Spectrum Resource Sharing in Heterogeneous Vehicular Networks: A Noncooperative Game-Theoretic Approach With Correlated Equilibrium

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***Abstract*—In this paper, with the aims of alleviating the pressure from the shortage of spectrum resource and addressing the inefficient spectrum utilization, we investigate the spectrum sharing for moving vehicles in Heterogeneous Vehicular Networks (HVNs) consisting of the macrocells and the Road Side Units (RSUs) with Cognitive Radio (CR) technology. We first propose an incentive mechanism for encouraging macrocells to share spectrum resource with vehicle users, in which the CR-enabled RSUs perform sensing the spectrum availability in the surrounding urban environments. Furthermore, the downlink resource allocation for vehicle users associated with different RSUs is modeled as an n-person game and solved by designing a noncooperative game theoretic approach. By considering transmission power constraint of RSU and inter-RSU interference, the resource allocation and interference mitigation among RSUs are formulated via maximizing the overall utility in the HVNs. We design a game theoretical strategy optimization algorithm based on regret-matching and then derive the correlated equilibrium solution. Moreover, we propose a heuristic power control algorithm for further mitigating the inter-RSU interference in the noncooperative game based resource allocation. Simulation results demonstrate that the proposed approach can achieve the correlated equilibrium with fast convergence and significantly improve the system performance in high mobility HVNs.**

***Index Terms*—Correlated equilibrium, heterogeneous vehicular networks, non-cooperative game, *n*-person game, resource allocation.**

Manuscript received November 16, 2017; revised March 29, 2018 and June 11, 2018; accepted July 6, 2018. Date of publication July 13, 2018; date of current version October 15, 2018. This work was supported in part by the National Natural Science Foundation of China under Grants 61301148, 61502162, and 61702175, in part by the Fund of State Key Laboratory of Geoinformation Engineering SKLGIE2016-M-4-2, in part by Hunan Natural Science Foundation of China under Grant 2018JJ2059, and in part by the Open Fund of State Key Laboratory of Integrated Services Networks ISN17-14. The review of this paper was coordinated by Prof. M.-C. Gursoy. *(Corresponding authors: Dong Wang; Keqin Li.)*

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Digital Object Identifier 10.1109/TVT.2018.2855683

I. Introduction

In RECENT years, vehicular networks have emerged as a new class of efficient information sharing and data dissemination technology among vehicles and existing infrastructures mainly because of their wide range of applications in Intelligent Transport Systems (ITS) and Internet of Vehicles [1]. Since the demands of mobile traffic and wireless service from vehicle to vehicle and vehicle to infrastructure communications are rising dramatically, vehicular networks suffer from heavy traffic load which also brings great pressure on the existing cellular networks. To satisfy the ever increasing of mobile traffic, the authors in [2], [3] propose the Heterogeneous Vehicular Networks (HVNs) consisting of the macrocells and the Road Side Units (RSUs), wherein the RSUs offload the traffic from the congested macrocell and improve the system throughput as well as support the vehicular traffic service.

However, heterogeneous vehicular networks exhibit many unique characteristics, which pose great challenges to achieve efficient and reliable V2X communications [4]. As large number of vehicles are distributed over a limited region, the available spectrum resource becomes scarce. The Federal Communications Commission (FCC) has assigned 75MHz bandwidths for dedicated short range communications, while this is insufficient to support the varieties of mobile traffic service [5].

To fulfill the growth of vehicular communications and cope with the shortage of spectrum resource, Cognitive Radio technology incorporated into HVNs is recognized as a key lever to efficiently utilize the spectrum resource [6], [7], in which RSUs with CR capability sense the vacant radio resource in surrounding environments so that the secondary users (i.e., vehicle users and macrocell users) can use the available spectrum without causing additional interference to the primary users. Therefore, the spectrum efficiency can be significantly improved in HVNs and CR-enabled RSUs can provide critical wireless connectivity to vehicle users [8]. Once the vacant spectrum resources are known, the effective radio resource allocation approach is needed. Although spectrum allocation schemes with CR technology have been studied in wireless communication networks, it is more challenging and complicated for HVNs due to the ever-changing of the urban environments and the fast moving of vehicle users [2], [3].

A. Literature Review

The problem of resource allocation in wireless communication networks has drawn much attention, which has been investigated in existing research works, e.g., [9]–[14]. In [9], the authors present an overview of cognitive radio networks and focus on the recent advances in resource allocation techniques. In addition, game theory [10] is considered as an efficient tool for tackling the problem of spectrum allocation in wireless communication networks on account of limited resource and lots of secondary users. In [11], the non-cooperative differential game theory is applied to perform resource allocation. In [12], the authors investigate resource allocation by virtue of non-cooperative game solution in Two-Tier Femtocell Networks and prove that this game converges to its Nash Equilibrium (NE) point [13]. In [14], the authors formulate the reciprocal behaviors as a three-tier game and demonstrate the additional configurations of control channel protocol to obtain the game equilibrium. According to these works [9]–[14], the dynamic spectrum allocation is able to offer a feasible way to resolve the shortage of spectrum resource when an unexpected increase of spectrum demand arises in macrocell networks. The majority of these works are appropriate for the static or low speed users, nevertheless, they do not take the high mobility of devices or users into consideration, which is typical in the vehicular environments.

The existing works have contributed efforts to resource allocation for the vehicular scenarios. In [15], the authors study radio resource sharing by designing Separate Resource Block allocation and Power control (SRBP) algorithm for D2D based V2V communication, where the D2D communication has been proposed as a possible enabler for V2V applications [16]. In [17], the authors utilize the linear programming (LP) method for maximizing the available spectrum resource in the CR based high speed vehicle networks. A semi Markov decision process based resource allocation scheme is proposed in [18] to facilitate video streaming application in terms of peak signal-to-noise ratio and smooth playback. To mitigate the interference in vehicular networks, two graph based resource-sharing schemes are investigated in [19]. In [20], the authors consider the problem of cooperative communications scheduling by graph theory in vehicular networks. In [21], the authors formulate the subband assignment problem by using the graph-based approach. In [22], the authors propose a coalition game model based on two-sided matching theory for cooperation among cloud service providers to share their idle resources. In [23], the authors investigate the joint resource blocks assignment and transmission power allocation in the Full-Duplex cellular-VANET heterogeneous networks. [24] achieves a Nash equilibrium for a matrix game by devising Karush-Kuhn-Tucker nonlinear complementarity approach (NCA on KKT), which is used for the optimization of resource allocation in the cloudlet resource management.

In this work, we focus on studying the spectrum resource sharing in the Heterogeneous Vehicular Networks from different perspectives, i.e., to encourage the sharing of precious radio resource between macrocell and RSUs by incorporating cognitive capabilities and exploiting spectrum sensing, on the other hand, to develop game-theoretic approach for resource allocation based on the available spectrum, which can guarantee fast convergence such as to satisfy the high-dynamic in the urban vehicular environments.

B. Motivations and Contributions

In this paper, we investigate the spectrum resource sharing for vehicle users in Heterogeneous Vehicular Networks. First, in order to cope with the shortage of spectrum resource in HVNs, we wish to identify and exploit the available spectrum such as TV White Space (TVWS). According to [25], [26], TV band can provide available spectrum for unlicensed users, i.e., the vehicle users in this study, and enable connected vehicular networks. To this end, the CR-enabled RSUs perform spectrum sensing the white space in surrounding environments and hence implement the spectrum reusing between the vehicle users and the macrocell users. Note that according to the FCC's regulation, the spectrum database access can be used to obtain the available spectrum for addressing the increasing demand of mobile data from connected vehicles, which saves the time for searching the TVWS. In our study, the RSUs can perform both database access and spectrum sensing. We then propose a non-cooperative game-theoretic approach with correlated equilibrium for resource allocation, with the aim of improving the spectrum efficiency among RSUs and obtaining maximum achievable data rate for vehicle users in the downlink LTE system. It is a decentralized approach, since each RSU acts independently and is unware of how other RSUs select their own strategies. In particular, the set of correlated equilibrium game includes the set of Nash equilibrium, while it is more preferable than Nash equilibrium [27]. To meet the needs of the high mobility of vehicles in urban environments, the proposed game theoretic method is able to converge quickly and in the meantime without degrading the macrocell performance. The main contributions are summarized as follows:

i) We propose an incentive mechanism based spectrum reusing method for macrocell and RSUs, which encourages macrocell to share the available spectrum resource with the RSUs, with the purpose of improving the spectrum utilization by reusing the white space spectrum and decreasing the interference to macrocell users.

ii) Considering transmission power constraint of RSU and inter-RSU interference, the problem of resource allocation for moving vehicles associated with different RSUs is formulated as the n-person game. To resolve this, we propose a non-cooperative game approach and design a game theoretical strategy selection algorithm based on regret-matching. Moreover, we design a graph coloring based algorithm to form the strategy set and derive the correlated equilibrium solution for the non-cooperative game based resource sharing problem. The pro-

TABLE I
DESCRIPTION FOR KEY PARAMETERS

Notation	Description
N_r	Number of RSUs
R_{rsu}	Coverage radius of RSU
$\widetilde{N}$	Finite set of RSUs
$\widetilde{A^r}$	Set of strategies associated with RSU r
$\widetilde{U^r}$	Utility of RSU r
N_w	Total number of the white spectrum
ρ	Accuracy during spectrum sensing
N_v	Number of vehicle users
N_b	Available spectrum allocated to RSUs
$SINR$	Signal-to-Interference plus Noise Ratio
P_i^r	Transmission power of vehicle i in RSU r
d_i^r	Distance between RSU r and vehicle user i
h_i^r	Channel gain of vehicle user i in RSU r
$\delta_i^r(t)$	Indicator function
D_T^r	Average utility difference
ξ	Probability distribution
R_T^r	Degree of 'regret'
S_0	Threshold value
P_{MAX}^r	Maximum transmission power for RSU r
θ_T	Empirical distribution

posed game theoretical approach is proven that a quick-converge correlated equilibrium can be achieved.

iii) We formulate the joint optimization problem of resource sharing and power control for RSU with the objective of further mitigating the inter-RSU interference. To solve this, we propose a heuristic power control algorithm (HPCA) to adjust transmission power of RSU. We perform extensive simulations in the urban scenario. Simulation results demonstrate that the proposed algorithm can effectively mitigate the interference between RSUs and significantly improve the utility level in high dynamic HVNs.

The remainder of this paper is organized as follows. We present the HVNs and the incentive mechanism in Section II. In Section III, the non-cooperative game-theoretic resource allocation is formulated. In Section IV, we derive the correlated equilibrium solution for the proposed game-theoretic approach. The simulation results, together with the performance analysis, are given in Section V. Finally, we conclude the paper in Section VI.

II. SYSTEM MODEL

In this section, we present the system model of HVNs in urban scenario. Then we propose an incentive mechanism based spectrum reusing method in order to fully utilize the available spectrum for vehicular communications. We summarize the notations and descriptions of key parameters in Table I.

A. HVNs

The HVNs consist of macrocells and RSUs, which provide an efficient way to offload the wireless and mobile service of vehicle users from macrocells. As illustrated in Fig. 1, we consider a total of N_r fixed RSUs underlying the coverage of a macrocell base station (MBS) in urban scenarios with a grid-like street layout, where RSUs are deployed near the road intersections with covering radius R_{rsu} and provide wireless service for vehicle users. Besides, the RSUs are incorporating cognitive capability hence they are able to sense the environment and detect the available spectrum such as TVWS [25], [26], which the FCC and the Office of Communications (Ofcom) allow the vehicle users to access for addressing the increasing demand of mobile data from vehicular communications. The connection and information exchange between MBS and RSUs are supported by LTE [28].

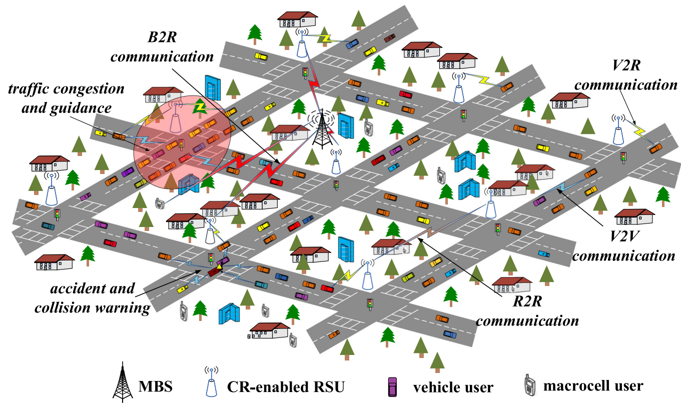

Fig. 1. The communications in HVNs.

We assume that the arrival of the macrocell users follows Poisson process with the arrival rates λ_m [18]. The arrival of vehicle users requiring for wireless service also follows Poisson process with parameter λ_v. Owing to advances in land vehicle localization technology, the locations of land vehicles can be obtained by global positioning system (GPS) [29] or through cooperative localization method [30].

In addition, the vehicles are assumed moving in a bidirectional way, such as from east to west or from north to south. When the vehicles move into the transmitting range of CR-enabled RSU, the vehicle users will initialize spectrum resource request to RSU once they have wireless service demands. The wireless services of vehicle users can be classified into two parts in the vehicular communications, namely the real-time service (such as collision alarm, road congestion information, voice over IP etc.) and flexible service (such as Internet access and entertainments). The RSU will decide whether or not respond the request based on the usage of the spectrum and the variety of wireless services. When there are available spectrum bands, the vehicle users with real-time service have the priority to access the spectrum resource.

B. Incentive Mechanism Based Spectrum Reusing

In the urban area, large number of vehicles pose heavy burden for the current cellular communication system, for instance, the LTE and LTE-A, in providing reliable connection for the requirement of V2X communications [31]. In other words, besides the macrocell users, the licensed spectrum resources in the cellular system are not enough that can be used for the massive vehicle users in HVNs. To solve this problem, it is essential to discover and utilize the available spectrum including unlicensed spectrum so as to address the increasing demand of wireless services from vehicular communications.

Therefore, motivated from [14], we propose an incentive mechanism for allowing the macrocell to share the available spectrum with the vehicle users, which enables an effective way to cope with the problem of spectrum resource shortage. First, we need to identify the vacant spectrum that vehicle users can use. To achieve this, the RSUs with CR capability sense the available spectrum bands in surrounding environments, and then send the information back to the MBS. According to the FCC's latest TVWS regulation [25], the secondary users, i.e., the vehicle users and macrocell users, can obtain the availability information of TVWS spectrum database. This helps to reduce the operation time for searching the available spectrum. As a coordinator during the spectrum sharing, the MBS collects and analyzes the information of the white spectrum with accessional system cost, such as the increasing of the transmission overhead, computation and storage space. On the basis of reciprocity in the incentive mechanism, the macrocell users can use the available spectrum and the MBS will allocate a definite proportion of available spectrum resource to the RSU-tier, hence the benefit is mutual, i.e., the use of sensed spectrum provides additional radio resource for both macrocell users and vehicle users, on the other hand, the vehicle users would not cause interference to the macrocell users.

Let N_w denote the total number of the white spectrum sensed by the RSUs. Note that the spectrum sensing can not be absolutely accurate. We define ρ as the accuracy during spectrum sensing and $0 < \rho < 1$. Let N_a denote the total number of the available spectrum and we have $N_a = \rho N_w$. Assume that $0 < \zeta < 1$ denotes the ratio of spectrum assigned to macrocell. Let N_b denote the quantity of the vacant spectrum bandwidth allocated to RSUs. We then have $N_b = \rho(1 - \zeta)N_w$. As a result, the vehicle users will not cause interference to the macrocell users. The spectrum resources mentioned in this paper are the resource blocks (RBs), which are referred to the time-frequency resource block unit in the downlink LTE system. We can assume the RSU is able to identify the type of traffic services (i.e., the real-time traffic with high priority and flexible traffic with low priority) of the vehicle users when they move into the transmitting range of an RSU. The RSU will preferentially allocate the spectrum resource to vehicle users with the requirement of real-time traffic service owing to the limited available spectrum bandwidth. When the entire available spectrum is occupied in RSU, the RSU would not accept requests of either real-time service or flexible traffic service. In this case, the ongoing flexible traffic service will not be terminated even the vehicle user with real-time service arrives. Besides, the RSU will withdraw the spectrum resource allocated to the vehicle users when they depart from the RSU or their traffic services end. Hence, this occupied spectrum resource will be available to other vehicles which are within the coverage of the RSU.

III. Noncooperative Game-Theoretic Resource Allocation

In this section, we deal with resource allocation problem in RSU-tier of HVNs among RSUs sharing the available spectrum resource that can be obtained according to Section II. In the practical urban environment, the RSUs, i.e., the selfish players, compete for the available spectrum to maximize their own interests, which can be modeled as an n-person game [13]. However, this leads to the inefficiency known as the 'tragedy of commons' [32]. In the case of this study, it implies that the RSUs act individually for their interests while ultimately harm the utilization of the limited spectrum resource. This occurs even they are aware of that it is not the long-term interests of any other RSUs. The cooperation between RSUs offers an effective way to overcome this hurdle and solve the concern for efficiency. Nevertheless, this relies on stable and large number of information exchange among RSUs and results in the increasing of transmission overhead and signaling processing burden in the HVNs. Therefore, we solve the n-person game with a distributed manner. To achieve this, we propose a non-cooperative game-theoretic approach to implement spectrum resource allocation between RSUs, in which the players (the RSUs) choose the strategy independently, with the purpose of maximizing the overall utility and achieving the correlated equilibrium.

A. Formulation of Noncooperative Game

The resource allocation problem is modeled as a noncooperative game, which can be defined as

$$\Gamma = \{\widetilde{N}, \{\widetilde{A^r}\}, \{\widetilde{U^r}\}\}, \tag{1}$$

where $\widetilde{N}$ denotes the finite set of RSUs. $\widetilde{A^r}$ and $\widetilde{U^r}$ denote the strategy set and the utility of RSU r, respectively. $r \in \{1, 2, \ldots, N_r\}$ and N_r denotes the number of RSUs. We define $\widetilde{A^r} = \{A_1^r, A_2^r, \ldots, A_k^r\}$ and $k \in \{1, 2, \ldots, N_b\}$. A_k^r is used to describe one single strategy of that the k-th RB is allocated to RSU r. $A_k^r = 1$, if the k-th RB is assigned to RSU r; otherwise, $A_k^r = 0$.

B. Utility Function

We consider the downlink Signal-to-Interference plus Noise Ratio (SINR) of RSU r transmitting to its associated vehicle i, which can be calculated by

$$SINR_i^r(t) = \frac{P_i^r(t)(d_i^r)^{-\gamma} h_i^r \delta_i^r(t)}{\sum_{m \neq r} (d_i^m)^{-\gamma} P_i^m(t) h_i^m \delta_i^m(t) + N_0}, \tag{2}$$

where $t \in \{1, 2, \cdots, T\}$ denotes the time interval. $P_i^r(t)$ denotes the transmission power when RSU r communicates with the vehicle user i. d_i^r denotes the distance between RSU r and vehicle user i. γ is the path loss exponent. d_i^m denotes the distance between RSU m and vehicle user i. $m \in \{1, 2, \cdots, N_r\}$ and $m \neq r$. Let Δt denote the duration of the time interval. h_i^r is the channel gain of vehicle user i in RSU r. According to the results in [33], the channel fading gain changes slightly with small Δt, for instance, the channel gain is almost constant when Δt is less than $1s$ in a wide-range dynamic vehicular environments. Hence, we set $\Delta t = 1s$ in this study. The interference consists of two parts, namely, the additive white Gaussian Noise (AWGN) denoted by N_0 and the co-channel interference. $\sum_{m \neq r} (d_i^m)^{-\gamma} P_i^m(t) h_i^m \delta_i^m(t)$ denotes the co-channel interference on the RSU r transmitting to the vehicle user i from other vehicle user sharing the same RBs. $\delta_i^r(t)$ is the indicator function, which can be expressed as

$$\delta_i^r(t) = \begin{cases} 1, & \text{Resource block is assigned to vehicle } i \\ 0, & \text{otherwise.} \end{cases} \tag{3}$$

When vehicle i enters into the coverage of RSU r and initializes the request for spectrum resource, the RSU r will decide whether the resource is allocated to this vehicle user. If the RSU accepts the request, $\delta_i^r = 1$; otherwise $\delta_i^r = 0$, when the RSU refuses the request or the vehicle departs from RSU r. We define the achievable data rate of a vehicle user as utility function, which can be given by

$$U_i^r(t) = w_i^r \log(1 + SINR_i^r(t)), \tag{4}$$

where w_i^r is the spectrum bandwidth that RSU r transmit information to the vehicle i.

Therefore, the utility function can be obtained by

$$U = \sum_{t=1}^{T} \sum_{r=1}^{N_r} \sum_{i=1}^{N_v} U_i^r(t), \tag{5}$$

where N_v denotes the total number of vehicle users. Our aim is to maximize the overall utility and improve the system performance. Therefore, the inter-RSU interference should be mitigated and thus acceptable by controlling the transmission power of RSUs for protecting the minimum communication demand from the vehicle users.

IV. Correlated Equilibrium Solution For the Proposed Game-Theoretic Approach

In this section, we focus on investigating the correlated equilibrium [13] for the proposed non-cooperative game. In essence, correlated equilibrium is the probability distribution on n-tuples of actions that are interpreted as the distribution of play instructions given to the players, namely the RSUs in this study. Individual strategies of the RSUs at present, where each RSU is an independent entity and its action will not be affected by others, are guided by 'regret measures' based on observation of past periods. As a result, the RSUs may either continue playing former strategy or switch to another strategy.

A. Formulation of Strategy Set

We design a graph coloring (GC) algorithm with the aim of obtaining the set of strategies, specifically, a single strategy is referred to how to assign radio resource to an RSU and the strategy set is the strategy combination that an RSU can use.

In the first step, we need to caculate the relationship matrix $M \in R^{N_r \times N_r}$ of RSUs. The relationship matrix formation depends on the relative geographic position of the RSUs, for example, if RSU r is the neighbor of RSU j, $M_{r,j} = 1$, otherwise, $M_{r,j} = 0$. Here we have $r, j \in [1, 2, \ldots, N_r]$. In the next step, we allocate the spectrum resource on the basis of that the adjacent RSUs cannot share the same resource blocks. The strategy set formation is presented in Algorithm 1. The computational complexity of Algorithm 1 is $O(N_r^2 N_b)$, where N_r denotes the number of the RSUs and N_b denotes the quantity of the available spectrum allocated to RSUs.

Algorithm 1: Strategy Set Formation Based on GC.

Input: The relationship matrix of RSUs $M \in R^{N_r \times N_r}$. $B \in R^{N_r}$ denotes which RBs can be used by RSUs.
Output: The strategy set $\widetilde{A^r}$ for the RSUs

Initialization: $B = ZERO$
for $r = 1, 2, ..., N_r$ **do**
  B_r++
  while $B_r \le N_b \, and \, r \le N_r$ **do**
    for $j = 1, 2, \cdots, r$ **do**
      if $M_{r,j} == 1 \, and \, B_r == B_j$ **then**
        B_r++;
      end if
    end for
  end while
  if $B_r \le N_b; r == N_r$ **then**
    Update $\widetilde{A^r} \leftarrow B$
  else if $B_r \le N_b \, and \, r < N_r$ **then**
    r++
  else
    $B_r = 0$
    r- -
  end if
end for

B. Correlated Equilibrium

According to the above analysis, the strategy set for the proposed non-cooperative game-theoretic approach might be large in some cases, which depends on the number of available resource blocks, but still finite. Therefore, the equilibrium points for the proposed game must be existent based on [27].

Definition 1 (Correlated equilibrium): The correlated equilibrium in (1) is a strategy combination which needs to satisfy

$$E\widetilde{U^r}(A_p^r, \widetilde{A^{-r}}) \ge E\widetilde{U^r}(A_q^r, \widetilde{A^{-r}}), \tag{6}$$

$$A_p^r, A_q^r \in \{A_1^r, A_2^r, \ldots, A_{S_r}^r\}, p \ne q, \tag{7}$$

where $\widetilde{A^{-r}}$ denotes that the strategy combination of all RSUs except RSU r. $E\widetilde{U^r}(A_p^r, \widetilde{A^{-r}})$ is used to denote the expected utility of RSU r when the strategy set of RSU r contains the specified strategy A_p^r. In similar manner, $E\widetilde{U^r}(A_q^r, \widetilde{A^{-r}})$ is the expected utility of RSU r when a single strategy A_q^r is included in $\widetilde{A^r}$. S_r denotes the size of strategy set.

A correlated equilibrium distribution is a probability distribution ξ_{pq} which satisfies

$$\sum_p \sum_q \xi_{pq} = 1, \tag{8}$$

$$\xi_{pq} \ge 0, \forall p, q \in \{1, 2, \ldots, S_r\}, p \ne q. \tag{9}$$

Let D_T^r denote the average utility difference for RSU r applying strategy A_p^r to replace strategy A_q^r at time interval T, where A_q^r was played at previous time intervals till $T - 1$. Based on the concept of regret-matching [13], the resulting difference can be obtained as

$$D_T^r(p,q) = \frac{1}{T}\sum_{t=1}^{T}[U_t^r(A_p^r, \widetilde{A^{-r}}) - U_t^r(A_q^r, \widetilde{A^{-r}})]. \quad (10)$$

Finally, we formulate a degree of 'regret' at T for not playing the strategy A_p^r, which is denoted by $R_T^r(p,q)$, where RSU r applied the strategy A_q^r in the past. $R_T^r(p,q)$ can be obtained by

$$R_T^r(p,q) = max\{D_T^r(p,q), 0\}. \quad (11)$$

Therefore, the probability distribution $\xi_{T+1}^r(p)$ and $\xi_{T+1}^r(q)$ of RSU r regarding the strategy p and q at $T+1$ on the basis of the historical utility are formulated as

$$\xi_{T+1}^r(p) = \frac{1}{\mu}R_T^r(p,q), \quad (12)$$

$$\xi_{T+1}^r(q) = 1 - \sum \xi_{T+1}^r(p), \quad (13)$$

where $\forall p, q, \in \{1, 2, \ldots, S_r\}, p \neq q$. μ is a large enough parameter, which is used to ensure that the value among the probability distribution is greater than zero [13].

Proof of the convergence for the non-cooperative game.

Let θ_T denote the empirical distribution of $\widetilde{A^r}$ and $f(A_p^r, \widetilde{A^{-r}})$ denote the occurrences of a single strategy $(A_p^r, \widetilde{A^{-r}})$ that has been selected during a time period $[1, T]$. The definition of $(A_p^r, \widetilde{A^{-r}})$ can be seen in (7). Therefore, θ_T can be obtained by

$$\theta_T(A_p^r, \widetilde{A^{-r}}) = \frac{f(A_p^r, \widetilde{A^{-r}})}{T}. \quad (14)$$

According to the theoretical analysis in [13], θ_T converges to correlated equilibrium when $T \to \infty$.

Hence, we have proved the existence of the correlated equilibrium for the non-cooperative game-theoretic resource allocation approach. Next, with the aim of enhancing the utilization of the CR-sensed spectrum resource and achieving the correlated equilibrium with fast convergence, we propose the non-cooperative game-theoretic strategy selection algorithm so as to enable the RSUs to perform resource allocation for vehicular communications.

C. Noncooperative Game Based Resource Allocation

The problem of spectrum resource allocation can be formulated as follows.

$$\text{maximize} \quad \sum_{t=1}^{T}\sum_{r=1}^{N_r}\sum_{i=1}^{N_v} U_i^r(t), \quad (15)$$

$$\text{s.t.} \quad P_i^r(t)\delta_i^r(t) \le P_{MAX}^r, \forall r, t, i, \quad (16)$$

$$SINR_i^r(t) \ge S_0, \forall r, t, i, \quad (17)$$

$$\delta_i^r(t) \in \{0, 1\}, \forall r, t, i, \quad (18)$$

$$P_i^r(t) > 0, \forall r, t, i, \quad (19)$$

where P_{MAX}^r stands for the maximum transmission power of RSU r. Constraint (16) gives the transmission power constraint, which is used to avoid the unnecessary interference to other RSUs. S_0 denotes the minimum SINR required for RSU and

Algorithm 2: Non-Cooperative Game-Theoretic Strategy Selection.

The set of strategies is formed by graph clouring algorithm. N_r denotes the number of the RSUs. S_r denotes the size of strategy set.

for $T = 1, 2, 3, \ldots$ **do**
  for $r = 1, 2, \cdots N_r$ **do**
    Calculate the difference in the average utility of RSU r by using (9) and (10) and then update the probability distribution based on (12) and (13)
    for $p = 1, 2, \cdots, S_r$ **do**
      if $\xi_{T+1}^r(p) > 0$ **then**
        Let A_p^r be one of the candidate strategies
      end if
    end for
    Update the strategy set by randomly choosing a strategy from the candidate list
  end for
end for

hence (17) is used to maintain the V2R connection at an acceptable level. According to (3), the function $\delta_i^r(t) \in \{0, 1\}$ is used to guarantee that the same resource blocks would not be reused in adjacent RSUs. Constraints (18) and (19) are integer constraint and the non-negative power constraint, respectively. The formulated problem in (15)-(19) is a mixed-integer programming problem, which turns out to be non-convex and usually NP-hard when maintaining the balance between the interference and the transmission power [34]. It is a challenging task to find an optimal solution for power adjustment and RB allocation, since it requires an exponential run time to solve it.

We devise the non-cooperative game-theoretic approach to calculate the achievable data rate. The vehicle users with relatively high SINR in their associated RSUs will be assigned with RBs. Then we calculate the historical utility matrix and update the probability distribution. In the following step, we obtain the candidate strategy list from the strategy set, where all such better choices get positive probabilities. Note that the strategy set can be obtained by the proposed GC method presented in Algorithm 1. Further, we update the spectrum allocation strategy by randomly choosing strategy from the candidate list. The procedure of the non-cooperative game-theoretic strategy selection is presented in Algorithm 2. According to the definitions of probability distribution in (12) and (13), the choice of μ is used to guarantee that $\xi_{T+1}^r(q) > 0$. Based on (11)-(13), a positive probability of playing the same strategy can be obtained as in the previous period. The strategy selection is based on regret-matching, a larger μ results in lower $\xi_{T+1}^r(p)$ of applying A_p^r to replace A_q^r. It can be considered as an inertia parameter [13]. If RSU r plays according to the procedure of Algorithm 2, the empirical distribution θ_T in (14) converges almost surely to the set of correlated equilibrium distributions of the non-cooperative game for any large μ. Therefore, the convergence to the correlated equilibrium of the non-cooperative game-theoretic algorithm can be guaranteed and the convergence speed changes

Algorithm 3: Heuristic Power Control Algorithm (HPCA).

Initialization: $P_i^r(t) = 0, \forall r \in \{1, 2, \cdots, N_r\}$, where N_r denotes the number of the RSUs.
for $t = 1, 2, 3, \ldots$ **do**
  for each RB **do**
    $\widehat{P}^r(t) \leftarrow \arg_{P_i^r(t)}(SINR_i^r(t) = S_0)$
  end for
  for $r = 1, 2, 3, \cdots$ **do**
    $P_i^r(t) = min\{max\{\widehat{P}^r(t)\}, P_{MAX}^r\}$
  end for
end for

with μ. The proposed game-theoretic approach is implemented iteratively for converging to the correlated equilibrium point. The computational complexity of Algorithm 2 is $O(N_T N_r S_r)$, where N_T is the number of time intervals, N_r is the number of the RSUs and S_r denotes the size of strategy set.

Optimization of $P_i^r(t)$.

For the sake of simplicity, $P_i^r(t)$ in the problem (15)-(19) can be set to constant transmission power (CTP), such as the maximum transmission power of RSU. However, this may aggravate the inter-RSU interference and ultimately lower the overall utility. Therefore, in order to further mitigate the inter-RSU interference and enhance the energy efficiency, we investigate the adjustable transmission power based RBs allocation. Note that the problem in (15)-(19) is non-convex. To solve it, we propose a heuristic power control algorithm (HPCA) to adjust transmission power of RSU, which is presented in Algorithm 3. The proposed non-cooperative game-theoretic approach is a joint method with power adjustment and RB allocation, which aims to find the suboptimal solution for the formulated problem in (15)-(19).

Let $\widehat{P}^r(t) = \{P^1(t), P^2(t), ..., P^r(t), ..., P^{N_r}(t)\}$, which is used to denote the set of constrains. The set of transmission power of vehicle user i in RSU r can be given by

$$P^r(t) = \{P_1^r(t), P_1^r(t), ..., P_i^r(t), ..., P_{N_v}^r(t)\}. \quad (20)$$

The RSU r can obtain the transmission power set $P^r(t)$ when the SINR of each vehicle user in RSU r, namely $SINR_i^r(t)$, is equal to the threshold value S_0 according to (17). If the RB k is reused by the vehicle users in the adjacent RSU, then update the candidate transmission power set $\widehat{P}^r(t)$. In order to avoid the unnecessary interference to the adjacent RSU, RSU r chooses the optimal transmission power $P^r(t)$ by using

$$P^r(t) = min\{max\{\widehat{P}^r(t)\}, P_{MAX}^r(t)\}. \quad (21)$$

The computational complexity of Algorithm 3 is $O(N_T (N_r + N_b))$, where N_T is the number of time intervals, N_r is the number of the RSUs and N_b denotes the quantity of the available spectrum allocated to RSUs.

V. Results and Performance Evaluation

In this section, we conduct simulations considering an urban area including several roads and intersections, which are within the coverage of macrocell and multiple RSUs are deployed around the MBS (See as illustrated in Fig. 1). Each vehicle user is associated with the nearest RSU in urban scenario. The average speed and moving direction of vehicles satisfy the requirements of motor vehicle driving in urban area, for example, the maximum speed limit is 80 kilometers per hour. The vehicle density captures the average quantity of vehicles on the road, where the high vehicle density is on account of the high arrival rates of vehicle. The other simulation parameters are listed in Table II, which are suggested from [35], [36].

TABLE II
Simulation Parameters

Parameter	Value
Macrocell radius	1500 m
RSU radius	200 m
Maximum Tx power of RSU	18 dBm
Maximum Tx power of MBS	46 dBm
Carrier frequency	2.6 GHz
Amount of RSU in a MBS	9
Noise power	-104 dBm
Path loss mode	ITU UMa/UMi [35]

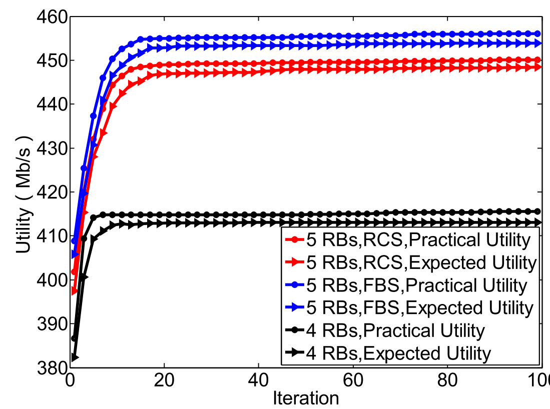

Fig. 2. The practical utility vs. the expected utility.

We first evaluate the practical utility, which is the achievable data rates of real-time updating the strategy sets via Algorithm 2. The expected utility can be obtained on the basis of expectation of the practical utility and empirical distribution. Moreover, we consider the vehicle is moving at the speed of 40 km per hour and the density of vehicles is set to 100veh/km/lane in urban scenario. We obtain the strategy sets through graph coloring method (Algorithm 1) when there are 4 RBs available for total 9 RSUs in the HVNs. The results from Fig. 2 demonstrate that the practical utility and expected utility grow rapidly at the first 6 or 7 iterations and then turn to be flat after 8 iterations. From this point, the proposed non-cooperative game-theoretic approach can converge quickly, which is also supported from the results in Figs. 3 and 4. In other words, the empirical distribution of strategy combination converges to the correlated equilibrium distribution. Based on (14), as T increases to an appropriate rather than a considerable value, the selected strategy combination based on Algorithm 2 will be one of correlated equilibriums and obey the correlated equilibrium distribution. In the following simulations, we mainly consider practical utility.

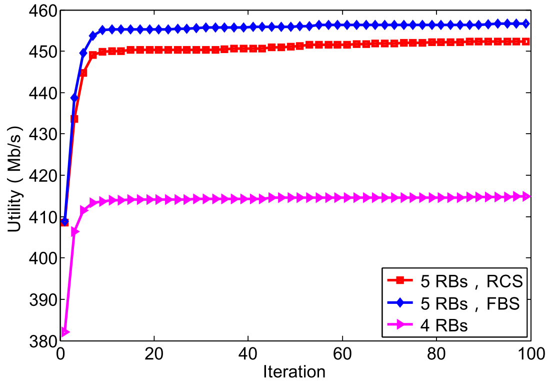

Fig. 3. The average utility in various resource blocks.

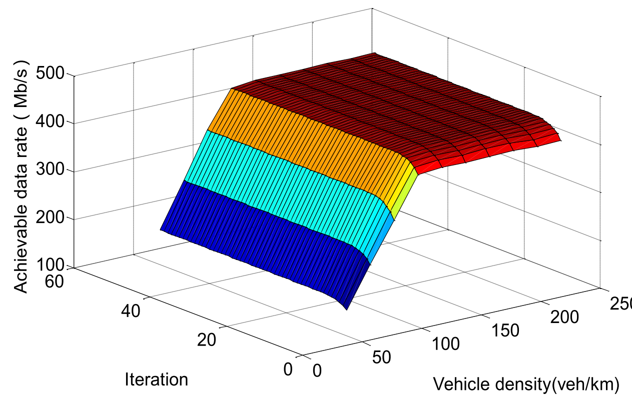

Fig. 5. The average utility when the number of RBs is 5.

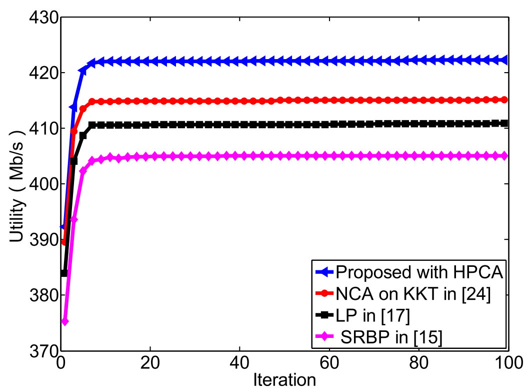

Fig. 4. The average utility when the number of RBs is 4.

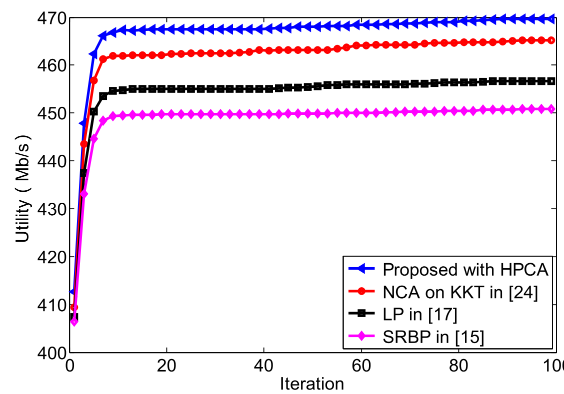

Fig. 6. The achievable data rate vs. vehicle density.

Then we analyze the utility performance of the proposed method under various available spectrum resources. It is noteworthy that the size of strategy sets is tightly dependent on the quantity of resource blocks. For instance, we obtain 6720 strategy sets for total 9 RSUs via graph coloring method (Algorithm 1) when there are 5 RBs available in the HVNs. Intuitively, such large number of strategy sets will increase the computational expense and thus degrade the system performance. Hence, to lower the computational complexity, we put forward to two methods for retrieving a subset of strategy from the original set, i) we randomly choose N_C strategies, which is referred to so-called RCS; ii) we arrange the strategies in descending order according to the interference between the RSUs, and then select the first N_C best strategies (FBS). Here N_C is far less than the size of original strategy sets. Fig. 3 presents the average utility performance when different number of RBs can be allocated to the RSUs. In addition, for comparison purposes, we study the results with RCS and FBS methods. As shown in Fig. 3, the RSU-tier with 5 RBs shows significant increasing of utility when comparing to the case of 4 RBs. In particular, it can obtain better utility with FBS when comparing with the RCS method.

Figs. 4 and 5 present the utility results, which are obtained by applying various methods and the number of RBs is 4 or 5, respectively. In this simulation, resource allocation based on Separate Resource Block allocation and Power control (SRBP) algorithm in [15], the linear programming (LP) method in [17], Karus-Kuhn-Tucker (KKT) nonlinear complementarity approach (NCA on KKT) in [24], are compared to the proposed approach in terms of the average utility for the optimization of the transmission power of RSU. The proposed method is based on the game-theoretic approach wherein the RCS and HPCA are used. It is observed that the performance of the proposed method outperforms the comparative methods, the RSUs with the adjustable transmission power can achieve a higher data rate when comparing to conventional methods. This is due to the fact that the RSUs appropriately adjust the transmission power which can reduce the interference and thus gain a better system performance.

We then assess the performance of the proposed approach in the high-dynamic environment. To this end, we investigate the impact on the system utility in terms of two critical parameters related to HVNs, i.e., vehicle density and vehicle velocity. Fig. 6 illustrates the achievable data rate under the varying of vehicle density. First of all, the proposed approach can achieve a quick convergence of the utility at the first 5 or 6 iterations and then turn to be flat after 8 iterations, which are also validated from Figs. 2 and 3.

Besides, we should notice a fact in vehicular environment, that is, when vehicles are entering into the communication range of an RSU in the meantime some vehicles are leaving from it to the next RSU. This leads to a balance of the vehicles served by each RSU. As a result, the RSUs can release the radio resource assigned by the departing vehicles to the new arrival vehicles. For this reason, from Fig. 6, we can observe that the utility is in a growing trend as the vehicle density is increasing. When

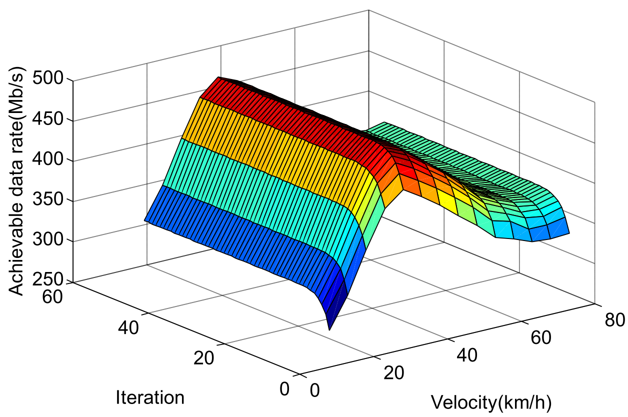

Fig. 7. The achievable data rate vs. vehicle velocity.

the number of arriving vehicles is coming larger, for instance in Fig. 6, the vehicles density exceeds 150 veh/km/lane, the utility maintains a steady level after reaching the peak value. The reason behind this is that limited spectrum resource being utilized in the RSU-tier is not able to satisfy the requirement from an excess of arriving vehicles.

Fig. 7 presents the changing of the achievable data rate when considering vehicle mobility. The vehicles in this area are moving with the average speed. It can be seen that the achievable data rate converges within 7 iterations. The system performance increases when the vehicle moves faster. The utility, i.e., the achievable data rate, is in the optimal condition when the vehicle velocity reaches 35km/h. After that, the achievable data rate however gradually drops due to the continuous increasing of vehicle mobility, which indeed deteriorates the link quality of connection between the vehicle users and their associated RSUs.

VI. Conclusion

In this paper, we investigate the radio resource allocation in HVNs by designing the non-cooperative game approach considering the mobility of vehicles. We first propose an incentive mechanism for encouraging macrocell to share spectrum resource with vehicle users, in which the CR-enabled RSUs perform sensing the spectrum availability in the surrounding environment. Then we formulate the resource allocation for moving vehicles associated with different RSUs as an n-person game. Considering transmission power constraint and inter-RSU interference, we derive the correlated equilibrium solution for the non-cooperative game based resource sharing to maximize the overall utility. Within the proposed approach, we design the strategy set formation algorithm based on graph coloring and propose heuristic power control algorithm (HPCA) to further mitigate the inter-RSU interference. Simulation results demonstrate that the proposed algorithm can achieve quick convergence and effectively control the inter-RSU interference as well as satisfy the system requirement in fast-moving environment.

In this study, handover issues have not been considered when a vehicle user moves cross the coverage of RSUs, which may cause failure for V2R connection especially in the high dynamic vehicular scenarios. For the future work, we will devote enough vigor to resolve handover and mobility management problems in HVNs.

References

[1] J. A. Guerrero-ibanez, S. Zeadally, and J. Contreras-Castillo, "Integration challenges of intelligent transportation systems with connected vehicle," *IEEE Wireless Commun.*, vol. 22, no. 6, pp. 122–128, Dec. 2015.

[2] K. Zheng, Q. Zheng, P. Chatzimisios, W. Xiang, and Y. Zhou, "Heterogeneous vehicular networking: A survey on architecture, challenges, and solutions," *IEEE Commun. Surv. Tut.*, vol. 17, no. 14, pp. 2377–2396, Fourth Quarter 2015.

[3] Q. Zheng *et al.* "Dynamic performance analysis of uplink transmission in cluster-based heterogeneous vehicular networks," *IEEE Trans. Veh. Technol.*, vol. 64, no. 12, pp. 5584–5595, Dec. 2015.

[4] Z. He, D. Zhang, and J. Liang, "Cost-efficient sensory data transmission in heterogeneous software defined vehicular networks," *IEEE Sensors J.*, vol. 16, no. 20, pp. 7342–7354, Oct. 2016.

[5] Y. Han, E. Ekici, H. Kremo, and O. Altintas, "Resource allocation algorithms supporting coexistence of cognitive vehicular and IEEE 802.22 networks," *IEEE Trans. Wireless Commun.*, vol. 16, no. 2, pp. 1066–1079, Feb. 2017.

[6] C. X. Wang *et al.* "Cellular architecture and key technologies for 5G wireless communication networks," *IEEE Commun. Mag.*, vol. 52, no. 2, pp. 122–130, Feb. 2014.

[7] H. Vu-Van and I. Koo, "Cooperative spectrum sensing with collaborative users using individual sensing credibility for cognitive radio network," *IEEE Trans. Consum. Electron.*, vol. 57, no. 2, pp. 320–326, Jul. 2011.

[8] A. Goldsmith, *Wireless Communications*. Cambridge, U.K.: Cambridge Univ. Press, 2013.

[9] G. I. Tsiropoulos, O. A. Dobre, M. H. Ahmed, and K. E. Baddour, "Radio resource allocation techniques for efficient spectrum access in cognitive radio networks," *IEEE Commun. Surv. Tut.*, vol. 18, no. 1, pp. 824–847, First Quarter 2016.

[10] J. Nash, "Non-cooperative games," *Ann. Math.*, vol. 54, pp. 286–295, 1951.

[11] H. Xu and R. Lin, "Resource allocation for network security risk assessment: A non-cooperative differential game based approach," *China Commun.*, vol. 13, no. 4, pp. 131–135. May 2016.

[12] E. E. Tsiropoulou, P. Vamvakas, and S. Papavassiliou, "Supermodular game-based distributed joint uplink power and rate allocation in two-tier femtocell networks," *IEEE Trans. Mobile Comput.*, vol. 16, no. 9, pp. 2656–2667, Sep. 2017.

[13] S. Hart and A. Mas-Colell, "A simple adaptive procedure leading to correlated equilibrium," *Econometrica*, vol. 68, no. 5, pp. 1127–1150, Sep. 2000.

[14] P. Y. Chen, W. C. Ao, S. C. Lin, and K. C. Chen, "Reciprocal spectrum sharing game and mechanism in cellular systems with Cognitive Radio users," in *Proc. IEEE Globecom Workshop*, Dec. 2011, pp. 981–985.

[15] W. Sun, E. G. Strom, F. Brannstrom, Y. Sui, and K. C. Sou, "D2D-based V2V communications with latency and reliability constraints," in *Proc. IEEE Globecom Workshop*, Austin, TX, USA, Dec. 2014, pp. 1414–1419.

[16] L. Liang, G. Li, and W. Xu, "Resource allocation for D2D-enabled vehicular communications," *IEEE Trans. Commun.*, vol. 65, no. 99, pp. 3186–3197, Apr. 2017.

[17] T. Jiang, Z. Wang, L. Zhang, D. Qu, and Y. C. Liang, "Efficient spectrum utilization on TV band for cognitive radio based high speed vehicle network," *IEEE Trans. Veh. Technol.*, vol. 13, no. 10, pp. 5319–5329, Oct. 2014.

[18] H. He, H. Shan, A. Huang, and L. Sun, "Resource allocation for video streaming in heterogeneous cognitive vehicular networks," *IEEE Trans. Veh. Technol.*, vol. 65, no. 10, pp. 7917–7930, Oct. 2016.

[19] R. Zhang, X. Cheng, Q. Yao, C. X. Wang, Y. Yang, and B. Jiao, "Interference graph-based resource-sharing schemes for vehicular networks," *IEEE Trans. Veh. Technol.*, vol. 62, no. 8, pp. 4028–4039, Oct. 2013.

[20] K. Zheng, F. Liu, Q. Zheng, W. Xiang, and W. Wang, "A graph-based cooperative scheduling scheme for vehicular networks," *IEEE Trans. Veh. Technol.*, vol. 62, no. 4, pp. 1450–1458, May 2013.

[21] T. D. Hoang, L. B. Le, and T. Le-Ngoc, "Resource allocation for D2D communication underlaid cellular networks using graph-based approach," *IEEE Trans. Wireless Commun.*, vol. 15, no. 10, pp. 7099–7113, Oct. 2016.

[22] R. Yu *et al.* "Cooperative resource management in cloud-enabled vehicular networks," *IEEE Trans. Ind. Electron.*, vol. 62, no. 12, pp. 7938–7951, Dec. 2015.

[23] T. Yang, R. Zhang, X. Cheng, and L. Yang, “A graph coloring resource sharing scheme for full-duplex cellular-VANET heterogeneous networks,” in *Proc. Int. Conf. Comput., Netw. Commun.*, 2016, pp. 1–5.

[24] R. Yu, J. Ding, X. Huang, M. T. Zhou, S. Gjessing, and Y. Zhang, “Optimal resource sharing in 5G-enabled vehicular networks: A matrix game,” *IEEE Trans. Veh. Technol.*, vol. 65, no. 10, pp. 7844–7856, Mar. 2016.

[25] H. Zhou *et al.*, “TV white space enabled connected vehicle networks: Challenges and solutions,” *IEEE Netw.*, vol. 31, no. 3, pp. 6–13, May/Jun. 2017.

[26] Y. Han, E. Ekici, H. Kremo, and O. Altintas, “Vehicular networking in the TV white space band: Challenges, opportunities, and a media access control layer of access issues,” *IEEE Veh. Technol. Mag.*, vol. 12, no. 2, pp. 52–59, Jun. 2017.

[27] R. J. Aumanni, “Correlated equilibrium as an expression of Bayesian rationality,” *Econometrica*, vol. 55, no. 1, pp. 1–18, 1987.

[28] S. Sun, J. Hu, Y. Peng, X. Pan, L. Zhao, and J. Fang, “Support for vehicle to-everything services based on LTE,” *IEEE Wireless Commun.*, vol. 23, no. 3. pp. 4–8, Jun. 2016.

[29] Z. Xiao, P. Li, V. Havyarimana, H. M. Georges, D. Wang, and K. Li, “GOI: A novel design for vehicle positioning and trajectory prediction under urban environments,” *IEEE Sensors J.*, vol. 18, no. 13, pp. 5586–5594, Jul. 2018. doi: 10.1109/JSEN.2018.2826000.

[30] M. Rohani and D. Gingras, “A new decentralized Bayesian approach for cooperative vehicle localization based on fusion of GPS and inter-vehicle distance measurements,” *IEEE Intell. Transport. Syst. Mag.*, vol. 7, no. 2, pp. 85–95. Apr. 2016.

[31] M. Xie, Y. Shang, Z. Yang, Y. Jing, and H. Zhou, “A novel MBSFN scheme for vehicle-to-vehicle safety communication based on LTE network,” in *Proc. IEEE 79th Veh. Technol. Conf. Spring*, Sep. 2015, pp. 1–5.

[32] G. Hardin, “The tragedy of the commons,” *Science*, vol. 162, pp. 1243–1248, 1968.

[33] S . Jangsher and V. O. K. Li, “Backhaul resource allocation for existing and newly arrived moving small cells,” *IEEE Trans. Veh. Technol.*, vol. 66, no. 4, pp. 3211–3219, Jul. 2017.

[34] S . Jangsher and V. O. K. Li, “Resource allocation in moving small cell network,” *IEEE Trans. Wireless Commun.*, vol. 15, no. 7, pp. 4559–4570, Jul. 2016.

[35] “Mobility enhancements in heterogeneous networks (Release 11),” 3rd Generation Partnership Project, Sophia Antipolis Cedex, France, Tech. Rep. TR36.839 v11.1.0, Jan. 2013.

[36] “Small cell enhancements for E-UTRA and E-UTRAN physical layer aspects (Release 12),” 3rd Generation Partnership Project, Sophia Antipolis Cedex, France, Tech. Rep. TR 36.872, May 2013.

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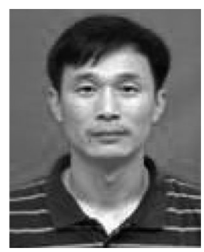

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