A Novel Incentive Model for VANETs in Coalition Games

By Darshan Raajasekaran, Rishhabh Naik, Rohan Sequeira, Sudharsan Babu Srikanthan

Abstract

With the world moving towards the next generation of autonomous vehicles and on-board sensor networks, the need to exchange information and services has increased. Research in Vehicular Ad Hoc Networks (VANETs) has increased since 2016 with the primary goal of improving link stability, incentive protocols for link utility, etc. Research over the last couple of years has focused on game theoretical approach in VANETS through the introduction of coalitional games (with the core of focus on forming stable coalition structures). This research project has been an attempt to model our own incentive mechanism using reputation, reward and cost based utility function. In the coalition game approach, nodes are allowed to transfer between coalitions based on the characteristic (stability) function that we have defined. Payoff distributions have been modeled based on the new coalitions formed when nodes join a coalition.

Keywords

Mobile Ad Hoc Networks (MANETs), Vehicular Ad Hoc Networks (VANETs), Intelligent Transportation System (ITS), Coalition Structure Generation (CSG), V2V (vehicle to vehicle), Peer to peer (P2P), Loss Aversion, Nash Equilibrium, TU Game Theory.

Introduction

Vehicular Ad Hoc Networks (VANETs) are a specific case of Mobile Ad Hoc Networks (MANETs) in which vehicles are involved [1,2]. VANETs are different from traditional MANETS in the aspect that they have a highly dynamic topology with links being frequently disconnected and there being large variations in the link quality. They are also one of the key elements in the development of next generation Intelligent Transportation Systems (ITS). These systems provide a wide range of services such as packet content distribution, file and multimedia sharing and non-safety related information dissemination.

There are various applications in a wide range of scenarios for the vehicular ad hoc networks (VANETs) [1,2,3]. VANETs can enable simple one hop information dissemination of messages having crucial information about a node's cooperative awareness, and it can also enable multi-hop dissemination of information packed messages over very long distances. Since VANETs and MANETs are so similar, considering one was built from the other, their interest areas and applications also generally coincide, although there might be differences in few metrics involved, contingent on the application in question. One particular constraint in these models that need to be kept in mind is that the vehicles do not move in a random and haphazard fashion, instead they move in an organized and stable manner. Another factor that is being considered in the following applications is that the vehicles are restricted in their maximum range of free motion, that is, the vehicles are forced to move in a highway or motorway, and cannot, for instance, pull over.

This research project focuses solely on the non-safety applications of VANETS [2,4]. With the modelling of incentive protocols it is preferred that the mechanism is applied to packet content distribution, multimedia transmission among other non-safety applications. We seek to only design the protocol and model the distribution. The reward and payoff functions that are later discussed in this paper , can then be extended to TU games.

In the following section, we first summarize the work that has been done by other researchers and discuss the advantages and limitations of their models before seeking to define our functions.

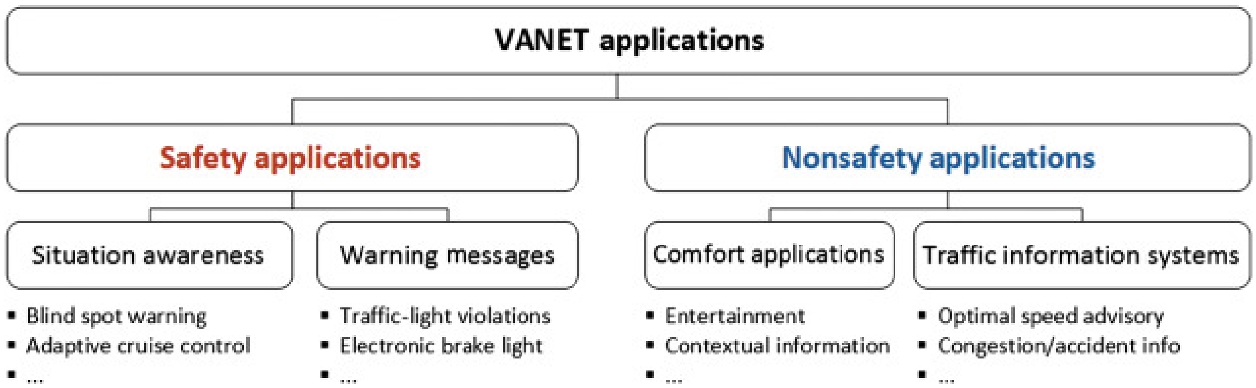

Fig 1. Table depicting VANET applications

Literature Survey

In the paper by Chengzhe Lai, Kuan Zhang, et. al., SIRC: A Secure Incentive Scheme for Reliable Cooperative Downloading in Highway VANETs [4], published in IEEE Transactions on Intelligent Transportation Systems Journal in 2017, the authors propose a secured incentivized plan which is aimed to attain a unbiased and consistent cooperative download mechanism in a vehicular ad hoc network (VANET). It essentially motivates proxy nodes to download a portion of a file and pass it on to the requesting node, and while forwarding it, the nodes receive an incentive for the transaction. To ensure that the transaction's security is strong and unfalliable and cooperation is truthful, there are routine checks set up virtually with its associated verifying electronic signature. To make sure that there is no cheating process involved after nodes get paid before the transaction even, the paper proposes that a part of the payment gets sent before the transaction and receives full payment only after the client recognizes and verifies that it has received the packets. The authors also specify that during the cooperative forwarding mechanism, a gain-sharing protocol is set up along with an iteratively adding Camenish-Lysyanskaya electronic signature should therefore increase cooperation and avert cheating and selfish nature of the nodes. An algorithm is defined to penalize the vehicles which are dishonest or do not contribute to the coalition. The paper also places major focus on testing the security prowess while not losing out on download speeds, with detailed simulations run in comparison with other technologies and modelling it to withstand security breaches such as injection or removal attack, free riding attack, submission refusal attack, denial of service (DOS) attacks and proves that it reigns supreme against them with minimal cryptographic computing and communicating problems.

In a paper by H. E. Manoochehri and R. Z. Wenkstern, Dynamic Coalition Structure Generation for Autonomous Connected Vehicles [5], published in IEEE International Conference on Agents (ICA) in 2017, the authors propose a decentralized and dynamic coalition structure generation (CSG) methodology to relay information between connected vehicles in vehicular ad-hoc networks (VANET). The clusters elect a cluster head, a deputy cluster head and also assign coalition ports (edge nodes capable of communicating with neighbor coalition). They've defined three states based on absolute difference between ideal coalition size and the current coalition size, specifically stable, internal stable (leaders communicate and decide whether to merge or not), and external stable (individual vehicles decide if splitting at the vehicle level would be beneficial).Our research on incentivized mechanisms for VANETs has been influenced by the research put forth by H.E. Manoochehri et. al. The advantage of this paper is that it considers real time parameters such as distance and relative speed while calculating utility.

In a paper by Selo Sulistyo, Sahirul Alam and Ronald Adrian, Coalitional Game Theoretical Approach for VANET Clustering to Improve SNR [6], published in Hindawi's Journal of Computer Networks and Communications in 2019, the authors propose a clustering method formed using coalitional game theory modelled for network management in VANET. Stability of the cluster is the primary metric on which the performance of a cluster is scored upon. Their model also focuses upon optimum link quality to enable high-speed transceiving. It aims to improve the average V2V (vehicle to vehicle) SNR (signal to noise ratio) and total channel capacity while simultaneously holding the cluster stable. They propose an iterative algorithm which seeks to model each vehicle forming clusters with other vehicles and depends upon V2V SNR, connection lifetime and relative speed between the vehicles.

In a research done by Walid Saad, Zhu Han, Merouane Debbah, et. al., at the University of Illinois at Urbana-Champaign in coordination with Research Council of Norway, Coalitional Game Theory for Communication Networks: A Tutorial [7], focuses on game theoretic cooperations, mainly coalitional games and their impacts and possible applications in wireless communication and networking. They classify the coalitional games in their research into three different types: canonical coalitional games, coalition formation games and coalitional graph games. They have classified the coalitions in such a way to make it more application oriented. For these three categories, the authors present their key properties, algorithms, math techniques, and ways for application in the real world.

In a paper by Jiaqi Liu, Shiyue Huang, Hucheng Xu, et. al., Cooperation Promotion from the Perspective of Behavioral Economics: An Incentive Mechanism Based on Loss Aversion in Vehicular Ad-Hoc Networks [8], published in MDPI Switzerland in 2020, the authors propose a loss-aversion based take on existing coalitional networks in vehicular ad-hoc networks. They assume a Gaussian distribution for the probability density function and integrate in parts to derive the expected utility of a node. The loss aversion is defined as an indicator function comparing the utility of the node's current coalition and the destination coalition. The advantage of this paper is that it effectively incorporates loss aversion mechanism into the utility function and develops an algorithm based on merge and split rules. The disadvantage of the paper is that the lack of a closed form expression for utility only specifies merge and split rules for entire coalitions, without considering preferences of a single vehicle.

In a paper by Auxeeliya Jesudoss, S.V. Kasmir Raja, Ashraph Sulaiman, Stimulating Truth-Telling and Cooperation among Nodes in VANETs through Payment and Punishment Scheme [9], published in Ad Hoc Networks in 2015, the authors define a Payment Punishment Scheme which can work well with existing coalition models to achieve optimum truth telling functionalities in iterative election process of nodes during clustering and incentivize standalone nodes to cooperate with each other to achieve best data transfer rates. Weights are calculated using Vickrey-Clarke-Groves model (VCG) in constant time intervals to elect a cluster head. To prevent cheating and misinformation, each node is assigned a utility function which it can increase by actively cooperating with other nodes in the coalition, data packets forwarding and also act as a watchdog using combined trust on importance factor (CIF), ie, monitor and report other nodes' performance.. The disadvantage of this paper is that it does not incorporate contributions of nodes to the coalition while calculating reputation, only considers votes.

In a paper by Yuxin Mao, Ping Zhu, et. al., A Game-Based Incentive Model for Service Cooperation in VANETs [10], published in the Concurrency and Computation: Practice and Experience online in Wiley in the year 2014, the authors have used a similar model as ours wherein they consider the situation of service requests and response of nodes in VANETs. The more the services provided by the node to other nodes in the coalition, the more services it receives. The goal of the authors is to support more reliable services in VANETs and they design incentive models for the same. They also provide game theoretical formulations for analysing the service cooperation in VANETs. The contribution of the node to the coalition is characterised by a contribution measure which is incremented at each time instant/slot by the payoff function. Service differentiation is achieved by introducing a probability measure defined for each node, which is proportional to the contribution of that node to the coalition. Hence, nodes with higher contributions will have a higher probability of service. The payoff function that is defined takes into account the cost of listening and replying to a service request. A connected graph is used to model the players in the coalition.

In a paper by Bridge Q. Zhao, John CS Lui, Dah-Ming Chiu, Analysis of Adaptive Incentive protocols for P2P Networks, published in IEEE Communications Society in 2009, the authors provide an generic analytical framework used to design and analyze a group of incentivizing protocols. They define a specific set of incentive protocols in which there is distributive learning between the peers participating in the coalition, and adapt their actions to the environment accordingly and then they also seek to evaluate the anticipated benefits and increase in performance and the sturdiness of the system configured with a specific incentivized protocol. The two models defined by the authors are Current-best Learning Model (CBLM) and Opportunistic Learning Model (OLM).

Overview of Model

We seek to design a mathematical model built on a novel reputation incentive protocol. We further extend this model to dynamic coalition structure generation while designing payoff functions when nodes transfer between coalitions.

Since, the nodes can be thought of as players that seek to maximize their own gain. There exist components to this game with the first being the a score assigned to the node/ player based on the ITS performance and contribution to the network/ coalition. Performance typically can be quantified using different approaches and we seek to relate it to the number of messages relayed by the network. This has been done because the application that we seek to accomplish is packet content distribution and the quality of service offered by the network will directly depend on the packets forwarded from nodes to the node that requests service. This parameter can be used to classify the nodes as selfish and unselfish. Typically, a node can be categorized as selfish when it only seeks to receive service and in the process does not forward/ relay messages requested by other nodes. Such nodes only seek to improve their own reception of content.

This is the driving factor behind the use of incentive models in game theory. Providing incentive to the nodes ensures some cooperation between different nodes in the network. This can further be extended to utility. Our utility function can be split into three parts; reputation, reward and cost on node levels and coalition level. The reputation is a measure that is directly proportional to the degree of cooperation with the other nodes, and is proportional to the number of messages relayed.

We infuse the concept of loss aversion while defining the reward gained by the node. The objective behind this is to maximize the rewards gained by the node and incentivising them to cross a predefined threshold of service by introducing an extra reward for crossing the threshold. This is similar to the Amazon shopping model wherein free delivery is given to consumers if they cross a certain purchasing threshold. From the concepts of behavioural economics, it is clear that the nodes will regard not getting the extra reward as a loss and the pain of that loss will be much greater than the pleasure of obtaining the reward.

This concept of loss aversion was introduced in the Cooperation Promotion from the Perspective of Behavioral Economics: An Incentive Mechanism Based on Loss Aversion in Vehicular Ad-Hoc Networks

[8]. The paper introduced loss aversion with the rudimentary utility function where an extra reward is given to a node when its reputation crosses a threshold. By the concept of loss aversion, nodes feel that if their reputation does not cross the threshold, the loss is much harder than the gain that they would have received. This indirect reward motivates the nodes to forward a significant portion of the message received, thereby improving the performance of the entire network. The third component of the utility function is the cost incurred. This cost occurs as a result of the power/energy spent in forwarding the messages of other nodes and the interference caused by the increase in the number of nodes in the coalition. This cost acts as a measure that prevent the nodes forming a grand coalition (i.e. all the nodes/players in the network are present in the same coalition).

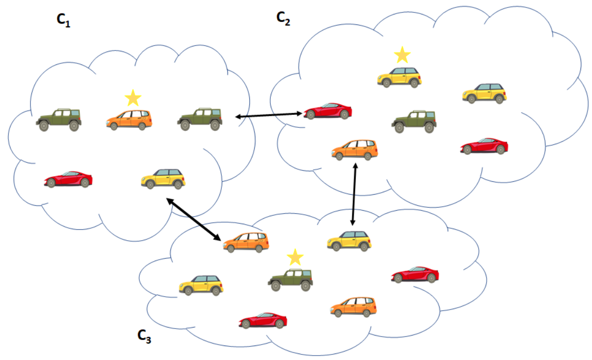

Fig 2. Depiction of coalition in VANETS and coalition ports communicating with each other

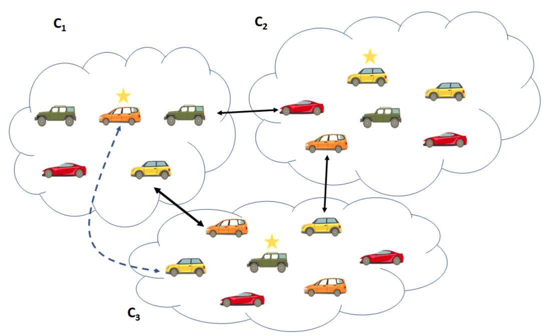

Fig 3. A node deciding to leave coalition C3 and join C1

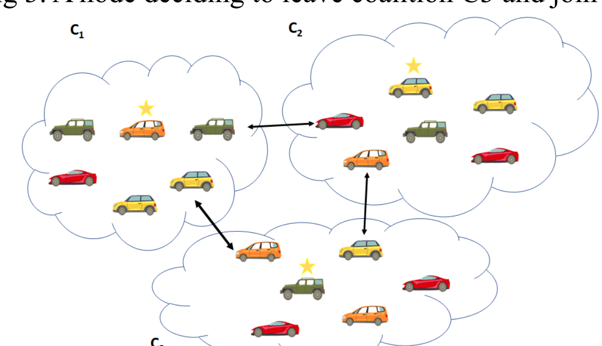

Fig 4. VANET setup after node X joins another coalition

The cost incurred by a node reduces its utility function. Cost is directly proportional to the number of nodes in the coalition. That is because as the number of nodes in the coalition increases , the interference increases due to more nodes transmitting within a smaller range which leads to packet loss. The cost per node is described as a function whose parameters of the number of messages requested. This can intivutely be described as the type of resource demanded by the nodes (essentially the node incurs a cost when it demands service from the other nodes). Therefore, along the reputation, reward and cost the number of messages can be thought of as the currency in the system. In order to collectively maximise their utility, the vehicle nodes form a coalition. For example in the case of video streaming, the vehicles can seek to improve their individual QoS by being in a coalition.

Coalitions

A coalition is basically an agreement between the vehicles wherein each vehicle stores the content of other vehicles and transfers it to the original vehicle at a later time. In the context of game theory, a coalition is a grouping of players in a game so as to ensure cooperation between them. Cooperative game theory assumes that groups of players, called coalitions, are the primary units of decision-making, and may enforce cooperative behavior. Consequently, cooperative games can be seen as a competition between coalitions of players, rather than between individual players.

TU Games are a category of cooperative games in which the utility is modelled as a transferable entity, for example bandwidth, as it can be allocated, deallocated and split between the players [12,13]. These games are generally easier to model and most of the game theoretic constructs are well defined for these kinds of games. NTU games on the other hand model the utility as a non transferable component, for example, SNR [14]. For this category of games, the analysis is somewhat more complicated than TU games. Hence, we use a TU model for this project. Now, that the utility function is described per node, we can seek to extend this to coalitions.

Cluster Head Selection

We propose that each coalition has its own cluster head. The advantage of this cluster head is to keep a track of the reputation values of each node in the coalition. This offers some mechanism to track the truth telling of the nodes. It also provides benefit during dynamic coalition formation when the merge and split is performed as a two stage process. In both cases, the nodes will inform the cluster head before leaving the coalition and similarly the nodes will request the cluster head before joining its coalition.

The selection of the cluster head will be done through an election process where all the nodes in the coalition will declare their weights. After all the nodes have declared their respective weights the cluster head will be chosen as the node that has the least weight. The weight is a function of various parameters associated with the nodes (microscopic properties which do not characterize the state of the channel). While the research project doesn't focus on the properties of the channel state, we model the weight on the sum of the relative euclidean distance between the node and all other nodes in the coalition, the relative velocity between the nodes and other nodes. The node with the lowest weight is elected as the cluster head. It is to be noted that the cluster head doesn't change rapidly. It is proposed that the cluster head node being connected to at least two other nodes, its status does not change. The formula is as follows:

$$W_i = -\kappa_1 D_i - \kappa_2 V_i + \kappa_3 M_i$$

D_i = relative distance of node 'i' in coalition 'S_m'
V_i = relative velocity of node 'i' in coalition 'S_m'

M_i = number of nodes within the range of node 'i' in coalition 'S_m'

κ_x= weighted constants

Incentive Mechanism

The reputation, reward and cost for every node in a coalition is being modelled, with the reputation is defined as the number if the ratio of the messages relayed by node i to node j to the messages relayed by node j to node i.

$$R_i^{S_m} = (\sum_{j \epsilon S_m} N_{f_{ij}} / \sum_{j \epsilon S_m} N_{f_{ji}})$$

The reward function is based on the loss aversion scheme. If the node's reputation crosses a certain threshold, then the node will receive an extra reward. The reward will be a constant multiplied by the difference between the number of messages forwarded and the set threshold. The indicator function ensures that the reward function is defined only for values of the when the reputation crosses the threshold and above.

$$\Re_i^{S_m} = \sigma * (\sum_{j \epsilon S_m} N_{f_{ij}} - \theta_{S_m}))^+ .1_{[\theta_{S_m}, \infty)}$$

The cost function for every node in a coalition is defined as a constant times the number of service requests issued by the node. We propose that as the number of requests increases the cost scales up. The value of gamma is defined in the simulation that we've executed in the following sections of the paper.

$$C_i^{S_m} = \gamma \sum_{j \epsilon S_m} N_{f_{ijreq}}$$

The utility function is defined as the sum of the reputation and reward function minus the cost incurred by the node. This ensures that the nodes that only request messages but do not relay messages are penalized thereby affecting the selfish nodes. The function provides a check on the selfish behaviour of the nodes promoting them to relay more messages in order to gain an extra reward. The utility function per node has been defined as follows:

$$U_i^{S_m} = R_i^{S_m} + \Re_i^{S_m} - C_i^{S_m}$$

Incentive Mechanism on Coalition Level

Since the model deals with coalitions, utility function has to be assigned on the coalition level. So, we seek to assign the reputation, reward and cost for the entire coalition. It is important to define these parameters as they form the basis to define the characteristic function of the coalition which quantifies the stability. The reputation for the coalition can be defined as the sum of the individual reputations of all the nodes .

$$R^{S_m} = \sum_{i \epsilon S_m} R_i^{S_m}$$

Similarly, the cost of a coalition scaling as the number of nodes in the coalition increases. With more nodes within close proximity the interference increases significantly and leads to an increase in cost. The cost function for the coalition is defined as follows:

$$C^{S_m} = \sum_{j \epsilon S_m} C_j^{S_m}$$

Similarly the reward follows the reputation, where on a coalition level it is defined as follows:

$$\Re^{S_m} = \sum_{i \epsilon S_m} \Re_i^{S_m}$$

Following the definition of the utility function as mentioned in the previous section, the utility function for the coalition is stated as:

$$U^{S_m} = R^{S_m} + \Re^{S_m} - C^{S_m}$$

We now define a stability (characteristic) function as a linear function of the relative speed, relative distance and the utility of a coalition as a whole. Note that this is on coalition level.This is useful as a preference relation can be defined based on this to help the node decide which coalition to join. For instance, if the node can join another coalition if by joining it increases the overall characteristic function of the new coalition. If there exists, more than one such coalitions preference relations are used.The preference relation is a binary relation that is transitive. If node 'i' prefers coalition 3 to coalition 4, that implies that the characteristic function when the node joins coalition 3 is more than the value of stability and if the node joined coalition 4. In general, higher the value of the stability function , better the coalition.

The transition of nodes from one coalition to another can be thought of as a two-stage process. Let's assume the node leaving the first coalition, in the first stage, we propose that the node will inform the cluster head, which in turn communicates with the neighboring cluster head of the node's intention. In the second stage, before the node seeks to join the coalition, we propose that it has to pay a portion of its reputation to the cluster head of the coalition that it seeks to join. This ensures that the cluster head is being paid for additional responsibility. It is a measure to prevent the nodes from constantly moving between the coalitions (as they lose a part of their reputation when joining a new coalition).

This can be seen from our definition of the characteristic function. We seek to keep the coalitions relatively stable. Meanwhile, as the number of nodes in a coalition increase, the cost increases thereby reduces the characteristic function.

$$v(S_m) = -\kappa_v V_{S_m} + \kappa_u U_{S_m} - \kappa_d D_{S_m}$$

V_s = relative speed of coalition 'S_m'
U_s = utility of coalition 'S_m'

D_s = relative distance of coalition 'S_m'

κ_x= weighted constants

The weights assigned to the characteristic function have to be such that the weight assigned to the utility function outweighs the sum of the weights assigned to the relative speed and velocity, The actual values can be determined empirically and we would seek to do it under the future scope.

Furthermore, the payoff function when the a node joins the coalition can be described as follows:

$$\Phi^{S_{m1_i},S_{m2}} = v(i^{S_{m1}} \cup S_{m2}) - v(S_{m2}*)$$

$v(S_{m2}*) = v(S_{m2})$ before node i joins coalition S_{m2}.

The above is the difference between the value of the new characteristic function after the node has joined and the value of the coalition before the node joined it. The payoff is divided equally among the members of the new coalition.

Stability of Coalitions

This cooperative game involves a set of players denoted by Ω = {1,...,N}. To analyse the proposed algorithm in terms of a coalition formation game, as per Huo et al. [16], the following conditions need to be satisfied.

Condition 1: Non-superadditivity

A game is said to be superadditive if the formation of bigger coalitions always results in better social utility (i.e. represented by the characteristic function), compared to being in smaller coalitions. In such types of games, the *grand coalition* (i.e. coalition consisting of all the players in the game) is always the optimal solution and all coalitional structures converge to the grand coalition [13]. The proposed game on the other hand, is non-superadditive. This is because of the inclusion of certain parameters like relative distance and velocity of the nodes in a coalition which would increase in the case of larger coalitions. Another factor that hinders the formation of larger coalitions is the interference among the different nodes in the coalitions as the number of messages would be larger which will lead to higher interference. In this case the cost function acts as a pull down function that seeks to limit the node payoffs and limits the size of the coalition. On account of the above factors, the proposed game is not super-additive.

Condition 2: The coalition structures do not converge to the grand coalition

The aforementioned limiting factors will always impose constraints on the coalition size and prevent the formation of the grand coalition. The utility of individual nodes in a coalition consists of a cost function that increases with the size of the coalition. In order to avoid incurring higher costs and obtaining reduced utilities, the nodes will try to form coalitions such that there is a trade off between the costs incurred and rewards obtained. The formation of the grand coalition goes against this objective [14,15]. Moreover, it is difficult for the cluster head to communicate with and manage the coalition in the case of a grand coalition. Hence, the vehicle nodes will always try to form an optimal structure that maximises the individual node payoffs in the presence of the limiting cost function, rather than forming a grand coalition.

Condition 3: The coalition structure is affected by the dynamic scenario

The proposed algorithm is an iterative one that seeks to converge to a final coalition structure that obtains the maximum social utility. The coalition utility in this case is also affected by dynamic factors such as the changes in relative speed and distance of the nodes in the coalition, the number of messages requested and serviced by the nodes and the entering and leaving of nodes in the coalition.

Condition 4: Coalition structure is restricted by some external factors in the game

Since there exists restrictions on the coalitional structure caused by external factors such as the relative distance and velocity of the nodes in the coalition. Moreover, the increase in size of the coalition leads to a higher cost function which is an additional constraint on the coalitional structure.

Since the proposed coalition formation strategy satisfies the above conditions, it is suitable to be modelled as a coalition formation game.

Convergence Analysis of the Proposed Algorithm

Nash equilibrium, or Nash stability, is the most efficient and commonly defined stability notion for a non-cooperative game consisting of two or more players. This equilibrium works under the assumption that no player can obtain better payoffs by unilaterally changing his/her strategy. Since our main objective is to show that under the proposed algorithm, the system converges to a stable coalitional structure, the notion of Nash stability is introduced and analysed. In other words, it is the maximum payoff that can be allocated to any player which is independent of the strategy of all other players. This notion, though primarily intended for non cooperative games, is applied to cooperative games to analyse the coalition formation in the perspective that, a stable coalition structure exists in which no node can obtain better payoffs by unilaterally changing its strategy which is in this case deciding to join or leave the current coalition structure.

New coalition structures are formed if and only if there exists at least one node 'i', that decides to change its coalition based on the proposed switch rule. Since the number of players involved in the game is always finite, the number of possible coalition structures that can be formed will always be finite. Hence, under the proposed switch rule, the vehicle nodes will iterate over all possible coalitions in a finite number of steps. Thus, there exists a non zero probability that the coalition structure will converge to a final structure Π_{final}. This implies that there exists a final coalition structure in which there does not exist any node that has the incentive to switch to other coalitions to maximize its payoff.

The final coalition structure Π_{final} *is Nash stable [12]*. This can be proved by contradiction. Consider that the final coalition structure Π_{final} is *not* Nash stable. This means that there exists another coalition $S_m \in \Pi_{final}$ and a node 'i', $i \notin S_m$, such that $v(S_m \cup i) > v(S_{\Pi final}\{i\})$. This means that when 'i' joins the new coalition S_m, it obtains a better social utility than in the original coalition. This contradicts the fact that Π_{final} is the final coalition structure. Hence, the final coalition structure Π_{final} is Nash stable.

Simulation

In order to validate our model and algorithms, we designed a controlled simulation using Python. We set the loop to run iteratively for every time instant, to count for delay time for activation of the algorithm and to ensure that the data received is accurate. We also normalize the maximum distance of transmission of a car from 200 meters to 20 units on the cartesian plane to ease mathematical analysis. We have set the radius of transmission to be 20 units. We then dynamically assigned the location of the various nodes in the coalition to be randomized on the cartesian plane, with padding given to ensure that each node is at a distance of at least 0.5 units away from one another.

The algorithm also models the coalition nodes such that at least a few nodes cannot communicate with one another directly, but have to transmit the information via another node. We then compute the Euclidean distance of each node from all other nodes, for example, if there are ‘n’ nodes in the coalition, then in order to elect the cluster head, we compute the Euclidean distance between node 1 and nodes 1-n and store them in a matrix, ie, a three dimensional array with dimension 1 representing the number of coalitions, dimension 2 representing cars in each coalition and dimension 3 representing the cars in the coalitions. To make the mathematical computation optimal, after running repeated simulations, we have empirically decided that the threshold for an activation function defining the ‘nearby’ or ‘far away’ characteristic would be 20 units and enables us to classify the Euclidean distance in a more orderly and legible fashion. Therefore, if a node is *nearby*, the activation function returns 1 as the value, and if a node is *far away*, then it returns 0. The values obtained are stored in a vector essentially denoting the adjacency matrix of each unique node in the coalition.

After the adjacency matrix is obtained, we use the Dijkstra’s Shortest Path Algorithm to find the shortest path from one node to another keeping the number of hops as the major factor during calculation. The program is modelled in a specific way, essentially ensuring that each node has to send a message, but the destination node is randomized at each time instant. Furthermore, the algorithm specifies another iterative loop designed to increment the message arrays. According to our model, we then compute the ratio of the messages forwarded to the messages requested, but with the constraint that even though node A might’ve requested information from node B, the probability that B sends the requested message is modelled as a random process, where it may or may not the send the data and store it in an array. To set a threshold for modelling loss aversion reward, we compute the mean of the thresholds of individual nodes stored in the array and specify an indicator function in such a way that if a node touches the threshold, the node receives a particular reward and if the node crosses the threshold, it receives a logarithmically limited incremental reward. To decrease the skew of the data in the reward matrix, we define a constant to normalize it and assign the constant a value of 10^-4. We then plot the utility of each node in a coalition in a discrete graph, to help visualize the difference between the utility of different nodes. Instead of using pre existing simulators like SUMO Network simulator based on Ns3, we have used Python to implement the algorithm from the bottom up using the mathematical model that was developed. Although this simulation does not provide a complete picture, it is a starting point for the validation of our model. More work will be done in the near future, so as to provide a more comprehensive analysis of the mathematical model which has been designed by us. This simulation is also a starting point for the algorithm implementation, and the study of coalition formation.

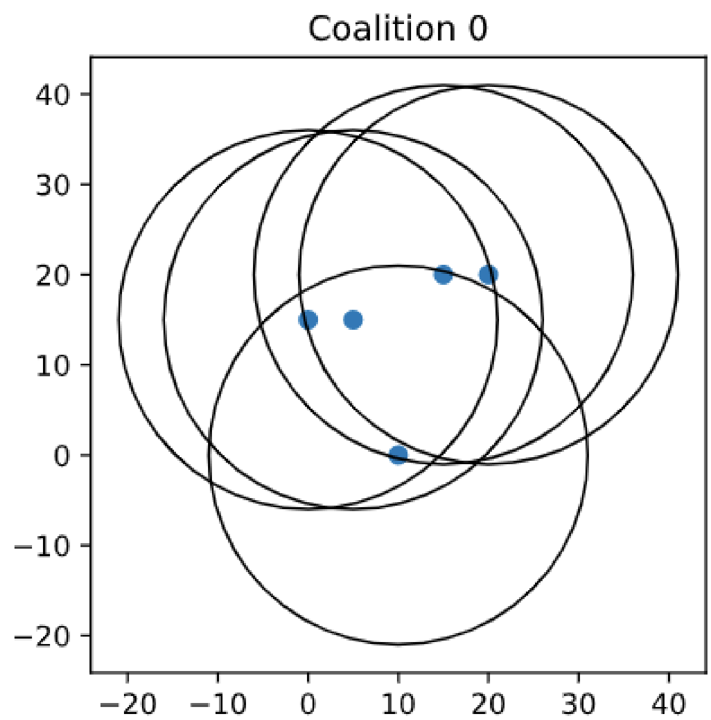

Fig 5. Communication range of nodes in Coalition 0 depicted using intersecting circles

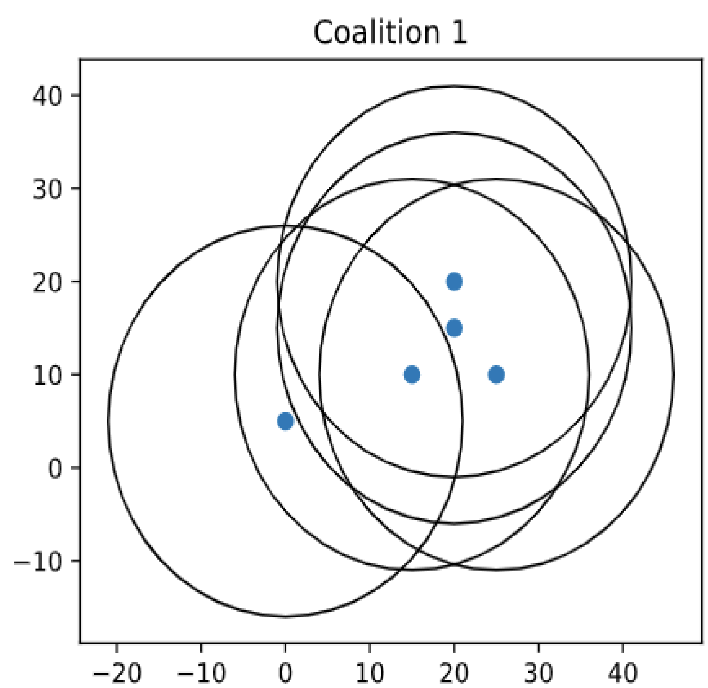

Fig 6. Communication range of nodes in Coalition 1 depicted using intersecting circles

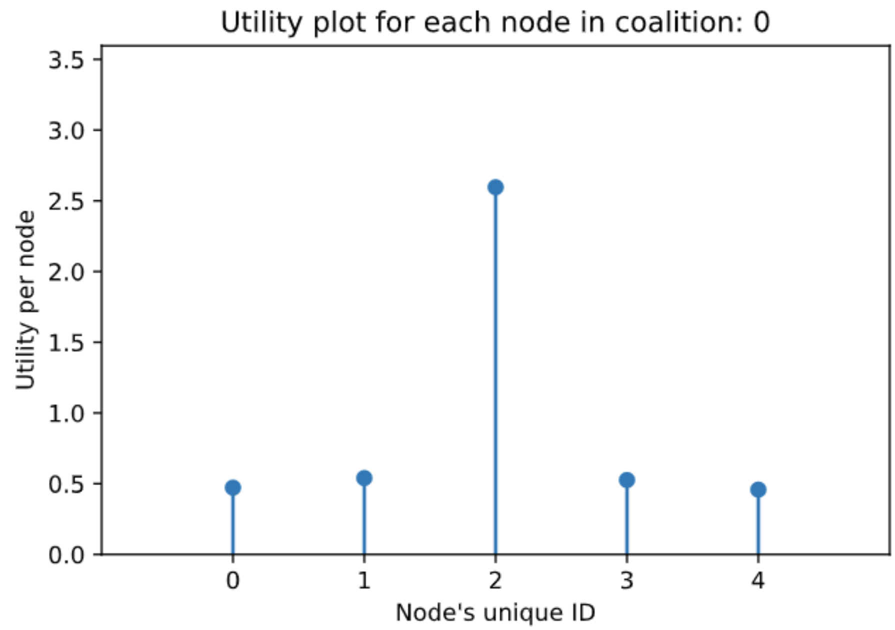

Fig 7. Utility plot for unique nodes in coalition 0 (high peak specifies coalition head)

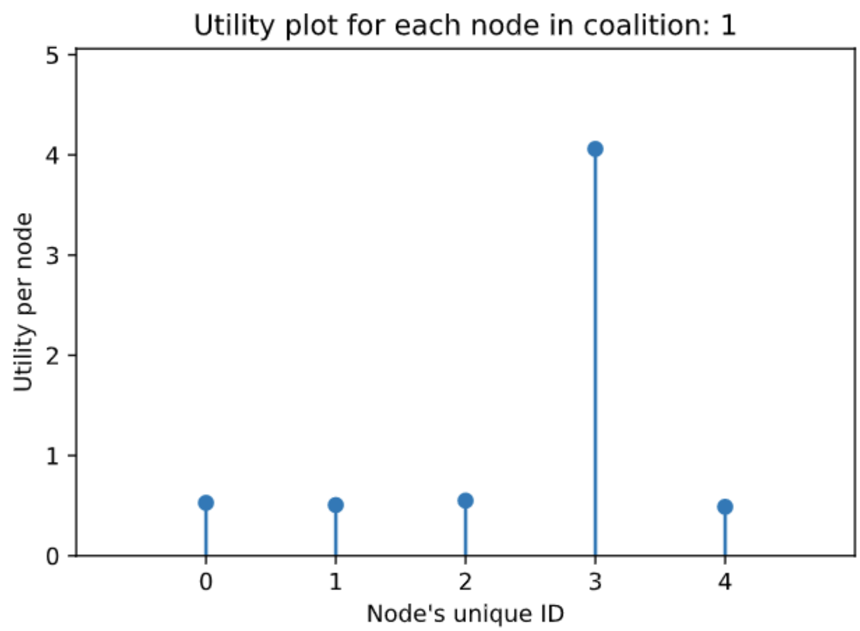

Fig 8. Utility plot for unique nodes in coalition 1 (high peak specifies coalition head)

Future Scope

There are changes that we seek to implement in the future in order to fully create an extensive mathematical model. Our work has focused on the nodes joining and leaving the coalitions at a vehicular level. We will seek to include another strategy where merger and splitting can be done on the coalition level. This would result in a more comprehensive model. Further truth telling using VCG can be added, at the cost of additional complexity. We will also focus on developing a distributed content lookup table which can be used by nodes to query and identify the vehicles that store the desired content, as well as developing a distributed content caching scheme to distribute the content among vehicles. Additional factors such as channel, link quality and interference among different vehicles will also be taken into account in future work.

References

[1] Tonguz, O., Wisitpongphan, N., Bai, F., Mudalige, P. and Sadekar, V., 2007, May. Broadcasting in VANET. In 2007 mobile networking for vehicular environments (pp. 7-12). IEEE.

[2] Paul, B., Ibrahim, M., Bikas, M. and Naser, A., 2012. Vanet routing protocols: Pros and cons. arXiv preprint arXiv:1204.1201.

[3] Cooper, C., Franklin, D., Ros, M., Safaei, F. and Abolhasan, M., 2016. A comparative survey of VANET clustering techniques. IEEE Communications Surveys & Tutorials, 19(1), pp.657-681.

[4] Lai, C., Zhang, K., Cheng, N., Li, H. and Shen, X., 2016. SIRC: A secure incentive scheme for reliable cooperative downloading in highway VANETs. IEEE Transactions on Intelligent Transportation Systems, 18(6), pp.1559-1574.

[5] Manoochehri, H.E. and Wenkstern, R.Z., 2017, July. Dynamic coalition structure generation for autonomous connected vehicles. In 2017 IEEE International Conference on Agents (ICA) (pp. 21-26). IEEE.

[6] Sulistyo, S., Alam, S. and Adrian, R., 2019. Coalitional game theoretical approach for VANET clustering to improve SNR. Journal of Computer Networks and Communications, 2019.

[7] Saad, W., Han, Z., Debbah, M., Hjorungnes, A. and Basar, T., 2009. Coalitional game theory for communication networks. Ieee signal processing magazine, 26(5), pp.77-97.

[8] Liu, J., Huang, S., Xu, H., Li, D., Zhong, N. and Liu, H., 2021. Cooperation Promotion from the Perspective of Behavioral Economics: An Incentive Mechanism Based on Loss Aversion in Vehicular Ad-Hoc Networks. Electronics, 10(3), p.225.

[9] Jesudoss, A., Raja, S.K. and Sulaiman, A., 2015. Stimulating truth-telling and cooperation among nodes in VANETs through payment and punishment schemes. Ad Hoc Networks, 24, pp.250-263.

[10] Mao, Y., Zhu, P., Wei, G., Hassan, M.M. and Hossain, M.A., 2016. A game‐based incentive model for service cooperation in VANETs. Concurrency and Computation: Practice and Experience, 28(3), pp.674-687.

[11] Zhao, B.Y., Lui, J.C. and Chiu, D.M., 2009, April. Analysis of adaptive incentive protocols for P2P networks. In IEEE INFOCOM 2009 (pp. 325-333). IEEE.

[12] Straffin Jr, P.D., 1993. Game theory and strategy (Vol. 36). MAA.

[13] Tadelis, S., 2013. Game theory: an introduction. Princeton university press.

[14] Han, Z., Niyato, D., Saad, W., Başar, T. and Hjørungnes, A., 2012. Game theory in wireless and communication networks: theory, models, and applications. Cambridge university press.

[15] Antoniou, J. and Pitsillides, A., 2012. Game theory in communication networks: cooperative resolution of interactive networking scenarios. CRC press.

[16] Huo, Y., Dong, W., Qian, J. and Jing, T., 2017. Coalition game-based secure and effective clustering communication in vehicular cyber-physical system (VCPS). Sensors, 17(3), p.475.