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Research Article

Spectrum Sharing with Dynamic Cournot Game in Vehicle-Enabled Cognitive Small-Cell Networks

Guilu Wu [1,2,3] **and Huilin Jiang** [4]

[1] *Jiangsu Provincial Engineering Laboratory of Pattern Recognition and Computational Intelligence, Jiangnan University, Wuxi 214122, China*
[2] *National Mobile Communications Research Laboratory, Southeast University, Nanjing 211189, China*
[3] *Key Laboratory of Industrial Internet of Things & Networked Control, Ministry of Education, Chongqing University of Posts and Telecommunications, Chongqing 400065, China*
[4] *School of Electronic Engineering, Nanjing Xiaozhuang University, Nanjing 211171, China*

Correspondence should be addressed to Huilin Jiang; huilin.jiang@njxzc.edu.cn

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Cognitive radio technology can effectively improve spectrum efficiency in wireless networks and is also applicable to vehicle small-cell networks. In this paper, we consider the problem of spectrum sharing among a vehicle primary user (V-PU) and multiple vehicle secondary users (V-SUs). This problem is modeled as a competition market, and the solution for V-SUs is designed using a non-cooperative game. A utility function that measures the profit of the V-PU considering quality of service (QoS) is proposed, aiming at maximizing the profit of the V-PU. Nash equilibrium is obtained as the best solution in our game. Then, the realistic vehicle-enabled cognitive small-cell network is considered in building the dynamic spectrum allocation problem. The V-SUs adjust their current strategies gradually and iteratively based on the observations on the strategies of the previous moment. This adjustment parameter is controlled by the frequency of adjustment. The stability analysis of the dynamic game is given out subsequently for dynamic spectrum allocation. The numerical results show the effectiveness of the proposed dynamic spectrum scheme for vehicle-enabled cognitive small-cell networks and Nash equilibrium point's existence.

1. Introduction

With the growth of vehicles and vehicle service requests in the modern society, lack of spectrum resources is getting worse in vehicle radio cognitive small-cell networks [1]. In many vehicle-enabled small-cell networks, the allocation of spectrum resources leads to low spectrum efficiency and is extremely unbalanced as of diverse type of services, users etc. The introduction of cognitive radio technology can intelligently use a large amount of idle spectra without affecting other authorized users and improve communication performance on high reliability. It is particularly important to apply cognitive radio technology in the vehicle-enabled small-cell environment to improve vehicle communication services [2–4] and enhance the radio resource efficiency [5]. Hence, researching on spectrum allocation in vehicle-enabled cognitive radio small-cell networks is particularly important.

Cognitive radio is able to investigate the communication parameters and further adapt itself to change network environments. The spectrum allocation in cognitive wireless networks has been a hot topic and discussed by researchers and developed in many related communication fields [6, 7]. Additionally, the dynamic spectrum sharing problems and solutions are presented on coexistence of both licensed users and unlicensed users in [8, 9]. Many key technologies in cognitive radio spectrum allocation involved policy choice issues.

The game theory is widely used as an effective tool for finding the Nash equilibrium point, which is the best strategy, in the game process [10–12]. Many works have focused on the application of game theory in cognitive radio technology. Gupta et al. [13] designed a suboptimal fairness power allocation algorithm based on Cournot game to maximize user or network throughput. The disadvantage of this method is that interference between subcarriers in OFDMA and cognitive radio-based IEEE 802.22 wireless regional area networks is not considered for subcarrier assignment. Tian et al. [14] presented a game model based on the prisoner's dilemma to analyze the sharing problem when users compete for spectrum. The pricing competition game model for pricing power control scheme is proposed in [15]. Neel et al. [16] studied convergence dynamics of the different types of games in cognitive radio networks. In these works, dynamic behavior of strategy has not been considered. The problem of pricing and spectrum allocation for cognitive radio networks in dynamic game environments is proposed in [17], while the issue on equilibrium is ignored in a competitive environment. The spectrum competition among users is often modeled as a game problem [12, 18]. But these works ignore to investigate the spectrum demanding function for the secondary users and stability analysis of game strategies. The utility maximization on pricing is analyzed in [19] to consider transmission rate and reliability. In vehicle-enabled cognitive small-cell networks, the vehicle could maximize its QoS and price when the service provider desires to maximize its revenue by game theory. In [20], a matrix game theory is exploited to run resource management and allocation for 5G-enabled vehicular networks, and a Nash equilibrium solution also can be achieved to improve resource efficiency and power consumption. However, few works consider spectrum resource price trading problem in dynamic mobile networks, such as vehicle-enabled cognitive radio small-cell networks.

In this paper, we adopt a game model to analyze this spectrum sharing problem in vehicle-enabled cognitive small-cell networks, where some primary vehicles are allocated with a licensed spectrum and unlicensed spectrum can be shared with the secondary vehicles. This spectrum sharing problem can be modeled as a competition market in which companies compete with each other with commodity supplied to the market to maximize the profit of the primary vehicles. And, the secondary vehicles compete for the spectrum offered by the primary vehicle according to its pricing function on the cost of the spectrum. The Nash equilibrium is also given out as the best response of the game process. In addition, we consider the dynamic game analysis when the vehicle secondary user cannot observe the pricing information and strategies of the other vehicle secondary users. Meanwhile, the spectrum stability is also analyzed in the dynamic game process.

The rest of this paper is organized as follows. Section 2 describes the system model and description. Then, the problem formulations and solutions for spectrum sharing are presented in Section 3. In Section 4, the dynamic game analysis and stability are presented. Section 5 gives out the performance evaluation results. Finally, the conclusions are generalized in Section 6.

2. System Model and Description

In this section, we briefly introduce the system model and the spectrum sharing problem in vehicle-enabled cognitive small-cell networks. Then, trading competition market is presented to solve the spectrum sharing problem, and we also define the role of various elements in networks for the trading market. At the end, the wireless transmission model is given out based on the received signal-to-noise ratio (SNR) on the vehicle.

2.1. Role Definition. In our spectrum sharing model, as shown in Figure 1, the SC-BS is used as the primary service provider (PSP) and the original vehicles (red) is the V-PUs. The entering vehicles (green and orange) are regarded as the V-SUs. Under the condition of meeting V-PUs spectrum requirements, the V-SUs share spectrum with V-PUs for the PSP. For the sake of simplicity and without loss of generality, we assume V-PUs and V-SUs work at overlay mode in vehicle-enabled cognitive small-cell networks. In addition, we also assume that vehicles are stable during the process of spectrum sharing for the convenience of research in this paper.

2.2. Precondition. In vehicle-enabled cognitive small-cell networks, a macrocell network which includes multiple small-cell networks is the constituent unit. In this case, vehicle-enabled cognitive small-cell networks form two types of planes correspondingly, including control plane (macrocell network) and data plane (small-cell network). The former is responsible for managing control information of vehicles and small-cell BSs (SC-BSs), and the latter is responsible for transmitting data messages. We assume that a vehicle-enabled cognitive small-cell network is a homogeneous network. All SC-BSs are randomly deployed in the infinite plane $\mathbb{R}^2$. And, these SC-BSs follow independent Poisson point processes (PPP). Every SC-BS has the same transmission power P_s. There are only one SC-BS and a few vehicles in one small-cell network. The boundary of small-cell can be computed by the Delaunay triangulation method, which connects all adjacent SC-BSs in a triangle to make vertical bisectors on each side of the triangle, so that several vertical bisectors around each SC-BS enclose a polygon, also called Poisson–Voronoi tessellation, in plane $\mathbb{R}^2$ corresponding with different small-cell areas [21, 22]. A single small-cell network is considered, as shown in Figure 1. In light of this, the geometric characteristics of a small-cell network can be extended to the whole vehicle-enabled cognitive small-cell networks according to Palm theory [23].

In Figure 1, the PSP has enough spectrum resources besides unused spectrum resources to offer services for V-PUs in this small-cell area. Besides, when other N V-SUs enter these small-cell networks, these vehicles need to request idle spectrum resources of SC-BS as of mass transmission messages to improve transmission efficiency. The distance between the vehicle (V-PU or V-SU) i, $i \in \{1, 2, \ldots, N\}$ and the PSP is denoted as d_i, $i \in \{1, 2, \ldots, N\}$.

2.3. Spectrum Sharing Competition Market. As can be seen from the above descriptions, the spectrum sharing problem can be modeled as a monopolistic market competition problem [24]. In a monopolistic competition market for commodities, competition with each other exists in several companies. The companies maximize their own profits by controlling the quantity and price of commodities supplied. In a general non-cooperative game model of the supply-demanding market, all companies compete with each other's output by product. For spectrum sharing model, secondary users share spectrum resources provided by primary users according to spectrum resource requirements in a competitive way. The profit of secondary users can be calculated based on the primary user pricing in the spectrum and the gains obtained through the spectrum utilization. The goal of all secondary users is to maximize their profits.

In our system model, as shown in Figure 1, the SC-BS provides redundant spectrum resources to entering vehicles, and we assume these entering vehicles could share spectrum provided through the SC-BS by competing with each other during trades. The size of the shared spectrum for the entering vehicles is designed as their strategy, and the profit that the entering vehicles get through sharing the spectrum is the most profit function.

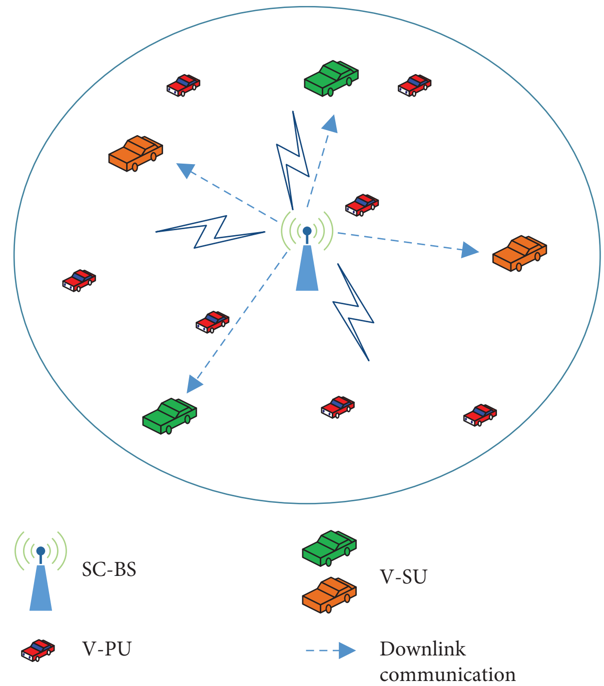

Figure 1: Spectrum sharing problem in vehicle-enabled cognitive small-cell networks.

2.4. Wireless Transmission Model. Due to vehicle mobility, the vehicle i, $i \in \{1, 2, \ldots, N\}$, in small-cell networks suffers the least path loss during wireless transmission. According to the path loss model, the received SNR of the V-SU is obtained by

$$\gamma_i = \frac{P_s (d_i)^{-n}}{\sigma^2}, \quad i \in \{1, 2, \ldots, N\}, \tag{1}$$

where n is the path loss factor and σ^2 represents the additive Gaussian white noise (AGWN) variance.

The vehicle movement causes constant change in transmission distance and SNR of the V-SU in further accordingly. In AGWN channel, the spectrum efficiency that a V-SU could obtain when using the PSP is expressed as

$$k_i = \log_2 (1 + K\gamma_i), \tag{2}$$

$$K = \frac{1.5}{\ln (0.2/\mathrm{BER}_i^{\mathrm{tar}})}, \tag{3}$$

where $\mathrm{BER}^{\mathrm{tar}}$ is the target bit-error rate (BER).

3. Problem Formulation and Solutions

In this section, a static game model in an ideal state is firstly established. In this model, all V-SUs can fully get the strategies and benefit functions of other V-SUs, that is, a centralized spectrum sharing scenario. A pricing function of the V-PU charging the V-SU is defined in this scenario. On the basis of pricing function, the utility function of the V-SU is also obtained. Finally, we can achieve the best response function of the V-SU and further get the best strategies with the V-SUs in this game.

3.1. Profit Function of V-SU. According to the system model, the participants in the game are all V-SUs. Each V-SU's strategy is the required spectrum size, and each V-SU's income function is the profit when the V-SU shares the spectrum with the V-PU and other V-SUs. The reward paid by the V-SU to the V-PU is proportional to the spectrum bandwidth it requires.

The pricing function that determines the size of the V-PU's charge to the V-SU is given by [25]

$$p(\vec{b}) = x + y \left(\sum_{b_j \in \vec{b}} b_j \right)^{\varphi}, \tag{4}$$

where x, y, and φ are all nonnegative numbers and $\vec{b}$ represents the set of spectrum components rented by the V-SUs, $\vec{b} = \{b_1, b_2, \ldots, b_N\}$. When $\varphi \geq 1$, equation (4) is a convex function. Meanwhile, we assume that the V-PU is willing to share spectrum with the V-SU and bids the same for all V-SUs in this article.

In order to ensure the QoS for networks in the case of spectrum sharing for the V-PUs and V-SUs, the QoS satisfaction [26] and the cost of spectrum sharing of the V-SU are considered in profit function. V-SUs rent V-PUs idle spectrum resources in vehicle-enabled cognitive radio small-cell networks. Therefore, the profit of the V-SU can be designed as follows:

$$U_i = \pi_i \log (1 + \kappa_i (1 - \eta) k_i b_i) - b_i p(\vec{b}), \tag{5}$$

where π_i is transmission link quality, κ_i is the V-SU's urgent degree for spectrum, and k_i and η are spectrum utilization for the V-SU and V-PU, respectively.

Submitting equation (4) into equation (5), equation (5) can be rewritten as

$$U_i = \pi_i \log\left(1 + \kappa_i (1-\eta) k_i b_i\right) - b_i \left(x + y \left(\sum_{b_j \in \overrightarrow{b}} b_j \right)^{\varphi} \right). \tag{6}$$

The marginal profit function for the V-SU i can be expressed as

$$\frac{\partial U_i}{\partial b_i} = \frac{\pi_i \kappa_i (1-\eta) k_i}{1 + \kappa_i (1-\eta) k_i b_i} - \left(x + y \left(\sum_{b_j \in \overrightarrow{b}} b_j \right)^{\varphi} \right) - b_i y \varphi \left(\sum_{b_j \in \overrightarrow{b}} b_j \right)^{\varphi - 1}. \tag{7}$$

From equation (7), we can see that the optimal spectrum bandwidth obtained by a V-SU depends on the strategy adopted by other V-SUs. Hence, all V-SUs satisfy with the final strategy when the game results are balanced.

3.2. Best Response Function. In static game, the result of game is Nash equilibrium. That is, given a set of participant strategies, if none of the participants can improve their profits by changing their actions, then all participants' profits have been maximized. In this article, the best reaction function method is adopted to solve Nash equilibrium. The best reaction function is the best strategy of the participant when other participants' strategies are given out.

The spectrum of other V-SUs is $\overrightarrow{b}_{-i}$, $\overrightarrow{b}_{-i} = \{b_j \mid j = 1, 2, \ldots, i-1, i+1, \ldots, N\}$ and $\overrightarrow{b} = \overrightarrow{b}_{-i} \cup \{b_i\}$, and then the best response function of the V-SU is derived as follows:

$$\mathrm{BR}\left(\overrightarrow{b}_{-i}\right) = \arg\max_{b_i} U_i\left(\overrightarrow{b}_{-i} \cup \{b_i\}\right). \tag{8}$$

If and only if

$$b_i^* = \mathrm{BR}\left(\overrightarrow{b}^*_{-i}\right), \quad \forall i, \tag{9}$$

the game reaches the Nash equilibrium, $\overrightarrow{b}^* = \{b_1^*, b_2^*, \ldots, b_i^*, \ldots, b_N^*\}$.

For game process, the Nash equilibrium solution needs to be verified from the following three aspects:

(1) In Cournot game, the number of V-SUs participating in the game is limited in vehicle-enabled cognitive small-cell networks

(2) During the Cournot game process, the V-SUs of the participating game must have the property of a quasiconcave function based on the continuity function

(3) In the non-cooperative V-SUs game based on game theory, the set interval of the V-PU's idle spectrum resources that all V-SUs end up competing is closed, and each V-SU competes the spectrum resources in the set. They are all within a certain range of values.

Up to our knowledge, conditions (1) and (3) are easy to realize. The following highlights condition (2). Furthermore,

$$\frac{\partial^2 U_i}{\partial^2 b_i} = -\frac{\pi_i \kappa_i^2 (1-\eta)^2 k_i^2}{\left(1 + k_i (1-\eta) k_i b_i\right)^2} - y\varphi \left(\sum_{b_j \in \overrightarrow{b}} b_j \right)^{\varphi - 1} - b_i y \varphi (\varphi - 1) \left(\sum_{b_j \in \overrightarrow{b}} b_j \right)^{\varphi - 2}. \tag{10}$$

Apparently, $(\partial^2 U_i / \partial^2 b_i) \leq 0$; therefore, condition (2) is established. The Nash equilibrium solution exists in our game model.

4. Dynamic Game Analysis

4.1. Dynamic Cournot Game. In an actual vehicle-enabled cognitive small-cell environment, the V-SU may only be able to observe the pricing information of the entering V-PU and cannot observe the strategies and benefits of other V-SUs. So, it is necessary to obtain Nash equilibrium for each V-SU on the basis of only interacting with the V-PU. Assuming all V-SUs are rational and trying to maximize their benefits, they can adjust the demanding spectrum b_i according to their respective marginal profit function. In this case, each V-SU can communicate with the V-PU and select the appropriate policy based on different pricing functions of the V-PU. The adjustment of the size of the V-SU i-shared spectrum (required spectrum) can be modeled as a dynamic game as follows:

$$b_i(t+1) = Q\left(b_i(t)\right) = b_i(t) + \nu_i b_i(t) \frac{\partial U_i(\overrightarrow{b})}{\partial b_i(t)}, \tag{11}$$

where $b_i(t)$ is the spectrum size that the V-SU competes at time t, ν_i is the speed of adjustment parameter (learning factor) of V-SU i, and $Q(\cdot)$ is the self-mapping function. Submitting equation (7) into equation (11), a dynamic game process can be expressed as

$$b_i(t+1) = b_i(t) + \nu_i b_i(t) \left(\frac{\pi_i \kappa_i (1-\eta) k_i}{1 + \kappa_i (1-\eta) k_i b_i} - \left(x + y \left(\sum_{b_j \in \overrightarrow{b}} b_j \right)^{\varphi} \right) - b_i y \varphi \left(\sum_{b_j \in \overrightarrow{b}} b_j \right)^{\varphi - 1} \right). \tag{12}$$

With increasing number of spectrum resources competing with the V-SUs, the bidding price of the SC-BS is also increased. The dynamic game process with equation (11) is also expressed as a matrix equation as follows:

$$\overrightarrow{b}(t+1) = Q(\overrightarrow{b}(t)). \tag{13}$$

The case of $\varphi = 1$ is considered in this article. In Nash equilibrium for all V-SUs, $b(t+1) = b(t) = b$, that is $b = Q(b)$. At this time, the V-PU pricing function is a linear function, which is consistent with the real situation of the V-PU in the vehicle-enabled cognitive small-cell networks. According to the linear pricing function, the fixed point b can be obtained by solving the following equation:

$$\begin{aligned} &\nu_i b_i(t)\left(\frac{\pi_i \kappa_i (1-\eta) k_i}{1+\kappa_i (1-\eta) k_i b_i} - \left(x + y\left(\sum_{b_j \in \overrightarrow{b}} b_j\right)^{\varphi}\right)\right. \\ &\left. - b_i y \varphi \left(\sum_{b_j \in \overrightarrow{b}} b_j\right)^{\varphi-1}\right) = 0, \quad i \in \{1, 2, \ldots, N\}. \end{aligned} \tag{14}$$

The Nash equilibrium point can be obtained $(b_1^*, b_2^*, \ldots, b_i^*, \ldots, b_N^*)$, where b_i^*, $i = 1, 2, \ldots, N$, is the size of spectrum sharing between V-SU i and V-PU.

4.2. Stability Analysis of Dynamic Game. By studying the eigenvalues of the Jacobian determinant, the stability of spectrum sharing is analyzed. According to the Routh–Hurwitz criterion [27], the fixed point is stable if and only if the eigenvalue of its corresponding Jacobian matrix J is within the unit circle. The Jacobian matrix J is expressed as

$$J(b_1, b_2, \ldots, b_N) = \begin{bmatrix} \frac{\partial b_1(t+1)}{\partial b_1(t)} & \frac{\partial b_1(t+1)}{\partial b_2(t)} & \cdots & \frac{\partial b_1(t+1)}{\partial b_N(t)} \\ \frac{\partial b_2(t+1)}{\partial b_1(t)} & \frac{\partial b_2(t+1)}{\partial b_2(t)} & \cdots & \frac{\partial b_2(t+1)}{\partial b_N(t)} \\ & \cdots & \cdots & \\ \frac{\partial b_N(t+1)}{\partial b_1(t)} & \frac{\partial b_N(t+1)}{\partial b_2(t)} & \cdots & \frac{\partial b_N(t+1)}{\partial b_N(t)} \end{bmatrix}, \tag{15}$$

where $J_{i,j}(i, j \in \{1, 2, \ldots, N\})$ denotes the element of matrix J.

According to equation (14), the solution $b(b_1, b_2, \ldots, b_N)$ is submitted into equation (15), and then the eigenvalues λ_i, $|\lambda_i| < 1$, $i = 1, 2, \ldots, N$ are solved. In this article, we discuss the case of $N = 2$. Hence, the Jacobian matrix J of two V-SUs can be written as

$$J(b_1, b_2) = \begin{bmatrix} J_{1,1} & J_{1,2} \\ J_{2,1} & J_{2,2} \end{bmatrix}. \tag{16}$$

Then, the eigenvalues of Jacobian matrix $J(b_1, b_2)$ can be obtained by solving

$$\lambda^2 - \lambda\left(J_{1,1} + J_{2,2}\right) + \left(J_{1,1}J_{2,2} - J_{1,2}J_{2,1}\right) = 0. \tag{17}$$

Hence,

$$(\lambda_1, \lambda_2) = \frac{\left(J_{1,1} + J_{2,2}\right) \pm \sqrt{4J_{1,2}J_{2,1} + \left(J_{1,1} - J_{2,2}\right)^2}}{2}. \tag{18}$$

5. Simulation Results

5.1. Simulation Parameter. To facilitate simulation, without loss of generality, we consider a vehicle-enabled cognitive small-cell networks consisting of one V-PU and two V-SUs. The available spectrum of the V-PU is $20MHz$, and the target BER of the V-SUs is 10^{-4}. For pricing function parameters, $x = y = 1$, and φ is determined by real environment.

5.2. Nash Equilibrium and Profit Function. The best response function of two V-SUs is shown in Figure 2. For different transmission link qualities and SNR, the optimal response function for each V-SU is nonlinear function of another V-SU, and the intersections of two function curves are the Nash equilibrium points (Arrow position), which are affected by system parameters. When channel quality is improved, the bandwidth of the V-SU is increased correspondingly. Then, one V-SU's bandwidth change affects the bandwidth of another V-SU. This conclusion is also applicable for multi-V-SUs situation ($N > 3$). In this case, the best response function of the V-SU is a spatial surface and the intersection is their Nash equilibrium points.

Figures 3–5 analyze the relationship between parameter φ in the pricing function and profit of the V-PU. In Figure 3, the different link SNR and spectrum demanding levels on profit of the V-PU is observed for different transmission link qualities. When one condition, e.g., the received SNR or transmission link quality, is fixed, improving the other conditions will increase the profit of the V-PU. Additionally, the profit of the V-PU is gradually increased with φ under different system conditions. Similarly, different spectrum demanding levels of the V-SUs and spectrum utilization of the V-PU change the profit of the V-PU and are plotted in Figure 4. The profit of the V-PU increases with different φ until reaching the maximum value for different spectrum demanding level κ and spectrum utilization η of the V-PU.

In the case of $\gamma_1 = \gamma_2 = 25\,\text{dB}$, $\eta_1 = \eta_2 = 0.4$, $\kappa_1 = \kappa_2 = 0.8$, the profit of the V-PU for different φ in the pricing function is plotted in Figure 5. With increasing number of the parameter φ, the profit of the V-PU from charging higher price is from the V-SU. However, when the price of spectrum resources continues to increase, the V-SU demanding for spectrum resources decreases, and the profit gained by the V-PU also decreases correspondingly. The results indicate that there is an optimal value (Ellipse mark) of φ for some V-SUs to maximize the profit of the V-PU.

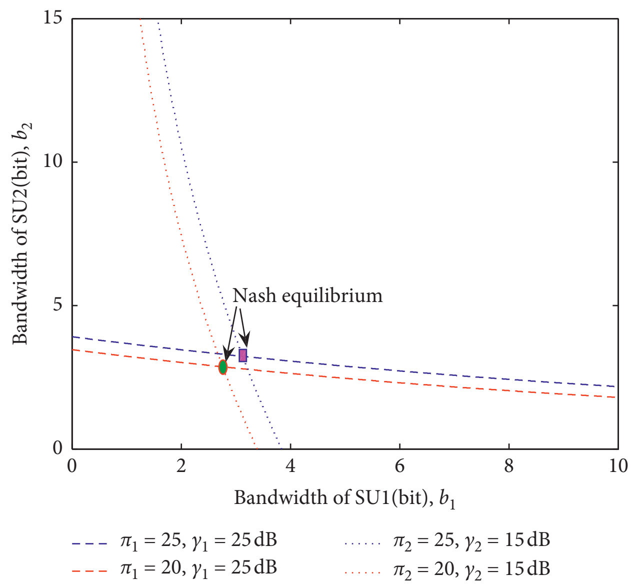

FIGURE 2: The best response function of the V-SU.

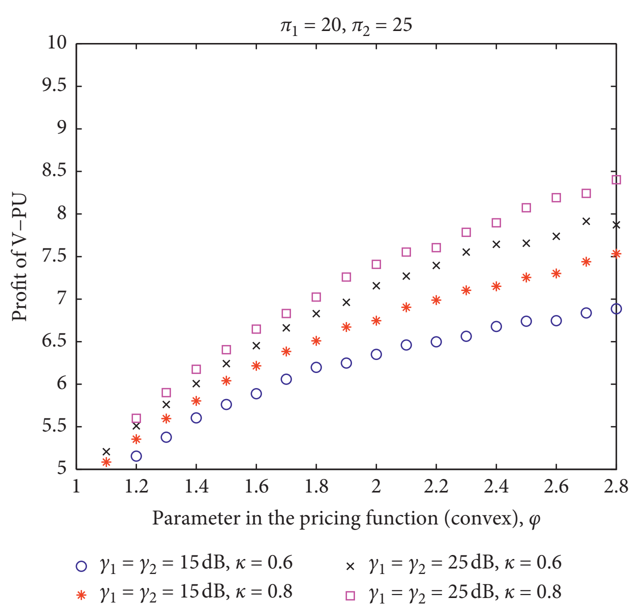

FIGURE 3: The profit of the V-PU vs. φ, on transmission link quality.

5.3. Dynamic Game and Stability Analysis. The dynamic behavior of the non-cooperation game with time t is examined at Figures 6 and 7, where $\pi_1 = \pi_2 = 30$, $\gamma_1 = \gamma_2 = 25$ dB, $\kappa = 0.6$ and $\eta = 0.4$. In this part, the dynamic game initialization strategy is $b_1(0) = b_2(0) = 2.525$ at V-SU 1 and V-SU 2. Obviously, the shared spectrum changes of the two V-SUs are shown in Figures 6 and 7, respectively, when the V-SU's practical edge benefit is used for spectrum sharing. The spectrum sharing will reach Nash equilibrium by adjusting reasonable learning factor and the Nash equilibrium is easy to reach for higher learning factor ν as of slow convergence. It is worth noting that higher learning factor may also result in non-convergence and further away Nash equilibrium.

According to the eigenvalues of the Jacobian matrix J in equation (15), the relationship between the adjustment speed parameters of V-SU 1 (ν_1) and V-SU 2 (ν_2) with the stability of spectrum sharing is shown in Figure 8. For different transmission link quality π, the stability region in $\nu_1 - \nu_2$ plane is marked (arrow pointing) in Figure 8. By solving equation (18), the eigenvalue is the relationship between ν_1 and ν_2. Therefore, the relationship can be obtained under satisfying for $|\lambda| < 1$.

6. Conclusions

We introduced game theory into the study of vehicle-enabled cognitive small-cell works. Firstly, the vehicle-enabled

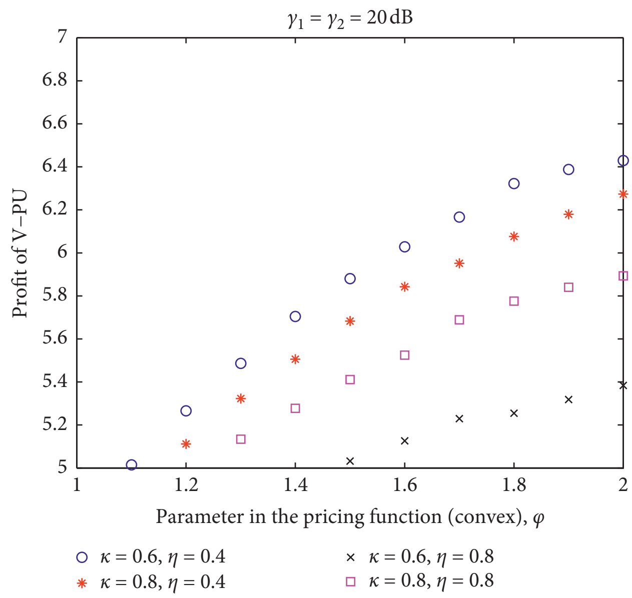

Figure 4: The profit of the V-PU vs. φ on received SNR.

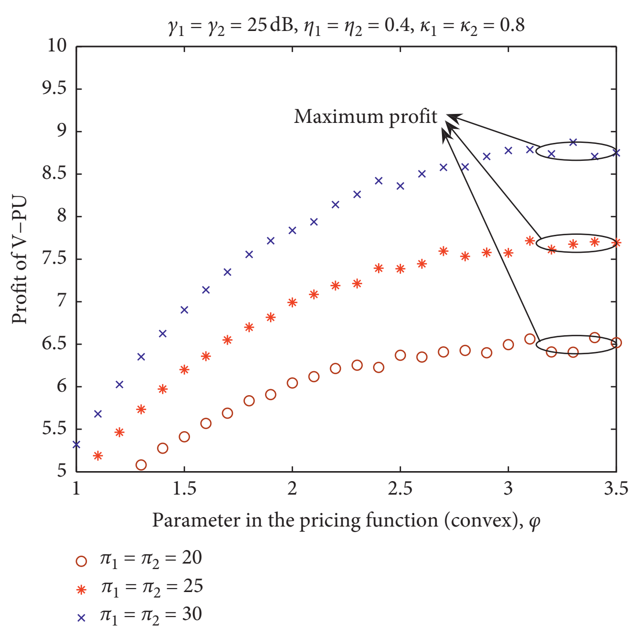

Figure 5: The profit of the V-PU vs. φ on spectrum utilization.

cognitive radio was analyzed through game theory, and the research was also presented as follows. Then, the system model for spectrum sharing problem in vehicle-based cognitive small-cell networks was established, and the Nash equilibrium on a static game for the best spectrum allocation of the V-SU was obtained. Afterwards, the dynamic game of spectrum sharing for the V-SU was analyzed, and finally the stability of the proposed dynamic game model was further investigated. The numerical results reveal that the proposed scheme can converge drastically to the Nash equilibrium state. The profit function was established with the goal of the V-PU's revenue, and the influence of the QoS of the V-SU on spectrum sharing and revenue was analyzed. In addition, the learning factor of the V-SU was analyzed during the dynamic game. The importance of learning factor to system was investigated, and the convergence of V-SUs could be improved by changing the learning factor.

In future work, the spectrum trading will consider topology changes of vehicle-enabled cognitive small-cell networks in real-time as a result of vehicle moving. In addition, the base station in trading market will play a key role for all computations in our further study.

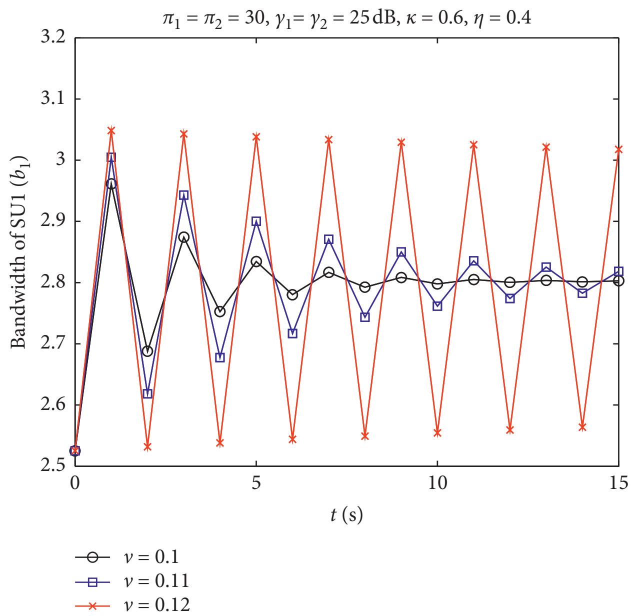

Figure 6: The dynamic behavior of the non-cooperation game for the V-SU 1.

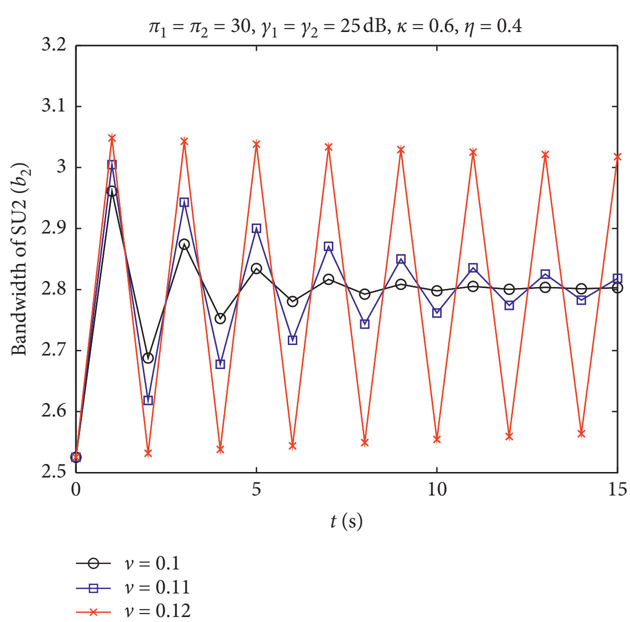

Figure 7: The dynamic behavior of the non-cooperation game for the V-SU 2.

Data Availability

The data used to support the findings of this study are included within the article.

Disclosure

Guilu Wu is currently at the School of Internet of Things Engineering, Jiangnan University, Wuxi 214122, China.

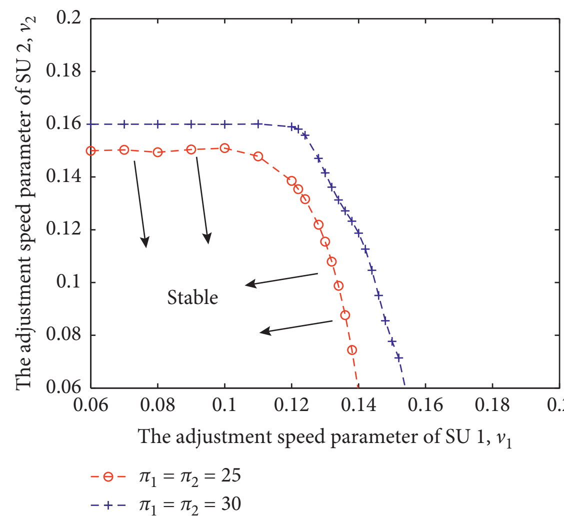

Figure 8: Stability region of dynamic game.

Conflicts of Interest

The authors declare no conflicts of interest.

Acknowledgments

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