An Agent-Based Simulation of an Adaptive Social Internet of Vehicles Recommendation System

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***Abstract*—To manifest numerous heterogeneous electronic devices of the futuristic Internet of Things (IoT) as an ensemble, the factors of connectivity and interaction/ information dispersion are (if not more) important as sensing / actuating, context-awareness and services provisioning etc. Internet of Vehicles (IoV) is turning out to be one of the first notable examples of IoT. Very rapidly, the meanings of these factors are changing due to the evolution in technologies from physical to social domain. For example, Social IoV (SIoV) is a term used to represent, when vehicles build and manage their own social network. Towards these futuristic systems, in addition to physical aspects, the social aspects of connectivity and information dispersion should also be explored. In this paper, an agent-based model of information sharing (for context-based recommendations) of a hypothetical population of smart vehicles is presented. Some important aspects are modeled under reasonable connectivity and data constraints. The simulation results reveal that the closure of social ties and its timing impacts the dispersion of novel information (necessary for a recommender system) substantially. It is also observed that as the network evolves as a result of incremental interactions, the recommendations guaranteeing a fair distribution of vehicles across equally good competitors is possible.**

***Index Terms*—Internet of Things, Social IoV, Agent-Based Model, Adaptive Behavior, Recommendation System**

I. Introduction

With the increase in number of vehicles equipped with IoT [1], the traditional Vehicular Adhoc Nwtworks (VANETs) are transforming into Internet of Vehicles (IoV) [**?**]. IoV is a progressive form of modern vehicles equipped with sensors, which can receive and transmit useful information for navigation and traffic management [2]. Another technology is Vehicular Sensor Networks (VSN), which enables passengers to exchange data related to entertainment, social networks, and situations [3]. Furthermore, the evolutionary pathway is taking us to the Social Internet of Vehicles (SIoV), which originated from [4] as an application engaging human social behavior into the physical vehicular networks. Later, it attained a more general form in which it is considered to be a network of vehicles in which vehicles build, and manage their own social network [5]. Just like social networking opening up a plethora of new recommendation applications, SIoV has an unlimited potential of changing what we do, and how we live. It can be used to recommend location- and profile-based services, including finding trustworthy services [6], vehicles navigation and monitoring [7]–[9], managing network access [10], targeted advertising [11], drivers behavior modeling [12], and more. Although these examples are mostly related to the vehicular networking, we can easily imagine a broader perspective wherever recommendation services in a dynamic and, evolving network of objects are involved, such as social networking, IoT, WSN, micro-robotics etc. Hence, the findings of this paper can be applied to any other related domain equally well.

All these technologies (at least for now) designed to be subservient to humanity, always have an intrinsic attachment with its users - drivers and passengers in case of SIoV. Therefore, when a vehicle is part of SIoV, it must build and deploy its network (of vehicles) in order to accomplish users' goals. But, then the resolution of the dichotomy of vehicular, and human social network turns out to be a real challenge. The model proposed in this paper builds on the belief that the evolution of inter-vehicle social network can be realized by examining the characteristics of the human social network. In this paper, we investigate the interfacing of these two kinds of networking, and the extend of users' satisfaction with respect to their goal achievement while making use of vehicular networking. In a nutshell, the focus of the paper is on investigating the potential of vehicular social networking towards achieving human goals. We perform this research by designing an agent-based model and simulating it in various conditions.

The study revolves around the competence of SIoV for providing accurate recommendations to the users in a dynamically changing environment. The changes occur in resources' quality and network dynamics. The concept behind the model makes use of basic assumptions such as IoT connectivity, principles of social network evolution, and users profiling. Some interesting what-if questions are asked against a couple of intuitive hypotheses.

The remainder of the paper is structured as follows. In Section II, we present the related work in detail. The proposed model is explained in Section Section III. Simulation settings and the analysis of the simulation results is presented in Section IV followed by Section V, which provides conclusion of the paper.

II. Background and Related Work

First social networking framework for VSN, RoadSpeak presented by the Smaldone et al. [4] for the commuters and named as a VSN. The passengers traveling along the same road can dynamically form interest groups or social communities based on the spatial and temporal preferences/interests to share messages using a chatting application. SocialDrive [13] is a crowdsourcing-based VSN for the socialization of the drivers to be aware of their driving status/behavior, to improve drivers safety and reduce fuel consumption. This framework leverages traditional social networks and cloud computing. Other VSNs based on traditional social networks includes [14], where drivers may share their driving experiences with other drivers in the social groups. These experiences of drivers are further aggregated based on the temporal and spatial context. In Roadcast [15], where vehicles can share content based on the query i.e., a vehicle can query other vehicles in the network. The system returns the highly matched content based on key-words, therefore, the result may not always be appropriate/useful, but it may be beneficial in the future for the other vehicles. However, in [16] vehicles spread the queries in a VSN, which impulses the potentially useful data in a bounded time towards the vehicles. Ning et. al [17] has presented case-studies of VSN applications in the context of smart cities. Yasr et. al. [18] studied information sharing in the VSNs through social relations to ensure that relevant and trustworthy information has to be shared in VSNs. Furthermore, information can be reliably shared in the social groups in terms of trust [19].

VSNs have been modeled and evaluated based on agent-based methodology. For instance, [20] presented a semantic-based multi-agent platform, which integrates semantic techniques and software agents to provide a framework for the VSN applications. This work was further extended by the authors in [21], which provides a service-oriented VSN platform that enables commuters to improve transportation efficiency by collaboration, including context aware mechanism to predict traffic congestion. An agent-based architecture for a swarm of socially aware IoV known as social vehicle swarms is proposed in [22], which leverages the agent-based modeling, big data, and cloud computing to analyze and reveal hidden patterns in social relationships.

The Social Internet of Things (SIoT) [23] enables IoT device to establish a social-like relationship to create social groups/communities based on common goals and interests. SIoV is an application of SIoT in the vehicular networks, where vehicles are social objects [24]. A middleware for SIoV was proposed by [25], which extends the intelligent transportation system (ITS) station for SIoT. Moreover, [2] presents an architecture for the SIoV, which outlines the main components, interrelations objects, and defines interactions. TNote [26] is a social network of vehicles, which defines the key aspects of the social structure of vehicles, their interactions, and relationships. This framework helps the vehicles to share efficiency and safety-related notes in communities.S-Aframe [27] is an agent-based multi-layer framework with context-aware semantic service that utilizes the context information and provides a high-level platform for the development of applications for SIoV of drivers, passengers, and pedestrians. Some other notable researches in these area are [28], [29], [30], [31], machine learning [32], [33], image processing [34].

However, all the presented papers have not addressed the incentive mechanism in SIoV to ensure cooperative involvement of users. It is linked to the selfishness of the users [35], therefore, we argue that users cooperate for common interests and useful recommendations, furthermore, it works as positive feedback in a whole system in sense of user's goal achievement and improvements in productivity, that stabilize the SIoV. In this paper, we have studied information dissemination in terms of recommendation system which is entangled to the user's goals and quality of experience that leads to successful SIoV strategies.

III. Model

A. Scenario and Motivation

Most of our time during the weekdays is consumed in traveling between home, work, school, and shopping. Drivers use ample applications such as navigators [36] to reduce the travel time or to switch between various possible choices. Realization of a recommendation system in collaboration with the capabilities of SIoV is an interesting topic. It is possible to accomplish this due to the recent industrial efforts. It is predicted that by 2020, 50 billion objects will be linked to the Internet, and the considerable number of objects will be vehicles [37]. In the Carestream project [38], technological integration is performed to provide data-driven services. The system collects a variety of information such as "vehicle status, driver activity, and passenger-trip information" from a network of approximately 30,000 chauffeured driven cars. The parameters such as pickup point, pickup time, arrive time, and destination are collectively used to initiate the user demand. These data fields motivated us to use the concepts of ID, $Time$ and $Duration$, to characterize a **resource**. Then, a vehicle (user) **plan** is created making use of User profiling (inspired by [39]), in which a user has to visit some resources every week.

A vehicle serves its user. The social networking of users are not considered in this model; only a network of vehicles is established. Therefore, a vehicle and its user are dealt with as a single entity or a **agent**. The *plan* of an agent consists of a number of activities. An **activity** is constituted by a source, a destination, a time and a duration. Agent's home is the *source* of an activity. A *resource* is the *destination* of an activity represented by identity (*ID*) of a resource, *time* is the time to reach to the resource, and *duration* is the time to stay at a resource. The initial plan is generated randomly choosing a number of resources and assigning an hour to visit a resource (a whole week is distributed in hours) and duration of a few hours.

The objective of the model (presented next) is to investigate the competence of SIoV in providing resource recommendation to the agents, particularly when there is no obvious/natural choice. This can happen if resources known to an agent are no more an attractive choice due to the poor quality of service or the agent individually having a much higher expectation. It is assumed that the interface between a vehicle and its owner (user) is seamless so that a vehicle does not only have information about its owner's plan but also if the current experience regarding a resource was good or bad.

Figure 1 presents an abstract realization of modeling modalities presented next.

B. Cases

An agent has a plan for several activities. Each activity requiring the agent to visit a *resource* at a particular time. An agent starts and ends an activity at its *source*. It visits a resource for a specific duration and returns back. The purpose of an activity is to get a service provided by the resource at the time of the visit. However, the quality of service provided is related to the agent's expectations - if the quality is less than expected, it will make the agent unhappy, and happy if the quality is up to the expectation. The model compares four cases.

In **case 1** of the model, we do not provide any alternative to an unhappy agent and it follows the activities of its plan without any change. Case 1 represents a situation in which agents are mute to the environment, also termed as *indifferent* case - due to the reason that the agents are not affected by the dynamics of the environment. The purpose of including this seemingly primitive case in experimentation is to demonstrate the strength of pure randomness. The mechanism is quite simple (indicated by transitions shown in yellow color in Figure 1). If it is time to visit a resource in the plan of an agent, the agent will move to the resource. As the duration to stay at the resource is completed, the agent comes back to the source.

Case 2 represents when agents are influenced by the environment extremely - extreme in the sense that they are affected by the environment once and for all and without any possibility of reconsideration. In this case, an agent after visiting resources with lesser quality than its expectations would never visit it again. Hence, this case is termed as *pessimistic*. The mechanism is again quite simple (indicated by transitions shown in green color in Figure 1). If it is time to visit a resource in the plan of an agent and the last experience of the agent (for that particular resource) was up to the expectation, the agent will move to the resource. As the duration to stay at the resource is completed, the agent comes back to the source and registers the experience is had at the resource which is equal to the quality of resource at the time of the visit. If it is time to visit a resource in the plan of an agent and the last experience of the agent (for that particular resource) was not up to the expectation, the agent will not visit that resource.

Although it should substantially reduce visits of agents to an underperforming resource, however, with an increasing number of underperforming resources, the plan of agents would be affected. After some time, most activities in the plan of agents would not be executed, and the number of *not possible* activities would surpass possible activities. This is particularly counterproductive if resources are able to improve their quality periodically - as suggested by *quality variability* mechanism given below. By comparing case 1 with case 2, we will analyze if indifference is better or being pessimistic.

Quality Variability becomes an important factor as it is directly related to the agent experience. We could have kept variability equal to zero i.e. assigning a static value to the resource quality, but it was avoided due to the lack of realism. We also deliberately avoided representing this variability as random walk to accommodate human control, which is partial in nature - the quality of resource decreases (increases) for some time and then switch its direction oppositely - which in our view most closely represents a simplistic human behavior. Hence, the individualistic behavior of being pessimistic cannot by any means considered a rational choice, when quality variability promises a previously under-performing resource to perform better now.

Quality variability also provides necessary conditions for models which are based on social networking dynamics and information sharing. The next two cases of the model are based on social networking between the vehicles.

The communication between vehicles through a mechanism such as a vehicular ad-hoc network (when vehicles come close to each other while visiting resources) results into friendship network. This network evolves with time and acts as a mean of novel information sharing in case an agent has a *not possible* activity. The activity is replaced by an activity which is registered as a possible activity in one of friend's list of activities. This strategy is **case 3**, which is termed as *reactive*, which means that agents react to 'bad' resource and replace them, where information about 'good' resources is available from the network they built. Transitions shown with blue color in Figure 1 represent case 3.

This need to be a seamless process, in which network creation, updating, and replacement of activities happen at vehicles level without the agent's knowledge. The only issue is how a vehicle would know about the agent's experience, which can potentially be achieved using IoT infrastructure. For example, sensing that the products being used are wasted or not, or any formal feedback mechanism, or even some other means such as semantic mining of conversation of family members. However, this should not be a grave concern. Nevertheless, reactivity happens through technological interference and is seamless.

Extending case 3 by explicitly performing closure on friendship ties is **case 4**. We named this case as *adaptive* strategy, in which the vehicular network of friendships is extended automatically based on theoretically proven evolution of network structure. Transitions shown with red color in Figure 1 represent case 4. Triadic closure is a concept, which states that if an agent A has a strong tie with both agents B and C, ultimately B and C would become friends. The question is given that the closure process is explicitly introduced into

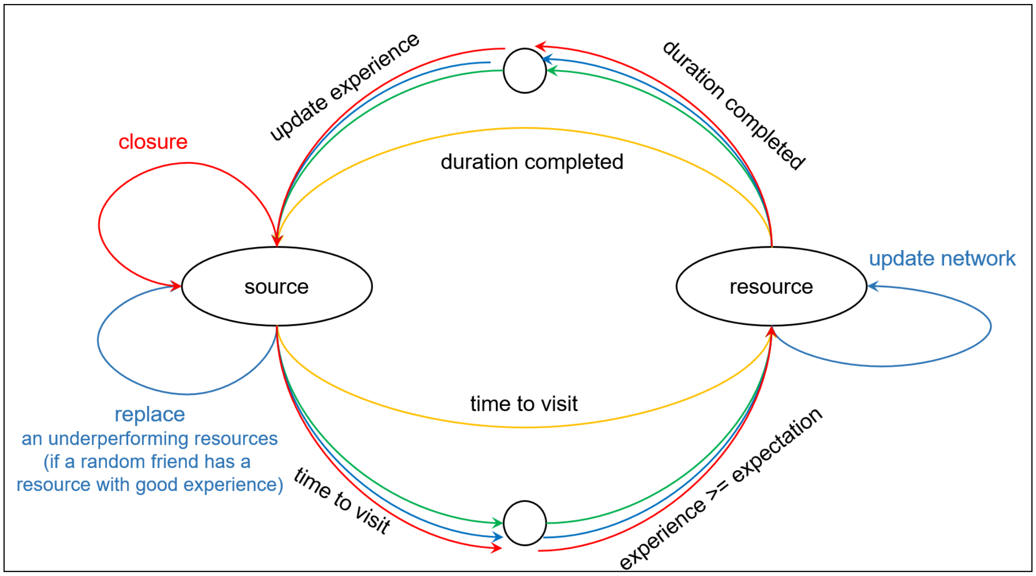

Fig. 1. Representation of the proposed model as a transition system - indifferent case (case 1): yellow, pessimistic case (case 2): green, reactive case (case 3): blue, and adaptive case (case 4): red.

the network, would that be helpful from the users perspective. For example, if a vehicle has a strong tie (due to repeated encounters/communications) with 2 vehicles, given that these two vehicles become friends, how much this process would guarantee the effectiveness of replaced activity when compared to case 3.

Hence, through this model, we can compare case 1 and case 2 and argue that randomness is an important factor. Case 3 and case 4 should be better than case 1 and 2. We compare case 3 with case 4 to see the potential of closure if we can perform triadic closure artificially.

IV. Simulation and Results

A. Simulation Setup

The model is created in NetLogo [40], a agent-based modeling environment. A grid of cells of size 75×75 is used to populate agents. There are three types of agents, two static and one mobile. The static *resource* and *source* agents are randomly placed in the environment. The count of resources is 15, available for 500 sources. Vehicles are mobile agents and a vehicle is attached randomly to a source. The users (owners of the vehicles) are abstract entities encapsulated within vehicles termed as agents. One simulation iteration is equal to one hour, hence, a week is equal to 178 hours. We have simulated 800 hours which is equal to more than 4 weeks (a month). Initially, a random weekly plan, constituted by three scheduled activities is generated (represented by ID, $time$ and $duration$ of a visit), which executes on weekly basis. Figure 2 depicts visual of simulation space when initialized.

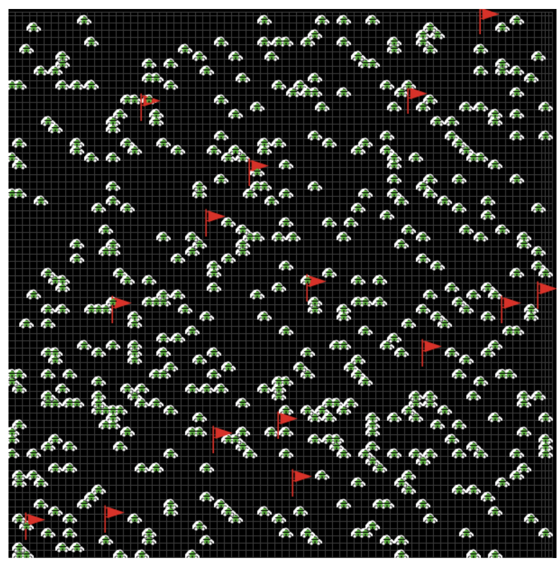

Fig. 2. A view of the simulation world, when initialized for 500 sources (green houses), 500 vehicles (white cars) and 15 resources (red flags).

B. Evaluation Parameters

The four case (as explained before) are evaluated based on three parameters:

- Experienced quality: When an agent visits a resource, it experiences the quality offered by that resource at that time. In one week, an agent has to visit three resources, that is why the quality-index is the average of three experiences of the agent at each hour. The quality-index of the whole simulation space is then an aggregation of all agents' experiences.
- Resources utilization: The population of agents at a resource at an hour determines its current utilization. Derived from it is the standard deviation of utilization of all resources.

- No or bad move: In case an agent has a time to visit and the move is not possible (due to bad experience of the agent with the resource), or agent moves to a resource which is providing a sub-standard service, the agent performs no move or a bad move is performed. This measure counts the total number of agents which performed no move or bad move at an hour.

C. Analysis of the Results

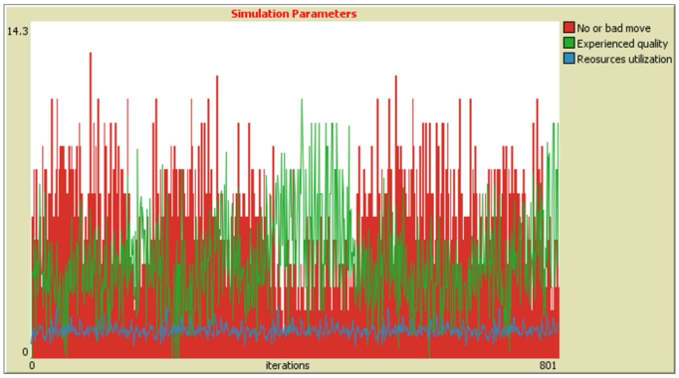

Fig. 3. Simulation results of case 1.

The graph shown in Figure 3 shows the progression of three simulation parameters for case 1. The number of agents which made a no (not possible in this case) or bad move are consistent through out 800 hours of simulation and hovers around 7 agents on average. This is around 50% agents which is expected. The quality experienced by the agents and utilization of the resources is also consistent throughout. These numbers have little quantitative significance and are used for qualitative comparison with other cases.

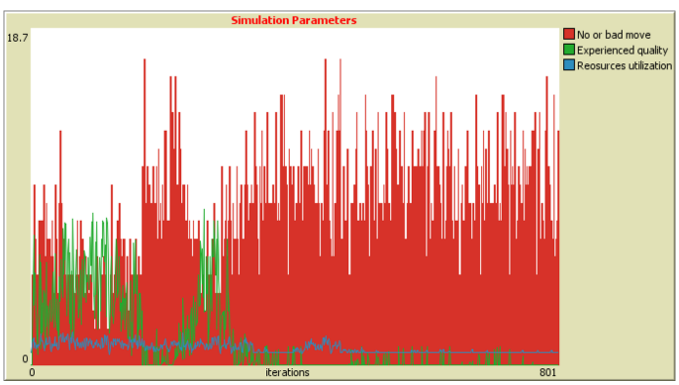

Fig. 4. Simulation results of case 2.

The graph shown in Figure 4 shows the progression of three simulation parameters for case 2. The number of agents which made a no or bad move are increasing as the simulation progresses. It may reach up to 10-12 agents on average. This is around 80% agents is really bad. The quality experienced by the agents and utilization of the resources also decreases considerably, thus making this case the worst case.

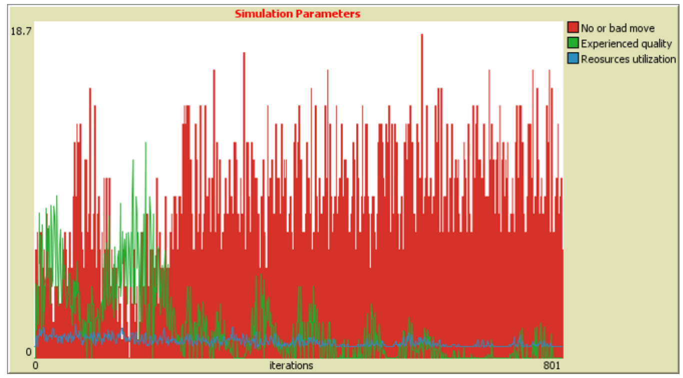

Fig. 5. Simulation results of case 3.

The graph shown in Figure 5 shows the progression of three simulation parameters for case 3, which is better than case 2 particularly in terms of the quality experienced by the agents and utilization of the resources. Hence recommendations acquired through SIoV help agents.

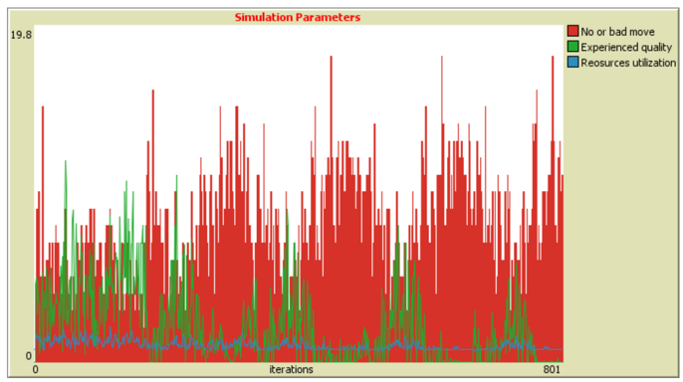

Fig. 6. Simulation results of case 4.

The graph shown in Figure 6 shows the progression of three simulation parameters for case 4, which is better than case 2 for sure, but this is also better when compared with case 3. The improvement in particular is in experienced quality of the agents which improves as a new starts throughout the simulation.

V. Conclusion

In a dynamically changing quality of service provisioning by resources, the vehicles with excluded resources in their plan can utilize their strong ties to have novel information about some resources that are not excluded at a particular time. Is this information turns out to be useful? We analyzed this question through an agent-based simulation. We simulation results reveal that SIoV based recommendation system facilitates information sharing that results in resources being distributed more fairly. Also the number of agents not performing an activity or visiting a potentially bad store in case of SIoV is decreased substantially when compared with individualistic agents.

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