Game based Cognitive Radio Bandwidth Allocation Scheme

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***Abstract*—Even though wireless Internet service has grown rapidly, the available wireless bandwidth resource is limited. So, efficient network bandwidth resources management has become an important issue. Recently, cognitive radio technology has been getting a lot of attention to improve bandwidth efficiency. In this paper, we propose an adaptive bandwidth management scheme based on the mechanism design and negotiation theory. According to the user`s utility, Quality of Service (QoS) and trust value, the proposed scheme allocates total resources while dynamically controlling the selfish users. In addition, the proposed scheme is able to make a control decision in a distributed manner. This approach can reduce the excessive number of operations and increase the primary user`s profit; it is practical for real world network operations. Simulation results show that the proposed scheme provides much better performance than the existing schemes.**

Keywords— Cognitive Radio; VCG Mechanism; Rubinstein Bargaining; Resource allocation

I. INTRODUCTION

Radio spectrum is the scarcest resource for wireless communications. Therefore, in the next generation wireless network, it may become congested due to diverse types of users and applications. Recently, regulatory bodies like the Federal Communications Commission (FCC) in the United States are recognizing that traditional fixed spectrum allocation can be very inefficient. In order to fully utilize the scarce spectrum resources, Cognitive Radio (CR) technology has becomes a promising approach, which allows unlicensed wireless users (secondary users: SUs) to dynamically access the licensed bands from legacy spectrum holders (primary users: PUs) on a negotiated or an opportunistic basis. Dynamic spectrum access in CR networks can enhance the radio resource utilization. To realize efficient spectrum usage, we must migrate from the current static spectrum access to a dynamic spectrum [1]-[3].

Most existing resource allocation approaches for CR networks assume that SUs are truthful, cooperative and always successful in operation. Therefore, SUs always send truthful information in interference environment, even though they can fail resource allocation. These assumptions are only available in an ideal theoretical situation. However, in the real world, untruthful SUs exist; they can lie in order to get more spectrum resource by using untruthful information. In such cases, the CR network administrator wishes to design a new protocol that extracts the missing information from the SUs. Due to this reason, we need a new game model to force selfish SUs to cooperate.

To effectively manage the limited spectrum resource, extensive research has been carried out. Nowadays, game theory has become a powerful tool to analyze and improve the performance of CR network control protocols. Game theory is the mathematical theory of interactions between self-interested agents. It can describe the possibility to react to the actions of the other decision makers and analyze the situations of conflict and cooperation. In particular, it focuses on decision making in settings where each player's decision can influence the outcomes of other players. In such settings, each player must consider how each other player will act in order to make an optimal choice. In the game theory, a game consists of player, strategies and payoff function [4]-[6].

Recently, researchers have proposed various algorithms to optimally share the spectrum resource using cognitive radio technologies. Auction game models also have been proposed for efficient spectrum sharing in CR networks. Initially, auction game has been studied extensively in the economics literature. Usually, it is implemented with efficient social choice functions; participants have private information about their preferences. An auction is a process of buying and selling goods or services by offering them up for bid, taking bids, and then selling the item to the highest bidder. In game theory, an auction game may refer to any mechanism or set of trading rules for exchange. A well-known auction mechanism is the Vickrey-Clarke-Groves (VCG) mechanism [7]. It is a generalization of the famous Vickery auction where bidders submit written bids without knowing the bid of the other bidders in the auction. The important properties of the VCG mechanism are direct-revelation and strategy proof [8]; each bidder reveals his/her true value no matter what strategies the other bidder chooses. However, the VCG mechanism needs a huge computational overhead. Therefore, the traditional VCG mechanism might be impractical for the system's overall operations.

In 1982, Israeli economist Ariel Rubinstein built up an alternating-offer bargain model based on the Stahl's limited negotiation model; it is known as a Rubinstein bargaining process. This model can provide a possible solution to the problem that two players are bargaining with the division of the benefits [9]. Most of all, the Rubinstein can significantly

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reduce the computational complexity and overhead. It is practical and suitable for real implementation.

In this paper, we propose a new spectrum allocation scheme for CR networks. In our game model, SUs are game players, and can make strategic decisions independently while maximizing their payoffs. By using the VCG mechanism, our proposed scheme is designed as a cooperative game model. In addition, to effectively reduce the computational overhead of VCG mechanism, we adopt the Rubinstein bargaining model. This integrated approach can simplify the implementation of VCG mechanism. Therefore, our proposed scheme effective controls selfish SUs to increase the total system utility while reducing the VCG mechanism time complexity.

This paper is organized as follows. Section II explains the related works. In Section III, we present the proposed algorithms in detail. In Section IV, performance evaluation results are presented along with comparisons with other schemes. Finally, concluding remarks are given in Section V.

II. RELATED WORKS

In this section, we introduce two game-theoretic models for the effective resource allocation in CR networks. In Section II-A, we present the desired properties of a VCG mechanism design to effectively control selfish SUs. In Section II-B, we introduce the Rubinstein Bargaining Model, which can help VCG mechanism design to decrease time complexity.

A. VCG mechanism

VCG mechanism is a field of Mechanism Design (MD) to study a solution concept for the class of private information games. Traditional *MD* consists of a specification of possible agent strategies and the mapping of each strategy from a set of strategies to an outcome. Agents are assumed to be autonomous and economically rational; they select a best-response strategy to maximize their expected utility with other agents. The family of *direct-revelation* and *strategy-proof* mechanisms has been derived from the *MD* theory and are referred to as *VCG* mechanism. The *VCG* mechanism has better computational properties than the original *MD* and provides a normative guide for outcomes and payments. When applying the *VCG* mechanism to complex *MD* problems, a feasible outcome can be obtained from the results of computationally tractable heuristic algorithms [10]. Each agent in the *VCG* mechanism is of a specific type. According to its type, an agent selects a specific strategy, which defines the agent's actions. Generally, an agent type is represented by θ, (e.g., each agent *i* is of type θ_i).

The *VCG* mechanism is a special case among traditional mechanisms, in which the agent-announced type ($\hat{\theta}$) is no longer necessarily truthful; the symbol $\hat{\theta}$ indicates that agents can misreport their true types. Based on agent-announced types, the choice rule ($k^*(\hat{\theta})$) is defined as follows [11]

$$k^*(\hat{\theta}) = \text{argmax}_{k\in\mathcal{K}} \sum\nolimits_{\text{i}} v_i(k,\hat{\theta}_i) \qquad (1)$$

where k is a feasible choice of the set of all possible choices and $v_i(k,\hat{\theta}_i)$ defines the agent i's outcome of a choice k with its type $\hat{\theta}_i$; the *VCG* mechanism implements the choice k^* that maximizes $\sum_i v_i(k,\hat{\theta}_i)$. Therefore, the *VCG* mechanism maximizes the total outcome of the system to the agents. Based on $k^*(\hat{\theta})$, the payment rule ($p_{vcg,i}(\hat{\theta})$) is defined as follows

$$p_{vcg,i}(\hat{\theta}) = v_i(k^*(\hat{\theta}),\hat{\theta}_i) - \{V_N - V_{N-i}\} \qquad (2)$$

where V_N is the total reported outcome of k^* and V_{N-i} is the total reported outcome of the choice that would be gotten without agent i, i.e., $V_N = \max_{k\in\mathcal{K}} \sum_{\text{i}} v_i(k,\hat{\theta}_i)$ and $V_{N-i} = \max_{k\in\mathcal{K}} \sum_{j\neq i} v_j(k,\hat{\theta}_j)$.

B. Rubinstein Bargaining Model

In Rubinstein-Stahl bargaining model, players have their own bargaining power (δ). The division proportion of the benefits can be obtained according to the bargaining power, which can be computed at each player individually. The higher the bargaining power, the more a player benefits from the bargaining. Players negotiate with each other by proposing offers alternately. After several rounds of negotiation, they finally reach an agreement as follows

$$\begin{aligned}&(x_1^*, x_2^*)\\ &= \begin{cases} \left(\dfrac{1-\delta_2}{1-\delta_1\delta_2}, \dfrac{\delta_2(1-\delta_1)}{1-\delta_1\delta_2}\right) & \text{if the } player\_1 \text{ offers first} \\ \left(\dfrac{\delta_1(1-\delta_2)}{1-\delta_1\delta_2}, \dfrac{1-\delta_1}{1-\delta_1\delta_2}\right) & \text{if the } player\_2 \text{ offers first} \end{cases} \qquad (3)\\ &\qquad s.t., (x_1^*, x_2^*) \in \mathbf{R}^2 : x_1^* + x_2^* = 1,\\ &\qquad x_1^* \geq 0, x_2^* \geq 0 \text{ and } 0 \leq \delta_1, \delta_2 \leq 1\end{aligned}$$

It is obvious that $\frac{1-\delta_2}{1-\delta_1\delta_2} \geq \frac{\delta_2(1-\delta_1)}{1-\delta_1\delta_2}$ and $\frac{\delta_1(1-\delta_2)}{1-\delta_1\delta_2} \leq \frac{1-\delta_1}{1-\delta_1\delta_2}$. That is to say, there is a first-proposer advantage in the bargaining process. Traditionally, the bargaining power in the *Rubinstein-Stahl's* model is defined as follows

$$\delta = e^{-\xi\times\Delta}, \qquad s.t., \xi > 0 \qquad (4)$$

where Δ is the time period of the negotiation round. Given the Δ is fixed (i.e., *unit_time*), δ is monotonic decreasing with the ξ. ξ is an instantaneous discount factor to adaptively adjust the bargaining power.

Especially, Rubinstein bargaining model provides a solution of a class of bargaining games that features alternating offers through an infinite time horizon. For a long time, the solution to this type of bargaining game was a mystery. Therefore, Rubinstein's solution is one of the most influential findings in cooperative game theory [11].

III. PROPOSED SCHEME

In this section, the proposed scheme is explained in detail. The proposed scheme is designed to provide an effective resource allocation for CR network. The main objective of our scheme is to maximize social welfare by the optimal resource allocation.

A. Bargaining process for distribution of resources

In CR network, SUs use the spectrum bandwidth that should not have interference. Due to this reason, only SUs who are in available interference distance can use spectrum bandwidth. To secure enough interference distance, SUs are grouped as clusters by exchanging SU's distance information, and can guarantee the mutual interference. The SUs are clustered as follows, i) all SUs exchange their distance information and perform the cluster operation only with SUs that are in their mutual interference, ii) in each cluster, leaders are selected by random process, iii) all SUs in each cluster send request message to leader, iv) leaders in each cluster send cluster request message to administrator, v) the administrator calculates each cluster leader's Signal to Interference plus Noise Ratio (SINR), and allocates allocation sequence number by using SINR.

To allocate the total resource, the administrator starts to bargain with each cluster leader, sequentially. In this paper, Rubinstein bargaining approach is used for the fairness allocation. In the Rubinstein bargaining model, the decision of patience factor values is a key issue. For the SU's patience factor on the aggregated SUs' payoff. If the sum of SU's utility increases, the total system payoff also increases. Therefore, δ_g can be defined as follows

$$\delta_g = \frac{1}{\alpha \times v + \beta \times q + \gamma \times tr}, \quad s.t., \ \frac{d\delta_g(v)}{dv} > 0, \delta_g(0) = 1 \text{ and } \delta_g(\infty) = 0 \qquad (5)$$

where α, β, γ are weighted factors for value (v), importance of traffic (q) and trust value (tr). In the proposed scheme, to provide the fairness for each leader, administrator decides patience factor (δ_A) to be the midpoint of all leaders' payoffs like as

$$\delta_A = \frac{2}{\sum_{j=1}^{m}(g_j(v) + g_j(q) + g_j(tr))} \qquad (6)$$

Based on the obtained δ_g and δ_A values, we can develop the Rubinstein bargaining process. The administrator collects each leader's bandwidth request, and defines each cluster's total request (g) as follows,

$$\mathrm{g}_j = \sum_{i=1}^{n} \mathrm{r}_i \qquad (7)$$

where r_i is the agent i's bandwidth request, and g_j is the cluster j's total request. According to the administrator's offer (x) and cluster j's offer (y), the equilibrium point of Rubinstein bargaining model can be obtained. Finally, the Rubinstein bargaining equilibrium point can be expressed as follows:

$$x^* = \frac{1 - \delta_{g_j}}{1 - \delta_A \delta_{g_j}}, \quad y^* = 1 - \frac{1 - \delta_{g_j}}{1 - \delta_A \delta_{g_j}} \qquad (8)$$

In this work, VCG mechanism is used to effectively control selfish users and resource allocation, which can increase a social welfare. However, the main disadvantage of VCG mechanism is the higher computation complexity. To reduce the computation complexity, firstly, we group all SUs into each cluster, and the Rubinstein bargaining model is applied to each cluster, iteratively. According to the Rubinstein bargaining process, we can distribute the total bandwidth resource (R) to each cluster. Finally, the VCG mechanism is used in each cluster to effectively control selfish users and resource allocation, which can increase a social welfare. Our distributed approach is more practical and justified for real network operations.

B. Resource allocation based on trust VCG mechanism

In the VCG model, vector of allocation K is defined as follows

$$\boldsymbol{K} = \{\emptyset, \tau^{1<-allo}, \tau^{2<-allo}, \dots, \tau^{i<-allo}\} \qquad (9)$$

Let $\emptyset$ and $<-allo$ be respective non-allocation and resource allocation, respectively. If the SU i gets the resource (k=$\tau^{i<-allo}, \boldsymbol{K} = \emptyset$), his cost function ($\mathrm{c}_i(\boldsymbol{K})$) is defined as $\mathrm{c}_i(\tau)$. The total system value function ($v_{allo}(\boldsymbol{K})$) can be defined as $v_{allo}(\boldsymbol{K}) = v_{allo}(\tau)$. We define the vector of successful probability $= [p_1(\tau), \dots, p_i(\tau)]$, and the SU i's successful probability ($p_i(\tau)$) can be defined as the ratio of the total successful task operation ($\sum_{l=1}^{L}(\tau_{l_{success}}^{i})$) to the total task ($\sum_{l=1}^{L}(\tau_l^i)$).

$$p_i(\tau) = \frac{\sum_{l=1}^{L}(\tau_{l_{success}}^{i})}{\sum_{l=1}^{L}(\tau_l^i)}, \qquad s.t., (p_i(\tau) \in [0,1] \qquad (10)$$

where τ_l^i represents whether the task allocation is allocated (0) or not (1), and $\tau_{l_{success}}^{i}$ represents whether the task is successfully operated or not. The expected value function ($\bar{v}_{allo}(\boldsymbol{K}, p)$) is defined based on the probability $p_i(\tau)$.

$$\bar{v}_{allo}(\boldsymbol{K}, p) = v_{allo}(\boldsymbol{K}) \times p_i(\tau) \qquad (11)$$

Each SU should send his own information about the probability ($\hat{p}$) and cost function ($\hat{c}$) to the administrator. At the same time, each SU also can send the un-trust information ($\hat{c}, \hat{p}$) to maximize his profit. In the proposed scheme, the resource allocation is adaptively controlled based on the accurate analysis of costs and payoffs. In more detail, the resource is allocated to the most suitable SU while maximizing the system efficiency.

$$k^*(\hat{c},\hat{p}) = arg\max_{k\in K}\left[\bar{v}(\boldsymbol{K},\hat{p}) - \sum_{i\in I}\hat{c}_i(\boldsymbol{K})\right] \quad (12)$$

Similar to the traditional VCG mechanism, the payoff of each SU is defined as the marginal contribution of the selected SU to the CR system; it is extracted by comparing the second best decision, excluding the selected SU. Without the best SU, the second-best expected payoff for the CR service, which allocates resource can be obtained as follows by considering success and fail cases.

$$\begin{aligned}\bar{u}_i(\hat{c},\hat{p}) = p_i(\tau)\Bigg[&v_{allo}\big(\boldsymbol{K}^*(\hat{c},\hat{p})\big) - c_i\big(\boldsymbol{K}^*(\hat{c},\hat{p})\big)\\ &- \max_{\boldsymbol{K}'\in\boldsymbol{K}_{-i}}\Big(\bar{v}_{allo}(\boldsymbol{K}',\hat{p}) - \sum_{j\in I_{-i}}\hat{c}_j(\boldsymbol{K}')\Big)\Bigg]\\ &+ \big(1-p_i(\tau)\big)\Bigg[-c_i\big(\boldsymbol{K}^*(\hat{c},\hat{p})\big)\\ &- \max_{\boldsymbol{K}'\in\boldsymbol{K}_{-i}}\Big(\bar{v}_{allo}(\boldsymbol{K}',\hat{p}) - \sum_{j\in I_{-i}}\hat{c}_j(\boldsymbol{K}')\Big)\Bigg]\\ = \bar{v}_{op}\big(\boldsymbol{K}^*(\hat{c},\hat{p}),p\big) &- c_i\big(\boldsymbol{K}^*(\hat{c},\hat{p})\big)\\ &- \max_{\boldsymbol{K}'\in\boldsymbol{K}_{-i}}\Big(\bar{v}_{allo}(\boldsymbol{K}',\hat{p}) - \sum_{j\in I_{-i}}\hat{c}_j(\boldsymbol{K}')\Big) \quad (13)\end{aligned}$$

where $\boldsymbol{K}_{-i}$ is a set of allocation without the SU i. With probability $(p_i(\tau))$, the expected utility $(\bar{u}_i(\hat{c},\hat{p}))$ is achieved based on the expected marginal contribution, which is the difference between the best and the second-best expected utility.

IV. PERFORMANCE EVALUATION

In this section, the effectiveness of the proposed scheme is validated through simulation. To emulate a real-world CR environment and for a fair comparison, we carefully select the system parameters as shown in Table 1. Using our simulation model, the performance of the proposed scheme is compared with the two CR resource allocation schemes; the traditional VCG scheme [12] and the single TBMs scheme [13].

TABLE I. SYSTEM PARAMETER

Name	Value
Size of network	1000m × 1000m
Number of node	10 ≤ node ≤ 25
Distance of inteference	100m ≤ Distance ≤ 300m
QoS value	Qos ≤ 1
Trust value	Trust ≤ 5
Utility value	10 ≤ utility ≤ 30
Number of iterations	100

Usually, the performance of CR systems depends on the sum of SUs' payoff, total system payoff, the SUs' satisfaction and task succession probability. In this paper, the performance measures are plotted as the number of SUs.

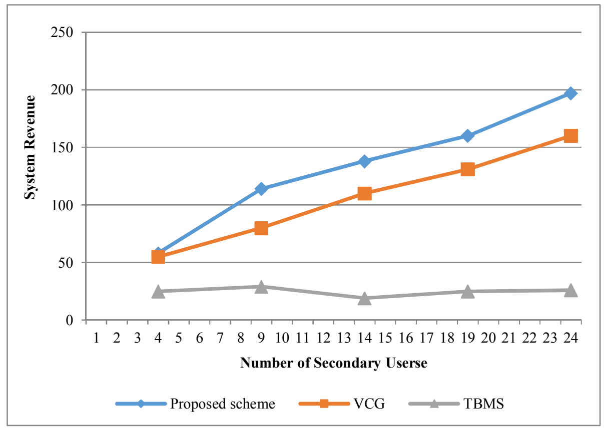

Figure. 1. Total system efficiency due to the number of SUs

In Figure 1, the system revenues of each scheme are compared to each other. System revenue is estimated as the total sum of successful SU task profits. From the service providers' point of view, it is a very important performance factor. From the simulation results, we can see that the system revenue of our proposed scheme is higher than the other existing schemes.

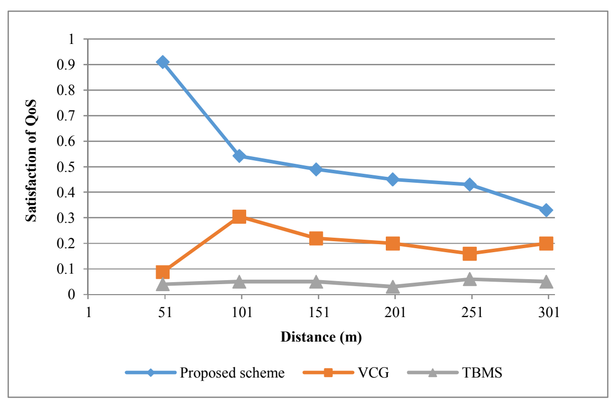

Figure. 2. Satisfaction of QoS with interference

Figure 2 shows the QoS satisfaction of SUs. From the viewpoint of SUs, QoS satisfaction is a critical issue. Usually, QoS evaluation factors are availability (uptime), bandwidth (throughput), latency (delay), error rate, and so on. However, as mentioned earlier, the proposed scheme is designed to concentrate on the social welfare aspect of bandwidth allocation. Therefore, the total amount of allocated bandwidth for successful task is assumed as a major QoS satisfaction factor. Under various operation times or the number of SUs, the proposed scheme can provide much better QoS satisfaction than other schemes.

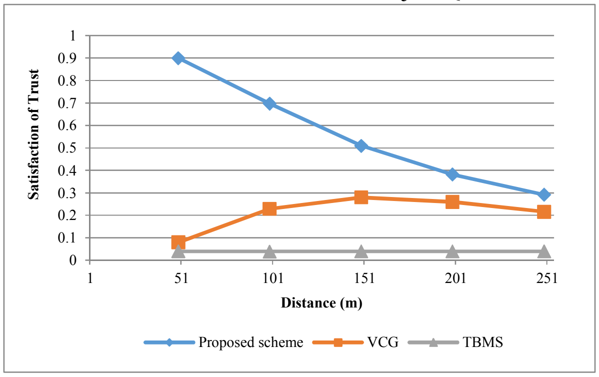

Figure. 3. Satisfaction of Trust with distance

Figure 3 shows the performance evaluation about trust satisfaction. When the administrator allocates the spectrum resource, trust satisfaction for all SUs is obtained. These results represent the system's satisfaction. Our proposed scheme considers the trust value, QoS satisfaction and SU's utility. Therefore, the proposed scheme can maintain a better trust satisfaction than other existing schemes.

V. CONCLUSION

Recently, the design of effective CR management algorithms has been one of intense research issues. In this paper, we propose a new adaptive bandwidth management scheme based on the VCG mechanism and Rubinstein bargaining model. Based on the SU's payoff, QoS and trust information, the proposed scheme can dynamically allocate the total bandwidth resources while maximizing PU`s profit. In addition, we make a control decision in a distributed manner. This distributed approach can reduce the excessive computation complexity of original VCG mechanism. It is a highly desirable feature for real-world CR system operations. Simulation results show that the proposed scheme can provides much better system performance than the existing schemes.

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