Traffic Demand-based Cooperation Strategy in Cognitive Radio Networks

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***Abstract*—Cognitive radio networks (CRNs) enable spectrum channels to be used by secondary users (SUs) without interfering with the transmission of primary users (PUs). Cooperation among SUs in CRNs not only improves sensing performance but also increases spectrum efficiency. In this work, we study a cooperation strategy in multi-channel CRNs, which allows an energy-constrained SU to selectively participate in cooperative sensing. We consider CRNs where SUs can make distributed decisions on cooperative sensing based on traffic demand. We formulate this problem as a non-transferable utility (NTU) coalition formation game problem, where each SU in a coalition has a coalition value that takes into account traffic demand and energy efficiency. We also propose a sequential coalition formation (SCF) algorithm to find the coalition structure. Simulation results show that our proposed algorithm achieves higher throughput and energy efficiency with a lower computational complexity compared to previously proposed coalition formation algorithm in [1].**

I. Introduction

Cognitive radio networks (CRNs) provide a promising solution to utilize the spectrum holes and improve the spectrum efficiency. In CRNs, secondary users (SUs) are able to access spectrum channels as long as they do not interfere with the transmission of primary users (PUs). In order to better utilize spectrum resources and guarantee the protection for PUs' transmission, SUs have to detect the channel availability before accessing the channel. Due to the shadowing and path loss, SUs may not be able to detect the channel accurately. Therefore SUs work cooperatively to sense the channel and share spectrum resources. This is called cooperative spectrum sensing and access in CRNs. Cooperation among SUs in CRNs improves both sensing performance and spectrum efficiency. However, cooperation in CRNs also incurs overhead, such as additional energy consumption spent on sensing. Therefore, how to obtain a high throughput while maintaining a high energy efficiency in CRNs is a challenging problem.

In the study of cooperation strategies in CRNs, several studies have been conducted to investigate throughput and energy efficiency in CRNs. In [1], Saad *et al.* analyze the tradeoff between spectrum sensing and spectrum access. They propose a joint cooperative spectrum sensing and access strategy to maximize each SU's utility, which takes into account sensing time and expected throughput. In [2], a cooperative sensing scheduling scheme is proposed to maximize the system utility of multi-channel CRNs. The utility function considers both sensing performance and energy efficiency. In [3], a spectrum sensing and access problem in multi-channel CRNs is formulated as a hedonic coalition formation game problem, in which the coalition payoff captures energy efficiency and sensing accuracy. A distributed algorithm is proposed to obtain the stable coalition structure of this game. In [4], an energy efficient transmission scheme is proposed to maximize energy efficiency in CRNs, in which the transmission power, sensing time, energy detection threshold, and the number of SUs are optimized. In [5], Zhang *et al.* propose a scheduling strategy to maximize aggregate utility of CRNs by appropriately assigning different SUs to multiple channels. The utility function, which is related to both sensing performance and network throughput, provides a reward to successful transmission and incurs a cost to failed transmission. In [6], Bayhan *et al.* consider the traffic demand of SUs and channel characteristics when distributing spectrum resources among SUs. They propose a centralized polynomial-time heuristic algorithm to find the optimal scheduling method that can maximize the system energy efficiency.

Although many strategies have been proposed to improve either the energy efficiency or throughput of SUs in CRNs, most of them do not consider individual traffic demand of each SU. They assume that SUs always have data to send and the spectrum channel is fully utilized when it is assigned to SUs, which, however, may not be the case in practice. The traffic demand of each SU varies from one to another and changes from time to time. The traffic demand of an SU depends on its application, e.g., an SU with a video streaming application usually has a higher traffic demand than an SU running a best-effort application. Also, the traffic demand may change over time, e.g., an SU with an environmental monitoring application aims to report the change of environmental factors (e.g., temperature). Its traffic demand changes with the environment along the time. Therefore, it is important to take the traffic demand of SUs into consideration when studying spectrum sensing and access in CRNs. Although traffic demand is taken into account in [6] and [7], they only study spectrum allocation without considering the spectrum sensing. Moreover, they aim at maximizing the aggregate utility instead of studying a cooperation strategy from the perspective of individual SU.

Most of the existing works assume that all SUs are supposed to participate in cooperative sensing (e.g., [2], [8]). In energy-constrained CRNs, for an SU having no data to transmit during a time slot, it is better to stay idle and save energy for next transmission instead of joining in cooperative sensing. Therefore, it is reasonable to let the SU make its individual decision on cooperation according to its traffic demand. Although the work in [9] applies evolutionary game theory to cooperation strategy design in CRNs and it assumes that SUs can choose to participate in cooperative sensing with a probability, it does not consider the energy efficiency and traffic demand of SUs.

In this paper, we study a traffic demand-based joint cooperative spectrum sensing and access strategy for individual SU in CRNs. Both throughput and energy efficiency are taken into account in this strategy. In our proposed cooperation strategy, SUs with low energy efficiency can refuse to perform cooperative sensing in order to conserve energy. This allows an energy-constrained SU to work more efficiently in CRNs. We apply the coalition formation game approach to analyze this problem, in which each SU is modeled as a player to maximize its individual utility that captures the expected throughput and energy efficiency. A sequential coalition formation (SCF) algorithm is proposed to obtain the final coalition structure. In summary, the main contributions are as follows:

- We study a cooperation strategy in CRNs with multiple channels, where each SU makes an individual decision on participating in cooperative spectrum sensing and access based on its traffic demand.
- We formulate this problem as a non-transferable utility (NTU) coalition formation game, in which each SU receives payoff according to its traffic demand and energy efficiency. We propose an SCF algorithm to determine the final coalition partition.
- Simulation results show that our proposed SCF algorithm obtain a final partition that has a higher throughput and energy efficiency than the Nash-stable partition obtained by a previously proposed algorithm in [1]. Moreover, our proposed algorithm has a lower complexity than the algorithm in [1].

The rest of this paper is organized as follows. Section II describes the system model. In Section III, we formulate a coalition formation problem and present a sequential coalition formation algorithm. Performance evaluation and comparison through simulation are presented in Section IV. Conclusion is given in Section V.

II. System Model

We consider CRNs with N secondary users (SUs) and M primary users (PUs). Each SU corresponds to a transmitter-receiver pair and each PU transmits data via a licensed channel. There are M licensed channels. Let $\mathcal{N} = \{1, 2, \ldots, N\}$ denote the set of SUs and $\mathcal{M} = \{1, 2, \ldots, M\}$ denote the set of PUs. Assume that CRNs work in a time slotted manner and the slot duration is T. At the beginning of each slot, SUs perform sensing before accessing the available channels and the sensing duration is τ. Each SU has a different amount of data in its buffer waiting to be transmitted and only the SUs participating in sensing can obtain access for channel use. Each SU selectively joins in cooperative sensing based on the knowledge of the traffic demand and channel capacity.

We assume that during the sensing stage, each SU can only sense one channel. This assumption is also made in [2] and [3]. In order to avoid interference between transmission of different SUs, we assume that a channel can only be accessed by one SU at a time. Let S_j denote the set of SUs choosing to sense and access channel $j \in \mathcal{M}$. We use $P_{f,i,j}$ and $P_{d,i,j}$ to denote the false alarm probability and detection probability of SU $i \in \mathcal{N}$ when it detects channel $j \in \mathcal{M}$, respectively. The detection probability is the probability that the channel is detected as busy when it is indeed busy. The false alarm probability is the probability that the channel is detected as busy when it is idle. Since we use the cooperative sensing method, in each coalition there is a fusion center collecting sensing results from SUs and making a decision on the channel availability. The fusion center uses OR rule to decide the availability of channels [10]. The false alarm probability and detection probability of the set of SUs S_j choosing to detect channel $j \in \mathcal{M}$ are given as

$$P_{f,j} = 1 - \prod_{i \in S_j} (1 - P_{f,i,j}), \tag{1}$$

and

$$P_{d,j} = 1 - \prod_{i \in S_j} (1 - P_{d,i,j}). \tag{2}$$

Let $W_{t,i}$ denote the transmit power of SU i and B_j denote the bandwidth of channel j. SU i can achieve a transmission rate of $R_{i,j}$ over the channel j as

$$R_{i,j} = B_j \log_2 \left(1 + |g_i|^2 \frac{W_{t,i}}{\sigma_n^2}\right), \tag{3}$$

where g_i denotes the channel gain of transmission link of SU i and σ_n^2 is the noise power.

We use $P_{I,j}$ to denote the probability that the channel j is idle. Since the slot duration T is very short, we assume that the information bits in SU i's buffer are D_i, which is a constant during a time slot. This assumption is also made in [6] and [7]. In order to encourage SUs with high traffic demand to participate in sensing and accessing channels, we give SUs chances to access channel according to their traffic demands. The probability that SU $i \in S_j$ can access channel j when this channel is detected as idle can be modeled as

$$P_i(S_j) = \frac{D_i}{\sum_{k \in S_j} D_k}. \tag{4}$$

We assume that SUs do not cheat at reporting the information of traffic demand when cooperating with other SUs. The behaviour of dishonest SUs is beyond the scope of this paper and may be analyzed in future work using mechanism design.

Given that SU i obtains access to an available channel j, since SU i cannot transmit more than the number of information bits in its buffer, the transmission time for SU i, denoted as $t_{i,j}$, is

$$t_{i,j} = \min\left\{\frac{D_i}{R_{i,j}}, T - \tau\right\}. \tag{5}$$

The probability that channel j is correctly detected as idle is $P_{I,j}(1-P_{f,j})$. The expected throughput that SU i can achieve if it chooses to sense and access channel j is

$$U_i(S_j) = \frac{P_{I,j}(1-P_{f,j})P_i(S_j)R_{i,j}t_{i,j}}{T}. \tag{6}$$

We also consider the power consumption of SU i, which includes power consumption of sensing and transmission. There are two cases that SU will perform transmission over channel j. The first case is that channel j is busy and it is detected as idle, which has a probability of $(1-P_{I,j})(1-P_{d,j})$. The second case is that channel j is idle and it is detected as idle, which has a probability of $P_{I,j}(1-P_{f,j})$. Therefore, the power consumption E_i can be modeled as

$$\begin{aligned} E_i(S_j) =& \{ ((1-P_{I,j})(1-P_{d,j}) + P_{I,j}(1-P_{f,j})) \\ & \times P_i(S_j)W_{t,i}t_{i,j} + W_{s,i}\tau \} \times \frac{1}{T}, \end{aligned} \tag{7}$$

where $W_{s,i}$ denotes the sensing operation power of SU i.

In addition to throughput, we consider energy efficiency as another factor that affects SUs' decisions on cooperative sensing. The energy efficiency of SU i in coalition S_j is defined as throughput over power consumption, which is

$$\eta_i(S_j) = \frac{U_i(S_j)}{E_i(S_j)}. \tag{8}$$

The objective of each SU is to maximize its throughput while keeping its energy efficiency above the lower bound value η_{min}. That is, during a time slot, each SU aims to transmit the data in its buffer as much as possible under the condition that its energy efficiency is not smaller than a predefined lower bound. When the traffic demand of an energy-constrained SU is very low, it may have to spend too much energy in order to transmit just several information data bits if it joins in cooperative sensing. In this case, where the cost of cooperation outweighs the payoff, this SU simply refuses to perform sensing and saves energy for transmission next time.

III. Coalition Formation

In this section, we formulate the individual cooperation strategy problem as an NTU coalition formation game. We propose a sequential coalition formation algorithm to obtain a final coalition structure.

According to coalitional game terminology, we refer to the set of SUs $\mathcal{N}$ as the set of players in this game, and denote the coalition value function as v. Then, this coalitional game is described by the pair of $(\mathcal{N}, v)$. This is an NTU game, because in this game the payoff of a coalition cannot be assigned a real value, instead different players receive different payoffs within each coalition. The value of a coalition S is defined by a $|S|$-dimensional vector. That is $v(S) = (x_i(S), \forall\ i \in S)$, where $x_i(S)$ represents the payoff that SU i receives in coalition S and is given as

$$x_i(S) = \begin{cases} U_i(S), & \text{if } \eta_i(S) \geq \eta_{min}, \\ 0, & \text{otherwise.} \end{cases} \tag{9}$$

Note that the coalition value of an SU is the expected throughput if its energy efficiency is higher than or equal to the lower bound η_{min}, and is equal to zero otherwise. Each SU can only choose to sense and access one of the M channels. All the SUs that choose the same channel form a coalition. We denote the coalition sensing and accessing channel $j \in \mathcal{M}$ as S_j. In addition, we define the set of the SUs that choose to quit sensing as S_{M+1} and the payoff of each SU in S_{M+1} is zero.

From (4) and (6), with more SUs joining one coalition, an SU in this coalition gets less chance to access channel, which may lead to a lower payoff. Therefore, the grand coalition, which includes all SUs in a coalition, is not the optimal partition for this coalitional game. In order to study this coalition formation problem, we define the preference of player i over different coalitions as follows:

Definition 1 [11]: SU $i \in \mathcal{N}$ prefers coalition S_k over S_m, where $S_k, S_m \subseteq \mathcal{N}$, is equivalent to $x_i(S_k) \geq x_i(S_m)$. This relation can be represented as

$$S_k \succeq_i S_m \Leftrightarrow x_i(S_k) \geq x_i(S_m). \tag{10}$$

Since the objective of an SU is to obtain a higher payoff by leaving or joining a coalition, the SU would leave its current coalition and join a new coalition if it prefers the new coalition over its current coalition according to *Definition 1*. A move of any SU will result in a new partition. Therefore, we study the stability of coalition partition by introducing the concept of Nash-stable partition, which is defined as follows:

Definition 2 [12]: A coalition partition Π of $\mathcal{N}$ is *Nash-stable* if $\forall\ i \in \mathcal{N}\ S_{\Pi}(i) \succeq_i S_k \cup \{i\}$ for all $S_k \in \Pi \cup \{\emptyset\}$, where $S_{\Pi}(i)$ denotes the set $S \in \Pi$ such that $i \in S$.

According to *Definition 2*, a coalition partition is Nash-stable if no player has an incentive to leave its current coalition and join a new coalition. Therefore, all players will stay in their current coalition in a Nash-stable partition. Since there are $(M+1)^N$ possible partitions given that the number of SUs and the number of channels are finite, we can use the exhaustive search algorithm to find all possible Nash-stable partitions of this coalitional game. However, the exhaustive search algorithm leads to a high computational complexity because the number of possible partitions grows exponentially with the number of SUs. Thus, we propose an algorithm with low complexity to obtain the final partition in the next section.

A. Sequential Coalition Formation (SCF) Algorithm

We propose the SCF algorithm, which is originated from the concept introduced in [13]. The sequential game of coalition formation is defined by the coalition value function v and the rule of order ρ, which means the coalition structure is formed step by step and at each step only one player can propose a coalition structure. Players make moves one by one according to the rule of order ρ. Once a player has joined a coalition S, it has to remain in this coalition, which means the next active player can only make a coalition proposal among the remaining players.

In the proposed algorithm, the rule of order ρ is determined by traffic demand of SUs. That means the SU with the highest traffic demand is the first one to make a move. Since SUs act selfishly, we assume that at each step the only active SU simply cares about its own payoff and chooses the best coalition to join. The active SU makes a decision based on the current coalition structure and remains in that coalition once it has joined a coalition. The coalition partition is formed step by step by each SU. Thus, the sequential coalition formation involves N iterations. Let $\Pi^{(k)}$ denote the partition formed in the k^{th} iteration. In $(k+1)^{th}$ iteration, SU $k+1$ becomes active. It can either join any coalition in $\Pi^{(k)}$ or form a singleton coalition, which yields the new partition $\Pi^{(k+1)}$ in $(k+1)^{th}$ iteration.

The proposed SCF algorithm is shown in Algorithm 1. At first, SUs communicate the traffic demand information with each other (lines 1 to 3) and the traffic demand information vector $\mathcal{D}$ is obtained (line 4). $Q(\mathcal{X})$ is a sorting function that maps a vector $\mathcal{X}$ to a $|\mathcal{X}|$-dimensional vector. It returns a vector with each element representing the sorted index of each $\mathcal{X}$'s element in descending order. For example, for $Y = Q(\mathcal{X})$, where $\mathcal{X} = (x_1, x_2, x_3, x_4)$ and $x_2 \geq x_3 \geq x_1 \geq x_4$, $Y = (2, 3, 1, 4)$, which means x_2 ranks first, x_3 ranks second, x_1 ranks third and x_4 ranks fourth in the sequence. The rule of order ρ is a vector obtained through sorting $\mathcal{D}$ by applying function $Q(\mathcal{D})$ (line 5). At the beginning of the sequential coalition formation, we form the initial partition by letting all SUs join quit sensing set S_{M+1} (line 6). After that, SUs make coalition formation decision one by one according to ρ. For example, the SU with the highest traffic demand makes the first choice. During each iteration, we first set the payoff of active SU i, which is originally in quit sensing set, to zero (line 8). Then SU i calculates its payoff in potential new coalition according to (9) (line 11) and compares it with its current payoff (line 12). It leaves its current coalition and joins a new coalition if it prefers the new coalition. Thus, a new partition is formed (line 13), and its payoff is updated (line 14). After N iterations, the final partition $\Pi^{(N)}$ and corresponding coalition payoff x_i are obtained (line 19).

To better explain our proposed SCF algorithm, we have the following example. Consider a CRN with $\mathcal{N} = \{1, 2, 3, 4\}$ and $\mathcal{M} = \{1, 2\}$. We denote S_3 as the quit sensing coalition. Without loss of generality, we assume that $D_3 \geq D_4 \geq D_2 \geq D_1$. Thus, we obtain $\rho = (3, 4, 2, 1)$ by calculating $Q(\mathcal{D})$. According to SCF algorithm, all SUs are in the quit sensing coalition S_3 initially. In the first iteration, SU 3 makes the first choice (i.e., $\rho(1) = 3$). Assume that SU 3 prefers channel 1 over channel 2, then SU 3 chooses channel 1 to sense and access. SU 4 ranks second according to ρ. Thus, SU 4 makes the second choice. Assume that $x_4(\{4\}_2) \geq x_4(\{3, 4\}_1) \geq x_4(S_3)$, SU 4 chooses to join coalition S_2. For SU 2, which ranks third, assume that $x_2(\{3, 2\}_1) \geq x_2(\{4, 2\}_2) \geq x_2(S_3)$. SU 2 joins coalition S_1. SU 1 is the last one to make a decision. It can choose to join $\{3, 2\}_1$ or $\{4\}_2$ or stay in quit sensing coalition S_3. Assume that the energy efficiency of SU 1 is lower than the energy efficiency lower bound no matter it joins $\{3, 2\}_1$ or $\{4\}_2$, SU 1 chooses to stay in coalition S_3 and quits sensing during this time slot. Therefore, the final partition is $\Pi^{(4)} = \{\{3, 2\}_1, \{4\}_2, \{1\}_3\}$.

Algorithm 1 Sequential Coalition Formation (SCF) Algorithm in Cognitive Radio Network

1: **for** each $i \in \mathcal{N}$ **do**
2: SU i broadcast its traffic demand D_i to other SUs and receives information from other SUs
3: **end for**
4: $\mathcal{D} := (D_1, D_2, \ldots, D_N)$
5: $\rho := Q(\mathcal{D})$
6: Set $\Pi^{(0)} := \{\{1, 2, \ldots, N\}_{M+1}^{(0)}\}$
7: **for** $i = 1$ to N **do**
8: Set $x_{\rho(i)} := 0$
9: **for** $j = 1$ to M **do**
10: Set $\Pi^{(i)*} := \big\{\Pi^{(i-1)} \setminus \{S_{M+1}^{(i-1)}, S_j^{(i-1)}\}\big\} \bigcup \{S_{M+1}^{(i-1)} \setminus \{\rho(i)\}, S_j^{(i-1)} \bigcup \{\rho(i)\}\}$
11: Calculate $x_{\rho(i)}(S_j^{(i-1)} \bigcup \{\rho(i)\})$ according to (9)
12: **if** $x_{\rho(i)}(S_j^{(i-1)} \bigcup \{i\}) \geq x_{\rho(i)}$ **then**
13: Set $\Pi^{(i)} := \Pi^{(i)*}$
14: Set $x_{\rho(i)} := x_{\rho(i)}(S_j^{(i-1)} \bigcup \{i\})$
15: **end if**
16: **end for**
17: **end for**
18: Calculate $x_i(S)$, $\forall\ i \in S$ and $S \in \Pi^{(N)}$
19: Output $\Pi^{(N)}$ and x_i, $\forall\ i \in \mathcal{N}$

IV. Performance Evaluation

In this section, we compare the performance between our proposed SCF algorithm and the switch rule-based coalition formation (SRCF) algorithm [1] from the perspective of aggregate throughput and energy efficiency, respectively. Moreover, we compare the computational complexity of these two algorithms by analyzing their running time.

Unless stated otherwise, we consider a CRN with ten SUs and six PUs (i.e., six licensed channels). The transmitter and receiver of each SU is randomly placed in a 100 m $\times$ 100 m square region. We model the channel gain of the link of SU i as $|g_i|^2 = 1/d_i^{\gamma}$, where d_i is the distance between the transmitter and receiver of SU i, and γ is the path loss exponent. We set γ to 2. According to IEEE Standard 802.22, we set the detection probability of every SU at each channel as 0.9 and the false alarm probability as 0.1. The probability that the channel is idle is randomly chosen between $[0.5, 1]$. The number of packets generated by each SU during a time slot follows Poisson distribution with an average rate of $\lambda = 0.2$ packet per time slot, and each packet is 20 kb.

The list of parameters is shown in Table I. We run the simulation on a computer that is equipped with Intel(R) Core(TM)2 Duo P7350 CPU 2.00 GHz processor and 2.00 GB RAM. We use MATLAB as simulation tool in the Windows 7 operation system. The performance of algorithms are compared under the same parameters setting.

TABLE I
LIST OF SIMULATION PARAMETERS

Parameter	Value
Number of SUs N	10
Number of PUs (licensed channels) M	6
Path loss exponent γ	2
Bandwidth of channel j B_j	100 kHz
Probability that channel j is being idle $P_{I,j}$	$[0.5, 1]$
False alarm probability of SU i when it detects channel j $P_{f,i,j}$	0.1
Detection probability of SU i when it detects channel j $P_{d,i,j}$	0.9
Noise power δ_n^2	0.01 mW
Transmission power of SU i $W_{t,i}$	100 mW
Sensing power of SU i $W_{s,i}$	50 mW
Slot duration T	100 ms
Sensing duration τ	5 ms
Average number of packets generated by SU during a time slot λ	0.2 packet per time slot
The lower bound of the energy efficiency η_{min}	50 kbit/Joule

When we apply the SRCF algorithm [1], different initial partitions may lead to different Nash-stable partitions. Therefore, we randomly set the initial partition and run SRCF algorithm 50 times to obtain 50 Nash-stable partitions. We calculate the average payoff of each SU and obtain the average coalition value of these Nash-stable partitions, which we denote as the *average Nash-stable partition*. To better compare SCF algorithm and SRCF algorithm, we analyze the results of average Nash-stable partition in following simulation.

Figure 1 shows the aggregate throughput of SUs in CRNs when we increase the number of PUs M (i.e., the number of channels) from 1 to 10. Results show that our proposed SCF algorithm has a better performance than the SRCF algorithm in terms of aggregate throughput. For both algorithms, the aggregate throughput increases with M at first. This is because the throughput is constrained by channel resources when M is small. Thus, with more channels become available, the traffic demand of SUs is satisfied and a higher aggregate throughput can be obtained. However, when M is large, increasing M further does not improve aggregate throughput too much, because the aggregate throughput is constrained by the traffic demand of SUs when channel resources are abundant.

Figure 2 shows the aggregate throughput of SUs as the number of SUs N increases from 2 to 20. Results show that performance of SCF algorithm is similar to or better than that of SRCF algorithm in terms of aggregate throughput. In our proposed SCF algorithm, SUs with high traffic demand are given priority to sense and access good channels (i.e., channel with high probability of being idle). Therefore the spectrum resources are utilized with a high efficiency. However, in SCF algorithm, SUs act selfishly and the channel resources can be occupied by SUs with low traffic demand. Thus, the aggregate throughput of SUs for SRCF algorithm is less than that for SCF algorithm. Besides, the number of SUs N increases the aggregate throughput when N varies from 2 to 20.

Figure 3 shows the average energy efficiency of SUs when we increase the number of PUs M from 1 to 10. In SRCF

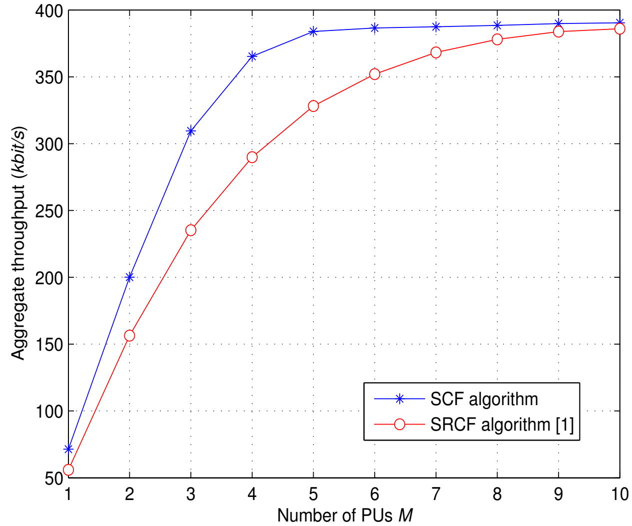

Fig. 1. Aggregate throughput versus the number of PUs M for $N = 10$.

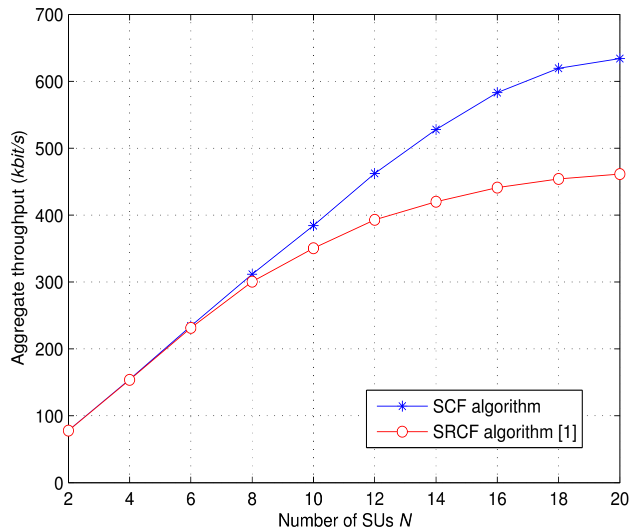

Fig. 2. Aggregate throughput versus the number of SUs N for $M = 6$.

algorithm, all SUs are supposed to participate in cooperative sensing. SUs with low traffic demand spend energy on sensing but may obtain a low throughput. However, in our proposed SCR algorithm, SUs with energy efficiency lower than the η_{min} choose to quit sensing and save energy for transmission next time. Thus, the average energy efficiency for SCF algorithm is higher than that for SRCF algorithm. Besides, for both algorithms, the energy efficiency increases with M when M is small. This is because SUs that participate in sensing obtain a low throughput when channel resources are insufficient, which leads to a low energy efficiency. As more channels become available, SUs achieve higher throughput and thus obtain a higher energy efficiency.

To provide an idea of the complexity of our proposed SCF

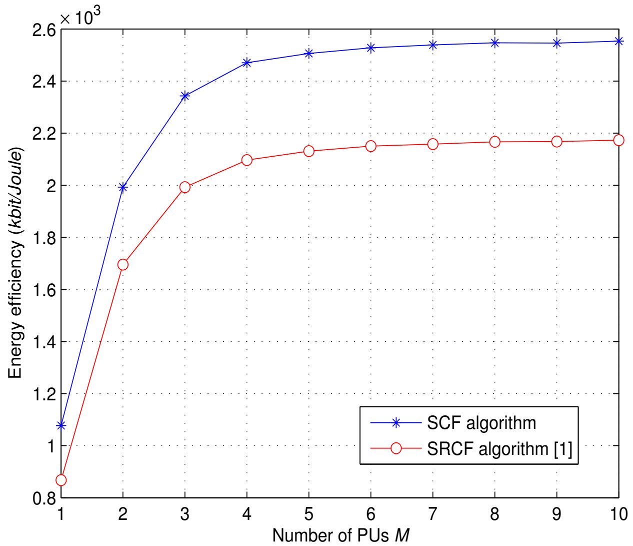

Fig. 3. System energy efficiency versus the number of PUs M for $N = 10$.

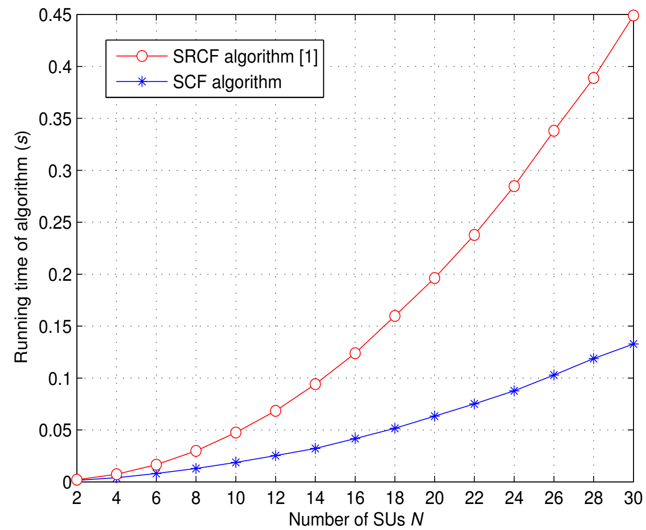

Fig. 4. Running time of algorithms versus the number of SUs N for $M = 6$.

algorithm compared with SRCF algorithm, we evaluate the running time of these two algorithms as the number of SUs N increases from 2 to 30. Results in Figure 4 show that the running time of the SRCF algorithm is almost three times that of our proposed SCF algorithm. Our proposed SCF algorithm involves only N iterations. During each iteration, the active SU only has to calculate coalition payoff M times before choosing the best coalition to join. However, for SRCF algorithm, in order to reach a Nash-stable partition, each SU has to calculate and compare its coalition payoff in M different coalitions whenever there is a change of partition. Thus, the complexity of SRCF algorithm is higher than our proposed SCF algorithm. Therefore, SRCF algorithm performs worse than our proposed SCF algorithm in terms of running time. When $N = 30$, our proposed SCF algorithm outperforms SRCF algorithm by over 60% in terms of running time.

V. Conclusion

In this paper, we studied the cooperation strategy in CRNs with multiple channels from the perspective of traffic demand of SUs. We proposed a joint cooperative spectrum sensing and access scheme, which allows energy-constrained SUs work more efficiently through selectively participating in cooperation. An NTU coalition formation game was formulated to study this cooperative sensing problem, in which each SU makes individual decision on joining in coalition to maximize a payoff that takes into account the expected throughput and energy efficiency. Since exhaustive search method leads to high computational complexity, we proposed a sequential coalition formation (SCF) algorithm. Simulation results showed that our proposed SCF algorithm obtains the final partition that outperforms the Nash-stable partition by the switch rule-based coalition formation (SRCF) algorithm in [1] in terms of aggregate throughput, energy efficiency, as well as computational complexity.

References

[1] W. Saad, Z. Han, R. Zheng, A. Hjorungnes, T. Basar, and H. V. Poor, "Coalitional games in partition form for joint spectrum sensing and access in cognitive radio networks," *IEEE Journal of Selected Topics in Signal Processing*, vol. 6, no. 2, pp. 195–209, Apr. 2012.

[2] X. Sun and D. Tsang, "Energy-efficient cooperative sensing scheduling for multi-band cognitive radio networks," *IEEE Trans. on Wireless Communications*, vol. 12, no. 10, pp. 4943–4955, Oct. 2013.

[3] X. Hao, M. H. Cheung, V. W. S. Wong, and V. Leung, "Hedonic coalition formation game for cooperative spectrum sensing and channel access in cognitive radio networks," *IEEE Trans. on Wireless Communications*, vol. 11, no. 11, pp. 3968–3979, Nov. 2012.

[4] Y. Gao, W. Xu, K. Yang, K. Niu, and J. Lin, "Energy-efficient transmission with cooperative spectrum sensing in cognitive radio networks," in *Proc. of IEEE Wireless Communications and Networking Conference (WCNC)*, Shanghai, China, Apr. 2013.

[5] T. Zhang and D. H. K. Tsang, "Cooperative sensing scheduling for energy-aware cognitive radio networks," in *Proc. of IEEE International Conference on Communications (ICC)*, Kyoto, Japan, Jun. 2011.

[6] S. Bayhan and F. Alagoz, "Scheduling in centralized cognitive radio networks for energy efficiency," *IEEE Trans. on Vehicular Technology*, vol. 62, no. 2, pp. 582–595, Feb. 2013.

[7] D. Gozupek, B. Eraslan, and F. Alagoz, "Throughput satisfaction-based scheduling for cognitive radio networks," *IEEE Trans. on Vehicular Technology*, vol. 61, no. 9, pp. 4079–4094, Jul. 2012.

[8] M. H. Cheung, V. W. S. Wong, and R. Schober, "SINR-based random access for cognitive radio: Distributed algorithm and coalitional game," *IEEE Trans. on Wireless Communications*, vol. 10, no. 11, pp. 3877–3897, Nov. 2011.

[9] B. Wang, K. Liu, and T. Clancy, "Evolutionary cooperative spectrum sensing game: How to collaborate?" *IEEE Trans. on Communications*, vol. 58, no. 3, pp. 890–900, Mar. 2010.

[10] Y.-C. Liang, Y. Zeng, E. Peh, and A. T. Hoang, "Sensing-throughput tradeoff for cognitive radio networks," *IEEE Trans. on Wireless Communications*, vol. 7, no. 4, pp. 1326–1337, Apr. 2008.

[11] K. R. Apt and A. Witzel, "A generic approach to coalition formation," in *Proc. of International Workshop on Computational Social Choice*, Amsterdam, Netherlands, Dec. 2006.

[12] A. Bogomonlaia and M. Jackson, "The stability of hedonic coalition structures," *Games Econ. Behaviour*, vol. 38, pp. 201–230, Jan. 2002.

[13] F. Bloch, "Sequential formation of coalitions in games with externalities and fixed payoff division," *Games and Economic Behavior*, vol. 14, no. 1, pp. 90–123, May 1996. [Online]. Available: http://ideas.repec.org/a/eee/gamebe/v14y1996i1p90-123.html