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A Fast Cloud-based Network Selection Scheme Using Coalition Formation Games in Vehicular Networks

Ke Xu, *Student Member, IEEE,* Kuang-Ching Wang, *Senior Member, IEEE,* Rahul Amin, *Member, IEEE,* Jim Martin, *Member, IEEE,* and Ryan Izard, *Student Member, IEEE*

***Abstract*—Leveraging multiple wireless technologies and radio access networks, vehicles on the move have the potential to get robust connectivity and continuous service. To support the demands of as many vehicles as possible, an efficient and fast network selection scheme is critically important to achieve high performance and efficiency. So far, prior works have primarily focused on design of optimization algorithms and utility functions for either user or network performance. Most such studies do not address the complexities involved in the acquisition of needed information and the execution of algorithms, making them unsuitable for practical implementations in vehicles. This paper proposes a fast, cloud-based network selection scheme for vehicular networks. By leveraging a compute cloud's abundant computing and data storage resources, vehicles can leverage wider scope network information for decision making. Vehicles select best access networks through a coalition formation game approach. A one-iteration fast convergence algorithm is proposed to achieve the final state of coalition structure in the game. Through extensive simulation, the proposed network selection scheme was shown to balance system throughput and fairness with built-in utility division rule of the framework. The algorithm efficiency showed eight-fold enhancement over a conventional coalition formation algorithm. Such features validate the potential of implementation in practice.**

***Index Terms*—network selection, vertical handoff, coalition formation games, vehicular networks, heterogeneous wireless networks.**

I. Introduction

UBIQUITOUS broadband Internet connectivity has been brought to automobiles on the road by a multitude of wireless communication technologies, e.g. Wireless Fidelity (Wi-Fi), Dedicated Short-range Communications (DSRC), Worldwide Interoperability for Microwave Access (WiMAX), and Long-term Evolution (LTE). Recently, automotive manufacturers such as Mercedes-Benz [1], network device manufacturers like Cisco [2], service providers like Google [3], transportation agencies [4], and academic researchers [5] have shown great interest in connected vehicles, such as driving assistance, telematics, traffic management, etc [6]. However, despite several solutions from academia to enhance throughput like using directional antennas [7] or network coding [8], and the ability of mobile phones to support multiple technologies (e.g., 4G + Wi-Fi) today even on the move, performance of continuous data transfer (either uplink or downlink) remains limited and fluctuates highly. The two root causes of this limitation are high mobility and limited network resources.

Mobility is the most important challenge for vehicular networks. Due to mobility, vehicles experience widely variable communication channel conditions on the road caused by obstacles such as buildings, trees, street layout etc., resulting in unstable received signal strength (RSS). Such influences directly cause intermittent connectivity on the road. Another critical influence due to mobility is dynamic network topology. While today's cellular technologies are capable of horizontal (same technology) and vertical handoff (different technologies), handoff across operators and technologies is less frequent and not optimal. For vertical handoff, oftentimes end users might make network selection based on cost instead of accurate knowledge of performance, such as choosing free roadside Wi-Fi instead of 3G/4G data usage. With insufficient network information, users are unable to make accurate network selection decisions based on their application needs, especially when traveling through different regions.

The other critical factor is limited availability of network resources. Today, 3G/4G cellular technologies provide good coverage in urban areas; beyond urban areas, such coverage degrades quickly. Different technologies also present different characteristics, resulting in constraints in coverage, capacity, and data rates of individual connections.

Network selection schemes have been a topic receiving significant attention for the objective of achieving improved vehicle connectivity performance, cost efficiency and overall network efficiency. Numerous studies have proposed different schemes for vertical handoff[1] [9]–[21]. The schemes fall into

[1] Vertical handoff (VHO) is performed between different types of access network interfaces, in contrast to horizontal handoff (HHO) performed between the networks with a same technology. In this paper, network selection includes both VHO and HHO.

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K. Xu is with the Department of Electrical and Computer Engineering, Clemson University, Clemson, SC 29634 USA (email: kxu@clemson.edu).

K.-C. Wang is with the Department of Electrical and Computer Engineering, Clemson University, Clemson, SC 29634 USA (email: kwang@clemson.edu).

R. Amin is with MIT Lincoln Laboratory, Lexington, MA 02421 USA (email: rahul.amin@ll.mit.edu).

J. Martin is with the School of Computing, Clemson University, Clemson, SC 29634 USA (email: jim.martin@cs.clemson.edu).

R. Izard is with the Department of Electrical and Computer Engineering, Clemson University, Clemson, SC 29634 USA (email: rizard@clemson.edu).

two typical categories: utility-based optimization and game theoretic frameworks. In [13], an example of the former category, a centralized multi-attribute optimization is proposed based on the weighted sum of spectral efficiency, fairness, and battery lifetime utilities. In [18], an example of the latter category, a coalition formation game is proposed to achieve cooperation among roadside units (RSUs[2]) for prioritized data delivery to vehicles. Both solutions require non-trivial computing complexity. With the scarce memory and processing capacity on typical RSUs or a custom provisioned server, practical implementation of such solutions must trade off scope and granularity of network information for algorithmic efficiency.

Recently, cloud computing is becoming increasingly viable for providing any-time, any-place data processing and storage resources. Application vendors (e.g., Apple, Google) and network providers (e.g., AT&T, Verizon) are promoting mobile cloud computing services. Researchers have proposed a number of mobile cloud computing platforms, e.g. MobiCloud as a geo-distributed platform providing fast communication for cloud resource access [22], and VehiCloud as a service-oriented cloud architecture providing routing service by predicting vehicles' future locations [23]. As an emerging trend, mobile cloud computing technologies can address the two core vehicular networking challenges by allowing offload of more complex computations to cloud.

The objective of this paper is to design an efficient and fast network selection scheme for vehicular networks, by leveraging cloud-based strategies. The solution proposed is expected to achieve better performance for both vehicles and networks. The major contributions in this paper fall into four aspects:

1) Proposing a cloud-based network selection approach to allow performance optimization for vehicles using wider scope of information, as fundamental and necessary to overcome vehicle computing and information limitations for enabling advanced services;
2) Proposing a coalition formation game model for vehicular networks, achieving fairness via built-in utility division rule in the game instead of hand-tuned weighted fairness metric in utility function;
3) Proposing a fast convergence algorithm for solving a coalition formation game, making possible optimization for larger scale networks, enabling practical implementation of coordinated algorithms in vehicular networks;
4) Evaluating the proposed scheme using three typical vehicular scenarios that demonstrate a realistic range of network topologies, resource availability and mobility pattern.

The rest of the paper is organized as follows. Section II introduces background of network selection and prior approaches. Section III describes the system structure, and Section IV presents the network model and utility functions. The coalition formation game for vehicular network is formulated in Section V. Section VI proposes a one-iteration network selection algorithm to achieve Nash equilibrium. Section VII compares and analyzes the performance of the proposed network selection scheme. The paper concludes in Section VIII.

[2]This paper uses the term "RSU" to represent all types of statically deployed infrastructures in heterogeneous networks, including access points in wireless local area networks and base stations in cellular networks.

II. Background and Related Work

Different mathematical theories, e.g. utility theory, multiple attribute decision making (MADM), fuzzy logic, game theory, combinatorial optimization, Markov chains, etc., are used in modeling the network selection problem. A thorough survey on the prior work was presented in [9]. In this section, a small set that are most related to our work is identified.

MADM is widely studied, mostly considered for network selection problems, and refers to making preference decisions over the available alternative networks characterized by multiple attributes. Comparisons between the most popular MADM algorithms, e.g. Simple Additive Weighting (SAW), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), Multiplicative Exponential Weighting Method (MEW), and Grey Relational Analysis (GRA) are studied in [10]. A set of weights are required by MADM methods and has significant impact on the solution space. Choices for weights usually are based on imprecise end-user preferences [24], simulation results [12], and conclusions from statistics [13]. Analytical Hierarchy Process (AHP) is a popular method to determine weights according to relative dominance by dividing a complicated problem into a hierarchy of attributes [14]. In [13], a central global resource controller is used to make an optimal decision based on the weighted sum of spectral efficiency, fairness, and battery lifetime utilities. The weights are calculated using empirical values from network providers and AHP method.

In addition to MADM, [9] broadened the survey to include fuzzy logic, Markov chains, and game-theoretic methods for optimizing joint multiple-attribute utility in heterogeneous wireless networks. The work concluded that game-based algorithms are more appropriate for decentralized decision making rather than centralized decision making, when network resources are limited. The reason is that the equilibrium of a game has the tendency to uniformly distribute users into different networks if the utility is highly correlated to the bandwidth. However, such equilibrium is not the best solution if the bandwidth in the networks is sufficient.

In a game, players seek to maximize their payoffs by choosing strategies that deploy actions depending on the available information at a certain moment. A widely adopted solution of a game is Nash equilibrium, where each player cannot benefit anymore by changing his/her strategy while keeping the other players' strategies unchanged. Game-based network selection algorithms are distributed in nature, since decision-making processes are conducted by each independent player. An extensive survey on game-based network selection algorithms was made in [11], dividing recent works into 3 categories (users vs. users, users vs. networks, and networks vs. networks), 2 types (non-cooperative, cooperative) and 16 typical game models. Most approaches involving end users are non-cooperative [25], in which players select his/her strategy individually (typically bandwidth and application quality of

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service requirements for users, and profit for networks). In [26], the proposed model can learn to match different user demands to balance user quality of experience and handoff cost. Other work has also proposed cooperative approaches that jointly consider improving payoffs for the other players [27]. Cooperative approaches, which are more frequently studied in networks vs. networks games, are mostly focused on spectral efficiency, resource allocation, admission control, and load balancing problems [28]. In [29], the proposed user-network association game introduces localized cooperation to achieve satisfactory tradeoff between users' demands and networks' computational complexity. Although most works consider both users' preferences and network performance, payoffs are still biased on one party (either users or networks), with the other party's metrics performing as constraints.

Recently, coalition formation games have been considered as an effective framework for a distributed and cooperative approach to allocate resources/tasks or select networks [15]–[20]. In a coalition formation game, players can self-organize into stable coalition structures without obtaining higher payoffs by switching current coalitions (namely, Nash equilibrium). In these works, the framework of coalition formation games is consistent and the utility functions vary based on different objectives and metrics. Among these models, a typical three-phase algorithm is used, which consists of *Phase I*- resource discovery, *Phase II*- an iterative coalition formation loop, and *Phase III*- data transmission in the ultimate coalitions. The convergence in *Phase II*, after several iterations, is necessary to achieve Nash equilibrium, which is time-consuming and a critical limitation for implementation. Although there are efficient algorithms for other game models, e.g. online selection [26], sub-problems decomposition algorithms [29], a fast convergence algorithm for coalition formation game is still needed to be developed. In [15], a coalition formation game based on Markov chains is proposed for efficient bandwidth sharing among vehicles. In [18], a coalition formation game is proposed for prioritized data coordination among RSUs. The two models increase the utility/payoff by 17% and 20+%, respectively, compared to the non-cooperative scheme. Although these two models are targeting vehicular networks, no particular vehicular environments are considered and measured. Furthermore, the performance of all the above game-based models are only compared to theoretical optimal and non-cooperative schemes.

To propose an efficient cooperative approach for network selection, this paper formulates vehicular networks using a coalition formation game model. The motivation of using coalition formation game is that such game has clear and simple abstraction of cooperative and competitive relationship between users (utility division rule in (11)), between networks (coalition utility), and between users and networks (preference relation in Definition 2). The coalition formation game also provides a structure with flexibility of customizing utility functions, and with the built-in fairness feature. To overcome difficulties of vehicle computing limitations and information acquisition in conventional game-based distributed systems, a cloud-based system for network selection is proposed. A one-iteration algorithm is proposed to break through the limitation

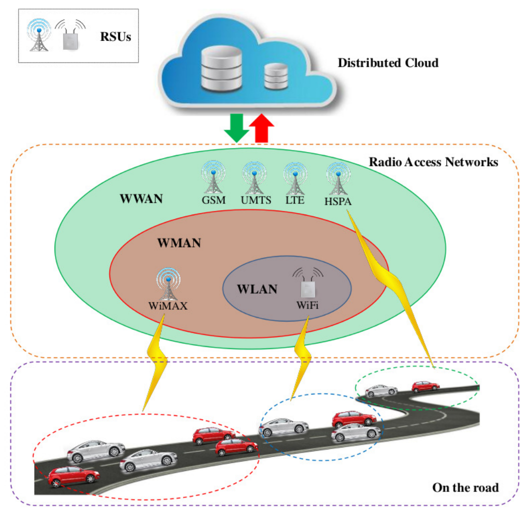

Fig. 1. Overview of the cloud-based system for network selection.

of long convergence time in conventional iterative coalition formation algorithms [16], [17], [20]. The performance of the proposed network selection scheme is compared with a centralized optimal solution [13] instead of theoretical analysis and is evaluated in three typical vehicular scenarios, which are rarely considered in the related studies.

III. The Proposed Cloud-Based System

This section first gives an overview of the system, then describes the distributed database in the cloud, and lastly discusses key assumptions.

A. System Overview

The overview of the proposed cloud-based system is depicted in Fig. 1. The overall system consists of a distributed cloud, multiple types of radio access networks (RANs), and a set of active vehicles in the coverage area. The distributed cloud is a key component in the proposed system, which takes charge of establishing, maintaining the database, computing tasks for network selection strategies, and communicating with RSUs and vehicles. The cloud is geographically distributed and can be flexibly accessed by vehicles according to their locations. Multiple servers at different geographical locations, which could be either real physical machines or virtual machines, reside in the cloud. The cloud connects to the Internet and provides information access to all federated network operators. In the cloud, a distributed database optimizes data maintenance and updates based on geographical location. Database updates are provided by both local resources including RSUs' and vehicles' information and remote resources such as road traffic flow information. The database has full knowledge of the network configurations and status, and the cloud is able to compute handoff cost and provide optimal handoff strategies for vehicles. The network selection decision is client-based. The cloud is used to collect and disseminate necessary information after computing and processing. All RSUs send updates of their status such as the number of

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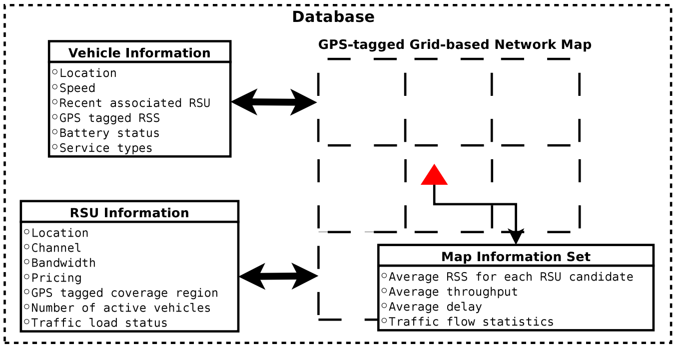

Fig. 2. Information in the database.

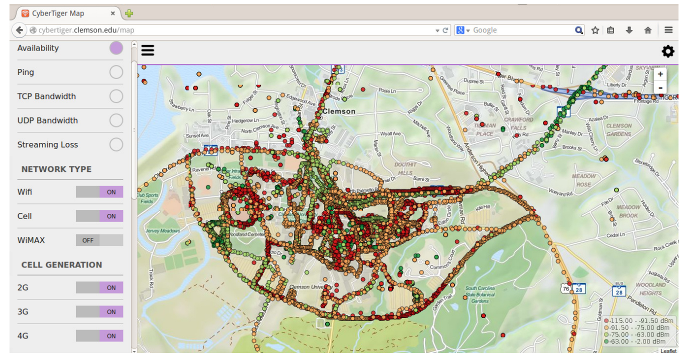

Fig. 3. CyberTiger coverage map.

active vehicles and traffic load to the cloud. The vehicles are equipped with GPS devices, and the on-board device connecting to the network is assumed to be able to import data from GPS and integrate different wireless access technologies. Vehicles periodically report their status, including current location, speed, RSS, and battery status, through associated RSU to the cloud, about $1 \sim 5$ Hz based on GPS's updating rate. The updates will not add much traffic to the network since the packet length is typically very short (less than 100 B) [30]. Eventually, the vehicle's device executes handoff based on received information from the cloud. Note that the proposed system leaves the handoff execution rights to the vehicles. This is designed to provide flexibility in case a vehicle cannot reach the cloud or is disconnected; in such cases, the device will make the handoff decision by itself following the regular approach, e.g. based on RSS. In short, this system could be viewed as a centralized computing and distributed execution system, which is different from the global centralized full-duty system in [13].

B. Distributed Database

The proposed cloud-based system consists of a distributed database, where every site in this distributed database works together to allow seamless access by vehicles as their locations change. This subsection first introduces what information is stored in the distributed database. Second, it explains how to build and maintain the database.

1) Information in the database: Each site in the distributed database consists of three parts: vehicle information, RSU information, and a GPS-tagged, grid-based network map, as illustrated in Fig. 2. The vehicle and RSU information is based on periodic updates from the vehicles and the RSUs, respectively. This information, which includes time stamps, reflects the updated and changing status and conditions on the vehicles and RSUs. The grid-based network map records historical information, such as RSS, throughput, and traffic flow for each grid corresponding to GPS locations. The statistics are important for making network selection decisions. For example, using average normalized RSS based on most recent information in a grid for a certain RSU could avoid instantaneous signal fluctuation. There might be situations however where older information can help to improve the accuracy of a decision. The network map and vehicle/RSU information sets are able to exchange information with each other.

2) Database maintenance: The database maintenance includes database establishment and updates. Preliminary information collection is used for initially establishing the database, in particular for the network map. During the collection procedure, a testing vehicle records the RSS corresponding to specific RSUs mapped into grids and then uses software tools to obtain performance samples. The database requests the traffic flow statistics from remote resources periodically and records the network map. Online updates are for real-time updates of vehicle/RSU information, which obtain the information from periodic update messages sent by active vehicles and RSUs. Some update information, e.g. RSS, number of active vehicles, etc. is added to historical records in the map.

As an example, the CyberTiger project at Clemson University provides a prototype of a distributed database for a single local area [31]. CyberTiger offers measurements of heterogeneous wireless systems by "crowdsourcing" an accurate and visualized coverage and performance map on campus, shown in Fig. 3. Students download and run Android or iPhone applications that interact with performance servers. The client obtains data points that include the time, the GPS location, the handset make and operating system version, the active radio interface, the wireless operator, the signal strength, and the results of the performance assessment that has been selected. The possible performance assessment includes an IP-based ping, a UDP or TCP throughput set, or a video streaming test. The client device information is periodically transferred to the CyberTiger database. If connectivity was lost in that location, the data sample is entered in the local device database, and is re-transferred once the device re-establishes IP connectivity.

C. Key Assumptions and Discussions

The common open challenge of the proposed cloud-based system is the cloud communication latency and inherently intermittent connectivity. Large communication latency and packet losses caused by connectivity discontinuity will make critical information, provided by the cloud, unusable or expired. Hence the vehicles' decisions or actions will regress to traditional solutions, getting no benefits from the cloud. This paper assumes every vehicle is equipped with a GPS device, which is able to periodically report the vehicle's location and driving information to the cloud. Nowadays, GPS devices are inexpensive and widely adopted, and more and more cars or mobile devices also already embed GPS components. The requirement for the cloud is powerful computing ability to analyze vehicles' movements and predict future locations. As a result, the cloud has the ability to sense potential high packet loss rates or connectivity breaks beforehand, and then decides the timing of sending any necessary information. The cloud is assumed to be push-based, so that the timeliness of pushing all necessary information or decisions to vehicles could be guaranteed based on the analysis and predictions. In the proposed game-based network selection algorithm, once the cloud determines a certain vehicle will need to execute a handoff soon, map-based information for network selection will be sent to the desired vehicle. Though propagation conditions vary, the cloud is able to push information before critical and persistent signal strength drop, ignoring instantaneous disturbances. Such decisions are based on long-term history records in the map-based information database stored in the cloud.

IV. Network Model and Utility Functions

This section introduces the network model and utility functions for vehicular networks.

A. Network Model

The system considers a network consisting of N vehicles in the service areas of K RSUs, which are the same or are of different types. The set of vehicles is denoted as $\mathbb{V} = \{v_1, \ldots, v_N\}$. Each vehicle is equipped with at least one type of radio or multi-radio devices to get access to different RANs. At time t vehicle v's GPS coordinate is $(lat, lon)_v^t$, $v \in \mathbb{V}$, where lat and lon are the latitude and the longitude, respectively. The set of RSUs is denoted as $\mathbb{A} = \{a_1, \ldots, a_K\}$. RSU $a \in \mathbb{A}$ has a coverage distance C_a. Each RSU $a \in \mathbb{A}$ offers a total bandwidth B_a and a maximum link transmission capacity μ_a, in bits per second. Each queue on a RSU is modeled as an M/G/1 queuing system. The average packet arrival rate for each vehicle $v \in \mathbb{V}$ is denoted as λ_v.

At time t, each vehicle $v \in \mathbb{V}$ makes a decision to select and access a best network. Each RSU $a \in \mathbb{A}$ serves a set of vehicles $S_a^t \subseteq \mathbb{V}$, consisting of $|S_a^t|$ active vehicles who access RSU a's network. Here, the set of vehicles denoted as S_a^t, in which all vehicles join RSU a's network and request for services at time t, forms a coalition. At a given time, a vehicle is only allowed to use one single network interface, which implies coalitions are disjoint. In fact, "coalition" is the term in coalition formation game, and more details are introduced in Sec. V. It is defined here for the ease in understanding utility functions formulated in the next subsection.

B. Utility Functions

A utility function is quantified for each user to select the best network. In the proposed coalition formation game framework, users can choose any appropriate utility function. The only requirement is the designed utility function must be a non-increasing function in terms of the number of members in the coalition. Such requirement actually comes from the proposed fast convergence coalition formation algorithm, which is described in Sec. VI. The design of utility functions differs much in terms of different demands and objectives in the networks. The attributes considered in utility functions could be any performance metrics, such as throughput, delay, jitter, etc., or availability metrics, such as average RSS, battery status, sojourn time, or pricing metrics such as per-time-unit cost. Furthermore, the metrics could be user-centric, or network-centric, such that utility functions could be designed as user-oriented or network-oriented, or a combination of both.

In this paper, two typical performance-driven utility functions are considered, along with two representative utility functions using the SAW and GRA methods respectively.

Before presenting the utility functions, several attributes need to be introduced first. The RSUs' availability is associated with vehicle's location, given as:

$$\epsilon_v^t(a) = \mathbb{1}_{C_a}\left((lat, lon)_v^t\right) = \begin{cases} 1 & if\ d_a^t \le C_a \\ 0 & if\ d_a^t > C_a \end{cases} \quad (1)$$

In (1), $d_a^t = \sqrt{(lat_v^t - lat_a)^2 + (lon_v^t - lon_a)^2}$ is the distance between vehicle v's current location and RSU a's location, where (lat_a, lon_a) is the RSU a's location. Therefore, vehicle v is able to get a set of available RSUs at time t, which could be represented as $\boldsymbol{\epsilon}_v^t = \{a_i : \epsilon_v^t(a_i) = 1, a_i \in \mathbb{A}\}$. The average RSS information of every RSU in the grid is stored in the database. Whenever the vehicle sends the updated GPS locations the server pushes the RSS information back to the vehicle. The location based RSS of RSU a can be given as:

$$\delta_a^v = \mathbf{RSS}_a\left((lat, lon)_v^t\right) \quad a \in \boldsymbol{\epsilon}_v^t, v \in \mathbb{V} \quad (2)$$

Therefore, vehicle v is able to get a set of RSUs' average RSS at time t, which could be represented as $\boldsymbol{\delta}_{\mathbb{A}}^v = \{\delta_a^v, a \in \boldsymbol{\epsilon}_v^t\}$. The actual transmission rate is determined by modulation and coding schemes, which depend on RSS information. So the transmission rate for vehicle v at time t in RSU a's network could be denoted as $\mu_v^t(\delta_a^v)$ which is a function of the RSS value, where $0 < \mu_v^t(\delta_a^v) \le \mu_a$. The modulation and coding schemes depend on specific radio access technologies and vary between different network operators.

Two typical and generic performance metrics are throughput and delay, which are the most commonly considered attributes in MADM methods. Given the M/G/1 queuing model, the normalized throughput in coalition S_a^t is calculated as:

$$\eta(S_a^t) = \min\left(\frac{\sum_{v \in S_a^t} \lambda_v \cdot \overline{L}_v}{\mu_v^t(\delta_a^v)}, 1\right) \quad (3)$$

In (3), $\overline{L}_v$ is the average packet size in bits for vehicle v, and $\eta(S_a^t)$ is equal to the utilization $\rho(S_a^t)$ for coalition S_a^t in RSU a's network. The closed form expression of delay in coalition S_a^t can be calculated using Pollaczek-Khinchine (P-K) formulas:

$$\tau(S_a^t) = \begin{cases} \frac{\rho(S_a^t)\cdot\left(1+\frac{\sigma_a^2}{(1/\overline{\mu}_a)^2}\right)}{2\overline{\mu}_a(1-\rho(S_a^t))} & \rho(S_a^t) < 1 \\ +\infty & \rho(S_a^t) \ge 1 \end{cases} \quad (4)$$

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where $\frac{1}{\overline{\mu}_a} = \sum_{v\in\mathbb{V}}\left(\frac{\lambda_v\cdot\overline{L}_v}{\sum_{i\in\mathbb{V}}\lambda_i\cdot\overline{L}_i}\cdot\frac{1}{\mu_v^t(\delta_a^t)}\right)$ is the average transmission rate in coalition S_a^t, and $\sigma_a^2 = E\left[\left(\frac{1}{\mu_v^t(\delta_a^t)}\right)^2\right] - \frac{1}{\overline{\mu}_a^2}$ is the variance of the average service time.

1) Utility function I- available bandwidth: The first utility function is available bandwidth. At time t, assume the number of vehicles served by RSU a is $|S_a^t|$, and assume the total bandwidth B_a is equally allocated among all the vehicles in the coalition S_a^t. The available bandwidth of RSU a seen by a vehicle $v \in \mathbb{V}$, which is not in the coalition S_a^t currently, is given as:

$$U_b(S_a^t) = \frac{B_a}{|S_a^t|+1} \quad a \in \mathbb{A} \tag{5}$$

In (5), the right-hand equation means the bandwidth allocated to the vehicle v, if it decides to handoff to RSU a's network being a member of S_a^t.

2) Utility function II- power of the network: Two principal performance metrics for any vehicle v is throughput and delay. To capture the fundamental tradeoff between throughput and delay, the power of a network is considered to use the ratio of throughput to delay as a metric for evaluating the effectiveness of a resource allocation scheme [17]. The power of RSU a's network is the ratio of throughput to packet delay in the coalition S_a^t:

$$U_p(S_a^t) = \frac{\eta(S_a^t)^\beta}{\tau(S_a^t)^{1-\beta}} \quad a \in \mathbb{A} \tag{6}$$

where $\eta(S_a^t)$ is the aggregate throughput in the network served by RSU a; $\tau(S_a^t)$ is the average delay of packets in the same network; and $\beta \in (0,1)$ is the tradeoff factor between throughput and delay. The factor β is chosen based on the relative emphasis placed on throughput versus delay.

To compare with different methodologies, two representative MADM methods, SAW and GRA are considered. The next two utility functions are used for these two methods, respectively. In this section, throughput and delay are used as two attributes in the SAW and GRA methods. Both SAW and GRA are based on the weighted sum of multiple attributes, so an appropriate normalization method is necessary. Max-Min, which calculates the proportional ratio between the considered value and the best value for the attribute, is used as the normalization method. If the attribute is larger-the-better, it is called upward attribute; likewise, it is called downward attribute if it is smaller-the-better [9]. For simplicity, to be normalized, the attributes are converted to be upward. Therefore, the normalized throughput and delay are given as:

$$\tilde{\eta}(S_a^t) = \frac{\eta(S_a^t) - \min_{a\in\boldsymbol{\epsilon}_v^t}(\eta(S_a^t))}{\max_{a\in\boldsymbol{\epsilon}_v^t}(\eta(S_a^t)) - \min_{a\in\boldsymbol{\epsilon}_v^t}(\eta(S_a^t))} \tag{7}$$

$$\tilde{\tau}(S_a^t) = \frac{\frac{1}{\tau(S_a^t)} - \min_{a\in\boldsymbol{\epsilon}_v^t}\left(\frac{1}{\tau(S_a^t)}\right)}{\max_{a\in\boldsymbol{\epsilon}_v^t}\left(\frac{1}{\tau(S_a^t)}\right) - \min_{a\in\boldsymbol{\epsilon}_v^t}\left(\frac{1}{\tau(S_a^t)}\right)} \tag{8}$$

3) Utility function III- simply additive weighting (SAW): SAW is the simplest and most widely used MADM method. The utility function is calculated as a weighted average of normalized attributes:

$$U_{SAW}(S_a^t) = w_\eta \cdot \tilde{\eta}(S_a^t) + w_\tau \cdot \tilde{\tau}(S_a^t) \quad a \in \mathbb{A} \tag{9}$$

4) Utility function IV- gray relational analysis (GRA): GRA considers the distance from the evaluated value of an attribute to the best reference value, which is calculated as:

$$U_{GRA}(S_a^t) = \frac{1}{w_\eta \cdot |\tilde{\eta}(S_a^t) - \tilde{\eta}_0^t| + w_\tau \cdot |\tilde{\tau}(S_a^t) - \tilde{\tau}_0^t| + 1} \quad a \in \mathbb{A} \tag{10}$$

where $\tilde{\eta}_0^t$ and $\tilde{\tau}_0^t$ are the best reference values of normalized throughput and delay, respectively.

The four utility functions given in this section are all larger-the-better, and are calculated for a given coalition S_a^t, $a \in \mathbb{A}$. Note that the utility functions used in the proposed network selection system are not limited to these four functions or throughput-delay related functions. The next two sections discuss the utility function requirements and the proper use of the utility functions for network selection.

V. Game Formulation in Vehicular Networks

Coalitional games have been widely explored in different disciplines to study the behavior of rational players when they cooperate to form groups, referred to as coalitions. A fundamental tutorial on coalitional games is given in [32]. Coalition formation games as an important class in coalitional games, are frequently used for network selection in the field of networking [15]–[20]. Similar to that of previous works, in this section, a coalition formation game for network selection in vehicular network is formulated.

A. Coalition Formation Games

In the considered vehicular network, N vehicles are players in a coalition formation game. Since $S_a^t \subseteq \mathbb{V}$ is a coalition formed by $|S_a^t|$ active vehicles who access RSU a's network ($a = a_1, \ldots, a_K$) at time t, all the coalitions in the networks form a coalition structure, referred to as a coalition partition. The definition of a coalition partition is given as,

Definition 1. *A coalition partition is defined as the set* $\Pi^t = \{S_{a_1}^t, \ldots, S_{a_K}^t\}$, $|\Pi^t| = K$ *which partitions the players set* $\mathbb{V}$ *at time* t, *i.e.,* $\forall a, S_a^t \subseteq \mathbb{V}$ *are disjoint coalitions such that* $\cup_{a=a_1}^{a_K} S_a^t = \mathbb{V}$.

In Definition 1, the number of coalitions is constant with respect to time if there are a fixed number of RSUs in the particular service area.

For every coalition $S_a^t \subseteq \mathbb{V}$, the utility function $U(S_a^t)$ represents the total utility value that can be achieved in the coalition. The four utility functions given in Sec. IV-B are considered as $U(S_a^t)$ (denoted as $U_b(S_a^t)$, $U_p(S_a^t)$, $U_{SAW}(S_a^t)$, and $U_{GRA}(S_a^t)$, respectively, for ease of identification). In the coalition formation game, $U(S_a^t)$ is a transferable utility shared by all members in the coalition S_a^t, which could be arbitrarily apportioned between the coalition members. Define $\phi_v(S_a^t)$ as the payoff received by a vehicle $v \in \mathbb{V}$ after dividing the utility $U(S_a^t)$ with any payoff division rule. In this paper, a fair allocation rule is used for payoff division, resulting in the payoff of any vehicle $v \in S_a^t$ be

$$\phi_v(S_a^t) = U(S_a^t)/|S_a^t| \tag{11}$$

B. Hedonic Coalition Formation

Hedonic coalition formation is a popular method to study the conditions of forming coalitions in the game [16]–[20], which is used in this paper. Two conditions must be satisfied if a coalition formation game is to be classified as hedonic-1) the payoff of any player depends solely on the composition of members of the coalition to which this player belongs, and 2) the coalitions form as a result of the preferences of the players over their possible coalitions' set [16], [20]. As such, the first condition can be satisfied given the utility functions in Sec. IV-B in the formulated game in Sec. V-A. To satisfy the second condition, a preference function is first defined for any vehicle $v \in \mathbb{V}$,

$$f_v(S_a^t) = \begin{cases} \phi_v(S_a^t) & a \in \boldsymbol{\epsilon}_v^t \\ 0 & otherwise \end{cases} \tag{12}$$

Second, each vehicle must build preferences over its own set of possible coalitions from the available RSU set $\boldsymbol{\epsilon}_v^t$. Each vehicle must be able to compare the coalitions, and order them based on which coalition the vehicle prefers to join as a member. A preference relation is defined for each vehicle to evaluate its preferences over the coalitions.

Definition 2. *For any player $i \in \mathbb{V}$, a preference relation or order $\succeq_i$ is defined as a complete, reflexive, and transitive binary relation over the set of all coalitions that player i can possibly form, i.e., the set $\{S_{a_k}^t \in \Pi^t : i \in S_{a_k}^t\}$.*

For any vehicle $v \in \mathbb{V}$, the preference relation of the proposed hedonic coalition game is denoted as:

$$S_{a_i}^t \succeq_v S_{a_j}^t \Leftrightarrow f_v(S_{a_i}^t) \geq f_v(S_{a_j}^t) \tag{13}$$

where $S_{a_i}^t, S_{a_j}^t \subseteq \mathbb{V}$, $S_{a_i}^t, S_{a_j}^t \in \Pi^t$ are any two coalitions that contain vehicle v, and $a_i, a_j \in \boldsymbol{\epsilon}_v^t$. In (13), $S_{a_i}^t \succeq_v S_{a_j}^t$ indicates that player v prefers to be part of coalition $S_{a_i}^t$, over being part of coalition $S_{a_j}^t$, or at least v prefers both coalitions equally. Further, using the asymmetric counterpart of $\succeq_i$, denoted by $\succ_i$, $S_{a_i}^t \succ_v S_{a_j}^t$, indicates a strict preference.

Therefore, the formulated hedonic coalition formation game is defined by the pair $(\mathbb{V}, \succ)$ where $\mathbb{V}$ is the set of players, and $\succ$ is a profile of preferences, i.e., preference relations, $(\succeq_1, \ldots, \succeq_N)$ defined for every player in $\mathbb{V}$.

VI. A One-Iteration Network Selection Algorithm

The remaining problem is to design an algorithm to form coalitions in the formulated game. Given a similar network switch rule is followed by all the players in the game, a typical three-phase coalition formation algorithm was proposed in these existing works [16], [17], [20], which is summarized in Sec. II. *Phase II* is the most important step to form a converged final coalition partition. The convergence of a final partition Π_{final}^t in *Phase II* requires a loop, although the existing algorithms are all designed for distributed decision-making by players. The convergence time is not trivial especially involving thousands of vehicles in heterogeneous systems, which is challenging with fast-changing topologies.

TABLE I
The proposed network selection algorithm.

Algorithm I Network selection algorithm for duration $[t, t+\Delta t)$
Step 1: Information update and collection
1: Vehicle information update, such as $(lat, lon)_v^t$, $v \in \mathbb{V}$, etc.;
2: Information retrieval in the database;
3: Utility function $U(\cdot)$ calculation;
Step 2: Coalition formation
4: Run **Algorithm II** forming a final coalition partition;
5: Notify vehicles with the best coalition to join;
6: Vehicles make handoff decision and execute handoff;
Step 3: Data transmission and database update
7: Data transmission between RSUs and vehicles;
8: Information update, such as traffic load, bandwidth usage, etc.

TABLE II
The proposed one-iteration coalition formation algorithm.

Algorithm II Coalition formation algorithm for duration $[t, t+\Delta t)$
Input: $\mathbb{V}$, $\mathbb{A}$, $U(\cdot)$
Output: $\mathbf{x}^{t^*}$, Π^{t^*}
1: Initialization: $\Pi^{t^*} = \{S_{a_1}^{t^*}, \ldots, S_{a_K}^{t^*}\}$; $S_{a_k}^{t^*} = \{\emptyset\}, a_k \in \mathbb{A}$; $x_v^{t^*} = 0, v \in \mathbb{V}$;
2: **for** v in $\mathbb{V}$ do
3: **for** a in $\mathbb{A}$ do
4: $f_v(S_a^t \cup \{v\}) \leftarrow U(S_a^t \cup \{v\})$; /*following (11) and (12)*/
5: **end for**
6: $x_v^t = \arg\max_a f_v(S_a^t \cup \{v\})$;
7: $S_{x_v^t}^t = S_{x_v^t}^t \cup \{v\}$;
8: **end for**
9: $S_{a_k}^{t^*} = S_{a_k}^t, a_k \in \mathbb{A}; \Pi^{t^*} = \{S_{a_1}^{t^*}, \ldots, S_{a_K}^{t^*}\}; x_v^{t^*} = x_v^t, v \in \mathbb{V}$.

Motivated by this limitation, a three-step network selection algorithm is proposed in Table I. In *Step 1*, by updating locations of all vehicles the necessary information could be retrieved from the cloud database, used for utility calculation; in *Step 2*, a one-iteration coalition formation algorithm is conducted to form a final coalition partition and vehicles execute handoffs according to the results; in *Step 3*, data is transmitted in the networks and the cloud updates the database. The most important procedure in Algorithm I is the coalition formation algorithm in *Step 2*, which is illustrated in Algorithm II. First, Nash equilibrium is introduced for understanding the convergence of Algorithm II.

Nash equilibrium is a widely used solution in game theory. Generally speaking, Nash equilibrium is a strategy profile, where each player's strategy is the best response to others' strategies in the profile. A best response represents the optimal strategy of a player that maximizes the utility given others' strategies. Since all players have their best responses, none of them have the incentive to deviate from their current strategies. For the formulated game, Nash equilibrium is defined as,

Definition 3. *Denote $x_v^t \in \boldsymbol{\epsilon}_v^t$ as the decision of selecting networks by any vehicle $v \in \mathbb{V}$, and $\boldsymbol{x}_{-v}^t$ is the decision set of all other vehicles except v. Nash equilibrium is the decision profile $\mathbf{x}^{t^*} = \{x_{v_1}^{t^*}, x_{v_2}^{t^*}, \ldots, x_{v_N}^{t^*}\}$, where v's best response at time t is $BR_v(\boldsymbol{x}_{-v}^{t^*}) = x_v^{t^*}, \forall v \in \mathbb{V}$. The coalition partition*

TABLE III
THE LOCATIONS AND COVERAGE RANGES OF BSS/APS

	BS/AP location	Coverage radius (m)
EVDO	(750,1000)	1500
HSPA	(1250,1000)	1500
WiMAX	(750,1000)	1000
LTE	(1250,1000)	1000
Wi-Fi	AP1:(650,1250) AP2:(650,750) AP3:(1000,1250) AP4:(1000,750) AP5:(1250,1250) AP6:(1250,750)	250

$\Pi^{t^*} = \{S_{a_1}^{t^*}, \ldots, S_{a_K}^{t^*}\}$ *resulting from* $\mathbf{x}^{t^*}$ *is Nash-stable.*

As a result of Definition 3, Theorem 1 is proven to state the sufficient and necessary conditions in the formulated $(\mathbb{V}, \succ)$ game.

Theorem 1. *At time t a decision profile $\mathbf{x}^t = \{x_{v_1}^t, x_{v_2}^t, \ldots, x_{v_N}^t\}$, resulting in a coalition partition $\Pi^t = \{S_{a_1}^t, \ldots, S_{a_K}^t\}, \forall k \in \mathbb{A}, S_{a_k}^t \subseteq \mathbb{V}$, is a Nash equilibrium, if and only if*

$$\begin{aligned} & f_v\left(S_{a_i}^t\right) \geq f_v(S_{a_j}^t \cup \{v\}) \\ & \quad \forall v \in \mathbb{V}, v \in S_{a_i}^t, v \notin S_{a_j}^t, a_i, a_j \in \boldsymbol{\epsilon}_v^t \end{aligned} \tag{14}$$

Proof: Refer to [33]. ∎

Motivated by sequential Chinese restaurant games [34], a fast algorithm is proposed in Table II to construct a Nash-stable coalition partition in the formulated $(\mathbb{V}, \succ)$ game. Algorithm II is simple and short. For each time step, the algorithm only needs to examine the values of the preference function for all players sequentially, and then it goes to the final coalition partition after one iteration. In Theorem 2, the final coalition partition $\Pi^{t^*} = \{S_{a_1}^{t^*}, \ldots, S_{a_K}^{t^*}\}$ obtained by Algorithm II is proven to be Nash-stable.

Theorem 2. *Given the condition that $U(S_a^t)$ is a non-increasing function in terms of $|S_a^t|, \forall a \in \mathbb{A}$, the output decision profile $\mathbf{x}^{t^*} = \{x_{v_1}^{t^*}, x_{v_2}^{t^*}, \ldots, x_{v_N}^{t^*}\}$ of Algorithm I is a Nash equilibrium and the corresponding $\Pi^{t^*} = \{S_{a_1}^{t^*}, \ldots, S_{a_K}^{t^*}\}$ is Nash-stable.*

Proof: Refer to [33]. ∎

Since the sequence of calculating a player's payoff is fixed in each iteration, the Nash equilibrium obtained by Algorithm II is unique. The important condition which guarantees Algorithm I is able to obtain a Nash equilibrium is the utility function $U(\cdot)$ must be a non-increasing function in terms of the number of members in the coalition. It is easy and straightforward to prove that the four utility functions in Sec. IV-B are all non-increasing functions, thus satisfying such condition.

VII. RESULTS AND ANALYSIS

Simulation is conducted to evaluate the performance of the proposed network selection approach.

A. Simulation Description

In the simulation scenario as shown in Fig. 4, a 2km*2km grid area (the square with dash line) is considered, covered by 5 types of RANs- HSPA(3G), EVDO (3G), WiMAX (4G), LTE (4G), and IEEE 802.11g (Wi-Fi). There is one base station for each cellular network, and six access points for Wi-Fi networks. The locations of the BSs/APs and the coverage range of each RAN refer to Table III. Data rates and and modulation and coding schemes (MCS) refer to the parameters of Table A-1-A-5 in the Appendix in [35]. The five types of RANs provide large diversity in terms of data rates and coverage ranges. Note this paper does not consider differentiated data services for different RANs, and vehicles also do not have preferences on RAN types. So a decision for selecting a certain network only depends on calculated value of the defined utility function. The total simulation time is 10000 seconds, and the time step is 1 second, which means the cycle of forming a new coalition partition or centralized scheduling is 1 second. Three scenarios are considered- highway, intersection and Manhattan, shown

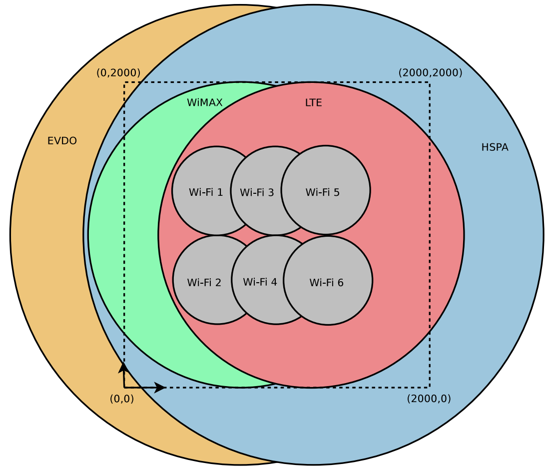

Fig. 4. RAN coverage of the simulation scenario.

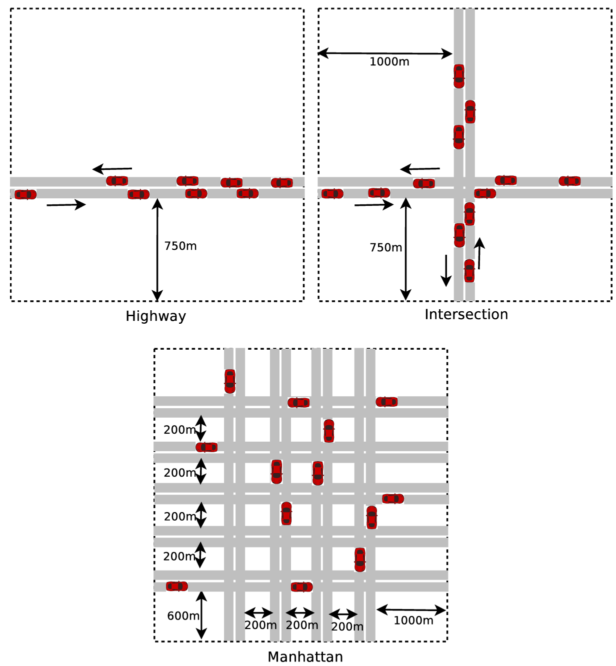

Fig. 5. Vehicular scenarios.

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in Fig. 5. In each scenario, the total number of vehicles is 100. Each road has two bi-directional lanes, shown as the gray lines in Fig. 5. The width of lanes and size of vehicles are neglected in the simulation. In the highway and intersection scenarios, all vehicles keep a constant speed towards one direction, indicating a constant traffic flow. In the Manhattan scenario, each vehicle uniformly chooses a speed below a maximum speed. The probability of going straight is 0.5 and taking a left or right is 0.25 each at each intersection. The simulation time is sufficiently long to obtain performance statistics, especially for the Manhattan scenario with random turning for vehicles at each intersection. For simplicity, a vehicle is assumed to re-enter into the region from the other end of a road once it moves out of the region. Since the proposed game-based scheme is focused on selecting the best network out of all available networks, a vehicle can see at least one available network in the considered region. The methods of extending coverage, such as relaying or using ad-hoc mode, is out of the scope of this paper.

The performance metric evaluated in this section needed to be defined beforehand is the fairness metric, given as:

$$\gamma = \frac{\left(\sum_{v\in\mathbb{V}} \theta_v\right)^2}{|\mathbb{V}| \cdot \sum_{v\in\mathbb{V}} \left(\theta_v\right)^2} \tag{15}$$

The fairness γ defined in (15) follows the definition of Jain's Fairness [13]. In this section, θ_v on the right-hand side of (15) is vehicle v's throughput, indicating the fairness is throughput-based.

B. Comparisons with Centralized Optimal Algorithm in [13]

The original optimization in [13] considers a weighted sum of three attributes- spectral efficiency, fairness, and power consumption. In order to avoid weighting effects, this subsection considers centralized optimization in [13] in terms of a single attribute instead of multiple-attribute utility, in particular, spectral efficiency and fairness, respectively. For both optimization, three minimum data rate requirements for vehicles' quality of service (512Kbps, 768Kbps, 1024Kbps) are measured in the simulation. The average speed in all cases is 13.4 m/s. The system throughput and fairness comparisons are shown in Fig. 6. As shown, there is a tradeoff between throughput and fairness. Once one vehicle sees good signal quality, it will try to get as much bandwidth as possible for data transmission assuming spectral efficiency optimization, which leaves other vehicles in the same network with less bandwidth. Likewise, with fairness optimization, the bandwidth is allocated fairly, sacrificing some vehicle's large data rates in good coverage areas. In Fig. 6, the results of the coalition formation game show that the performance is neither biased on spectral efficiency nor fairness optimization, rather it naturally captures the tradeoff between the two. The reason is the utility division rule in (11) guarantees the fairness of host utility among vehicles. In all three scenarios, the performance has similar features for all the cases in Fig. 6.

The fairness metric used by the centralized optimal algorithm is defined explicitly and quantitatively in [13] (the combined utility function (equation (11a)) includes fairness functions defined by (4) and (5) in [13]). Furthermore, weights are needed to be determined if using MADM methods, e.g. AHP method. Compared to such algorithm, the proposed game-based scheme does not include fairness functions in utility functions. The fairness is embedded in the payoff division rule of coalition formation game in (11). The proposed game-based scheme provides a framework with the feature of embedded fairness, and readers have flexibility to define their own utility functions for coalitions according to their own demands or requirements. The framework always assures fairness of host utility defined by users. The four throughput-based utility functions in this paper are used as an example to evaluate fairness performance.

C. Comparisons among Different Utility Functions

Fig. 7 shows throughput, delay, and fairness performance among four utility functions discussed in Sec. IV-B versus arrival bit rate. The average speed in all cases is 13.4 m/s. The tradeoff factor in (6) is $\beta = 0.5$, and the weights in (9) and (10) are $w_\eta = w_\tau = 0.5$. In Fig. 7, the throughput linearly increases first and then saturates when the arrival bit rate per vehicle increases and reaches 2 Mbps. In all three scenarios, the throughput of the utility function U_b is slightly higher than the other three. Similarly, the delay performance of the utility function, U_b, is also slightly better than the other three in all scenarios. This is reasonable because the utility function U_b tries to select the network with the most available bandwidth, so that the delay could be reduced with higher bandwidth. The price for getting higher throughput and lower delay with U_b is to sacrifice fairness by $5 \sim 10\%$ as shown in Fig. 7, which is approximately the range of improvement for the throughput. U_{SAW} and U_{GRA} have very close performance in Fig. 7, and U_p gets slightly better performance in terms of fairness. The fairness around an arrival bit rate of 1 Mbps is higher than that with saturation, because non-saturation data for all vehicles' packets is more likely to be sent out instead of being backlogged. With more complex road topology and dynamic movement pattern in the Manhattan scenario, the throughput deteriorates by up to about 5% and 15% compared to the highway and intersection scenarios, respectively. The intersection scenario could yield the highest throughput because vehicles have a chance to see more networks compared with the highway scenario but with constant movement compared with the Manhattan scenario. Fig. 8 shows throughput, delay, and fairness performance vs. average speed. The arrival bit rate per vehicle is set as 1000 Kbps in the simulation. In Fig. 8, with the increase of the average speed, the throughput is nearly constant, the delay decreases, and the fairness slightly decreases for all cases. The delay's change is more significant in the Manhattan scenario, which is because vehicles have a high probability of traversing high bandwidth networks with a high speed in a more dynamic road topology.

D. Comparison with Conventional Coalition Formation Algorithms in [16]

Fig. 9 compares the average running time for forming an ultimate coalition partition in one coalition formation cycle

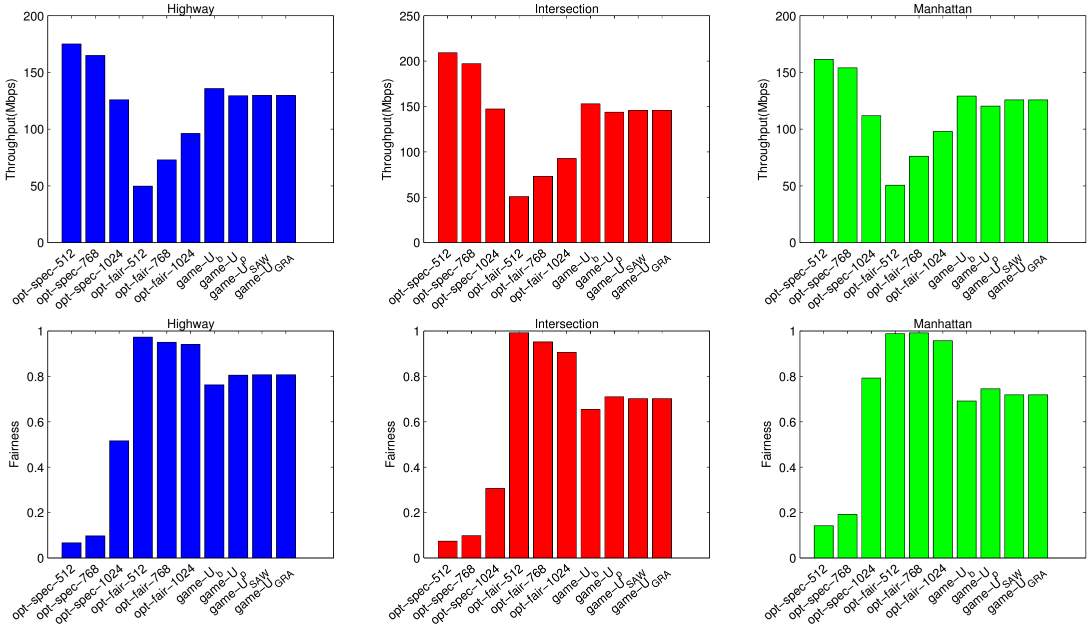

Fig. 6. Comparison with centralized optimization algorithm in [13]. (*opt-spec* and *opt-fair* represent optimization on spectral efficiency and fairness respectively)

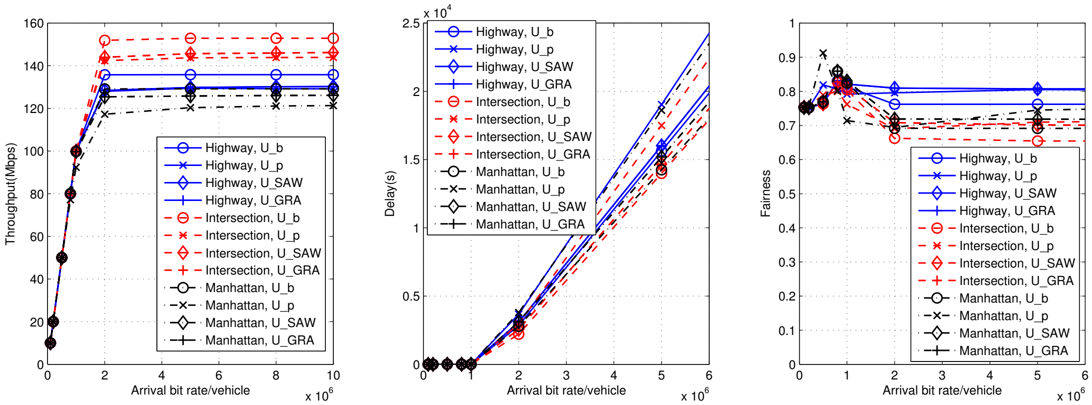

Fig. 7. Throughput, delay and fairness v.s. arrival bit rate per vehicle.

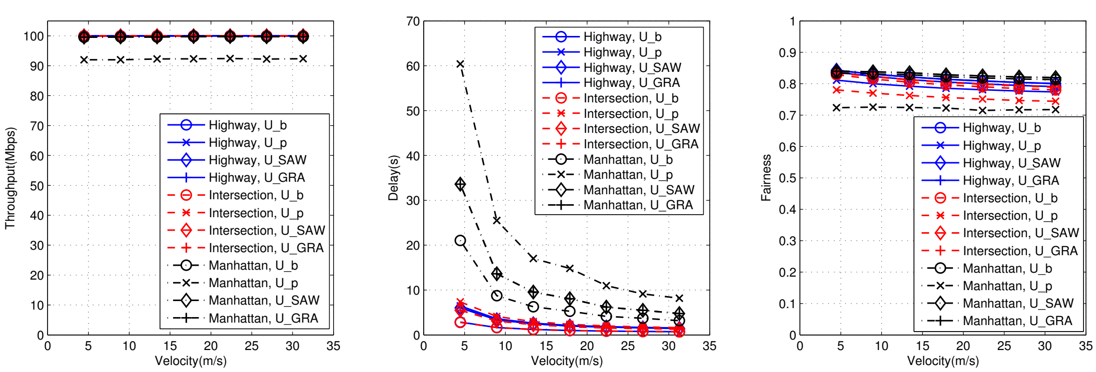

Fig. 8. Throughput, delay and fairness v.s. average speed.

(1 second) between the proposed algorithm and conventional algorithm in [16]. The two algorithms both run on the same virtual machine with 3.4 GHz CPU and 10.5 GB memory. The utility function U_b is used. In Fig. 9, with the increase of

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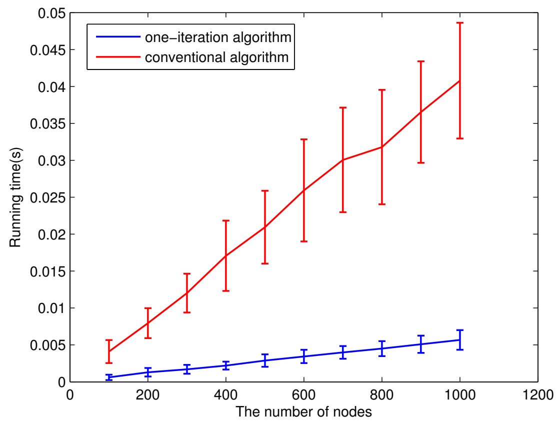

Fig. 9. Average running time for one scheduling interval of proposed coalition formation algorithm and conventional algorithm.

the number of vehicles, the running time for both algorithms linearly increases, but the slope for the conventional algorithm is about 8 times steeper than the proposed algorithm. Hence, in one formation cycle, the running time of the conventional algorithm is 8 times as that of the proposed algorithm, leaving less time for data transmission if being implemented in practice. If the overhead of the coalition formation is too large, the coalition formation game is not usable in the real world because after finishing computation for coalition partition, many vehicles will have already moved to other locations, resulting in the final coalition partition being outdated. From the point of view of network scalability, under the same hardware and software conditions, with the same running time limit for formation, the proposed algorithm actually is able to handle a network whose size is 8 times that of the one handled by the conventional coalition formation algorithm.

The running time of optimization on spectral efficiency in Sec. VII-B is much longer. AMPL software is used for linear programming in the same virtual machine with the same simulation setting. When the number of vehicles is 100, the running time for one cycle is already about 4 seconds (the total running time for 10000-second simulation is more than 10 hours), which actually is beyond the scheduling cycle duration itself.

VIII. Conclusions and Future Work

This paper presented a cloud-based network selection scheme using a coalition formation game in vehicular networks. The proposed scheme leverages the database maintained in the cloud to assist vehicles on the move to select the best networks. Vehicles are able to make decisions based on the information provided by the cloud in a wider network-awareness scope. Given the considered four throughput-based utility functions, the proposed coalition formation game is able to tradeoff the network and individual vehicles' performance with the built-in utility division rule. Not limited by throughput-based fairness, the proposed scheme offers a built-in fair framework with the flexibility of defining any type of utility functions. The framework always assures fairness of host utility defined by users. Furthermore, the proposed coalition formation algorithm accelerates the convergence to the final coalition partition, indicating a great potential to support a larger-scale network of up to 8 times in size compared to the one using the conventional algorithm. Through extensive simulation under different conditions in terms of road topology, network availability and mobility pattern, the above two features (a fair framework and fast convergence) are validated as two main contributions in this area, especially for practical implementation.

Two areas of future work are envisioned: 1) Implement the proposed network selection scheme combining the CyberTiger database and mobile devices (ORBIT based nodes) [36]; 2) Investigate more utility functions based on specific users' or network operators' expectations and demands.

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References

[1] IHS iSuppli, [online] 2011, http://gallery.mailchimp.com/e68b454409061ef6bb1540e01/files/Embedded_Telematics_in_the_Automotive_Industry_sw_iS.pdf (Accessed: Dec. 4, 2014).

[2] Passenger vehicles, Cisco, [online] 2013, http://www.cisco.com/web/strategy/transportation/passenger.html (Accessed: Dec. 4, 2014).

[3] Google, [online] 2013, http://www.google.com/about/careers/lifeatgoogle/self-driving-car-test-steve-mahan.html (Accessed: Dec. 4, 2014).

[4] Intelligent transportation systems, RITA, [online] 2013, http://www.its.dot.gov/ (Accessed: Dec. 4, 2014).

[5] K. Xu, and et. al., "Throughput modeling for multi-rate IEEE 802.11 vehicle-to-infrastructure networks with asymmetric traffic," in *Proc. ACM MSWiM 2011*, Miami, FL, USA, 2011, pp. 299-306.

[6] K. Xu, and et. al., "Location based data delivery schedulers for vehicle telematics applications," in *Proc. IEEE VTC Fall 2012*, Quebec City, QC, Canada, 2012, pp. 1-5.

[7] K. Xu, and et. al., "Performance modeling for IEEE 802.11 vehicle-to-infrastructure networks with directional antennas," in *Proc. IEEE VNC 2010*, Jersey City, NJ, USA, 2010, pp. 215-222.

[8] K. Xu, and et. al., "Network coding for efficient broadband data delivery in infrastructure-based vehicular networks with openflow," in *Proc. IEEE GREE 2013*, Salt Lake City, UT, USA, 2013, pp. 56-60.

[9] L. Wang and G.-S. Kuo, "Mathematical modeling for network selection in heterogeneous wireless networks- a tutorial," *IEEE Commun. Survey & Tutorials*, vol. 15, no. 1, pp. 271-292, 2013.

[10] E. Stevens-Navarro and V. W. S. Wong, "Comparison between vertical handoff decision algorithms for heterogeneous wireless networks," in *Proc. IEEE VTC Spring 2006*, Melbourne, Australia, 2006, pp. 947-951.

[11] R. Trestian, and et. al., "Game theory-based network selection: solutions and challenges," *IEEE Commun. Survey & Tutorials*, vol. 14, no. 4, pp. 1212-1231, 2012.

[12] S. Lee, and et. al., "Vertical handoff decision algorithms for providing optimized performance in heterogeneous wireless networks," *IEEE Trans. Veh. Technol.*, vol. 58, no. 2, pp. 865-881, 2009.

[13] R. Amin, and et. al., "Balancing spectral efficiency, energy consumption, and fairness in future heterogeneous wireless systems with reconfigurable devices," *IEEE J. Sel. Areas Commun.*, vol. 31, no. 5, pp. 969-980, 2013.

[14] M. Lahby, and A. Adib, "Network selection mechanism by using M-AHP/GRA for heterogeneous networks," in *Proc. IEEE IFIP 2013*, Ghent, Belgium, 2013, pp. 1-6.

[15] D. Niyato, and et. al., "Coalition formation games for bandwidth sharing in vehicle-to-roadside communications," in *Proc. IEEE WCNC 2010*, Sydney, Australia, 2010, pp. 1-5.

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[16] W. Saad, and et. al., "Hedonic coalition formation for distributed task allocation among wireless agents," *IEEE Trans. Mobile Comput.*, vol. 10, no. 9, pp. 1327-1344, 2011.

[17] W. Saad, and et. al., "A selfish approach to coalition formation among unmanned air vehicles in wireless networks," in *Proc. IEEE GameNets 2009*, Istanbul, Turkey, 2009, pp. 259-267.

[18] W. Saad, and et. al., "Coalition formation games for distributed cooperation among roadside units in vehicular networks," *IEEE J. Sel. Areas Commun.*, vol. 29, no. 1, pp. 48-60, 2011.

[19] W. Saad, and et. al., "Hedonic coalition formation games for secondary base station cooperation in cognitive radio networks," in *Proc. IEEE WCNC 2010*, Sydney, Australia, 2010, pp. 1-6.

[20] Y. Cao, and et. al., "Distributed hedonic coalition formation for dynamic network selection of multiple services," in *Proc. IEEE PIMRC 2012*, Sydney, Australia, 2012, pp. 926-931.

[21] K. Xu, and et. al., "Cloud-based handoff as a service for heterogeneous vehicular networks with openflow," in *Proc. IEEE GREE 2013*, Salt Lake City, UT, USA, 2013, pp. 45-49.

[22] D. Huang, and et. al., "MobiCloud: building secure cloud framework for mobile computing and communication," in *Proc. IEEE SOSE 2010*, Loughborough, UK, 2010, pp. 27-34.

[23] Y. Qin, and et. al., "VehiCloud: could computing facilitating routing in vehicular networks," in *Proc. IEEE TruseCom 2012*, Liverpool, UK, 2012, pp.1438-1445.

[24] W. Luo and E. Bodanese, "Optimising radio access in a heterogeneous wireless network environment," in *Proc. IEEE ICC 2009*, Dresden, Germany, 2009, pp. 1-5.

[25] J. Antoniou, and et. al., "Access network synthesis game in next generation networks," *Elsevier Computer Net.*, vol. 53, no. 15, pp. 2716-2726, 2009.

[26] Z. Du, and et. al., "Dynamic user demand driven online network selection," *IEEE Commun. Lett.*, vol. 18, no. 3, pp. 419-422, 2014.

[27] J. Antoniou, and et. al., "Cooperative user-network interactions in next generation communications networks," *Elsevier Computer Networks*, vol. 54, no. 13, pp. 2239-2255, 2010.

[28] D. Niyato and E. Hossain, "A cooperative game framework for bandwidth allocation in 4G heterogeneous wireless networks," in *Proc. IEEE ICC 2006*, Istanbul, Turkey, 2006, pp. 4357-4362.

[29] Z. Du, and et. al., "User-demand-aware wireless network selection: a localized cooperation approach," *IEEE Trans. Veh. Technol.*, vol. 63, no. 9, pp. 4492-4507, 2014.

[30] U.S. Department of Transportation, [online] 2005, http://www.its.dot.gov/research_docs/pdf/59vehicle-safety.pdf (Accessed: Dec. 4, 2014).

[31] CyberTiger, [online] 2013, http://cybertiger.clemson.edu/ (Accessed: Dec. 4, 2014).

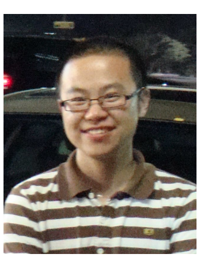
[32] W. Saad, and et. al. "Coalition game theory for communication networks: a tutorial," *IEEE Signal Process. Mag.*, vol. 26, no. 5, pp. 77-97, 2009.

[33] [online] 2014, http://www.clemson.edu/~kwang/paper/xu_tvt_2014_appendix.pdf (Accessed: Dec. 4, 2014).

[34] C.-Y. Wang, and et. al., "Sequential Chinese restaurant game," *IEEE Trans. Signal Process.*, vol. 61, no. 3, pp. 571-584, 2013.

[35] J. Martin, and et. al., "Limitations of 4G wireless systems," in *Proc. Wireless@VT2011*, Blacksburg, VA, USA, 2011, pp. 1-8.

[36] R. Izard, and et. al., "An openflow testbed for the evaluation of vertical handover decision algorithms in heterogeneous wireless networks," in *Proc. TRIDENTCOM 2014*, Guangzhou, China, 2014, pp. 1-10.



Ke Xu (S'11) received the B.S. and M.S. degrees in electrical engineering from Harbin Institute of Technology, China in 2007 and 2009, respectively.

Since 2009, he has been with Clemson University, Clemson, SC, US, where he is now a Ph.D. Candidate in the Department of Electrical and Computer Engineering. He was a research intern with Dell Research, Santa Clara, CA, and Mitsubishi Electric Research Labs, Cambridge, MA, in 2014, and 2011-2012, respectively. He has worked on NSF GENI projects since 2010. He was a prime integration developer of Dell OpenGENI rack (opengeni.net), which is commercialized and servicing global educational and research institutions. His current research interests include vehicular networks, wireless networking and communications, computer networks, cloud computing, future Internet, and SDN.

Mr. Xu is a student member of the IEEE and the ACM.

Kuang-Ching Wang (S'98-M'04-SM'13) received B.S. and M.S. degrees in electrical engineering from the National Taiwan University, Taipei, Taiwan, in 1997 and 1999, and M.S. and Ph.D. degrees in electrical and computer engineering from the University of Wisconsin, Madison, in 2001 and 2003, respectively.

He is currently with the Department of Electrical and Computer Engineering, Clemson University, Clemson, SC, as an Associate Professor. He has participated in a number of large scale wireless and wired research networking system projects, including the DARPA SensIT Program (2000-2003) deploying the largest scale outdoor distributed sensor system, and the NSF Global Environment for Network Innovation project (GENI, 2009-2014) deploying SDN, WiMAX, and compute racks for nationwide research experimentation. He is the PI for "Clemson NextNet" - a NSF campus cyber-infrastructure project for building university wide SDN infrastructure and support framework. He was a member on the US Ignite mentoring team for SDN integration with broadband applications. He was on sabbatical with Stanford's ON.Lab in 2012, with a team he prototyped the first SDN-Internet peering solution. Aside from above, he has developed testbeds with different wireless technologies including Wi-Fi, WiMAX, and Zigbee sponsored by NSF, USDOT, SCDOT, BMW, Cisco Systems, and CH2M Hill.

Dr. Wang is a member of the IEEE and the Association for Computing Machinery.

Rahul Amin (S'07-M'14) is a member of Technical Staff in Airborne Networks Group at MIT Lincoln Laboratories. His research interests include resource allocation, network optimization and network integration problems in both ad hoc and infrastructure based wireless networks. Before joining MIT Lincoln Laboratories in December 2013, he was a Research Assistant in the Networking Lab for the School of Computing at Clemson University and focused on radio resource management strategies for next generation heterogeneous wireless networks. As a Masters student, he worked as a Research Assistant in Department of Electrical and Computer Engineering at Clemson University and collaborated on a vehicular broadband connectivity project with BMW IT research center in Greenville, SC.

Jim Martin (M'88) is an Associate Professor in the School of Computing at Clemson University. His research interests include broadband access, wireless networks, Internet protocols, and network performance analysis. Current research projects include heterogeneous wireless systems and DOCSIS 3.x cable access networks. He has received funding from NSF, NASA, the Department of Justice, Cisco, IBM, CableLabs, and BMW. Dr Martin received his Ph.D. from North Carolina State University. Prior to joining Clemson, Dr Martin was a consultant for Gartner, and prior to that, a software engineer for IBM.

Ryan Izard (S'10) received his B.S. degree in Computer Engineering from Clemson University, Clemson, SC, US, where he is now a Ph.D. student in the Department of Electrical and Computer Engineering. In the Summer of 2014, he is with Big Switch Networks, Inc. in Mountain View, CA, US, where he is a R&D intern for the Floodlight team. His current research interests include vehicular networks, wireless networking and communications, cloud computing, and SDN. Mr. Izard is a Student Member of IEEE.