Cooperative Network for Vehicular Communications: Game Theoretic Distribution of Reward among Contributing Vehicles

M. Bilal, P. M. L. Chan, and W. Khan

Abstract— Vehicular Ad-hoc Networks (VANET) have gained significant interest in industry and academia for their ability for improving driver safety, comfort and entertainment services while on the road. . Due to the requirements for VANET for handling high mobility, movement in a special pattern, frequent network partitions, and intermittent network connectivity, the service provision, routing of messages and other VANET related goals are harder to achieve. In this paper, game theoretic concepts are applied on VANET routing for vehicles especially Emergency Vehicles (EV), to efficiently route the vehicle from a source to destination. A probabilistic route selection mechanism is designed by conditioning on density, number of junctions and number of traffic lights. The vehicle route clearance is also performed by enabling the vehicles on the road to share warning message. The level of cooperation by other vehicles in clearing the route is calculated by employing Expectation Maximization (EM) algorithm which is very well known for computing the maximum likelihood estimates when data is hidden/missing. Finally, the reward is distributed among each vehicle using the game theoretic concept called the Shapley Value. This is novel as the system ensures that the route is cleared for the emergency vehicle efficiently through a reward payment scheme.

Index Terms—VANETs; Game Theory; Reward Distribution; Classification; Expectation Maximization; Shapley Value; Probabilistic Analysis; Bayesian Analysis.

I. BACKGROUND AND REVIEW

VANETS are of very interesting nature and have gained importance in past decade with the development of new protocols dedicated to vehicular communication. The logic behind VANETs is to frequently form/reform the groups of communicating vehicles in order to provide on-road safety and security. Therefore, publicly targeted aims of VANETs are to

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Wasiq Khan is a final year PhD student at the University of Bradford, UK. His research interests are in speech recognition, wireless communications, and artificial intelligence. email: wkhan6@bradford.ac.uk improve the driving behaviour and to reduce the number of fatalities for which the protocols are being developed very rapidly. Most of the previous research is based on improved message delivery techniques between vehicles and infrastructures in order to reduce message collision and drop rate. This is very helpful as it strengthens the ability of vehicular networks and provides chances for practical implementation keeping in mind the high associated deployment costs. However, the main aim still revolves around improved and safe driving behaviour for which all the protocols are being developed. Wireless Access in Vehicular Environments (WAVE) standard [1] is a detailed standard sponsored by Intelligent Transportation System (ITS) that is being developed and improved for the past decade. This standard provides many opportunities for researchers to work on different VANET related topics for example networking services, resource management and security and safety.

There are many organizations and bodies jointly working on VANETs at present and some also proposed test beds for vehicular communication. Car-to-Car Consortium (C2CC) [2] provide a detailed list of the projects related to vehicular networks and actively plays an important role in organising VANETs related events. Fleetnet [3] is also a German based project carried out from 2000-2003 in which a wireless multihop ad hoc network for inter vehicle communication was developed to improve the driver's and passenger's safety and comfort. Cooperative Intersection Collision Avoidance System (CISAS) [4] focused on the development and demonstration of cooperative intersection collision avoidance system for both violations and gaps. A Europe based initiative called Intelligent Car Initiative (ICI) [5] launched by the European Commission Information Society in 2006 to remove bottlenecks in rolling out intelligent systems and to speed the development of smarter, safer and cleaner transport for Europe.

Some work in reference to cooperative driving also focuses on cooperative message relay and reward payment to cooperative drivers. Most of it includes the incentive based systems for cooperatively broadcasting and forwarding of the message within the network. A game theoretic cooperative stimulus protocol for Mobile Ad hoc Networks (MANETs) is proposed in [9] where 'The Core' is used to distribute the cost incurred for message relay equally among the nodes based on

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the amount of energy consumed by each node. Since wireless nodes in MANETs are battery constrained, they are considered as rational trying to save their battery life. Based on their consumption of energy and computations, the authors select a best route to forward the message where the aim is to reduce the amount of cost incurred to successfully transfer the message.

Another related work in [10] focused on the cooperation in VANETs offered by the vehicles in order to relay the message. The battery constraint is not considered as an issue in their work since vehicles are not battery constrained unlike MANETs. The vehicles are prevented from cheating by introducing an incentive scheme for those vehicles which successfully receive a number of copies of the same message from their neighbours. The focus in their paper is on improved message delivery among vehicles using a game theoretic concept called 'The Core'.

[26] consider the distance from the source to the destination location as a decision parameter and the route selection process is repeated iteratively at each intersection. This is similar to the algorithm proposed in this paper. However, the proposed algorithm does not only consider the static distance parameter into account. Live traffic information obtained from the road-side units and the junctions and traffic lights on each route between the intersections are taken into account. This is helpful in deciding at each intersection which route is the most economical based on real time information. In order to reduce the complexity and the overhead of the route selection algorithm, the selection is performed at each new intersection where a vehicle is responsible for choosing one road section from a limited number of given choices.

[27] also proposed a labeling algorithm for best route selection where the problem is considered as a closed loop adaptive shortest-path routing problem (CASPRP) with the objective of identifying only the immediate links instead of whole path. Similar to [26], [27] also do not use live traffic information and the number of turns in the form of traffic lights and junctions. As a conclusion, the advantage of proposed algorithm over these algorithms lies in using the live information as well as the distance from the source to the destination for the purpose of deciding the most suitable route.

In addition to the cooperative routing, efficient message routing is also an important aspect of cooperative driving and emergency situations. The drivers en-route are required to be aware of the route selected by the emergency vehicle. This further requires efficient broadcast of the message among these drivers. The broadcast of the message is one of the most studied topic of vehicular networks to date and there is a large body of literature proposing broadcasting techniques. For example [28] propose an efficient broadcast of the message with the vision of a smart city. A semi broadcasting technique is proposed in [29] where the aim is to reduce the congestion in dense environments by selecting clusters of vehicles and strictly limited forwarder vehicles of the message between those clusters. Time delay sensitive protocols are also proposed which obtain similarity with the proposed work in this paper in terms of efficiently informing the vehicles enroute [30, 31]. However, unlike these protocols, the proposed work is largely focused on cooperative behaviour of drivers and route selection by emergency vehicle in order to improve the emergency services.

The distinction between the literature and proposed work is the use of game theoretic concepts and probabilistic route selection. The emergency services are considered very common and important in all areas and the time sensitive emergency services should be efficient and collision free. There have also been some initiatives proposed for improved driving behaviour and emergency services on the road such as [6, 7, 8, 11]. However, in most of the proposed work, the deployment of speed humps and use of specified roads for the EVs have been emphasized. For example in most of the game theoretic vehicle routing protocols, the focus has been on message reception rate, battery power and the use of less dense roads. The importance of other route clearance parameters such as traffic lights, junctions and the cooperation of drivers en-route have not been considered in any of the related work to the best of authors' knowledge.

The paper is organized as follows: Section 2 explains the network architecture. Section 3 explains the design of cooperative algorithm that is further divided into subparts. Before the algorithm, a detailed explanation is provided which explains how the network is expressed as a VANET game and what are the important considerations to be taken into account from game theoretic point of view. Section 4 provides the performance evaluation of the concepts implemented in this paper and finally the paper is concluded in section 5.

II. COOPERATIVE VANET ARCHITECTURE

The main aim of this work is to improve the emergency services, therefore there is the necessity to focus on efficient route selection and also the cooperation from other vehicles. In normal situations, the drivers cooperate and clear the route by listening to the siren which is not always achievable. In dense scenarios, because of the unidirectional siren and short distance between EV and other vehicles, it is sometimes not possible for the drivers to know the direction the EV is approaching which makes it difficult to react in the required time since they have limited maneuverability. Therefore, the traffic may be unintentionally disrupted or collisions may occur. In order to reduce these risks, a warning message broadcast by the EV may help informing the drivers about its location and direction well before they are required to react. This can help clearing the route beforehand and is possible by offering the drivers an incentive to be cooperative. Due to the rationality of the humans, this offer can impose cooperation among them where they can gain the reward by cooperating marginally. Game theory is a strong mathematical tool that is used in different research fields to study the nature of human acts where agreements or conflicts between different parties exist. Therefore, we chose game theoretic concept called 'The

Shapley Value' to provide the best estimate of the reward to be paid to each driver based on their marginal contribution. The marginal contribution of each player is a very important component of this scenario for which the iterative EM algorithm is applied. This provides further clarification of the amount of the reward to be paid to each driver.

In addition to the cooperative game theoretic concepts, a quick route selection mechanism for EV based on real time situations can also help reduce the service time and improve the performance of EV. For this purpose, a probabilistic route selection algorithm is also proposed in this paper which is used to select the best route based on live traffic, number of junctions and number of traffic lights on that route. This algorithm is flexible to include other parameters and provide the solution based on combined Bayesian analysis on all of them. For live information, it is necessary that the vehicle must acquire the information from main control authority for example Traffic Control Authority (TCC) also recommended in other related research [10]. The total gain or value is assumed to be offered by the EV (through TCC) and always greater than the cost incurred by all vehicles. The cost is taken as the time spent by each vehicle to clear the route in the presence of other vehicles and efforts in terms of receiving the emergency message, storing it in its storage space and forwarding it. The functionality of this scenario includes three different parties; the EV, TCC and vehicles on the route having following assumptions which are necessary for any VANET;

- 1) The EV shall be supported with the Global Positioning System (GPS) to determine its position in the network .
- 2) The On-Board Unit (OBU) of EV shall be mounted with the Dedicated Short Range Communication (DSRC) technology for wireless communication with other vehicles.
- 3) The EV shall broadcast the emergency message to all vehicles within its transmission range while it moves on the route.
- 4) The TCC shall provide the live traffic information to EV on different possible routes from which a route can be selected.
- 5) The Reward distribution algorithm shall be able to operate in real time from junction to junction as the EV moves on the roads and broadcasts the messages to vehicles on the routes.
- 6)Both route selection algorithm and reward distribution algorithm shall be scalable and shall be able to operate on different routes other than selected for this work.
- 7) The marginal contribution is fairly calculated for each vehicle that cooperates with the EV.

From the above requirements and assumptions, it is clear that all three entities are active entities in the network functioning fully throughout the emergency service provision. Similar to other cooperative VANETs, The VANET game is represented as a combination of intersections/junctions for the vehicles (nodes). Edges between the nodes represent road sections. The node and edge objects are represented by a frame structure, where a node frame stores all the information of crossroads/junctions and the link frame stores information about the road segment between two different communicating nodes. Because of the compactness of the graphical representation of the game, the required number of parameters for both the game theory and traffic perspective are dependent on the size of largest local neighbourhood of every driver in the network.

The network consists of OBUs and Road-Side Units (RSUs) in a dense or sparse traffic environment. Several research works have promoted the use of WAVE mode Basic Service Set (WBSS) for vehicular networks [13, 14, 15]. Here, an OBU should operate on the control channel after entering into the VANET environment to gather necessary network information. It has to establish a WBSS to confirm its existence in the network and to communicate with other nodes. For this purpose, it has to periodically broadcast Wave-mode Service Announcement (WSA) frame over the control channel. After attaching to the network, the RSU or OBU is required to broadcast these announcements within the network to inform other OBUs about the services it provides (e.g., road conditions, accident warning message etc). The service provider OBU is responsible for advertising the services to other OBUs before performing the actual communication and for that purpose, is required to register its Provider Service ID over the control channel (PSID). The PSID is used by other OBUs to acquire services and communicate with other OBUs. For each OBU, the user settings bind the PSID to those services offered by the service provider OBU or RSU (in VANET game, the OBU is the service advertiser).



Figure 1: Network Architecture for VANET

Figure 1 shows the overall network architecture of VANET consisting of vehicles, EV and TCC. The vehicles acquire their positions though the GPS and this information is used for the EV to calculate its distance from that vehicle at the time when the message was received from that vehicle. The OBU of EV communicates with the TCC to receive the route related information that is traffic, number of junctions and number of traffic lights. The EV also broadcasts the warning message to

the vehicles on its route and maintains a list of all those vehicles which receive the message and reply with their position and direction.

III. ALGORITHM DESIGN

This section is divided into three tasks which are route selection, coalition formation and reward distribution. These tasks are explained in a sequence which starts from the route selection, followed by coalition formation of cooperating vehicles and finally distributes the reward to each vehicle in the coalition. The important part of the coalition formation and reward distribution stage is that they are performed from junction to junction as the EV follows the selected route. This reduces the complexity of calculations and increases the efficiency of the system. The tasks are explained below

A. Probabilistic Route Selection

It is necessary for a routing protocol to take the salient characteristics of the network into account and include almost such as vehicle-to-vehicle all possibilities (V2V) communication in both sparse and dense conditions and also vehicle-to-infrastructure (V2I) communication. As such, the protocol must have the ability to support the mobility of vehicles, the positioning of fast vehicles and data exchange in high dynamic network. [25] provide a qualitative comparison of routing protocols for VANETs by classifying them into three sets of categories of criteria which are objectives, characteristics and assumptions. In their work, they compared well known protocols from last decade and classified them into different categories based on above criteria. For more details, the reader is referred to their paper.

Following the criteria, this paper is also classified into a hybrid category where it is designed for the objective of providing improved emergency services using both V2V and V2I communication. The characteristics based feature of this work is that it uses the terminology of gathering real time information from TCC and maintaining the positions of vehicles in a list in order to distribute the reward based on their marginal contribution. The real time information received from the TCC includes live traffic, number of junctions and number of traffic lights. The route as a sequence of junctions having the highest probability is chosen as the suitable route. The assumptions based criterion enforces the use of GPS to acquire the position and attach it in the message. This is helpful in calculating the marginal contribution of each vehicle when it receives the warning message from EV and replies back by attaching its position and direction in the reply.

The parameters in this paper are evaluated using Bayesian analysis [12] that expresses the relation between conditional probabilities which need not have information about the other probability in the same workspace. In a VANET game, the conditional probabilities are applied on available routes based on the parameters that are associated to every route separately. According to Bayes theorem, the probability for certain events in the presence of alternative events is as follows:

$$P\left(A/B\right) = \frac{P\left(B/A\right)P\left(A\right)}{P\left(B\right)} \tag{1}$$

Where P(A) is the prior probability that is independent of B, $P(\mathbf{B})$ is the marginal probability independent of information about A, P(A/B) is the posterior probability that is dependent on B's information and P(B/A) is the likelihood of B that depends on A's information. Using (1) the probability of the routes to be selected can be obtained according to traffic, number of traffic lights and the number of junctions/turns that are denoted as R_i^t , R_i^l and R_i^j respectively where i is the route number to be evaluated. It is clear that the number of traffic lights and number of junctions are not the probabilistic values. However, the decision on route selection together with the traffic density is based on real measurements. Also, the likelihood is not a probability distribution over the parameters, and its integral with respect to parameters does not (necessarily) equals one. The likelihoods and priors are provided in this section based on real time values associated to each route.

Traffic density affects the driving behaviour in terms of the speed of the vehicle and the possible deviations to other possible routes. At different times of the day, the traffic density of the roads changes especially during peak hours. This information has the highest priority in the proposed model as it influences the accuracy of traffic checks on each route. Even if the live traffic information is available to EV, the traffic density alone is not a complete solution for route selection due to the effect of the other two parameters on the driver's behaviour. Suppose the EV has selected a route based only on the traffic density. There may be another route that has a slightly higher traffic density but with less number of cross junctions or traffic lights, which would make that route more desirable.

Another important point is the number of turns to be made which is similar to the number of traffic lights to be traversed. However the difference between both the criteria is the variation in the speed of the vehicle. A route may be clear for the EV before it reaches the turn but this may still cause disruption for the EV as it will have to slow down when it arrives at the junction. This is the reason why the number of junctions to be traversed by the EV has the second highest priority in route selection, followed by the number of traffic lights. Based on these explanations, the posterior is calculated for each route which is the product of three posteriors.

If there are n different routes in the VANET, the prior selection probability of each route can be defined as 1/n. With the prior information on traffic density, the number of traffic lights and the number of junctions on route i, the likelihood of the EV to choose that route can be calculated which can be used to calculate the posterior using (1). The general equations for posterior probability for any possible route i to be chosen based on traffic, number of traffic lights and number of junctions/turns is as follows:

$$P(R_i | R_i') = \frac{P(R_i' | R_i) P(R_i)}{P(R')}$$
⁽²⁾

$$P(R_i | R_i^l) = \frac{P(R_i^l | R_i) P(R_i)}{P(R^l)}$$
⁽³⁾

$$P(R_i | R_i^j) = \frac{P(R_i^j | R_i) P(R_i)}{P(R^j)}$$
⁽⁴⁾

Where $P(R_i'|R_i)$, $P(R_i^j|R_i)$ and $P(R_i'|R_i)$ are the likelihoods and are calculated as follows.

$$P(R_i^t | R_i) \propto \frac{1}{2\pi\sigma_t} \exp\left(-\frac{|t(R_i)|^2}{2\sigma_t^2}\right)$$

Where

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$$t(R_{i}) = \begin{cases} 4 & if |R_{i}^{t} - A^{t}| = 0\\ \frac{1}{|R_{i}^{t} - A^{t}|} & if R_{i}^{t} - A^{t} < 0\\ \frac{4}{|R_{i}^{t} - A^{t}|} & if R_{i}^{t} - A^{t} > 0 \end{cases}, A^{t} = \frac{\#vehicles}{\#routes}$$
$$P(R_{i}^{j}|R_{i}) \propto \frac{1}{2\pi\sigma_{j}} \exp\left(-\frac{|j(R_{i})|^{2}}{2\sigma_{j}^{2}}\right)$$

Where

$$j(R_i) = \begin{cases} 4 & \text{if } |R_i^j - A^j| = 0\\ \frac{1}{|R_i^j - A^j|} & \text{if } R_i^j - A^j < 0\\ \frac{4}{|R_i^j - A^j|} & \text{if } R_i^j - A^j > 0 \end{cases}, A^j = \frac{\# \text{ junctions}}{\# \text{ routes}} \end{cases}$$
$$P(R_i^j | R_i) \propto \frac{1}{2\pi\sigma_i} \exp\left(-\frac{|l(R_i)|^2}{2\sigma_i^2}\right)$$

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Where

$$l(R_{i}) = \begin{cases} 4 & if |R_{i}^{l} - A^{l}| = 0\\ \frac{1}{|R_{i}^{l} - A^{l}|} & if R_{i}^{l} - A^{l} < 0\\ \frac{4}{|R_{i}^{l} - A^{l}|} & if R_{i}^{l} - A^{l} > 0 \end{cases}, A^{l} = \frac{\#lights}{\#routes}$$

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and $\sigma_t = \sigma_j = \sigma_l = 2$ and $P(R_i) = \frac{1}{\# routes}$ The first terms in $t(R_i)$, $j(R_i)$ and $l(R_i)$ are set to 4 in

case if the traffic, junctions or lights on a route is equal to the average traffic, junctions or lights respectively. These quantities are set to greater than 1 because of the denominators in likelihoods. Smaller numerator values cause higher likelihood which makes it difficult to distinguish between higher posterior probabilities from lower ones. The EV is required to organize the values received from TCC in the matrix form and assign the weights to all possible routes based on the traffic density along with the number of cross junctions and number of turns on each route. From Figure 2, all the possible routes from a start point (BTC) to an end point (BRI) are obtained from the adjacency matrix, which contains a $n \times n$ matrix consisting of all junctions along with the information edge (road segment) from one junction to other connecting junctions.



Figure 2: Possible routes based on adjacency matrix for nodes 1-8

For clarification and easier manipulation of data, the intersections are numbered from source to destination in Figure 2. The two dimensional values belong to the correspondence of the parameters on a specific junction with other junction. For example, in the above adjacency matrix, the value 1 in the third row and sixth column represents the connection of Junction 3 with Junction 6. This means there is a direct connection between junctions 3 and 6. The matrix contains positive values for those intersections which are connected to each other by roads and this is similar to a graphical game in which nodes are connected to other nodes with edges to indicate that there is direct connection between the nodes. The graph can be bi-directional, which means that traffic on both sides can affect the performance of the EV. In this paper, the graph taken for experiments is bidirectional allowing traffic from both ends to affect the performance of EV.

It is important to know the behaviour of the probability distributions for varying parameters for which some sample experiments were performed from low to high traffic density. Similarly, the experiments were performed to check the behaviour of the distributions of other two parameters which are junctions and traffic signals. For these sample experiments, the low values were set to 0 and high values were set 1 for each parameter. The likelihoods for routes with variable parameters calculated using above equations are provided in the following figures (from Figure 3 (a) to (c)). Note the values are shown in terms of units where

0 = Very low density, 0.5 = Medium density and 1 = Very high density



Figure 3: (a) Probability of route \dot{i} given the density (b) Probability of route \dot{i} given the No. of traffic lights (c) Probability of route \dot{i} given the No. of junctions

The posterior for each parameter is calculated by multiplying the likelihoods with prior probabilities given above. The desired output is the single entity which must provide the maximum posterior for a route to be selected as the best route. Therefore, the posteriors obtained from above three parameters are multiplied and the maximum posterior is chosen using

$$R_{s} = \arg \max \prod_{i=1}^{n} \left(P\left(R_{i}^{\prime} | R_{i}\right) P\left(R_{i}^{j} | R_{i}\right) P\left(R_{i}^{\prime} | R_{i}\right) \right) \quad (5)$$

Where R_s is the suitable route selected for the EV to traverse, and i is the route number.

B. The Coalition Formation

The next important task after route selection is to impose cooperation by offering reward in terms of fuel credits. The selection of vehicles which helped clearing the route and associating them to coalitions of different types is of not less importance in this research. Due to the dynamic nature of VANETs, the properties of each vehicle change over time. Moreover, the vehicles on or near the junctions or crossing roads may change their directions and new vehicles may enter the route which the EV has chosen. These properties are unpredictable and cause uncertainty when assigning vehicles to coalition. For this purpose, hidden information about each vehicle is required by the EV such as speed, position, direction and their distance from the nearest junction. It may not be possible for every vehicle to attach its distance from the nearest junction/signal in their reply due to the length of the road, its position and the range in which it can broadcast the message. Therefore, the coalition formation in this paper is proposed from junction to junction where the EV broadcasts the emergency message to all vehicles en-route to receive replies from all contributing vehicles with position and directional information.

In this paper, the classical Expectation Maximization (EM) algorithm is used to form coalitions. There is a large body of literature utilizing the features of EM algorithm in a range of fields, especially related to classification [18, 23], Image Processing [21] and Artificial Intelligence [19, 20, 22]. The difference between EM in this paper and other classification

techniques is the information that is missing in the scenario and used to assign each vehicle a class. For example, traditional k-means clustering algorithm creates the clusters based on Euclidean distance of each data point to the centroids which are prior information. Also the number of clusters to be created is given as a prior in k-means algorithm. Dbscan [18] also separates the clusters based on Euclidean distance but without providing the desired number of clusters to be generated as prior. However, the main component of cluster formation process in both techniques is the distance between centroids and each data point whereas in VANETs, there are other missing parameters to be included in the coalition formation. This, for example can include how far the vehicle is from junction at the time when emergency vehicle is approaching, what is the direction, speed of that vehicle? All this information is required to decide the amount of contribution of each vehicle. The EV moves from one junction/signal to another and records the replies from all vehicles on its way and applies EM for coalition formation, and the same procedure is applied again from the current junction/signal to the next proposed by the route selection process. In the experiments, two road segments having the angle $\theta \ge 25$ or a road segment having a bend with $\theta \ge 25$ is considered to have a junction or braking point where the vehicles have to slow down. Further details of this are given in the results section. The aim of the EM is to assign each vehicle to a coalition given its position, direction and speed. The steps of the algorithm are given below

1. Initialize three types of coalitions $\{C_1, C_2, C_3\}$ using $\{1/n, 1/n, 1/n\}$ weights equal and $\Lambda = diag(\Delta d_1, \Delta d_2, \Delta d_3, d)$. Where n = 3 is the desired number of classes, Δd_1 is the distance of a vehicle from start junction, Δd_2 is the distance of a from mid vehicle road (calculated as (Start + End)/2) and Δd_3 is the distance of a vehicle from end junction. Initial values are diag(5.5,5.5) which are updated using the Maximisation step of EM algorithm (step 3 below) The prior given to the algorithm is $\theta = (\mathbf{P}_{V_{k}}, \mathbf{P}_{E}, \mathbf{P}_{SJ}, \mathbf{P}_{MJ}, \mathbf{P}_{EJ})$. Where \mathbf{P}_{V_k} is the position of kth contributing vehicle on the road, \mathbf{P}_E is the position of EV at the time when the reply was received by kth vehicle, \mathbf{P}_{SJ} is the position of the start junction/signal, \mathbf{P}_{MJ} is the position of mid road and \mathbf{P}_{EJ} is the position of end junction/signal. \mathbf{P}_{SJ} , \mathbf{P}_{MJ} and \mathbf{P}_{EJ} are stationary.

2. E-Step: Calculate the Likelihood of a contributing vehicle V_k on the road belonging to a specific coalition using the following

$$L\langle C_i | \Lambda, \theta \rangle = \frac{1}{2\pi |\Lambda|} \exp\left(-\frac{1}{2} (F\theta_{i+2} (V_k, EV)) \Lambda^{-1} (F\theta_{i+2} (V_k, EV))^T\right)$$
(6)

Where

$$F\theta_{i+2} = \left[f\theta_{i+2}(V_k) \quad f\theta_{i+2}(EV) \quad f_E(V_k) \quad \vec{d}_k \right]$$

$$f\theta_{i+2}(V_k) = \sqrt{(\theta_{i+2}(x) - V_k(x))^2 + (\theta_{i+2}(y) - V_k(y))^2}$$

$$f\theta_{i+2}(EV) = \sqrt{(\theta_{i+2}(x) - EV(x))^2 + (\theta_{i+2}(y) - EV(y))^2}$$
(8)

$$f_E(V_k) = \sqrt{(V_k(x) - EV(x))^2 + (V_k(y) - EV(y))^2}$$
(9)

 d_k = direction of Vehicle V_k

The maximum likelihood estimate is then given by

$$\gamma_{k} = \frac{L\langle C_{i} | \Lambda, \theta \rangle}{\sum_{j=1}^{n} L\langle C_{j} | \Lambda, \theta \rangle}$$
(10)

3. M-Step: Update the parameters in Λ to predict the increase in likelihood using

$$\begin{split} \Lambda = diag \!\!\left(\sqrt{\!\frac{\left(\sum\limits_{i}\prod\limits_{i=1}^{n}\Delta d_{1} \times L\langle C_{i}|\Lambda, \theta \rangle\right)^{2}}{\sum\limits_{j=1}^{n}L\langle C_{j}|\Lambda, \theta \rangle}}, \sqrt{\frac{\left(\sum\limits_{i}\prod\limits_{i=1}^{n}\Delta d_{2} \times L\langle C_{i}|\Lambda, \theta \rangle\right)^{2}}{\sum\limits_{j=1}^{n}L\langle C_{j}|\Lambda, \theta \rangle}}, \\ \sqrt{\frac{\left(\sum\limits_{i}\prod\limits_{i=1}^{n}\Delta d_{3} \times L\langle C_{i}|\Lambda, \theta \rangle\right)^{2}}{\sum\limits_{j=1}^{n}L\langle C_{j}|\Lambda, \theta \rangle}}, \sqrt{\left(d_{k}-d_{E}\right)^{2}}} \right) \end{split}$$

 Assign each vehicle a class which provides the maximum posterior probability using

$$\arg\max\prod_{k=1}^{n}\gamma_{k} \tag{11}$$

5. Check for convergence, if not return to 2, end otherwise

Thus, the aim is to maximize the maximum likelihood estimate γ_k in step 2 and achieve its maximized value until the algorithm converges. The results of the EM algorithm applied on Figure 8(b) are given in Performance Evaluation section.

C. Game Theoretic Reward Distribution

This section provides a basis for distributing the reward among contributing vehicles using the game theoretic concepts. In order to proceed with how Shapley Value is applied in VANET game scenario, it is important to explain how the VANET is expressed as a game and what strategies are available to drivers while driving to cooperate with the EV. After forming the coalitions using EM algorithm, the important question is how to distribute the overall value among various coalitions in the system. One solution to this issue is the bargaining among the players to determine the distribution of the overall value v(N) among the players. The marginal

contribution of a player i in the game is given by:

$$MC_i = v(N) - v(N \setminus \{i\})$$
⁽¹²⁾

Where v(N) is the value of grand coalition and $v(N \setminus \{i\})$ is the value of grand coalition when player *i* is not included. An axiomatic solution for allocating the collective benefit or cost among the players in the game is by assuming the existence of an outside authority to interpret that the value is a Shapley value denoted by Φ [11]. The Shapley value is based on four axioms, namely, efficiency, symmetry, additivity and dummy. A game is efficient if the addition of the Shapley values of all players results in the sum of the whole game. Symmetry means that the players receive the same payoff if they are in different subsets of the game as long as they contribute. Dummy means that if a player doesn't contribute to the game, she will not receive any benefit. Finally, additivity means that players get the same payoff whether they contribute to the game or work individually.

The Shapley value is the unique solution to the measure of utility of players in a game that always exists and satisfies all four axioms mentioned above. Recalling the coalitional game of $N = \{1, 2, 3, ..., n\}$ players and v characteristic function from the set of all coalitions to set of real numbers R with $v(\emptyset) = 0$, where v(S) is the total payoff a coalition S receives in the game, the Shapley value is defined by an operator that assigns each player in the coalition an expected marginal contribution by considering all the possible orderings of the players in that coalition. With the probability of a player *i* chosen randomly for each permutation of *n*!, the marginal contribution of player *i* in the game is defined by

$$\phi_i(v) = \frac{1}{n!} \sum_{S \subset A \setminus \{i\}} (v(S \cup \{i\}) - v(S))$$
(11)

Where n is the number of players in the grand coalition, s is the number of coalition (a number specifying the number of vehicles from one intersection to another in VANET game). On the basis of equation 13, Shapley assigns a marginal contribution to every player in the coalition and results in the fairness of the distribution of the gain the coalition is capable to achieve. The expected distribution of the overall payoff for each player i in the game can be achieved from 13 as follows:

$$\phi_i(v) = \sum_{s=0}^{n-1} \frac{s!(n-s-1)!}{n!} \sum_{S \subset A \setminus \{i\}} \left(v(S \cup \{i\}) - v(S) \right)$$
(14)

Where s is the number of players in coalition S preceding player i. In the context of multiplayer cooperative games for VANETs, a set A of n agents exists, where each agent has a strategy set S_i from where it can pick a strategy $s_i \in S_i$. A vector of strategies $s \in S$ determines the outcome for each player, where in general, the outcomes for different players are different. A player may prefer some strategy over the others because of the outcomes of a particular strategy. For example, a player *i* weakly prefers S_1 over S_2 if S_1 yields better outcome or equally good outcome as S_2 . In this VANET game, the players (drivers) have two main strategies, which is either S_1 = Cooperate or S_2 = Refuse. The players strongly prefer S_1 over S_2 because S_1 strictly yields the outcome that is better than the outcome yielded by S_2 . Now these players are divided into coalitions on the roads. The preferences of players on strategies is an important step and the simplest way to specify preferences is by assigning, for each player, a value of each outcome. In some games it is natural to think of the values as payoffs to players and in others as the costs incurred by the players.

Since the number of players in VANET game is very large, the players are divided into coalitions in which they interact with each other to generate a value that depends on their coalition S. The set of possible outcomes of cooperation among the players in $S \subseteq A$ is denoted by v(S), where each outcome is denoted by a vector R^{s} whose *i* th component specifies the utility that the player $i \in S$ derives in this outcome. This type of game with utility function V is called the cooperative game with non-transferrable utilities (NTU). However, in this paper, cooperative game with transferrable utilities (TU) is implemented, where the value generated by a coalition can be divided in an arbitrary way among the players in S. In other words, a TU game is defined by specifying a function $v: 2^A \mapsto \mathbf{R}$ which gives the value $v(S) \in \mathbf{R}$ generated by each coalition S. The set of all possible in such outcomes а game is defined as $v(S) = \{x \in \mathbb{R}^S : \sum_{i \in S} x_i \le v(S)\}$, which means that the payoff of each player in the coalition sums up to the overall value generated by the coalition and sum of payoffs of all players in S is less than or equal to v(S).

For simplicity, a road section of a small length with only three vehicles is chosen as an example. The same criteria can be used for games of large structures with large number of players similar to the VANET game. However for very large games, NTU assumption seems more promising since the marginal contribution of each player is usually unknown and the utility function does not increase exponentially. The following example is based on TU assumption as the number of players involved is very less. Some more examples with larger structures are given in performance evaluation section. In this example, it is assumed that three vehicles are on a road section with traffic lights, where vehicle A is approaching a traffic light and vehicles B and C are in a normal driving condition with no effective change in the speed, unlike vehicle A. Using EM algorithm, it can be seen in Figure 4, that the coalition which A joins has the higher value because

of its position that is very near to the traffic signal and it is harder for it to clear the route quickly compared to vehicle B and C.



Figure 4: Cooperation of A, B, and C according to their positions

The game is initially given monetary units where each player contributes 4 units when it is not in any coalition. The overall value of the game is $v(N) = 2^3 = 8$. According to the above scenario the value generated by all possible coalitions and the marginal contribution from each player while joining a coalition are given below.

$$v(A) = 4, v(B) = 4, v(C) = 4, v(AB) = 6, v(BC) = 4, v(AC) = 6, v(ABC) = 2^3 = 8$$

The marginal contributions of three players A, B and C in all possible orderings of the players are

 $v(A) = 4, MC_{A} = v(A) - v(\emptyset) = 4$ $v(B) = 4, MC_{B} = v(B) - v(\emptyset) = 4$ $v(C) = 4, MC_{C} = v(C) - v(\emptyset) = 4$ $v(AB) = 6, MC_{A} = v(AB) - v(B) = 2 \text{ and } MC_{B} = v(AB) - v(A) = 2$ $v(BC) = 4, MC_{B} = v(BC) - v(C) = 0 \text{ and } MC_{C} = v(BC) - v(B) = 0$ $v(AC) = 6, MC_{A} = v(AC) - v(C) = 2 \text{ and } MC_{C} = v(AC) - v(A) = 2$ $v(ABC) = 8, MC_{A} = v(ABC) - v(BC) = 4, MC_{B} = v(ABC) - v(AC) = 2$ and $MC_{C} = v(ABC) - v(AB) = 2$

Where MC_A , MC_B and MC_C are the marginal contributions of players A, B, and C respectively and obtained using equation 8. The unique Shapley value for each player are obtained as follows

$$\phi_A = \frac{10}{3}, \phi_B = \frac{7}{3}, \phi_C = \frac{7}{3}$$

And $\phi_A + \phi_B + \phi_C = v(N) = 8$

From the above values for each player, the first axiom of Shapley value is satisfied where v(N) is v(ABC) = 8.

D. Shapley Value Evaluation in Special Conditions

This section, being not a part of algorithm design, contributes equally in explaining the last stage of the algorithm which is a part of reward distribution. In addition to the solution for coalitional gain, the players (drivers) have the responsibility to agree on a joint collaborative action set by the TCC within the game. This, for example, could occur at intersections with traffic lights where the vehicles have to obey the traffic signals rules as well as cooperate with the EV by clearing the route. This creates a scenario known as correlated equilibrium, where issues such as stability of coalitions and payoff distributions are not critical, since all the vehicles are already bound by traffic rules and regulations.

The correlated equilibrium in a VANET game defines the difference between the payoff of a player on road section and that of a player stopped at a traffic signal. The traffic signal in the following example provides a shared randomization that can be viewed as a binary random variable, alternatively displayed as red and green signal to orthogonal streets. A traffic signal situation is considered where two players are driving on orthogonal streets. The payoffs are supposed to capture the situation in which these two drivers speed towards the intersection. Both players have two options: 'Stop' or 'Go'. The two pure Nash equilibria in this game are based on the two strategies in which one player stops and the other goes, and vice versa. These Nash equilibria create the following two probability distributions on pure strategy profiles:

	siop	80	siop	80	
stop	(0	1)	(0	0)	
go	0	0)	$\left(1\right)$	0)	

The row entry is for player 1 and the column entry is for player 2. Now, suppose that a trusted third party (traffic authority) draws from this distribution, and recommends to each player to play according to the outcome (randomization between (Stop, Go) and (Go, Stop)). If the upper right box in first matrix is chosen, e.g. the recommendation is that player 1 stop and player 2 go (i.e. green light for player 2). What is remarkable about this distribution of recommendations is that it is self-enforcing: A correlated equilibrium is a probability distribution $\{p_s\}$ on the strategy profiles that obeys the following conditions: For each player i, and every two different strategies j, j' of i, where j is the recommended strategy, the expected utility of playing j is no smaller than that of playing j': This can be expressed in words as a player having two strategies of 'Stop at red signal' and 'Go at red signal (break the rule)', according to correlated equilibrium, the recommendation is to 'Stop at red signal', then the payoff of stopping at red signal will be higher than the payoff of that player breaking the red traffic light signal. The mathematical form of this form of equilibrium is

$$\sum_{s \in S_{-i}} (u_{sj} - u_{sj'}) p_{sj} \ge 0$$
⁽¹⁵⁾

Here $s \in S_{-i}$ denotes the strategy profiles of all players except player i; if $s \in S_{-i}$, s_j denotes the strategy profile in which player i plays j and others play s. Relating this property to the VANET traffic light example concludes that the inequality in Equation 15 strictly occurs in the game since all the drivers know their own components of outcomes for the strategy they play (Stop if the signal is red otherwise collision will occur, and go if signal is green otherwise collision might occur or traffic will be disturbed). For players in VANET game, if strategy j is to stop at the red signal and j' is to deviate, the utility u_s will result in better outcome than that of u_{s_j} . Therefore, in the context of the Nash Equilibria, the Correlated Equilibria generalize the Nash Equilibria and can be viewed as (possibly arbitrary) distributions $p(\vec{a})$ over joint actions satisfying a certain conditional property, where \vec{a} is denoted as the action played by a player in the game (Stop or go). From (15), the correlated equilibrium of VANET game states that the vehicles on traffic lights must satisfy the following condition

 $\forall i \in [1, \dots, n]: \mathbf{E}_{\vec{a} \sim p_{ai \rightarrow b}} \left[M_i(\vec{a}) \right] \geq \mathbf{E}_{\vec{a} \sim p_{ai \rightarrow b}} \left[M_i(\vec{a}[i: \neg b]) \right]$ (16) Where $E_{\vec{a} \sim P_{\vec{a}=\vec{b}}}[M_i(\vec{a})]$ is the expectation over those cases in which value $a_i = b$ is revealed to player *i* i.e. the expectation of a vehicle over obeying the rules and clearing the route and $E_{\vec{a} \sim P_{ai=b}} \left[M_i \left(\vec{a} [i: \neg b] \right) \right]$ is the expectation over same case but player deviates to play $a_i = \neg b$, i.e. by not obeying the rules and disrupting EV process. The important point to consider here is the situation when EV is approaching the intersection where the traffic light is red at that instance. The EV is allowed to play the action 'Go' even in the red signal. However the vehicles playing the action 'Stop' continue to believe the actions of the other players (stopped at the red signal as well as the players going at the green signal) and expect that the recommendations are self enforcing. In this VANET case, the players on the red signal reduce their distances between each other and attempt to clear a significant space for EV to play the 'go' action as shown in Figure 5



Figure 5: Variance of correlated equilibrium in emergency situation

In emergency case, the 'Stop' action concludes the welfare of all the players at four different sides of intersection that changes the payoff matrix of each player according to his/her action and variation of recommendation imposed by traffic authority for a small amount of time. The matrix given above becomes of the following form

	stop	go	stop	go
stop	(1	0)	(0	0)
go	0	0)	(1	0)

The Stop action for both players (upper left box in the first matrix) brings a better outcome for both of them when EV is

approaching the intersection. This guarantees that the intersection will most likely be space free for EV to 'Go' as the traffic from all the sides will be stopped (Figure 5). The upper right box in first matrix is also shown as better outcome for player 1 (player at red signal) since it's action is independent from player 2's action (player at green signal) so Stopping and clearing the route for EV will provide a better outcome for player 1 regardless of what action player 2 chooses. However in the simulations of this VANET game, player 2 is always recommended to 'Stop' to receive the better payoff due to the fact that the players are rational. The VANET game in the remaining sections is evaluated according to the Correlated Equilibrium on intersections.

E. Overall System Design Structure

Figure 6 shows the overall approach for route selection followed by the coalition handler and Shapley Value evaluator. As can be seen in the diagram, the algorithm is separated into two different phases; the route selection phase for EV and The Shapley Value Evaluation phase for cooperating vehicles. The route selection algorithm utilizes a probabilistic route selection model, whereas the Shapley Value evaluator uses the cooperative game theoretic concepts for fair reward distribution among cooperating vehicles. The input to the Shapley Value evaluator is provided by coalition handler which classifies each vehicle from previous junction to currently arrived junction using EM algorithm. The Shapley Value evaluator and coalition handler are also iterative processes which are performed at the arrival of EV at every new junction. The system is built by combining the functional entities and inter-relating their actions and their relationships with each other. The entities in this scenario are Location Information Provider (LIP), Route Information Provider (RIP) and Traffic Density Information Provider (TDIP).



Figure 6: Emergency Scenario Algorithm



A. Simulation Design

The city of Bradford is simulated in this work in which the EV is moving from the Bradford Town Centre (BTC) to the Bradford Royal Infirmary (BRI), which is approximately two miles. A terrain view of the proposed scenario has been taken from Google images between BTC and BRI. The terrain image has then been converted into a shape file format supported by EstiNet [13] for the purpose of network creation. This is required to reduce the simulated network creation time and to enable the use of exact values in terms of distance and position of each junction. Figure 7(a) shows the terrain view of simulated area from BTC to BRI. Figure 7(b) shows the converted .shp format of the terrain image.



Figure 7(a) Terrain view from BTC to BRI



(b) Shape file format for network structure creation



Figure 8(a): Sample Simulation Road structure

The road structure created from shape file is similar to the real road structure of the chosen scenario. This feature enables the realistic simulation of a real environment and collection of realistic results in the system. In addition, the tool enables the possibility of placing obstacles in the network so that the signal can be blocked or weakened due to the surrounding conditions e.g. buildings and trees and other objects which may cause interruption in the connection.

Figure 8 shows the structure of the network converted in Estinet which is used for experiments in this paper. The network consists of vehicles mounted with the DSRC technology IEEE 802.11p that can cover the range of up to 1000 meters and can provide communication between high speed vehicles with the speeds of up to 120mph. The simulator supports different types of standards for vehicular communications, including IEEE 802.11a/b/p, GPRS, WiMAX support and 802.11p. This road structure is created from a real world road structure of a city in United Kingdom in order to evaluate the performance of the protocol in realistic scenarios. Figure 8(b) shows the complete structure of the network along with the vehicles with IEEE 802.11p standard deployed on the roads. The numbers of vehicles on the roads has been varied which are given in Table 1.

The Shapley Value evaluation for the scenario is performed in MATLAB (2011b) which can process the factorial of up to 170 therefore proving that it can calculate the results for coalitions of sizes of up to 170 vehicles each. However, the analysis in this paper is not at that complicated level and none of the coalitions is of size more than 30. Therefore, although the coalitions are varied from size 4 to 23 in this paper, the scenarios with highly dense traffic conditions can still be analysed without computation errors. A diagram of the simulated graphical VANET along with the important parameters such as nodes, edges, start point (BTC), end point (BRI), and possible routes to traverse are shown in Figure 9.



Figure 9: Graphical structure of VANET game



(b) VANET structure with vehicles deployed on roads

B. Simulation Parameters

To discover the best route to follow, the EV requires the traffic density, number of junctions, and number of traffic lights on each route that is used to decide between different available routes. These parameters are provided by TCC. There are 11 different main routes from BTC to BRI given to the EV in simulation. The information provided to the EV about these routes includes the density, number of junctions, and number of traffic lights on each route. The values used in the simulation are given in Table 1

Table 1. Simulation	parameters for	emergency	scenario
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Route Number (Ri)	Traffic R_i^t	Number of junctions R_i^j	No. of Traffic Lights R_i^l
1	N = 102	7	5
2	N = 96	9	7
3	N = 49	6	5
4	N = 123	8	7
5	N = 132	10	7
6	N = 111	6	7
7	N = 75	8	9
8	N = 83	9	6
9	N = 92	8	6
10	N = 65	11	10
11	N = 57	8	8

C. Simulation Results

Route Selection

The results in this scenario heavily depend on the performance of the EV in terms of the time it takes to deliver the services. Also in addition to reducing the service delivery time, this section also deals with the cooperation of all the other vehicles based on the movement of the EV. In the beginning of the process, a whole route is selected containing a sequence of intersections based on three impact parameters discussed in the earlier sections. Continuous checks on every intersection based on these three parameters help EV obtain the latest real time traffic information on every road and select the most suitable route according to this real time information.

From Table 1, it can be seen that some routes strongly compete with each other for route selection. The most suitable route in VANET game is route number 3 because it is less

congested than all the other routes and contains less number of cross roads than route number 1,4,7,9, and 11. Table 2 gives the probabilities calculated for all the routes in the network using 5.

Table 2: Probabilities for the competing routes						
Route	$P\left(\frac{R_i}{R_i}\right)$	$P\left(\frac{R_i}{R_i}\right)$	$P\left(\frac{R_i}{K}\right)$			
1	0.7730	0.7276	0.7712			
2	0.7143	0.0009	0.0088			
3	0.7957	0.7751	0.7712			
4	0.7926	0.0181	0.0088			
5	0.7938	0.2039	0.0088			
6	0.7880	0.7751	0.0088			
7	0.7953	0.0181	0.2583			
8	0.7935	0.0009	0.7022			
9	0.3771	0.0181	0.7022			

10

11

0.7956

0.7957

The individua	al posterior p	probabili	ties assigr	ned to ear	ach ro	oute
based on three	parameters	contain	different	values	than	the

0.4515

0.0181

0.4826

0.0088

ones given above in the table. This is because each route has its own posterior for three parameters which is independent of the posteriors of other routes and only dependent on the information provided by the TCC. This is given in the Figure (10) below followed by the joint posterior probability of each route in Figure 11 showing the best selected route as route 3.

Figure 12 compares travel time, in seconds, of the EV following a route selected by the probabilistic route selection model with the travel time of the EV when the other three competitive routes are chosen. In this figure, it can be seen that route 3 provides the best result since the EV consumes less time when using route 3 compared to the other routes to move from the source address to the destination address. This could be attributed to the fact that route 3 has the least number of junctions and traffic lights and also low traffic density. The simulation shows that choosing route 3 enables the EV to complete its journey in approximately 300 seconds, whereas the other competitive routes consumed on average approximately 400 seconds. Figure 13 shows the screenshots of the simulator where route selection model selects the next suitable junction from a sequence of junctions whenever the EV is at a reasonable distance from a junction/intersection (50 meters).







Figure 11: Best selected route using probabilistic route selection algorithm



Figure 12 Route Selection Model Performance

	emo©localhost:/usr/local/nctuns/bin 📃 + 🗙 🏹
<u>F</u> ile <u>E</u> dit <u>V</u> iew <u>T</u> ermi	I <u>H</u> elp
Car 127 open car pro Road structure path: job//cooperative.roa Read road structure Current Time: 20.0 Current Time: 22.0 Current Time: 23.0 Current Time: 23.0	Le fail. Use default value tome/nctuns/.nctuns/coordinator/workdir/nctuns-1304087164- structure cceed. sec Event#: <insert:4150, dequeue:4147,="" rest:614-<br="">sec Event#: <insert:4070, dequeue:4106,="" rest:614-<br="">sec Event#: <insert:4106, dequeue:4106,="" rest:614-<br="">sec Event#: <insert:4109, dequeue:4109,="" rest:614-<br="">sec Event#: <insert:4109, rest:614-<br="">sec Event#: <insert:4109,< td=""></insert:4109,<></insert:4109,></insert:4109,></insert:4109,></insert:4109,></insert:4109,></insert:4109,></insert:4109,></insert:4109,></insert:4109,></insert:4109,></insert:4109,></insert:4109,></insert:4109,></insert:4109,></insert:4109,></insert:4109,></insert:4109,></insert:4109,></insert:4109,></insert:4109,></insert:4109,></insert:4109,></insert:4109,></insert:4109,></insert:4109,></insert:4109,></insert:4109,></insert:4109,></insert:4109,></insert:4109,></insert:4109,></insert:4109,></insert:4109,></insert:4109,></insert:4109,></insert:4109,></insert:4109,></insert:4106,></insert:4070,></insert:4150,>
Current Time: 25.0 Current Time: 26.0 Current Time: 27.0 Junction information for I	sec Event#: <insert:3937, dequee:3958,="" rest:613=""> sec Event#: <insert:3930, dequee:3954,="" rest:613=""> sec Event#: <insert:3930, dequee:3959,="" rest:614=""> sec Event#: <insert:3958, dequee:3959,="" rest:613=""> -> Reaching junction 2 -> the next junction to go is junction 8, Please</insert:3958,></insert:3930,></insert:3930,></insert:3937,>
go straight on junction 2.	Junction 8 EV
Current Time: 30.0	sec Event#: <insert:3960, dequeue:3960,="" rest:614=""></insert:3960,>

Figure 13: Screenshot from coordinator window for next intersection prompt Coalition Formation and Reward Distribution

The vehicles on the selected route attempt to maintain the correlated equilibria by collaborating with EV. From junction to junction, EV obtains a list of vehicles which contribute in route clearance and also differentiates them into classes according to their level of contribution. The position, speed and direction of each vehicle play an important role in classifying itself in one of the classes which is then used to calculate the units of reward to be allocated to it. The cooperation is divided into three different monetary units which are 2, 3 and 4. The lowest is for vehicles which have higher speeds and located outside the reasonable range of junction/signal (>150 meters) at the time when received the message from EV and cleared the route.

Unit 3 is for vehicles which are in the same/opposite direction as that of EV and near the junction/signal to which the EV approaches but they are already leaving it with an additive increase in their speed. Unit 4 has the highest priority and cooperation value as it is assigned to those vehicles which are in a very close proximity of the junction/signal and in the direction approaching that junction/signal. These vehicles have very low speed and move in a dense environment with less chances of lane switch or route clearance. The application of EM algorithm for the classification of contributing vehicles in coalitions worked well in the scenario considered in this paper. On the route followed by the EV and the connecting road segments to the junction/signals traversed by the EV, the vehicles are classified into three possible classes and shown in Figure 14



In the above figure, there are three types of coalitions formed which are assigned different colors. It can be seen that only the vehicles which are affected by the EV are classified and they are classified based on their positions and directions. Also all the clusters are shown in the figure after one complete run of the simulation which means all clusters at each junction are present in the figure. The vehicles approaching or on the junctions are given the highest priority and colored as red. Some vehicles on the road sections are also colored red. This is because of the level of tolerance taken by the algorithm to separate the road segments from other road segments and consider them as separate junctions. As mentioned in the EM

algorithm $\theta \ge 25$ causes a braking point in the road segment, therefore the EM algorithm assigns higher priority to those vehicles which are closer to those braking points. After assigning the units to each vehicle from one junction/signal to another, the EV distributes the reward among all those vehicles using the Shapley Value. In order to avoid the complexity of calculations for the Shapley value, an example of 4 contributing vehicles (Ellipse 1 in Figure 14) is taken as a coalition on a road segment and their rewards based on the Shapley Value are calculated below. It is to be noted that the size of coalition at each step of reward distribution may be different resulting in different overall payoff to be paid.

v(A) = 2, v(B) = 4, v(C) = 4, v(D) = 2 v(AB) = 6, v(AC) = 6, v(AD) = 4, v(BC) = 8, v(BD) = 6, v(CD) = 6, v(ABC) = 10, v(ABD) = 8,v(BCD) = 10, v(CDA) = 8, v(ABCD) = 16

Efficient route selection may not be a complete solution as the EV may still encounter high traffic density in the selected route. In these cases, it is important that other vehicles in the road assist the EV by clearing the route for the EV. Here, the idea of cooperative networking and routing plays a vital role in enforcing vehicles on roads to change lanes, stop on side or even change their route. The complexity of the distribution mechanism depends on the size of coalition. However, the coalition size has been varied to check the accuracy of the Shapley Value evaluation. To save the space and avoid large calculations, the coalitions of size 4, 5 and 6 have been analysed in this section. However the algorithm can compute the values for a coalition size of up to 170 vehicles. The Shapley value showed the exact results regardless of the size of the coalition. The scenario with 6 (Ellipse 2 in Figure 14)



Figure 15: Shapley Value scenario with coalition size 6

The explanation of this sub coalition outputs, marginal contributions of players in the sub coalitions and Shapley value of each player in sub coalition are provided in Table 3. For the sake of simplicity, some of the orderings of the players of the given coalition S in the following table have been omitted

Table 3: Shapley Value results for contributing vehicles

	1.7				0			
S	v(S)	MC_A	MC_B	MC_C	MC_D	MC_E	MC_F	
A	2	2	-	-	-	-	-	
В	4	-	4	-	-	-	-	
С	4	-	-	4	-	-	-	
D	2	-	-	-	2	-	-	
Ε	4	2	-	-	-	4	-	
F	2	2	-	-	-	-	2	
ABCDE	12	2	4	4	2	4	2	
ABCDF	16	2	4	4	2	4	2	
ABCEF	14	2	4	4	-	4	2	
ABDEF	16	2	4	-	2	4	2	
ACDEF	14	2	4	4	2	4		
BCDEF	14	-	-	4	2		-	
ABCDEF	16	2	4	4	2	-		
	18	2	4				-	
		Shapley	Value	results				
Size=4		36/12	60/12	60/12	36/12			
No coalition		48/12	48/12	48/12	48/12			
Size=5								
No coalition		60/30	120/30	120/30	60/30	120/30		
Size=6		96/30	96/30	96/30	96/30	96/30		
No coalition		120/60	240/60	240/60	120/60	240/60	120/60	
		180/60	180/60	180/60	180/60	180/60	180/60	

In coalition of size 6, vehicles B, C and E are on the cross road whose marginal contributions are higher than the marginal contributions of A and D. From the above table, the addition of Shapley values of all players gives the value of coalition S, which is 12 for size=4, 16 for size=5, and 18 for size=6. ϕ_B , ϕ_C and ϕ_E are comparatively higher than ϕ_A and ϕ_D due to the positions of B, C and E. When compared to a system where no Shapley value is implemented, it can be seen that it is not possible to distinguish a contributing vehicle from a non-contributing vehicle. Therefore, the use of Shapley Value provides a good solution for distributing rewards in a VANET network.

V. CONCLUSION

The objective of this work is to design the protocol for efficient vehicle routing in vehicular network. The key parts of the vehicle routing are the route selection for the EV, and route clearance by cooperating vehicle on path. The vehicle route selection algorithm selects the most suitable route for the EV to follow using the Bayesian analysis. The benefit of this algorithm is it saves the EV's travel time from the source to the destination in order to deliver efficient time based services. The vehicles on the selected route also cooperate with the EV and clear its route before it approaches them. The game theoretic concepts for fair reward distribution showed improved results of the reward distribution among cooperating vehicles. The work proposed in this paper provides the foundation for some interesting and important aspects in vehicular networks.

A. Route Selection based on Predicted Information

Currently, the route and traffic information is assumed to be provided to the EV by traffic centre before it starts its journey from its source address to the destination address. The information can be exploited for use in case of emergency situations, for example, by using neural networks to predict traffic information on any route based on the time of the day using historical data. This will save network cost where the centralized RSUs will not be used for information exchange every time an emergency situation occurs.

B. Fair Reward Distribution

The cooperation level of each vehicle is measured in terms of units using its position at the emergency situation and the reward is then distributed among the vehicles. A vehicle on or approaching closely to junction/signal is given more importance and higher cooperation credits as the usual traffic on junctions/signals is higher than other road segments. Also, due to the dense surrounding environment, it is harder for a driver to locate the vehicle safely as well as to clear the route for EV. This concept aims to introduce credit based reward distribution system for vehicles which receive emergency warning message in advance and act prior to the arrival of EV. The EM algorithm classifying vehicles into different groups provides quick and efficient way of distributing the reward and improving traffic conditions.

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