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Complex Agent Network Approach to Model Mobility and Connectivity in Vehicular Social Networks

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Abstract: Advance technologies in mobile communication fields can be utilized in making vehicles to be behaving as intelligent objects. They interact with each other and may be collected in social groups creating Vehicular Social Networks (VSNs). Information sharing, on the other side is a main task that distinguishes these types of networks. However, high mobility is a significant constraint of such networks. Indeed there is no stable topology of the network. In this context, a good connectivity of the network will have impact factor to enhance communication of vehicles. Therefore, this study will analyze and model mobility and connectivity in VSNs using Complex Agent Network (CAN). This emerging term comes from combination of both Complex Network (CN) and Agent Based Model (ABM). While, the latter can model the behavior of vehicles at individual level, CN can totally give a comprehensive view to the entire network. The developed model in this study is to measure the effect and the impact of some parameters on the connectivity of the network. Results show that both communication range and density of vehicles have a significant effect on the network connectivity. On the other hand, Mobile Road Side Units (MRSUs) will be used to increase this connectivity of the network.

Key words: Agent based model, complex agent model, complex network, connectivity, IoV, MRSU, VANET, VSN

INTRODUCTION

Internet of Vehicles (IoV) and Vehicular Ad-hoc Network (VANET) are associated terms. Both are dedicated in developing the transportation systems exploiting advance technologies. However, the main difference between IoV and VANET is that the former uses the internet services. In addition, it needs a global ID which should be assigned to vehicles (Devare *et al*., 2016; Keertikumar *et al*., 2015). On the other hand, VANET can be considered as offline vehicular network while it is not involving the internet services. Vehicles which are intelligent objects have been regarded a main component of such networks. They have communication device, CPU andmemory that enable vehicles to exchange their knowledge. There are two scenarios of vehicle's communication in vehicular networks. These are Vehicle to Vehicle V2V and vehicle to infrastructure V2I. While V2V is achieving direct communication among vehicles, V2I is taken place between vehicles and Road Side Units (RSUs). The main constraints of vehicular networks are high mobility and unstable topology. Due to vehicle's moving out of communication range of each other there is no stable topology can be considered in vehicular networks. Density of vehicles also has a significant impact on changing the topology of the network. Furthermore, the environment in which vehicles are traveling is another factor that controls their behavior. In this context, there are three main environments for vehicular networks, urban, rural and highway environment. For each environment there are suitable methods that appropriate its nature. For instant, urban road traffic has high density and low speed whereas rural and highway usually have sparse vehicles (Islam *et al*., 2016; Hasson and Hasan, 2017).

According to the previous discussions, interaction of vehicles with each other has support the idea of creating social groups of vehicles, since, they can intelligently share information. As long as social objects in social networks are communicating to share their knowledge and stay in contact, vehicles in this context can be also regarded as social objects. In vehicular network, nonetheless, the story is different because unpredictable behavior of vehicles has made it a complex system. Further, its constraints should be taken in account to be considered as social network. On the other side, social network is also a complex system in which each social object can be represented as node. The relationship between nodes is represented as edge or link. Therefore, bridging social network and vehicular network is reasonable (Vegni and Hoscri, 2015).

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Besides as sharing information among vehicular social groups is an important task, connectivity of VSNs has paid attention of researchers. The connectivity of VSNs is the number of vehicles that should be removed from the network to become connected network. The less number of removed vehicles provides a high connectivity of the network (De and Dehori, 2014).

This study will analyze and model the mobility and the connectivity of VSN using CAN approach combining both ABM and CN. While the former provides a good understanding of vehicle's behavior at individual level, the latter gives a universal view of the whole network. By converting traveling agents (vehicles) into complex network over the time, a good picture can be virtually imagined and viewed to study the connectivity of the network.

Aims and nature of the project: Recently, IoV and VANET have a positive effect on developing the transportation system. Several applications of IoV have been highlighted to achieve intelligent transportation (Hasson and Hasan, 2017). These applications are ranging from safety applications to comfort applications. Avoiding collision and traffic jam are examples of safety applications while exchanging multimedia for entertainment purposes is an instant of comfort applications. Therefore, paying attention to such techniques has become a justifiable necessity. In the terms of socialites, vehicles can create friendships with each other, since, they are intelligent and self-organized. Like in SNs, information sharing is a main task of VSNs. In which vehicles are gathered in groups forming vehicular social communities.

Literature review: Connectivity of VANET has become a hot research direction, since, emergence of intelligent transportation systems. As it has a significant effect on sharing messages in VANET, there are several study have investigated connectivity of VANET.

In 2007 the node connectivity metrics have been presented by Ho and Leung (2007). The number of connected pairs of node, period of connected nodes and duration of path are the main metrics to evaluate the connectivity of node (Ho and Leung, 2017). Investigating the effect of roadside units on enhancing connectivity has done in highway scenario (Sou and Tongoz, 2011). Sou and Tongoz (2011) have emphasized in 2011 that, although, there are small number of road side units the connectivity has been improved. Aissa *et al*. (2015) researcher in 2015 have proposed a new clustering metrics to increase the connectivity of the entire network. Average velocity difference, relative velocity and average distance are the new metrics have been suggested to ensure stable clusters of vehicles. Routing protocol suggested by Pete and Jaini (2015) was dealt with the continuous connectivity. Their researcher have assumed that vehicles are traveling in both clockwise and inverse directions. They have focused on reducing the rate of packet loss. Another research in 2016 has been argued that the numbers of connected components and giant component have possessed a strong correlation and long communication range (Feng and Xu, 2016). This research has been implemented on taxis which are provided with GPSs. Researcher in 2016 have suggested a framework to study the minimum degree of node in k-connected Vanet. They have claimed that it is useful for studying connectivity and performance estimation in highway scenario (Ho and Leung, 2017).

Complex Agent Network (CAN): There are several complex systems around us that contain adaptive and autonomous agents (Sayama, 2015). Interaction of these agents with each other creates a complex collective behavior. To define such systems there is a need to model their agents at individual level. This modeling is to independently understand behavior of each agent. On the other hand, there is also a need to investigate the comprehensive behavior of these agents. In this event, ABM and CN are combined to cover both concepts of individual behavior and comprehensive behavior of the system's agents. The formal definition of CAN is similar to the definition of complex network. Mei *et al*. (2015) define CAN as in Eq. 1 basing on the definition of graph theory:

$$\text{Gagents}\ (t) = (\text{Vagents}\ (t), \text{Eagents}\ (t)) \tag{1}$$

where, Gagents (t) is CAN at time t that contains variable time agents and edges. Each agent in CAN is defined as Vagents (t) while edge as Eagents that represents the relationship between two agents. It is easy to realize that the definition of CAN replaces vertices in CN by agents that are changing their status over the time.

Agent Based Model (ABM): ABM is a general framework to model the dynamic systems (Sayama, 2015). In which many agents are interacting with each other to analyze their behavior. As VSNs are complex systems that contain many vehicles (agents) that behave in self-organized manner, ABM can model such these systems no matter how difficult they are. Sayama (2015) has defined ABM as "computational simulation models that involve many discrete agents". In the context of vehicular networks, ABM can be simply defined as a computational model

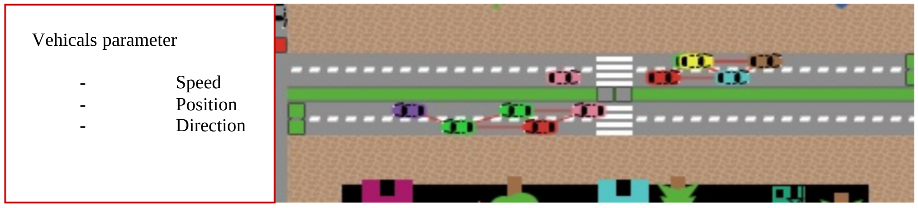

Fig. 1: ABM for VSN

that uses many discrete vehicles. According to this definition there are two key words are needed to explain. The first one is “computational”. Indeed ABM is not a mainly mathematical model but a computer model. It means that ABM uses computer to model agent’s behavior instead of mathematical ways. This is strongly advised, especially in social sciences as Hiroki claims. Actually, agreement with this opinion is fair enough. The second key words is “discrete” which means that each vehicle has clear parameters that specify the relationship between itself and its environment. Not this only, each vehicle will take an appropriate action basing on its status and the status of surrounding environment. It has been argued that there are certain features should be taken in account when ABM is designed. Table 1 shows the main of these features which are associated with VSNs. To clearly understand ABM for vehicular social groups, Fig. 1 shows a snapshot captured from the model that illustrates ABM’s schema.

As it is shown in Fig. 1 there are three casual social groups. One of them is 5 vehicles group in one direction. In another direction there are two groups, 4 vehicles group and single vehicle group. Each vehicle can interact with its neighbors if they are in the same direction and within the allowed communication range. Although, the pink single vehicle is traveling in the same direction of the four vehicles group it is not within the communication range. So, it is still in a single vehicle group. Moreover, vehicles will be gathered in another way called permanent or formal groups. In Fig. 1, colors of vehicles indicate to these formal groups. Therefore, a single casual group may contain several vehicles from different formal groups.

Complex Network (CN): Let us switching gear to the most important discussion, complex network. Since, the main contribution of this study is to investigate and model the connectivity of VSNs, analyzing the network needs to be carefully considered. So, analysis of topology and structure of the network will help in understanding the whole network. However, constrains of VSNs make this task more difficult. Due to high mobility the system does not have a stable topology as well as its behavior unpredictable. In this case, analysis of the system over

Table 1: Features of vehicles in AGM

Variables	Description
Status properties	Vehicles should be discrete objects
	Vehicles may have their own parameters
	Vehicles should have their own states
	Vehicles should have spatial location
Behavioral properties	Vehicles may be behaving with their environment
	Vehicle’s behavior is basing on predefined rules
	Vehicles is interacting with others
	ABM is often unsupervised learning

the running time is required. There are a variety of metrics which are used to analyze the network. Nonetheless, the next sections will discuss the most related to VSNs.

Connected component: In graph theory each undirected sub-graph whose nodes have path to reach each other is called connected component (Sayama, 2015). In this context, each group of vehicles in which all vehicles can directly or indirectly interact with each other is connected group. All casual groups in this study will be considered as connected groups.

Size of group: It is important to know how many vehicles and links in a group. Although, this metric does not tell how vehicles are organized in their groups it is important when there is a need to compare multiple groups. Comparing the groups with the same size may be similar in some sense to chemists who compare materials with the same mass. However, this metric is not a suitable way to describe topology of groups (Sayama, 2015).

Density and diameter of group: Density of groupis a fraction (0-1) that indicates the ratio of the number of links or edges in the group to the number of all possible vehicle’s edges. This metric may provide a prediction about the topology of groups. In other words, it can measure whether the number of edges is sufficient in a group to be enough connected (Sayama, 2015). This concept is called percolation of group, high percolation makes information diffusion among vehicles easier. If there is a group of vehicles (G) that has (V) vehicles and (L) links then D, the density of G is:

$$D(G) = \frac{L}{\frac{V\,(V-1)}{2}} \tag{2}$$

V(V-1)/2 it is the number of possible links in the Group (G) considering it as an undirected graph. High density will reduce the diameter of the group which is the longest path of all shortest paths of the group (Sayama, 2015).

Giant component: The largest connected component is called giant component. When the largest connected component forms a valuable portion of the entire network, it is then named giant component (De and Dehuri, 2014). That means each vehicle in giant component can reach all others directly or indirectly.

Clustering coefficient: Clustering coefficient is an important metric to measure the connectivity of group (De and Dehuri, 2014; Hasson and Abd, 2016). It indicates whether two nodes have a common neighbor to create a triple. If it is fully connected it is called as closed triple. This means that there is an edge between each node and its two neighbors in the triple. So, clustering coefficient is a ratio between the number of closed triples and the number of all triples in the group. This is global clustering coefficient on the other hand there is local clustering coefficient. Following two Eq. 3 and 4 explain both local and global clustering coefficient, respectively:

$$CC_i = \frac{\text{Number of closed triples when i is center}}{\text{Number of triples when i is center}} \quad (3)$$

CC_i it is local clustering coefficient of $node_i$. On the other side, global clustering coefficient is computed as:

$$CC = \frac{\text{Number of closed triples in the whole network}}{\text{Number of triples in the whole network}} \quad (4)$$

MATERIALS AND METHODS

Proposed model

Grouping social vehicles: There are two main methods to gather vehicles in social groups are suggested. The first one is related to permanent or formal grouping whereas the second one is to create temporary social groups of vehicles.

The Formal Social Grouping Algorithm (FSGA) is proposed to incorporate the social behaviors of drivers. So, new parameters are considered in this algorithm such as driver's habits and historical behaviors of drivers. FSGA builds a social profile for each vehicle including all social places which are visited by that vehicle. In this context, social behaviors of vehicles are collected by RSUs in historical data. RSUs are deployed at each entrance and exit of park. The algorithm assumes that each social place such as university, school, super market, company, etc. Has at least one park. Each vehicle will send a message to the corresponding RSU when it enters and exits a park. As a result historical data for each vehicle will be available that indicates to the social profile of that vehicle. Depending on these social profiles the algorithm will gather vehicles that have a similar behavior in one formal group. To understand FSGA the next definitions will hopefully give a good imagination of FSGA's research.

Algorithm 1: FSGA:

Let, P = {p_1, ..., P_m} the set of parks in a given urban region
Let, V = {v_1, …, v_n} the set of vehicles that are traveling during a time period
Let, T = { t_1, …, t_k} the set time periods
Each vehicle (Vi) will send a message to the corresponding RSU including the ID of the vehicle, the ID of the park and the time period as triple (V_i, P_j, T_k)
The time of the system will be divided into K = 6 periods
Predawn (up until 7 am)
Early morning (7-10 am)
Late morning (10 am-noon)
Afternoon (noon-4 pm)
Evening (4-7 pm)
Night (after 7 pm)
From collected historical data Social Patterns (SPs) will be driven
Each vehicle Vi, depending on its behavior will be assigned to the corresponding SP

In casual grouping on the other hand, vehicles are temporally grouped according to temporary interests. The interests here are in some sense related to the temporary behavior of vehicles. Set of vehicles that have the same temporary behavior can be gathered in a one casual group. Destination may be a temporary behavior so vehicles that have been traveling toward the same direction cab be collected in a casual group. Speed is also can be considered as temporary interests. Communication range should be also taken in account in casual grouping process. In this context it can be said all vehicles that have the same direction and in the same communication range can be gathered in a casual group. So, the CSGA is illustrated in the following lines.

Algorithm 2; CSGA:

Let, V = {v_1, …, v_N} the set of vehicles that are traveling in a certain urban region. Where N ranging (50, ..., 200)
Let, T = {t_1, …, t_K} the set of time units
Let communication rang R ranging (15, ..., 100)
For each time unit t_k Do
• For each vehicle v_i Do
  v_i asks its neighbors to create a casual group if they are in the allowed R and have the same direction
  Kill links of the neighbors if they are out of range or change their direction

Connectivity of VSN with MRSUs: Figure 2 shows the structure diagram of the proposed model. There are two main steps of this project. The first one is related to ABM

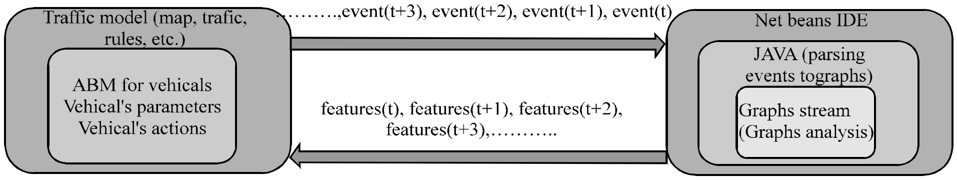

Fig. 2: The proposed model diagram

whereas the second is about how to parse the events which have been already happened in the first step to convert them into graphs. This bi-directionally manner can provide a brilliant picture to analyze the connectivity of VSNs. Net logo is a good simulation for modeling ABM (Monett and Navarro-Barrientos, 2016; Shanshan and Chunxiao, 2013; Hasson and Hasan, 2017). Graph stream on the other side is a Java library that provides good tools to analyze dynamic graph (GraphStream).

As it is clear in Fig. 2, all events will be translated into nodes (vehicles) and edges (relationships). These events will be then passed to the Java environment to be parsed into graphs. These graphs will be analyzed through graph stream. Features of these graphs will return back to the model to investigate the connectivity of network. To increase the connectivity of the network MRSUs will be used instead of using static RSUs. The vehicles that are frequently traveling through the same route such as public buses will be used as MRSUs. According to that MRSU algorithm is designed to improve the connectivity in VSN.

Algorithm 3; MRSU:

Let, $V = \{v_1, ..., v_N\}$ the set of vehicles that are traveling in a certain urban region. Where N is number of vehicles ranging (50, ..., 200)

Use algorith1 and algorith2 to combine vehicles in social groups

Let $MRSU = \{mrsu_1, ..., mrsu_M\}$ the set of vehicles that are frequently traveling in the urban region. Where MRSU is subset of V

$$M = \frac{Max(N)}{N\text{-}Min(N)} * f \quad (5)$$

where f is factor to balance the number of M with N, select f = 7.5.

Let, $T = \{t_1, ..., t_K\}$ the set of time units in the algorithm

Design ABM for the system

For each time unit t_k do

- Convert the VSN into a graph(G_k)
- Send G_k to GraphStream to measure its features
- Return back features of G_k to ABM

Return G with the best features

RESULTS AND DISCUSSION

To test the proposed model it is essentially to define some assumptions which are set in net logo Version 5.3.1.

- Set the number of vehicles (N) to 50.100 and 200 vehicles in the simulation
- The vehicles have grouped in seven permanent or formal groups
- Speed is set to 10-60 km/h
- The road map contains 6 street 3 of them are horizontal with length 2 km and remaining 3 are vertical with length 1 km each one has 4 lanes 2 for either direction. There are 9 intersections created by crossing of the 6 streets.
- The range of communication (R) is set to 30, 50 and 100 m according to the minimum range of IEEE.802.11p standard (Bhoi and Khilar, 2003; Hasson and Hasan, 2017)

The effect of density and communication range: As it is previously mentioned, giant component is a largest component. So, it indicates to the connectivity of the whole network. Figure 3 illustrates the positive effect of high number of vehicles (N) and wide range of communication (R) on enlarging giant components.

On the other hand net beans IDE 8.2 is downloaded from and graph streamver 1.3 from (GraphStream, 2017) they are used to analyze the graphs obtained from net logo. Figure 4-6 show the effects of (N) and (R) on some metrics. So, it is clear that the highdensity of vehicles (N) and wide range of communication (R) can lead to a good connectivity of the network.

The effect of mobile road side units: Vehicles that are frequently traveling in the same route such as public buses, taxis and cop cars can also be seen as unusual vehicles. The term of unusual vehicles means that they have a long duration time in roads. Therefore, they can be used as MRSUs to increase the connectivity of the network. Figure 7 illustrates this positive effect on the connectivity. As it is shown, giant component is larger than without using MRSUs. 10% of number of vehicles is used as MRSUs. However, the number of MRSUs depends on N and R. High density and wide R scenarios may not require a high number of MRSUs.

Comparing Fig. 7a with its corresponding Fig. 3e emphasizes that the MRSUs have a significant impact to enlarge the giant component. As it is clear the giant component with using MRSUs contains more than 50 vehicles whereas it contains 26 vehicles without using

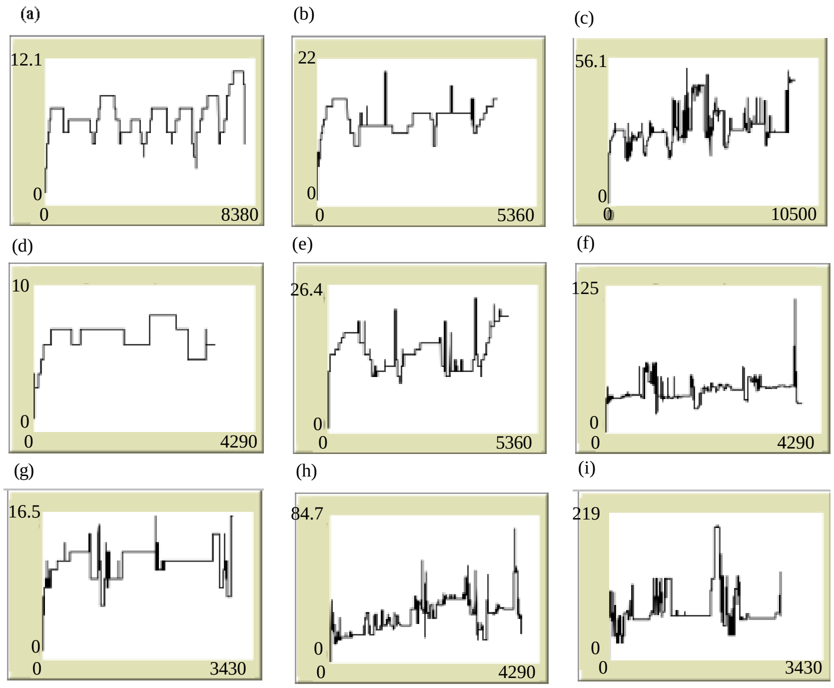

Fig. 3: Effect of R and N on giant component: a) R = 30, N = 50; b) R = 30, N = 100; c) R = 30, N = 200; d) R = 50, N = 50; e) R = 50, N = 100; f) R = 50, N = 200; g) R = 100, N = 50; h) R = 100, N = 100 and i) R = 100, N = 200

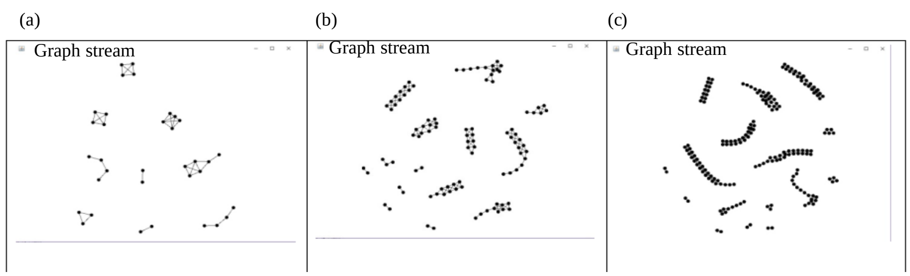

Fig. 4: Graph and some metrics in the network when R = 15 and N = 50 and 200: a) Connected components is 9; Diameteris: 3.0; Density is: 0.06926406926406926; Average clustering coefficient is 0.5588235294117646; b) Connected components is 14; Diameter is 9.0; Density is 0.0332033203320332; Average clustering coefficient is 0.5194761904761906 and c) Connected components is 16; Diameter is 15.0; Density is 0.0216769617936399; Average clustering coefficient is 0.5515660809778455

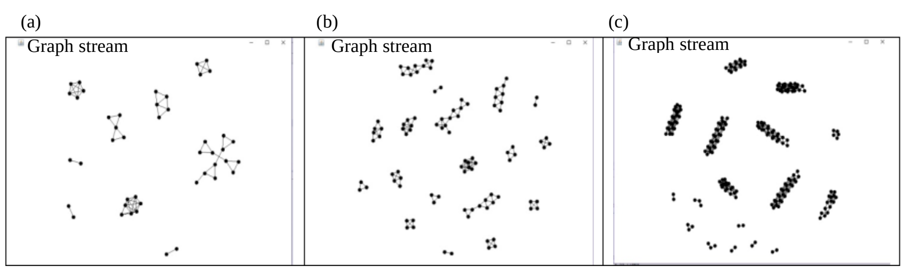

Fig. 5: Graph and some metrics in the network when R = 50 and N = 50, 100, 200: a) Connected components is 10; Diameter is 4.0; Density is 0.06521739130434782; Average clustering coefficient is 0.7177777777777777; b) Connected components is 18; Diameter is 5.0; Density is 0.032989690721649485; Average clustering coefficient is 0.734077380952381 and c) Connected components is 17; Diameter is 7.0; Density is 0.03758948327476246; Average clustering coefficient is 0.6951546752567155

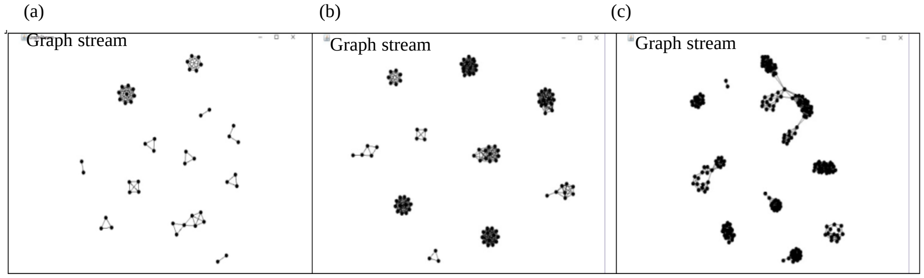

Fig. 6: Graph and some metrics in the network when R = 100 m and N = 50, 100 and 200: a) Connected components is 12; Diameter is 3.0; Density is 0.0769927536231884; Average clustering coefficient is 0.7801418439716313; b) Connected components is 10; Diameter is 3.0; Density is 0.09878293749261491; Average clustering coefficient is 0.9209793226097573 and c) Connected components is 9; Diameter is 10.0; Density is 0.05646464646464647; Average clustering coefficient is 0.8040006860171921

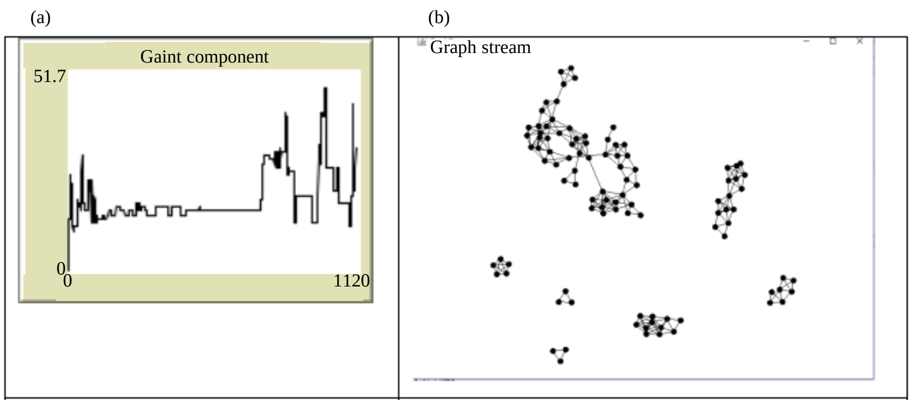

Fig. 7: The effect of MRSUs on gaint component and some metrics with N = 100 and R = 50 m: a) The effect on giant component; b) Connected components is 7; Diameter is 10.0; Density is 0.04836734693877551; Average clustering coefficient is 0.7410854577521244b. The effect on graph and some metrics of the network

MRSUs. On the other side, comparing Fig. 7b with its corresponding Fig. 5b states that diameter is bigger and the number of connected groups is smaller by using the MRSUs. As a result, the MRSUs can efficiently enhance the connectivity of the network.

CONCLUSION

As a nutshell, complex agent network may provide a good understand to analyze behavior of vehicles in VSNs. Where ABM models mobility of vehicles at individual level CN gives a comprehensive view on the entire network. The result emphasizes that communication range and density of vehicles have a significant effect on the connectivity of the network. This study may help in selecting an appropriate way to deploy road side units through VSNs. Increasing their connectivity may enhance information sharing task. On the other hand, this study suggests using MRSUs. In this event, the number of MRSUs can be variable depending on some conditions of the network such as density and communication range. In fact in scenario with high density of vehicles may not require more MRSUs because such this scenario may have already high connectivity.

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