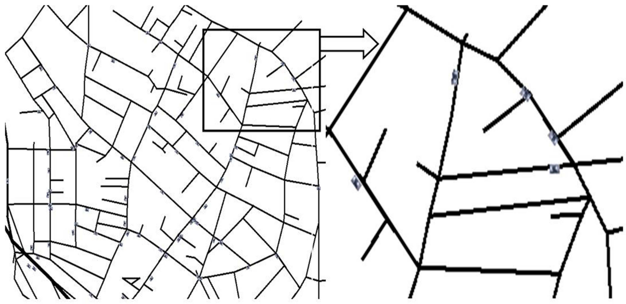

Fig. 5: Suffolk city map integrated with JIST/SWANs (vehicles are travelling on the roads of the city).

where R is used to specify the degree of decision making, x_i is the fuzzy variable and $\beta(x_i)$ is its membership function. Based on this defuzzification method, the output of the beacon rate is changed to the crisp value.

4 Performance Evaluation

4.1 Simulation Setup

In this section, we present the simulation setup to validate and evaluate the proposed approach. We have modeled and simulated the intelligent ABR approach with the scalable and reconfigurable JIST/SWANs. To simulate the designed fuzzy logic, we have modified the implemented fuzzy inference system in [17], then integrated with JiST/SWANs. Also, these simulations were executed on a Pentium(R) Dual-Core CPU 2.70 GHz and 2 Gb personal computer with installed Java $j2sdk1.6.0-18$. All simulation parameters are illustrated as follows:

Physical Layer: In order to model the wireless channel, we utilized 2-ray ground reflection model and shadow fading model (see section 4.2.2). Furthermore, each vehicle has a radio coverage range of 200 meters.

Mobility Model and Vehicular Scenario: To model the urban vehicular scenario, we used the realistic STreet RAndom Waypoint mobility model (STRAW) [18]. The STRAW has an efficient car following trajectory, lane changing model and real-time traffic controller over Suffolk city (Figure 5) map imported from the TIGER/LINE database [19]. Furthermore, we set the maximum speed of vehicles at 21 m/s. The simulation area is set at 750×940 meter (Suffolk city area), the maximum node density on the simulation area is 200 and 10 % or 20 % of 200 nodes selected as emergency vehicles.

Media Access Control (MAC) and Network Layer: The IEEE Standard 802.11 distributed coordination function (DCF) has been used to simulate the MAC layer of the protocol stack. The channel bandwidth used in our simulation is 3 Mbps. To store packets waiting for channel access, we used interface queue between MAC and Logical Link Control layer (LLC) with maximum 25 packets.

Traffic Model: The traffic source of the simulation is Constant Bit Rate (CBR) with a value of 36 kbps, which is based on UDP packet generation traffic. The number of vehicles that transmit packets is 5. During the simulation, the transmitted packet size is fixed on 1000 bytes.

Simulation Time: The total simulation time is 160 seconds. We set the settling time to 30 seconds at the beginning of simulation to remove the effect of transient behaviour on the results. The total simulation time also included 30 seconds of stop sending packets from the end of the simulation. Further, it is worth mentioning that each point in the performance figures exemplifies the average of 10 simulation runs. The 95 % of Confidence Interval (CI) has been calculated for the collected performance metrics, unless they are (CI) profoundly small.

Performance Metrics: The following metrics are considered in our performance evaluation: *Beaconing Load* (BL) is measured as the amount of beaconing packet traffic in bit/second that a node is able to receive during a time period t. More precisely, the BL is mainly measured as a function of traffic density and beacon rate. Further, a vehicle can calculate its BL by summing up its transmitted beacon message with all received beacon messages from vehicles within its coverage. *Probability of Cooperative awareness (PA)* is defined as the probability of beacon messages received by a node in the past second. More specifically, this metric is measured by calculating the distance of a node to the neighbour nodes within its coverage [20]. Thus, it depends upon the frequency of beacon transmission and the distance between vehicles which are within the same radio range. *End-to-end delay* is defined as the time duration subjected by all packets that are transmitted by the source and successfully reach at the destination.

4.2 Simulation Results

As mentioned earlier, we have evaluated our intelligent ABR approach based on various parameters. By varying the simulation parameters, we studied different experiments such as the effect of traffic density, the number of emergency vehicles and shadow fading.

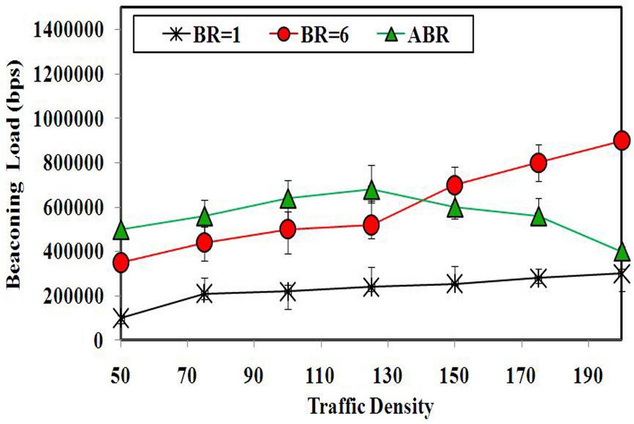

Fig. 6: demonstration of beaconing load variation with increased traffic density.

4.2.1 Impact of Traffic Density (Percentage of Directional Vehicles) with (10 % - 20 %) of Emergency Vehicles

First, we conducted our experiment based on 10 % of emergency vehicles. Figure 6 shows the increasing effects of traffic density on the Beaconing Load (BL) for the proposed ABR approach and fixed beaconing rate scheme (BRs are 1 and 6 beacon/second). Initially, at the scarce scenarios, the BL has values of 100, 350 and 498 kbps of BR=1, BR=6, and ABR respectively. Since BR_c of ABR is 9, it starts with a larger BL compared with the other fixed beaconing schemes. Notice that the BL trends of BR=1 and BR=6 are increasing proportionally as traffic density increases in the network. This is no surprise, since the frequency of beaconing is fixed as well as vehicular traffic density is increased, hence it causes more beaconing load in the network. On the contrary, as the number of node increases from 50-200, the BL trend of our ABR approach intelligently tunes with the traffic density until it reaches 400 kbps at 200 nodes. With increasing traffic density, the final destination of ABR is 400 kbps, which is lower than the starting point of 498 kbps. This observation proves that beaconing frequency generation has a higher impact than traffic density on the BL. This observation is accordant with analysis depicted in [12]. One thing that is noteworthy is the fact that there is a flip of BL (at 680 kbps) when traffic density varies from 102 to 128, and this is due to emergency vehicles maintaining their position accuracy.

By looking at Figure 7, which illustrates the effect of increasing traffic density (50-200) on the PA between vehicles, we observe that the trend of BR=1 and BR=6 are increasing in proportion to traffic density. It is a well known fact that increased traffic density leads to increased of cooperative awareness between vehicles within the same radio coverage [12]. This is due to the short distance between neighbour nodes in the vicinity zone as well as fixed BR on a specified value. On the other hand, our ABR approach consistently tunes the PA between vehicles with traffic density. Initially, the ABR approach starts from 0.46, and this value is then smoothly reduced to 0.32 at approximately 104 nodes of traffic density. This is because the value of BR is reduced adaptively with traffic density. However, we note a transition toward increasing PA values at a traffic density of 123 nodes. As it can also be seen, when the number of nodes is 50 or 200, the value of PA is 0.46 or 0.4467 respectively. This behaviour is due to reducing the frequency of beacon generation as the number of node increases. In addition, the impact of changing the beacon rate on probability of awareness is more effective than increasing traffic density.

Overall, in Figure 6, at fixed BRs (1 and 6 beacon/second), the observed BL trends are increasing while ABR approach is consistently tuning itself with the vehicular environment characteristics. The performance of ABR shows an average bandwidth gain of 380.2858 kbps over fixed beacon rate at maximum 200 nodes, with a travel speed 18 meter/second. In Figure 7, we have demonstrated that although the number of nodes is increased in the simulation field, the trend of PA is reduced to 0.4467.

In the second round of the experiment, we increase the generation ratio of emergency vehicles to (20 %). Figure 8 illustrates the BL versus traffic density. Since fixed BRs generation does not depend on the emergency status of vehicles, it remains on the same trend. In comparison with 10 % emergency vehicle generation, the ABR approach suffers from BL on the average of 24.9843 kbps. However, the ABR still has lower BL

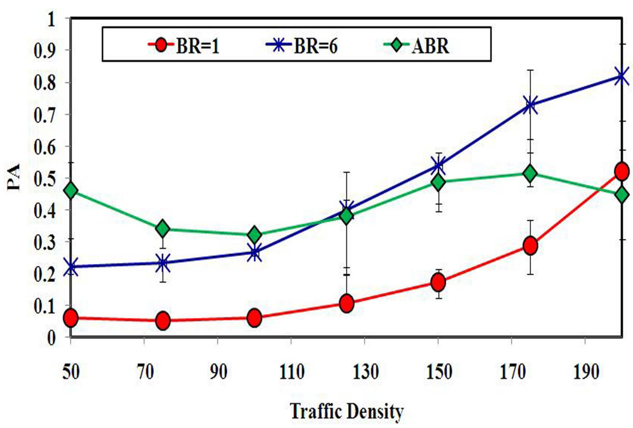

Fig. 7: The probability of cooperative awareness variation with increased traffic density.

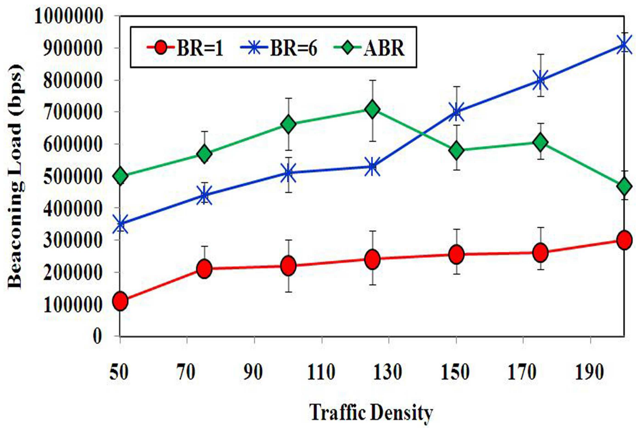

Fig. 8: Beaconing load with respect to traffic density for different value of fixed beaconing and ABR approach.

compared with fixed beaconing schemes. Recall that the ABR approach is based on the fuzzy inference system and one of the inputs is emergency status of vehicles. As the status of a vehicle is changed to emergency, its BL increases to maintain fresh knowledge status between neighbouring vehicles.

Now considering the PA metric, since emergency vehicles need high accuracy of neighbour nodes, it increases the BR and yields higher cooperative awareness. By looking at Figure 9, where the probability of awareness is plotted versus traffic density, we observe that precisely this is occurring. For all traffic densities (50-200), we notice an increase (compared with Figure 7) of the PA.

4.2.2 Impact of Channel Shadowing with 10% of Emergency Vehicles

In this section, we wanted to observe the performance of ABR approach under log-normal shadowing channel model. Thus, we use the same simulation settings as shown before, modeling the channel as a lossy channel by using log-normal shadow fading. Shadowing effect states that received signal power fluctuates in the presence of an object which obstructs the propagation path between transmitter and receiver. The received power fluctuates with "log-normal" distribution about the mean distance-dependent value [21]. The shadowing model is given by:

$$PL(d)[dB] = PL(d_0) + 10 \times \log \frac{d}{d_0} + X_\sigma \tag{5}$$

Where $PL(d)$ is the path loss at distance d between transmitter and receiver, $PL(d0)$ is the average path loss at a reference distance is $(d0)$, n is the path loss exponent and X_σ is a zero mean Gaussian distributed random variable with standard deviation σ. The values of path loss exponent n=2.8 and reference distance d_0=0.4 are used for the shadowing propagation model. To evaluate the proposed ABR approach with different channel conditions, we set the shadow standard deviation σ to 2 and 8.

Figures 10 and 11 illustrates the impact of different standard deviation (σ=2 and 8) on the BL and PA respectively. Figure 10 shows that the proposed ABR approach with higher σ (8) offers lower BL than the small value of σ. Recall that a node can find BL by summing up all received beacons from neighbour nodes with its own transmitted beacon messages, combined with the fact that shadowing increase packet loss in the

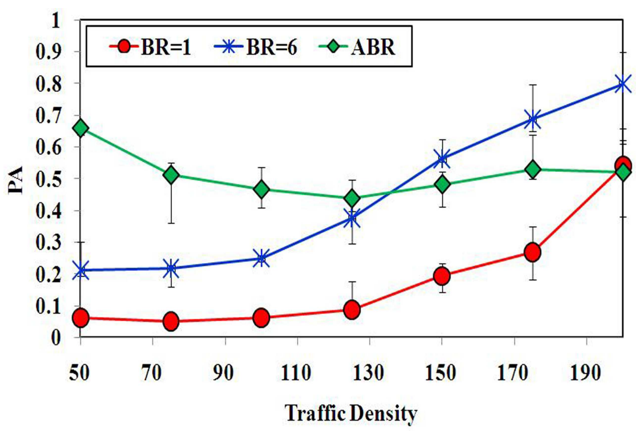

Fig. 9: Probability of awareness between vehicles with respect to traffic density.

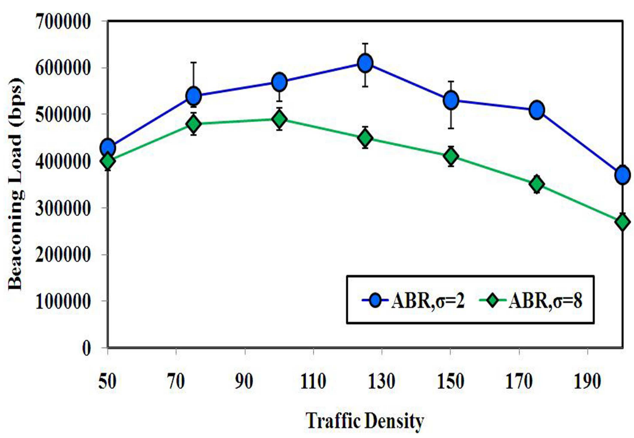

Fig. 10: Correlation between beaconing load and traffic density for different channel losses.

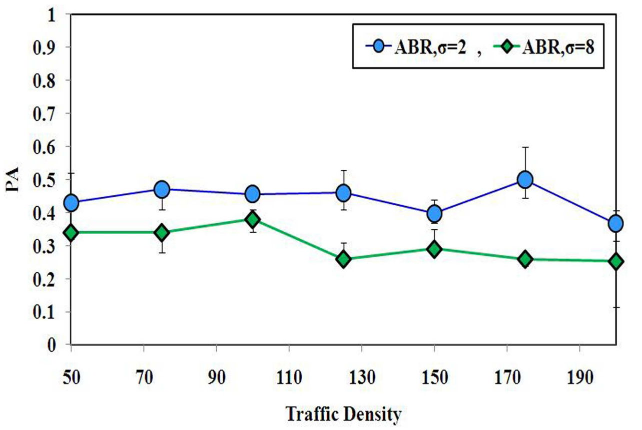

Fig. 11: Probability of awareness with respect to traffic density for $\sigma = 2$ and 8.

network by increasing link error rate. Therefore, we believe that this is due to increased beacon message losses that are transmitted from neighbour nodes. In addition, the beacon message is a broadcast traffic service, hence it cannot be retransmitted [22]. Accordingly the BL is reduced. Also, the average number of beacon messages that are lost due to channel shadowing is 69.39 kbps (this value is determined by calculating the difference of average beacon loss when σ is equal to 8 and 0).

Similarly, in Figure 11, the ABR approach with lower σ (2) performs better than the one with higher σ. The reason for this is the larger the σ of the Gaussian distributed variable X, the greater the error prone channel. This lossy channel leads to high beacon message losses in the network and hence outdated information about neighbour nodes. Therefore, when σ is 8, the vehicles have lower cooperative awareness than σ is equal to 2.

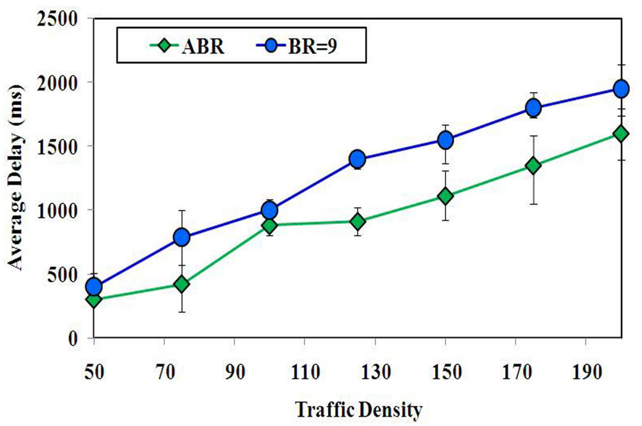

Fig. 12: Average end-to-end delay with respect to traffic density for the proposed ABR and BR=9 (10% of emergency vehicles and two ray are utilized).

Finally, Figure 12 illustrates the average packet delay as a function of vehicular density, with two ray ground model channel for ABR approach and fixed beaconing (BR=9) scheme.

Figure 12 confirms that our ABR approach offers lower average packet delay in comparison with constant beaconing scheme (BR=9). We coin the reasons why ABR approach has lower average packet delay. First, the ABR reactively tunes the beacon rate with traffic density and status of vehicles, hence it can reduce the overhead on the wireless channel between vehicles, which results in an increased opportunity for channel access and yields less delay. Second, at high network density (124-200 nodes), we can clearly see that the average delay per packet is higher. This is because the number of MAC layer collision increases when the network density increases. Moreover, in the fixed beaconing scheme, the trend of delay is higher due to high beacon processing delay [1]. Third, the ABR reduces packet loss due to collision or propagation, leading to smaller time duration for data transmission.

In addition, since the average time required by the fuzzy inference system to change the beaconing rate is 5.46 ms (this time tightly depends upon computer performance), its low computation time and overhead makes the proposed adaptive beaconing approach in vehicular networks feasible. Moreover, advances in chip manufacturing technology have made it practical to embed fuzzy decision making systems in hardware chips. Therefore, it is feasible that the implementation of our fuzzy logic based ABR approach, from software and hardware perspectives, promises to be of low complexity.

5 Conclusions

In this article, we proposed a fuzzy logic based adaptive beaconing rate control approach called ABR to tune the frequency of beaconing rate in response to vehicular traffic characteristics. This adaptive feature of the ABR approach makes it suitable for rapid arrival and departure characteristics of vehicular networks (sparse and dense scenarios). Simulations using a realistic city scenario have shown that the ABR approach- in contrast to a fixed beaconing scheme -compromises between beaconing load and cooperative awareness in different vehicular densities and emergency ratios. That is, we also showed that beaconing load is reduced on the cost of cooperative awareness between vehicles, if channel error is considered. We are currently working to optimize- us-

[1] This is the time spent in contention or accessing the channel.

ing swarm intelligent techniques- the membership functions of fuzzy variables to tune their fuzzy set with high dynamic vehicular networks.

References

1. Wireless acess for vehicular environment (wave), December 2010. http://www.standards.its.dot.gov/fact sheet.asp f=80.
2. E. M. van Eenennaam, W.K. Wolterink, G. Karagiannis, and G. Heijenk. Exploring the solution space of beaconing in vanets. In *Vehicular Networking Conference (VNC)*, pages 1–8. IEEE, 2009.
3. M. Torrent-Moreno, P. Santi, and H. Hartenstein. Distributed fair transmit power adjustment for vehicular ad hoc networks. In *3rd Annual IEEE Communications Society on Sensor and Ad Hoc Communications and Networks.*, volume 2, pages 479–488. IEEE, 2007.
4. J. Nzouonta, N. Rajgure, G. Wang, and C. Borcea. Vanet routing on city roads using real-time vehicular traffic information. *IEEE Transactions on Vehicular Technology*, 58(7):3609–3626, 2009.
5. R. Barr. *An efficient, unifying approach to simulation using virtual machines.* PhD thesis, Citeseer, 2004.
6. M. Artimy. Local density estimation and dynamic transmission-range assignment in vehicular ad hoc networks. *IEEE Transactions on Intelligent Transportation Systems*, 8(3):400–412, 2007.
7. L. Yang, J. Guo, and Y. Wu. Channel adaptive one hop broadcasting for vanets. In *11th International IEEE Conference on Intelligent Transportation Systems*, pages 369–374, 2008.
8. E. M. van Eenennaam, G. Karagiannis, and G. Heijenk. Towards scalable beaconing in vanets. In *FOURTH ERCIM WORKSHOP ON EMOBILITY*, pages 103–108, 2010.
9. S. Rezaei, R. Sengupta, H. Krishnan, X. Guan, and P. Student. Adaptive communication scheme for cooperative active safety system, 2008.
10. S. Rezaei, R. Sengupta, H. Krishnan, and X. Guan. Reducing the communication required by dsrc-based vehicle safety systems. In *IEEE Intelligent Transportation Systems Conference (ITSC)*, pages 361–366, 2007.
11. R. Fukui, H. Koike, and H. Okada. Dynamic integrated transmission control(ditrac) over inter-vehicle communications in its. In *IEEE Vehicular Technology Conference*, volume 1, pages 483–487, 2002.
12. R.K. Schmidt, T. Leinmuller, E. Schoch, F. Kargl, and G. Schafer. Exploration of adaptive beaconing for efficient intervehicle safety communication. *IEEE Network*, 24(1):14–19, 2010.
13. C.J. Huang, I.F. Chen, K.W. Hu, H.Y. Shen, Y.J. Chen, and D.X. Yang. A load balancing and congestion-avoidance routing mechanism for teal-time traffic over vehicular networks. *Journal of Universal Computer Science*, 15(13):2506–2527, 2009.
14. E.H. Mamdani. Application of fuzzy logic to approximate reasoning using linguistic synthesis. *IEEE Transactions on Computers*, pages 1182–1191, 1977.
15. B.S. Kerner. *The physics of traffic: empirical freeway pattern features, engineering applications, and theory.* Springer Verlag, 2004.
16. M. Myllyniemi, J. Vehkapera, and J. Peltola. Fuzzy logic-based cross-layer controller for wireless video transmission. In *12th IEEE Symposium on Computers and Communications*, pages 21–26, 2007.
17. jfuzzylogic, December 2010. http://jfuzzylogic.sourceforge.
18. D.R. Choffnes and F.E. Bustamante. An integrated mobility and traffic model for vehicular wireless networks. In *Proceedings of the 2nd ACM international workshop on Vehicular ad hoc networks*, page 78. ACM, 2005.
19. Tiger,tiger line and tiger related products. u.s. census bureau, December 2010. http://www.census.gov/geo/www/tiger/.
20. J. Mittag, F. Thomas, J. Harri, and H. Hartenstein. A comparison of single-and multi-hop beaconing in vanets. In *Proceedings of the sixth ACM international workshop on VehiculAr InterNETworking*, pages 69–78. ACM, 2009.
21. T.S. Rappaport. *Wireless communications: principles and practice.* Prentice Hall PTR New Jersey, 1996.
22. J. Villalón, P. Cuenca, and L. Orozco-Barbosa. Efficient joint unicast/multicast transmission over ieee 802.11e wlans. *Wireless and Mobile Networking*, pages 109–121, 2008.

Kayhan Zrar Ghafoor is currently a PhD candidate studying in the Department of Computer Networks and Communications, Universiti Teknologi Malaysia, Johor, Malaysia. Kayhan received his B.Sc degree in Electrical Engineering and M.Sc degree in Computer Science/Remote Monitoring System in 2003 and 2006 respectively. His current research interests include routing over Vehicular Ad Hoc Networks and Tactical Wireless Networks, as well as Artificial Intelligence and network coding applications. He has been as a reviewer of IJ of Wireless Personal Communications, IJ of Vehicular Technology, IAJ of Information Technology, IJ of Network Protocols and Algorithms as well as ISCI 2011 international conference. He is a member of IEEE Communications Society and International Association of Engineers (IAENG).

Kamalrulnizam Abu Bakar obtained his PhD degree from Aston University (Birmingham, UK) in 2004. Currently, he is associate professor in Computer Science at Universiti Teknologi Malaysia (Malaysia) and member of the Pervasive Computing research group. He involves in several research projects and is the referee for many scientific journals and conferences. His specialization includes mobile and wireless computing, information security and grid computing.

Martijn van Eenennaam received the B.Sc. and M.Sc. degrees in Telematics from University of Twente, The Netherlands, in 2007 and 2008 respectively. He is currently a Ph.D. candidate at University of Twente. His research interests include VANETs, flooding strategies and beaconing schemes and he is active in various projects concerning intelligent vehicles (C,MM,N, Connect and Drive, and the Grand Cooperative Driving Challenge).

R. H. Khokhar did his M.S in Statistics from University of the Punjab, Lahore, Pakistan. He received his M.S in Computer Science from Preston University, Pakistan. He received his second M.S in Computer Science by research from Universiti Teknologi Malaysia, Malaysia. Currently, he is doing his PhD in Computer Science at Universiti Teknologi Malaysia. His areas of interest are geographical routing and realistic propagation modelling in Vehicular Ad hoc Network.

Alberto J. Gonzalez received his B.Sc degree in telecommunication engineering, M.Sc. (Hons.) degree in Telecommunication Engineering and Management and M.Sc. degree in telematics in 2006, 2007 and 2009 respectively from the Universitat Politecnica de Catalunya (UPC), Barecelona, Spain. He joined the Department of Telematics Engineering in 2006 as research fellow. Since 2004 is collaborating with the i2CAT Foundation (Barcelona, Spain) in research and project management tasks. Participant of Euro-NF since 2008. His research interests include multimedia content adaptation, heterogeneous environments, peer-to-peer, video transmission, error resilience, multiple description video coding and network coding.