Coalitional Game Approach for Cooperation Strategy in Cognitive Radio Networks

by

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Abstract

Cognitive radio networks (CRNs) provide an effective solution to address the increasing demand for spectrum resources. The cooperation among secondary users (SUs) improves the sensing performance and spectrum efficiency. In this thesis, we study a traffic-demand based cooperative spectrum sensing and access strategy in a CRN with multiple SUs and multiple primary users (PUs). In the proposed strategy, each SU makes its own cooperation decision according to its traffic demand. When the SU has a high traffic demand, it selectively chooses channels to sense and access. When it has no data to transmit, it can choose not to perform sensing and save energy for future transmission.

In the first part of the thesis, we study the traffic demand-based cooperation strategy in CRNs, in which each SU senses at most one channel during a time slot. We formulate this problem as a non-transferable utility (NTU) coalition formation game, in which each SU receives a coalition value that takes into account the expected throughput and energy efficiency. In order to obtain the final coalition structure, we propose a sequential coalition formation (SCF) algorithm. Simulation results show that our proposed algorithm achieves a higher throughput and energy efficiency than a previously proposed coalition formation algorithm in [1].

In the second part of this thesis, we extend the cooperation strategy problem in CRNs by enabling each SU to sense multiple channels during the sensing stage. We formulate the problem as an NTU overlapping coalitional game. We propose an overlapping coalition formation (OCF) algorithm to obtain a stable coalition structure. The proposed OCF algorithm is proved to converge after a finite number of iterations. We also modify the SCF algorithm proposed in the first part of this thesis to address the problem in the new system model. The modified SCF algorithm requires a lower number of iterations and involves less information exchange among SUs. Moreover, an adaptive transmission power control scheme is proposed for SUs to further improve their energy efficiency. Simulation results show that our proposed algorithms achieve a higher throughput than the disjoint coalition formation (DCF) algorithm.

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List of Acronyms

CRN	Cognitive Radio Network
CSSA	Cooperative Spectrum Sensing and Accessing
DCF	Disjoint Coalition Formation
NTU	Non-Transferable Utility
OCF	Overlapping Coalition Formation
PUs	Primary Users
SCF	Sequential Coalition Formation
SRCF	Switch Rule-based Coalition Formation
SUs	Secondary Users

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Chapter 1

Introduction

This chapter first introduces the background of cognitive radio network (CRN), cooperative spectrum sensing and spectrum allocation methods in CRNs, and game theory applications in CRNs. Then, we present the motivation and contributions of our work. The list of publication and the structure of the thesis are shown at the end of this chapter.

1.1 Cognitive Radio Network

There is an increasing demand for spectrum resources due to rapid development of the mobile applications. However, spectrum channels are under-utilized by licensed users [2]. CRNs provide a promising solution to utilize the spectrum holes and improve spectrum efficiency [3]. In CRNs, secondary users (SUs) are allowed to access the spectrum channels as long as the transmission of primary users (PUs) is not interfered with. In this way, the spectrum white spaces are filled by SUs' transmission and spectrum efficiency can be improved.

In CRN, each SU corresponds to a pair of secondary transmitter and secondary receiver with or without a base station. The PUs are authorized to transmit data on licensed channels and their transmission should not be interfered by SUs. CRNs can be classified to *underlay* CRN and *overlay* CRN according to the way that spectrum is utilized [4]. In an underlay CRN, SUs can use spectrums only if the interference generated by SUs' transmission is below a predefined threshold. While, in an overlay CRN, spectrums are opportunistically accessed by SUs when they are temporarily not used by PUs. We consider the overlay CRN model in this thesis. To better utilize spectrum resources and guarantee the protection for PU's transmission, SUs have to detect the channel availability before accessing the channel. There are multiple detection techniques for SUs to perform spectrum sensing, such as energy detection, feature detection, matched filtering and coherent detection [5]. When the PUs are detected as idle (*i.e.*, the licensed channels are available), SUs can transmit on the channel. In order to use the channel with high efficiency, SUs need to consider which channels to choose and how the spectrum resources should be allocated, which is referred to as spectrum access and allocation in CRNs.

1.2 Cooperative Spectrum Sensing and Access in CRNs

For spectrum sensing in CRNs, an SU may not be able to detect the channel accurately due to the shadowing and path loss. Therefore, SUs work cooperatively to sense the channel and decide the channel availability based on fusion decision. This is referred to as *cooperative spectrum sensing*. After spectrum sensing, the use of available channels is shared among SUs. In the design of cooperative spectrum sensing and access (CSSA) strategy, the throughput and energy efficiency are two important factors that are widely considered. Many studies have been conducted to address the CSSA problem in CRNs. They developed different strategies to improve the throughput or energy efficiency in CRNs.

By optimizing the sensing parameters (*e.g.*, detection threshold and sensing duration) in cooperative sensing or developing efficient sensing scheduling methods, better sensing performance and a higher network throughput can be achieved [6], [7]. When maximizing the network throughput, the protection for the transmission of PUs needs to be guaranteed. Therefore, the constraints of power consumption and sensing performance are taken into account [8], [9]. Some works focus on developing scheduling algorithms to assign available channels to different SUs [10], [11]. In this way, the spectrum resources are allocated to SUs according to the channel characteristics and traffic demands, and a high system energy efficiency is obtained. In [12], the optimal sensing time, energy detection threshold and the number of SUs are determined to maximize the system energy efficiency.

1.3 Game Theory Applications in CSSA

In many existing works, the problem of CSSA in CRNs can be formulated as a game, where each SU is modeled as a player. Each player aims to maximize its individual payoff or improve the social welfare. In [13], the problem of cooperative spectrum sensing scheduling in CRNs with multiple channels is formulated as an evolutionary game, where each SU makes its own decision on whether to participate in sensing or not. An entropy-based coalition formation algorithm is developed to help SUs select which channel to sense. In [14], Jiang *et al.* study the channel access problem in CRNs by proposing a Bayesian learning based method to estimate the channel states, and a Markov decision process based approach to make channel access decision for each SU.

In order to obtain better cooperative sensing performance or distribute spectrum resources among SUs efficiently, the concept of coalitional game is also applied to the design of cooperation strategy in CRNs. The work in [1] investigates the tradeoff between spectrum sensing and spectrum access. The problem is formulated as a disjoint coalition formation game, where each SU aims to maximize its utility. A distributed algorithm is proposed to obtain the Nash-stable coalition structure. In [15], Hao *et al.* apply the hedonic coalition formation game theory to the cooperative spectrum sensing and access problem. The coalition payoff relates to energy efficiency and sensing accuracy. They propose a disjoint coalition formation algorithm to find the stable coalition structure. In [16], a coalitional game approach is applied to study the spectrum access of SUs, where SUs serve as cooperative relays of PUs and obtain channel access as a payment. It is shown that SUs form a grand coalition as the final coalition structure to maximize the system utility.

1.4 Motivation

Although several algorithms have been proposed to improve either the energy efficiency or throughput of SUs in CRNs, most of them do not consider traffic demand of each SU. In most of the previous works, SUs are assumed to have infinite data to transmit and the spectrum channel can always be fully utilized when it is assigned to SUs, such as [1] and [15]. This, however, may not be the case in practice. The traffic demand of SUs may change from time to time and vary from one to another. The amount of data that an SU needs to transmit depends on its application, *e.g.*, an SU with a video streaming application usually requires a higher throughput than an SU running a best-effort application. In addition, the traffic demand of an SU may change over time, *e.g.*, an SU with an environmental monitoring application aims to report the change of temperature. Therefore, when investigating the problem of the spectrum sensing and access in CRNs, it is necessary to take into account the traffic demand of SUs. Although in [10] and [17], the traffic demand of SUs is considered when studying the spectrum resource allocation problem, they do not consider spectrum sensing. Moreover, their objective is to maximize the aggregate system utility instead of developing a cooperative strategy from the perspective of individual SUs.

Most of the existing works assume that all SUs should participate in cooperative sensing (*e.g.*, [11], [18] and [19]). However, in an energy-constrained CRN, for an SU having no data to transmit during a certain time period, it may be better to stay idle to conserve energy for future transmission instead of participating in cooperative sensing.

Thus, it is reasonable to let SU make its own decision on cooperation according to its traffic demand. The work in [20] uses an evolutionary game approach to determine the cooperative sensing strategy of SUs. However, it does not consider the energy efficiency and traffic demands of SUs.

Although coalitional game theory is widely used in developing spectrum sensing and access strategies in CRNs, most of the previous works aim at formulating the problem as a disjoint coalition formation game and finding the non-overlapping coalition structure (*e.g.*, [1] and [15]). They assume that an SU can only join one coalition and perform cooperative sensing within that coalition. This assumption restricts the cooperation of SUs and limits the improvement of system utility. To relax this assumption, overlapping coalitional game theory can be used. In an overlapping coalitional game, each player can join multiple coalitions to maximize its payoff. Due to the nature of CRNs, SUs can broadcast their sensing results to other devices. This allows them to participate in multiple groups at the same time. Therefore, overlapping coalitional game can be applied to spectrum sensing and access problem in CRNs. For example, the work in [21] studies the cooperative sensing of SUs. The problem is formulated as an overlapping coalitional game and a distributed algorithm is proposed to find the stable coalition structure. However, this work focuses on improving sensing performance and does not consider spectrum resource allocation. Moreover, it does not take into account the associated cost of joining a coalition.

1.5 Contributions

In this thesis, we study a traffic demand-based joint CSSA strategy in CRNs. We consider a CRN with multiple SUs and multiple PUs. Each SU has to perform spectrum sensing if it wants to access the channel, and one channel can only be assigned to one SU at a time during the transmission stage. In the proposed cooperation strategy, each SU makes its own cooperation decision according to its traffic demand. When an SU has a high traffic demand, it participates in cooperative sensing and shares the spectrum resources with other SUs. If there is no data to transmit, the SU can choose not to perform sensing and save energy for future transmission. We apply the coalitional game approach to analyze the problem, in which each SU is modeled as a player to maximize its individual utility. In Chapter 2, we consider the case that each SU can only sense one channel during the sensing stage. In Chapter 3, we generalize the system model and enable each SU to sense multiple channels.

The main contributions of this thesis are as follows:

- In Chapter 2, we study a cooperation strategy in a CRN with multiple channel, where each SU can only sense one channel at a time. We formulate this problem as a non-transferable utility (NTU) coalitional formation game, in which each SU receives payoff according to its expected throughput and energy efficiency. We propose a sequential coalition formation (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 switch rule-based coalition formation (SRCF) algorithm proposed in [1]. Moreover, our proposed algorithm has a lower complexity than the SRCF algorithm.

- In Chapter 3, we extend the problem by enabling each SU to sense multiple channels during the sensing stage. Each SU makes individual decisions on how many and which channels to sense and access according to its own traffic demand. We formulate this problem as an NTU overlapping coalition formation game. To obtain the stable overlapping coalition structure, we propose an overlapping coalition formation (OCF) algorithm. We prove that our proposed algorithm converges to a stable coalition structure after a finite number of iterations. Moreover, we modify the SCF algorithm to address the problem in the new system model. The modified SCF algorithm has as good performance as OCF algorithm and requires a lower number of iterations and less information exchange among SUs. We also propose an adaptive transmission power control strategy to minimize the energy consumption spent on transmission while guaranteeing that the maximum expected throughput is obtained. Simulation results show that our proposed OCF and modified SCF algorithms outperform the disjoint coalition formation (DCF) algorithm in terms of aggregate throughput.

1.6 List of Publication

The following publication has been completed based on the work in this thesis.

- Zhiyu Dai and Vincent W.S. Wong, "Traffic demand-based cooperation strategy in cognitive radio networks," in *Proc. of IEEE Wireless Communication and Networking Conference (WCNC)*, Istanbul, Turkey, April 2014.

1.7 Structure of the Thesis

The rest of this thesis is organized as follows. In Chapter 2, we present the traffic-demand based cooperation strategy in CRNs with each SU sensing only one channel in a time slot. In Chapter 3, we extend the CSSA problem by studying the case that each SU is allowed to sense multiple channels. Conclusions and future work are given in Chapter 4.

Chapter 2

Traffic Demand-based Cooperation Strategy in CRNs

In this chapter, we study a traffic demand-based joint cooperative spectrum sensing and access strategy for individual SU in CRNs, where each SU senses at most one channel during the sensing stage. We present the system model and formulate the problem as a coalitional game. A sequential coalition formation (SCF) algorithm is proposed to obtain the final coalition structure. Then, we present the performance evaluation by comparing our proposed algorithm with the switch rule-based coalition formation (SRCF) algorithm. The summary is given at the end of this chapter.

2.1 System Model

We consider a CRN with N SUs and M 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 the CRN works in a time slotted manner and the slot duration is T. At the beginning of each time slot, if an SU chooses to participate in cooperative spectrum sensing and access, it will perform sensing before accessing the available channels and the sensing duration is τ. Each SU has different amount of data in its buffer waiting to be transmitted and only these 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 [11] and [15]. 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 [22]. 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

$$P_{f,j} = 1 - \prod_{i \in S_j} (1 - P_{f,i,j}), \tag{2.1}$$

and

$$P_{d,j} = 1 - \prod_{i \in S_j} (1 - P_{d,i,j}). \tag{2.2}$$

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

$$R_{i,j} = B_j \log_2 \left(1 + |g_i|^2 \frac{W_{t,i}}{\sigma_n^2}\right), \tag{2.3}$$

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 [10] and [17]. 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

$$P_i(S_j) = \frac{D_i}{\sum_{k \in S_j} D_k}. \tag{2.4}$$

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 thesis 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

$$t_{i,j} = \min\left\{\frac{D_i}{R_{i,j}}, T - \tau\right\}. \tag{2.5}$$

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

$$U_i(S_j) = \frac{P_{I,j}(1 - P_{f,j})P_i(S_j)R_{i,j}t_{i,j}}{T}. \tag{2.6}$$

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

$$E_i(S_j) = \Big(\big((1 - P_{I,j})(1 - P_{d,j}) + P_{I,j}(1 - P_{f,j})\big)P_i(S_j)W_{t,i}t_{i,j} + W_{s,i}\tau\Big)\frac{1}{T}, \tag{2.7}$$

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

$$\eta_i(S_j) = \frac{U_i(S_j)}{E_i(S_j)}. \tag{2.8}$$

The objective of each SU is to maximize its throughput while keeping its energy efficiency above the threshold 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 threshold. 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 chooses not to perform sensing and saves energy for transmission next time.

2.2 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.

2.2.1 NTU Coalitional Game Formulation

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

$$x_i(S) = \begin{cases} U_i(S), & \text{if } \eta_i(S) \geq \eta_{min}, \\ 0, & \text{otherwise.} \end{cases} \tag{2.9}$$

Note that the coalition value of an SU is the expected throughput if its energy efficiency is higher than or equal to the threshold 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 (2.4) and (2.6), 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 [23]: 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

$$S_k \succeq_i S_m \Leftrightarrow x_i(S_k) \geq x_i(S_m). \tag{2.10}$$

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 [24]: 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.

2.2.2 Sequential Coalition Formation (SCF) Algorithm

We propose the SCF algorithm, which is originated from the concept introduced in [25]. 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 concerns 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. 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). We also initialize coalition structure by setting it as the structure we obtained in last iteration (line 9). We assume that SU i leaves the quit sensing coalition and joins coalition j, which results in a new coalition structure $\Pi^{(i)*}$ (line 10). Then SU i calculates its payoff in potential new coalition according to (2.9) (line 12) and compares it with its current payoff (line 13). It leaves its current coalition and joins a new coalition if it prefers the new coalition. Thus, a new partition is formed (line 14), and its payoff is updated (line 15). After N iterations, the final partition $\Pi^{(N)}$ and corresponding coalition payoff x_i are obtained (line 20).

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

Algorithm 1 Sequential Coalition Formation (SCF) Algorithm in CRN

for each $i \in \mathcal{N}$ **do**
  SU i broadcasts its traffic demand D_i to other SUs and receives information from other SUs
end for
$\mathcal{D} := (D_1, D_2, \ldots, D_N)$
$\rho := Q(\mathcal{D})$
Set $\Pi^{(0)} := \{\{1, 2, \ldots, N\}^{(0)}_{M+1}\}$
for $i = 1$ to N **do**
  Set $x_{\rho(i)} := 0$
  Set $\Pi^{(i)} := \Pi^{(i-1)}$
  for $j = 1$ to M **do**
    Set $\Pi^{(i)*} := \big\{\Pi^{(i-1)} \setminus \{S^{(i-1)}_{M+1}, S^{(i-1)}_j\}\big\} \bigcup \{S^{(i-1)}_{M+1} \setminus \{\rho(i)\}, S^{(i-1)}_j \bigcup \{\rho(i)\}\}$
    Calculate $x_{\rho(i)}(S^{(i-1)}_j \bigcup \{\rho(i)\})$ according to (2.9)
    if $x_{\rho(i)}(S^{(i-1)}_j \bigcup \{i\}) \geq x_{\rho(i)}$ **then**
      Set $\Pi^{(i)} := \Pi^{(i)*}$
      Set $x_{\rho(i)} := x_{\rho(i)}(S^{(i-1)}_j \bigcup \{i\})$
    end if
  end for
end for
Calculate $x_i(S)$, $\forall\, i \in S$ and $S \in \Pi^{(N)}$
Output $\Pi^{(N)}$ and x_i, $\forall\, i \in \mathcal{N}$

SU 1 is lower than the energy efficiency threshold 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 $\Pi^{(4)} = \{\{3, 2\}_1, \{4\}_2, \{1\}_3\}$.

2.3 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

Table 2.1: 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 σ_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
The energy efficiency threshold η_{min}	50 kbit/Joule

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 2.1. We run the simulation on a computer

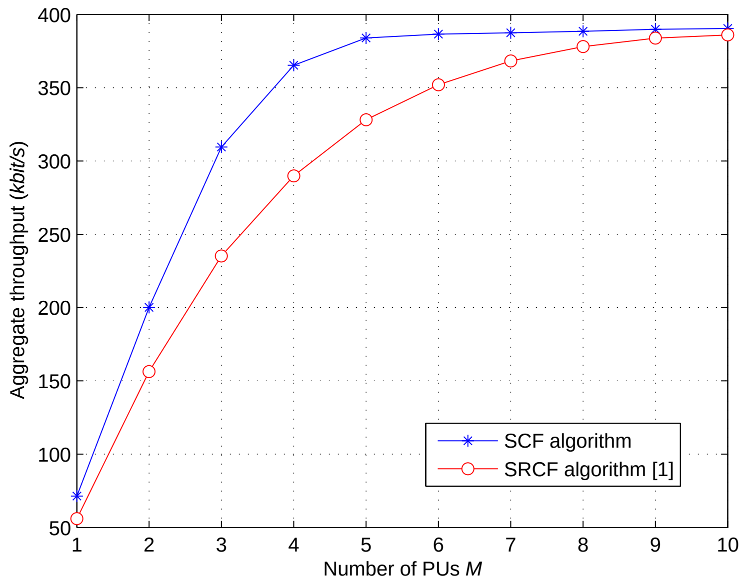

Figure 2.1: Aggregate throughput versus the number of PUs M for $N = 10$.

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.

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 the following simulation.

Figure 2.1 shows the aggregate throughput of SUs when we increase the number of

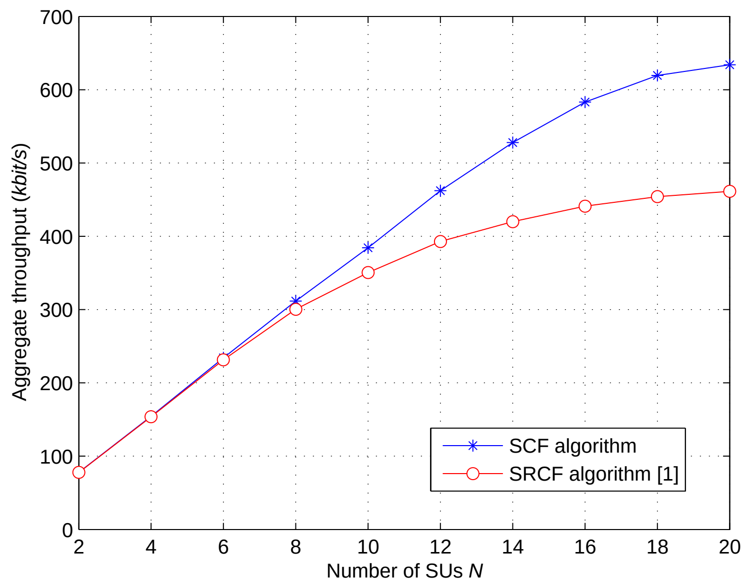

Figure 2.2: Aggregate throughput versus the number of SUs N for $M = 6$.

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, when more channels are 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 2.2 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

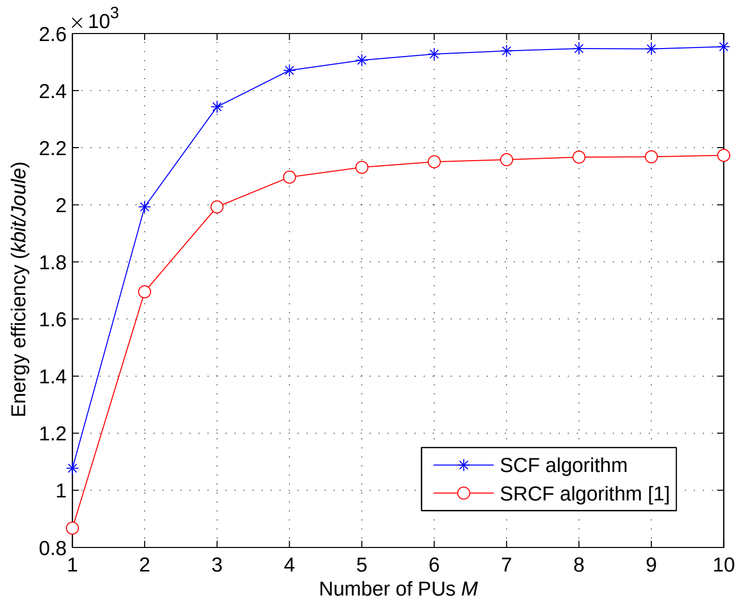

Figure 2.3: System energy efficiency versus the number of PUs M for $N = 10$.

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 SRCF 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 2.3 shows the average energy efficiency of SUs when we increase the number of PUs M from 1 to 10. In SRCF 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

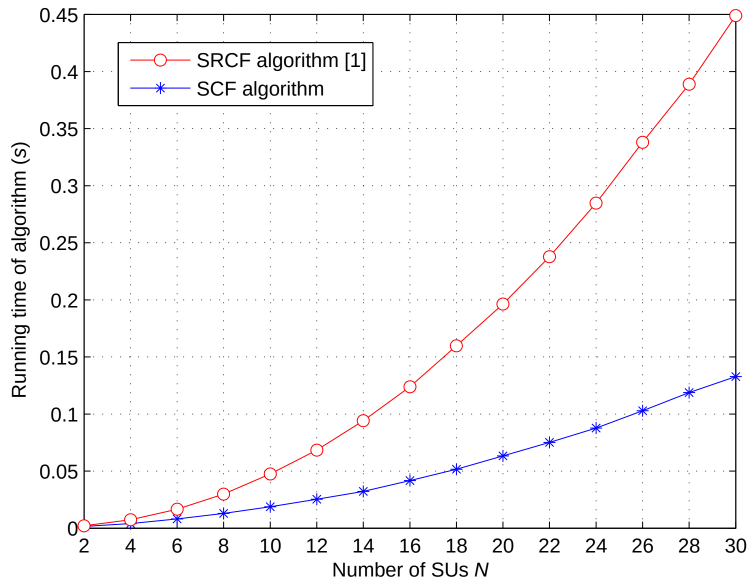

Figure 2.4: Running time of algorithms versus the number of SUs N for $M = 6$.

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 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 2.4 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.

2.4 Summary

In this chapter, 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 a high computational complexity, we proposed an SCF algorithm. Simulation results showed that our proposed SCF algorithm obtains the final partition that outperforms the Nash-stable partition by the SRCF algorithm in [1] in terms of aggregate throughput, energy efficiency, as well as computational complexity.

Chapter 3

Overlapping Coalitional Game Approach for Cooperation Strategy in CRNs

In the previous chapter, we study the cooperation strategy in CRNs, where each SU can only sense one channel at a time. In this chapter, we extend the problem by enabling each SU to sense multiple channels. We apply the overlapping coalitional game theory to the design of CSSA strategy in CRNs. We first present the system model, which is different from the system model proposed in Chapter 2. Then, we formulate the problem as an overlapping coalitional game and propose two coalition formation algorithms. The stability of the algorithms is analyzed and it is followed by the performance evaluation. A summary is provided at the end of this chapter.

3.1 System Model

In this chapter, we still consider a CRN with N SUs, M PUs, and a common base station. Each SU corresponds to a transmission link between the transmitter of the SU and the base station. Each PU transmits data via a licensed channel. Let $\mathcal{N} = \{1, 2, \ldots, N\}$ denote the set of SUs and $\mathcal{M} = \{1, 2, \ldots, M\}$ denote the set of PUs. Each SU can sense multiple channels and all the SUs sensing the same channel form a group. Each channel is sensed cooperatively by one group of SUs and the channel is assigned to one of the group members when it is detected as idle. Each SU has different amount of data in its buffer waiting to be transmitted and only the SUs participating in sensing can obtain access for channel use. SUs selectively participate in cooperative sensing based on the knowledge of the traffic demand and channel capacity. In order to avoid interference between transmission of different SUs, we assume that an idle channel can only be accessed by one SU at a time.

In Chapter 2, we assign certain values to detection probability and false alarm probability of each SU respectively. In this chapter, we calculate these two parameters based on specific sensing parameters. The detection probability of SU i at channel j is [22]

$$P_{d,i,j}(\varepsilon, \gamma_{i,j}) = Q\left(\left(\frac{\varepsilon}{\sigma_n^2} - \gamma_{i,j} - 1\right)\sqrt{\frac{N_s}{2\gamma_{i,j} + 1}}\right), \tag{3.1}$$

where $Q(.)$ is the tail probability for the standard normal distribution, ε is the detection threshold, σ_n^2 denotes noise power, $\gamma_{i,j}$ is the received SNR at SU i when it senses channel j, N_s is the number of sensing samples during the sensing stage in a time slot.

The false alarm probability of SU i at channel j can be expressed as [22]

$$P_{f,i,j}(P_{d,i,j}, \gamma_{i,j}) = Q\big(\sqrt{2\gamma_{i,j}+1}Q^{-1}(P_{d,i,j}) + \sqrt{N_s}\gamma_{i,j}\big). \tag{3.2}$$

According to (3.2), a high detection probability leads to a high false alarm probability. To protect the transmission of the PU j, we set a desired target value $\bar{P}_{d,j}$. When SUs perform cooperative sensing at channel j and use the OR rule to make a sensing decision, the cooperative sensing performance needs to satisfy the target value. When the target detection probability value at each channel is fixed, we can compute the target detection probability of each SU as [26]

$$\bar{P}_{d,i,j} = 1 - (1 - \bar{P}_{d,j})^{\frac{1}{|S_j|}}, \tag{3.3}$$

where $|S_j|$ denotes the number of SUs sensing channel j.

We apply the $\bar{P}_{d,i,j}$ obtained by (3.3) to calculate $P_{f,i,j}$ in (3.2). According to OR rule, we calculate the false alarm probability at channel j, which is $P_{f,j}$, according to (2.1).

In this chapter, we assume that each member in the same coalition obtains an equal chance to access channels. The probability that SU $i \in S_j$ can access channel j given that this channel is detected as idle is $\frac{1}{|S_j|}$. The probability that channel j is correctly detected as idle is $P_{I,j}(1-P_{f,j})$, where $P_{I,j}$ is the probability that channel j is idle. Thus, the probability that SU i is allowed to perform transmission over channel j without interfering the transmission of PU is

$$P^U_{i,j} = P_{I,j}(1 - P_{f,j})\frac{1}{|S_j|}. \tag{3.4}$$

Given that SU i is assigned to transmit data over channel j, the achieved throughput is

$$U_{i,j} = \frac{R_{i,j} t_{i,j}}{T}, \tag{3.5}$$

where $R_{i,j}$ is the transmission rate of SU i on channel j and it can be calculated according to (2.3), and $t_{i,j}$ is the transmission time of SU i on channel j according to (2.5).

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 probability that SU i is assigned channel j to transmit data is

$$P^E_{i,j} = \big((1 - P_{I,j})(1 - P_{d,j}) + P_{I,j}(1 - P_{f,j})\big)\frac{1}{|S_j|}. \tag{3.6}$$

The energy spent on data transmission is

$$E^t_{i,j} = W_{t,i,j} t_{i,j}. \tag{3.7}$$

The energy spent on spectrum sensing when SU i senses one channel is

$$E^s_{i,j} = W_{s,i,j} \tau. \tag{3.8}$$

In Chapter 2, it is assumed that an SU can only sense one channel in a time slot. However, in practice, SUs are able to sense multiple channels during the sensing stage [1]. We denote the set of channels that SU i chooses as A_i. Now we consider the expected throughput that SU i can obtain by choosing channel set A_i. Let $\mathcal{K}$ denote a subset of A_i. All the channels in set $\mathcal{K}$ are detected as idle and provide SU i an opportunity to perform transmission over the channel. The probability is $\prod_{j\in\mathcal{K}}(P^E_{i,j})\prod_{j\in A_i\setminus\mathcal{K}}(1-P^E_{i,j})$. Although SU may be provided with multiple channels to access, it can transmit over only one channel during the transmission stage in a time slot. It will choose the best one among these $|\mathcal{K}|$ channels, which can maximize its throughput (*i.e.*, $\max_{j\in\mathcal{K}}\{U_{i,j}\}$). If SU i chooses channel $\arg\max_{j\in\mathcal{K}}\{U_{i,j}\}$ to access among these offered channels, SU i may fail to transmit data due to the mis-detection of the primary user. The probability that SU i can successfully transmit data over this channel is $\frac{P^U_{i,\arg\max_{j\in\mathcal{K}}\{U_{i,j}\}}}{P^E_{i,\arg\max_{j\in\mathcal{K}}\{U_{i,j}\}}}$. Thus, the expected throughput that SU i can obtain is

$$U_i(A_i)=\sum_{\mathcal{K}\subseteq A_i}\left(\left(\prod_{j\in\mathcal{K}}P^E_{i,j}\prod_{j\in A_i\setminus\mathcal{K}}(1-P^E_{i,j})\right)\frac{P^U_{i,\arg\max_{j\in\mathcal{K}}\{U_{i,j}\}}}{P^E_{i,\arg\max_{j\in\mathcal{K}}\{U_{i,j}\}}}\max_{j\in\mathcal{K}}\{U_{i,j}\}\right). \tag{3.9}$$

As shown in (3.9), the expected throughput of SU i increases with the size of A_i. This is because by choosing more channels to sense, SU i obtains more opportunities to access channel and achieves higher throughput. However, for an energy-constrained SU, it should limit the energy spent on sensing in order to save enough energy for data transmission. Therefore, we need to consider the expected power consumption when SU i chooses channel set A_i. The power consumption contains two parts: sensing power consumption and data transmission power consumption. The power consumption spent on sensing each channel in A_i is inevitable to SU i. However, the power spent on transmission occurs only when SU i is performing data transmission over a specific channel. Thus the expected power consumption of SU i is

$$E_i(A_i) = \left(\sum_{\mathcal{K} \subseteq A_i} \left(\left(\prod_{j \in \mathcal{K}} P^E_{i,j} \prod_{j \in A_i \setminus \mathcal{K}} (1 - P^E_{i,j}) \right) E^t_{i, \arg\max_{j \in \mathcal{K}} \{U_{i,j}\}} \right) + \sum_{j \in A_i} E^s_{i,j} \right) \frac{1}{T}. \quad (3.10)$$

To reach a balance between throughput and power consumption, we propose the energy efficiency as a criterion to evaluate SUs' decision on cooperation. We define the expected energy efficiency of SU i as [27]

$$\eta_i(A_i) = \frac{U_i(A_i)}{E_i(A_i)}. \quad (3.11)$$

The objective of each SU is to maximize its throughput subject to energy efficiency constraint. 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 threshold. When the traffic demand of an energy-constrained SU is very low and SU participates in cooperative sensing, it may have to spend too much energy in order to transmit just several information data bits. In this case, the cost of cooperation outweighs the payoff, this SU can simply choose not to perform sensing and save energy for transmission next time. Moreover, all SUs choosing the same channel perform cooperative sensing and share the access to this channel. Thus, the problem is how each SU should cooperate with other SUs and which channel it should choose. We will address this problem in the next section.

3.2 Overlapping Coalitional Game for Cooperation Strategy

In this section, we formulate the CSSA problem as an NTU overlapping coalitional game. The payoff value of each SU captures the expected throughput and energy efficiency that can be obtained by joining multiple coalitions. For SUs to make distributed decision on coalition formation, we define three move rules that take into account both social welfare and individual payoff. We propose an overlapping coalition formation (OCF) algorithm to enable SUs to form a final stable coalition structure. The convergence of this algorithm is analyzed. Moreover, we modify the SCF algorithm proposed in Chapter 2 to address the problem in our new system model. The modified SCF algorithm has a lower computational complexity and requires less information exchange than OCF algorithm.

3.2.1 NTU Overlapping Coalitional Game Formation

In this CSSA strategy, SUs choose different channels to maximize their expected throughput while satisfying the energy efficiency requirement. All SUs choosing the same channel perform spectrum sensing cooperatively to improve the sensing performance, and share the spectrum resources based on the channel availability. We assume that all SUs sensing the same channel form a coalition. Therefore, we can formulate this problem as a coalitional game. Since in our system model, an SU can choose multiple channels and contribute to multiple coalitions, this is an overlapping coalitional game. Different from traditional disjoint coalitional game, in an overlapping coalitional game, a player is allowed to join more than one coalition. Therefore the coalitions are overlapped, where each player contributes to multiple coalitions and obtains higher payoff. In addition, in our system model, the payoff of each SU in one coalition depends on its traffic demand. Thus, the utility obtained by each SU in a coalition may be different and this utility cannot be transferred among different SUs. Therefore our formulated coalitional game is an NTU game. We first introduce the definition of an NTU overlapping coalitional game:

Definition 3 [28]. An NTU overlapping coalitional game $G = (\mathcal{N}, v)$ is given by a set of players $\mathcal{N} = \{1, \ldots, N\}$ and a function $v : S \to \mathbb{R}^{|S|}$, where $S \subseteq \mathcal{N}$ denotes a coalition formed by the players and $v(\emptyset) = \mathbf{0}$.

Corresponding to our system model, the players of this game refer to N SUs. They cooperate with each other and form different coalitions to sense and access different channels. The value function v maps each coalition $S \subseteq \mathcal{N}$ to an $|S|$-dimensional vector. We define the coalition value as the expected payoff that each SU can obtain in this coalition: $v(S_j) = (x_i(S_j), \forall\, i \in S_j)$, where $x_i(S_j) = P^U_{i,j} U_{i,j}$ according to (3.4) and (3.5). However, this is not the total payoff that SU i can obtain in the game, because SU i can join multiple coalitions in an overlapping coalitional game. We will discuss the total payoff of SU i in the following context.

In a coalitional game, players autonomously form different coalitions to achieve higher payoff. The collection of these coalitions is referred to as coalition structure. In a disjoint coalitional game, a coalition structure is a partition of $\mathcal{N}$ [29]. However, in an overlapping coalitional game, SUs are allowed to join multiple coalitions at the same time. Therefore, the coalitions are overlapped. We define the coalition structure Π as follows:

Definition 4 [30]. An overlapping coalition structure Π over a player set $\mathcal{N}$ is defined as a set $\Pi = \{S_1, \ldots, S_K\}$, where K is the number of coalitions. $\forall\ 1 \leq j \leq K$, $S_j \subseteq \mathcal{N}$ and $\cup_{j=1}^{K} S_j = \mathcal{N}$. Since coalitions can be overlapping, $\exists\ S_i, S_j \in \Pi$, $i \neq j$ such that $S_i \cap S_j \neq \emptyset$.

Since all the SUs choosing the same channel form a coalition, there are at most M coalitions. In addition, some SUs with very low traffic demand may prefer to stay idle to save energy for future transmission. Thus, they may choose not to perform sensing. We denote the set of SUs that quit sensing as S_{M+1}. Therefore, in our system model, the number of coalitions K is less than or equal to $M + 1$.

Since an SU can belong to more than one coalition, we consider the payoff that SU i obtains in an overlapping coalition structure. We cannot calculate the payoff of an SU by summing up all the payoff it obtains from all the coalitions it belongs to. Although an SU may be chosen by more than one channel at the same time, it can transmit over only one channel at a time. Therefore, we define the total payoff of SU i as follows

$$p_i(\Pi) = \begin{cases} U_i(A_i), & \text{if } \eta_i(A_i) \geq \eta_{min}, \\ -\infty, & \text{otherwise}, \end{cases} \tag{3.12}$$

where $A_i = \{j \mid \text{ SU } i \in S_j \text{ and } S_j \in \Pi\}$ is the set of channels that SU i chooses to sense and access. For example, consider an overlapping coalitional game $G = (\mathcal{N}, v)$, where $\mathcal{N} = \{1, 2, 3, 4\}$ and $\mathcal{M} = \{1, 2\}$. SUs form coalitions: $S_1 = \{1, 2\}_1$, $S_2 = \{2, 3\}_2$ and $S_3 = \{4\}_3$, where $S_1 = \{1, 2\}_1$ means SUs 1 and 2 form a coalition to sense and access channel 1. The collection of these coalitions $\Pi = \{\{1, 2\}_1, \{2, 3\}_2, \{4\}_3\}$ is the overlapping coalition structure of $\mathcal{N}$. The corresponding channel sensing sets for each SU are $A_1 = \{1\}$, $A_2 = \{1, 2\}$, $A_3 = \{2\}$, and $A_4 = \emptyset$.

When the expected energy efficiency of SU i is greater than the energy efficiency threshold η_{min}, the total coalition value of SU i is equal to the expected throughput it obtains by choosing the channel set A_i. Otherwise, it is equal to negative infinity. This definition guarantees that the energy efficiency of SUs during the coalition formation process will not be lower than the threshold. In addition, we define the payoff of each SU in set S_{M+1} as zero. Note that an SU cannot belong to S_{M+1} and S_j, $j \in \mathcal{M}$ at the same time. Once an SU decides to join quit sensing coalition S_{M+1}, it does not sense and access any channel. Thus, it does not belong to any other coalitions. Therefore, S_{M+1} is an isolated coalition and it is not overlapped with any other coalitions.

After defining the coalition value of SUs and overlapping coalition structure, we consider the preference order of SUs. The preference order helps SUs choose between two coalitions and select the better channel to sense and access. In some existing works (e.g., [1] and [15]), the SUs are selfish, which means an SU seeks to maximize its own payoff without considering the benefits of other SUs. In this case, the channel may be occupied by SUs with low traffic demands while SUs with high traffic demands are still in short of spectrum resources. This leads to a low utilization of the channels. Thus, we introduce a preference order that takes into account both social welfare and individual payoff. We define the social welfare as the value of a coalition structure Π and it is calculated as

$$u(\Pi) = \sum_{i \in \mathcal{N}} p_i(\Pi). \tag{3.13}$$

The value of a coalition structure is the sum of payoffs of all the players in a coalition structure. When considering the preference order of an SU, we take into account both individual payoff and coalition structure value as follows:

Definition 5 [30]. In an overlapping coalitional game $G = (\mathcal{N}, v)$, given two coalition structures Π_p and Π_q over $\mathcal{N}$, Π_p is i-preferred over Π_q, where $i \in \mathcal{N}$, is equivalent to $p_i(\Pi_p) > p_i(\Pi_q)$ and $u(\Pi_p) > u(\Pi_q)$. This relation is represented as

$$\Pi_p \succ_i \Pi_q \Leftrightarrow p_i(\Pi_p) > p_i(\Pi_q) \text{ and } u(\Pi_p) > u(\Pi_q). \tag{3.14}$$

According to Definition 5, a coalition structure is preferred over another only when the total payoff of the coalition structure and the individual payoff of an SU are both increased from one to the other. This preference order not only guarantees the increase of social payoff during the coalition formation process, but also keeps the spectrum efficiency above a certain level. Under this preference order, we show that, during the coalition formation process, the SUs can reach a stable coalition structure after a finite number of iterations in the following subsection.

3.2.2 Coalition Formation Algorithms

Based on the preference order, we define three *move rules*. During the process of overlapping coalition formation, SUs make their own decisions on joining or leaving any coalitions according to their preference order over different coalitions. There are three possible moves. First, SU joins a new coalition that it does not belong to. Second, SU leaves one of its current coalitions. Third, SU switches from one of its current coalitions to a new coalition. To provide a mechanism through which SUs can form different coalitions by performing above moves, we define three move rules as follows:

Definition 6. Join rule: Consider a coalition structure Π_p over a set of players N, where $S_j \in \Pi_p$ and $i \in \mathcal{N} \setminus S_j$. A new coalition structure is defined as $\Pi_q = \{\Pi_p \setminus S_j\} \cup \{S_j \cup \{i\}\}$. If $\Pi_q \succ_i \Pi_p$, then SU i joins S_j and Π_p changes into Π_q.

According to Definition 6, in coalition structure Π_p, SU i does not belong to coalition S_j at first. We assume that SU i joins coalition S_j and the current coalition structure Π_p changes into a new coalition structure Π_q. If Π_q is preferred over Π_p by SU i according to Definition 5, SU i joins coalition S_j and the current coalition structure Π_p is replaced by Π_q. Although the decision is made by SU i, it does not mean that SU acts selfishly without considering the effect of its move to other SUs. This is because an SU joins a new coalition only when its own payoff and the coalition structure value are both improved by this movement. For example, if SU i can increase its payoff by joining coalition S_j, however its movement is detrimental to other SUs in the game and leads to the decrease of the total payoff of all SUs, SU i is not allowed to join coalition S_j in this case. Therefore, individual payoff and social welfare are both taken into account in this join rule.

Definition 7. Quit rule: Consider a coalition structure Π_p over a set of players N, where $S_j \in \Pi_p$ and $i \in \mathcal{N} \cap S_j$. A new coalition structure is defined as $\Pi_q = \{\Pi_p \setminus S_j\} \cup \{S_j \setminus \{i\}\}$. If $\Pi_q \succ_i \Pi_p$, then SU i leaves S_j and Π_p changes into Π_q.

According to quit rule, SU i leaves one of its current coalitions j and Π_p changes into Π_q if this newly formed coalition structure is preferred over the current one by SU i. Although SU i can always increase its chance to access channels by joining more coalitions, it may still perform quit move sometimes. When there are too many other SUs in one coalition that SU i belongs to, SU i obtains little chance to access channels. Therefore, in this case, SU i may leave this coalition to increase its payoff according to quit rule.

Definition 8. Switch rule [15]: Consider a coalition structure Π_p over a set of players N, where $S_j, S_k \in \Pi_p$ and $i \in S_j$, $i \notin S_k$, and $i \in \mathcal{N}$. A new coalition structure is defined as $\Pi_q = \{\Pi_p \setminus \{S_j, S_k\}\} \cup \{S_j \setminus \{i\}\} \cup \{S_k \cup \{i\}\}$. If $\Pi_q \succ_i \Pi_p$, then SU i switches from S_j to S_k and Π_p changes into Π_q.

The switch rule combines the above two rules together. According to its definition, SU i switches from one of its coalitions to a new coalition when the resulted new coalition structure is preferred over the current one. The switch rule balances the size of different coalitions and improves the spectrum efficiency. During the coalition formation process, some channels may be chosen by many SUs while some other channels are sensed by few ones. When SUs find that their payoff can be improved by switching from the coalition with many members to another coalition with very few members, they perform switch moves. In this way, SUs autonomously distribute their contribution to different coalitions and channels are equally utilized.

In order to study the stability of the overlapping coalition structure, we define the *stability* of an overlapping coalition structure as follows:

Definition 9. An overlapping coalition structure Π over a set of players $\mathcal{N}$ is stable if $\forall\ i\ \in \mathcal{N}$, such that $i \in S_j$, $i \notin S_k$, and S_j, $S_k \in \Pi$, SU i will not deviate from S_j or join S_k.

According to *Definition 9*, for any SU i in a stable coalition structure, it will not leave any of its coalitions or join a new coalition. Therefore, all the SUs would stay in their current coalitions and do not make any changes.

Overlapping Coalition Formation (OCF) Algorithm

To reach a stable coalition structure, we propose an OCF algorithm as shown in Algorithm 2. This algorithm is a distributed algorithm, which is executed by each SU i, $\forall\ i \in \mathcal{N}$.

Algorithm 2 Overlapping Coalition Formation (OCF) Algorithm in CRN. It is executed by SU i, $\forall\ i \in \mathcal{N}$.

1: **Initialization**: Initialize coalitions $S_{M+1} := \mathcal{N}$; $S_j := \emptyset$, $\forall j \in \mathcal{M}$. Initialize the coalition structure $\Pi := \{S_1, \ldots, S_M, S_{M+1}\}$, and $\Pi_k := \Pi$, $\forall\ k \in \mathcal{N}$.
2: SU i broadcasts its traffic demand D_i to other SUs and receives information from other SUs.
3: SU i calculates the optimal transmission power $W_{t,i,j}^{opt}$ by solving problems (3.15) and (3.18), $\forall\ j \in \mathcal{M}$.
4: **repeat**
5: SU i randomly selects $k \in A_i$ and $j \in \mathcal{M} \setminus A_i$, where $A_i = \{j \mid \text{ SU } i \in S_j \text{ and } S_j \in \Pi\}$.
6: $\Pi_{Quit} := \{\Pi \setminus\ S_k\} \cup \{S_k \setminus \{i\}\}$.
7: SU i calculates $u(\Pi_{Quit})$ and $p_i(\Pi_{Quit})$ according to (3.11), (3.12) and (3.13).
8: $\Pi_{Join} := \{\Pi \setminus\ S_j\} \cup \{S_j \cup \{i\}\}$.
9: SU i calculates $u(\Pi_{Join})$ and $p_i(\Pi_{Join})$ according to (3.11), (3.12) and (3.13).
10: $\Pi_{Switch} := \{\Pi \setminus\ \{S_j,\ S_k\}\} \cup \{S_j \cup \{i\}\} \cup \{S_k \setminus \{i\}\}$.
11: SU i calculates $u(\Pi_{Switch})$ and $p_i(\Pi_{Switch})$ according to (3.11), (3.12) and (3.13).
12: **if** $\Pi_{Quit} \succ_i \Pi$ **then**
13: $\Pi := \Pi_{Quit}$,
14: **else if** $\Pi_{Join} \succ_i \Pi$ **then**
15: $\Pi := \Pi_{Join}$,
16: **else if** $\Pi_{Switch} \succ_i \Pi$ **then**
17: $\Pi := \Pi_{Switch}$.
18: **end if**
19: $\Pi_i := \Pi$.
20: $u(\Pi_i) := u(\Pi)$.
21: SU i broadcasts the information of updated coalition structure Π_i and its value $u(\Pi_i)$ to other SUs.
22: SU i receives the information of Π_n and $u(\Pi_n)$ from other SU n, $\forall\ n \in \mathcal{N} \setminus \{i\}$.
23: The collection of the updated information of coalition structure $\mathcal{T}_{info} := \{\Pi_1, \ldots, \Pi_N\}$.
24: $\Pi := \arg\max_{\Pi_n \in \mathcal{T}_{info}} \{u(\Pi_n)\}$.
25: **until** $\forall\ i \in \mathcal{N}$, $\forall\ k \in A_i$ and $j \in \mathcal{M} \setminus A_i$, the resulted Π_{Quit}, Π_{Join}, and Π_{Switch} satisfy that $\Pi_{Quit} \not\succ_i \Pi$, $\Pi_{Join} \not\succ_i \Pi$ and $\Pi_{Switch} \not\succ_i \Pi$, respectively.
26: SU i performs cooperative sensing within each coalition that it belongs to based on Π during sensing stage. When being assigned to channel j, SU i transmits data with the optimal transmission power $W_{t,i,j}^{opt}$.

In Algorithm 2, we initialize the coalitions by letting all SUs join quit sensing coalition S_{M+1} (line 1). Then SU i communicates the traffic demand information with other SUs (line 2). SU i calculates its optimal transmission power $W_{t,i,j}^{opt}$ (line 3) through solving problems (3.15) and (3.18), which will be discussed in the next section. After that, SU i makes coalition formation moves according to three move rules. At the beginning of each iteration, SU i randomly selects a coalition that it currently belongs to S_k and a new coalition it does not belong to S_j (line 5). SU i assumes that it leaves coalition S_k and a new coalition structure is formed (line 6). SU i calculates its resulted payoff and the value of this resulted new coalition structure (line 7). Similarly, it considers potential new coalition structures resulting from join move and switch move (lines 8, 10), and calculates their values (lines 9, 11), respectively. If the resulted coalition structure by quit move is preferred over the current one by SU i, the coalition structure is updated (line 13). If the quit move does not improve the coalition structure, SU i considers join move (line 14) and switch move (line 16). SU i updates the information of coalition structure and its value (lines 19 - 20) and communicates the updated information with other SUs (lines 21 - 22). All the updated coalition structure information form a set $\mathcal{T}_{info}$ (line 23). The coalition structure with the greatest value among $\mathcal{T}_{info}$ is selected as the new coalition structure (line 24). SUs repeated the coalition formation process until all SUs will not deviate from their current coalitions or join other new coalitions. In other words, the process converges to a stable coalition structure. After the coalition formation process, SU i cooperatively senses the channels with other SUs in corresponding coalitions according to Π. During the spectrum access stage, SU i sets its transmission power to the optimal value when it is allocated a channel to transmit data (line 26).

The convergence of the proposed OCF algorithm is guaranteed as follows:

Theorem 1. *The proposed OCF algorithm converges to a stable overlapping coalition structure after a finite number of iterations.*

Proof. Given that the number of channels M and the number of players N are finite, the number of possible overlapping coalition structures is $2^{M \times N}$. When implementing the OCF algorithm, the coalition formation process involves a sequence of moves of SUs, which result in a sequence of coalition structure $\{\Pi^{(0)'}, \Pi^{(1)'}, \ldots, \Pi^{(r)'}\}$, where r is the total number of moves made by SUs. According to Definitions 5 - 8, after each move of any SU, a new coalition structure with a higher value is formed. In addition, the number of possible coalition structures is finite. Therefore, r is a finite number. $\Pi^{(r)'}$ is the final overlapping coalition structure resulting from the last move of SUs. Assume that $\Pi^{(r)'}$ is not stable, according to Definition 9, there exists $i \in \mathcal{N}$ such that SU i will deviate from one of its current coalitions or join a new coalition. Thus, according to the proposed OCF algorithm, SU i will make join, quit or switch moves and $\Pi^{(r)'}$ will change into a new coalition structure. This contradicts with the fact that $\Pi^{(r)'}$ is the final coalition structure. Thus, $\Pi^{(r)'}$ is a stable coalition structure. Therefore, after a finite number of iterations, the proposed OCF algorithm converges to a stable overlapping coalition structure. $\square$

During the process of coalition formation, each SU seeks to improve its individual utility while increasing the total value of the coalition structure. The movement of SUs leads to a new coalition structure after each iteration. Thus, the OCF algorithm converges to a stable coalition structure. A larger payoff is obtained every time the coalition structure changes. Moreover, our proposed OCF algorithm is adaptive to the changes in network settings. Whenever new SUs join the network or more channels become available, traffic demand or channel condition changes, SUs can adaptively change their cooperation strategies and form different coalition structures according to Algorithm 2. Therefore, the traffic demand of SUs are still satisfied, network throughput and system energy efficiency are guaranteed when there are changes in network settings.

Modified Sequential Coalition Formation (SCF) Algorithm

Although the convergence of OCF Algorithm is guaranteed, the number of iterations required to reach a final stable coalition structure may grow exponentially with the number of SUs. Therefore, we modify the SCF algorithm proposed in Chapter 2 to address this issue. The modified SCF algorithm involves a lower number of iterations and requires less information exchange among SUs than the OCF algorithm.

Similarly to the SCF algorithm proposed in Chapter 2, the coalition structure is also formed step by step in the modified SCF algorithm. At each step, only one player can propose a coalition structure. Players make moves one by one according to the rule of order ρ, which is determined by traffic demand of SUs. Since in our new system model overlapping coalition structure is allowed, the active SU can join multiple coalitions based on the current coalition structure, which is different from the previous SCF algorithm.

Algorithm 3 Modified Sequential Coalition Formation (SCF) Algorithm in CRN.

for each $i \in \mathcal{N}$ **do**
  SU i reports its traffic demand D_i to the central coordinator.
  SU i calculates the optimal transmission power $W_{t,i,j}^{opt}$ by solving problem (3.15) and (3.18), $\forall\, j \in \mathcal{M}$.
end for
$\mathcal{D} := (D_1, D_2, \ldots, D_N)$
Central coordinator calculates $\rho := Q(\mathcal{D})$ and broadcasts the information of ρ to all SUs.
for $i = 1$ to N **do**
  if $i = 1$ **then**
    SU $\rho(i)$ initializes the coalitions $S_{M+1} := \mathcal{N}$; $S_j := \emptyset$, $\forall j \in \mathcal{M}$, and the coalition structure $\Pi := \{S_1, S_2, \ldots, S_{M+1}\}$.
  else
    SU $\rho(i)$ receives the information of Π from SU $\rho(i-1)$.
  end if
  for each $j \in \mathcal{M}$ **do**
    $\Pi_{Join} := \{\Pi \setminus\ S_j\} \cup \{S_j \cup \{\rho(i)\}\}$.
    SU $\rho(i)$ calculates $u(\Pi_{Join})$ and $p_{\rho(i)}(\Pi_{Join})$ according to (3.11), (3.12) and (3.13).
    SU $\rho(i)$ randomly selects $k \in A_{\rho(i)}$, where $A_{\rho(i)} = \{j \mid\ \text{SU } \rho(i) \in S_j \text{ and } S_j \in \Pi\}$.
    $\Pi_{Switch} := \{\Pi \setminus\ \{S_j,\ S_k\}\} \cup \{S_j \cup \{\rho(i)\}\} \cup \{S_k \setminus \{\rho(i)\}\}$.
    SU $\rho(i)$ calculates $u(\Pi_{Switch})$ and $p_{\rho(i)}(\Pi_{Switch})$ according to (3.11), (3.12) and (3.13).
    if $\Pi_{Join} \succ_{\rho(i)} \Pi$ **then**
      $\Pi := \Pi_{Join}$,
    else if $\Pi_{Switch} \succ_{\rho(i)} \Pi$ **then**
      $\Pi := \Pi_{Switch}$.
    end if
  end for
  if $i = N$ **then**
    SU $\rho(i)$ broadcasts the updated information of Π to other SUs.
  else
    SU $\rho(i)$ sends the updated information of Π to SU $\rho(i+1)$.
  end if
end for
SU i, $\forall\, i \in \mathcal{N} \setminus \{\rho(N)\}$, receives the updated information of Π from SU $\rho(N)$.
SU i, $\forall\, i \in \mathcal{N}$, performs cooperative sensing within each coalition that it belongs to based on Π during sensing stage. When being assigned to a channel, SU i transmits data with the optimal transmission power $W_{t,i,j}^{opt}$.

The modified SCF algorithm is shown in Algorithm 3. In this algorithm, SUs make distributed coalition formation decision. However, their behaviors are coordinated by a central coordinator. First, each SU reports its traffic demand information to the central coordinator (line 2) and calculates its optimal transmission power value (line 3). The traffic demand information from different SUs forms an information vector $\mathcal{D}$ (line 5). $Q(\mathcal{X})$ is a sorting function, which is defined the same with the sorting function in old SCF algorithm proposed in Chapter 2. Central coordinator calculates the rule of order ρ through sorting $\mathcal{D}$ with function $Q(\mathcal{D})$. The information of ρ is broadcast to all SUs (line 6). Then, SUs make coalition formation decision one by one according to ρ. For example, the SU with the highest traffic demand (*e.g.*, SU $\rho(1)$) makes the first choice. It initializes the coalition structure by setting all SUs in quit sensing coalition S_{M+1} (line 9). For other SUs, the active SU receives the updated information of Π from previously active SU (line 11). During the coalition formation process, each SU checks all the channels one by one to look for potential new coalition when it is active. For a new channel j, if SU prefers to sense channel j, SU can join coalition j or switch to coalition j, which means quit move is not considered in this algorithm. Specifically, the active SU first considers the potential new coalition structure by assuming that it joins coalition S_j (line 14). The SU calculates its new payoff and the value of the resulted coalition structure (line 15). Moreover, the active SU randomly selects a coalition it belongs to (line 16), and assumes that it switches from this selected coalition to coalition S_j (line 17). Also, the value of the potential new coalition structure resulting from switch move and SU's new payoff are calculated (line 18). If the resulted coalition structure by join move Π_{Join} is preferred over the current one Π, the coalition structure is updated (line 20). If the join move cannot improve the coalition structure, the resulted structure by switch move Π_{Switch}

is considered (line 21). After checking all the new coalitions, the currently active SU sends the updated information of Π to the next active SU (line 28). For the last active SU, it broadcasts the final coalition structure to other SUs (line 26). After the coalition formation process, SUs perform sensing cooperatively within each coalition that they belong to according to the final coalition structure. During the transmission stage, SUs perform data transmission with the optimal transmission power (line 32).

Although this SCF algorithm does not guarantee the stability of the final coalition structure, its performance in terms of throughput is as good as OCF algorithm, which will be shown by simulation results in the following section. Moreover, SCF algorithm has a lower computational complexity than OCF algorithm. During the process of coalition formation in SCF algorithm, each SU makes coalition formation move only when it is active and it checks each potential sensing channel only once. Therefore, there are at most $M \times N$ iterations when running SCF algorithms. On the other hand, in OCF algorithm, coalition formation movement takes place every time there is a new coalition structure preferred over current one. SUs moves from one coalition to another or join new coalitions until the final stable coalition structure is achieved. Since the number of the possible overlapping coalition structure is $2^{M\times N}$, there are at most $2^{M\times N}$ iterations, which is much more than the number of iterations required in SCF algorithm. Besides, SCF algorithm involves much less information exchange than OCF algorithm. In SCF algorithm, in addition to the exchange of traffic demand information, each SU only has to send the updated coalition structure information to the next active SU. In OCF algorithm, each SU has to exchange the information of updated coalition structure with others after each iteration, which consumes much more time and energy than running SCF algorithm.

3.3 Adaptive Transmission Power Control

In this section, we analyze the transmission power control strategy given that an SU has been assigned a channel. We prove that this adaptive transmission power control strategy achieves the optimal transmission power value, which minimizes the energy consumption spent on data transmission under the constraint that the maximum throughput of SU is achieved.

From (2.3), (3.5) and (3.7), we notice the transmission power affects the throughput and the energy spent on transmission. On one hand, increasing the transmission power leads to an increase of transmission rate, thus improve the throughput. On the other hand, more energy is required for data transmission when transmission power is increased. Therefore, it is reasonable for SU to adaptively change its transmission power to balance the tradeoff between throughput and energy consumption. Thus, our objective is to obtain the optimal transmission power that minimizes the energy consumption while achieving the highest throughput.

First, we assume that the transmission power of SU i varies from $W_{t,i}^{min}$ to $W_{t,i}^{max}$ (i.e., $W_{t,i}^{min} \leq W_{t,i,j} \leq W_{t,i}^{max}$). Consider SU i has been assigned channel j for transmission. Since the bandwidth of channel j is fixed, the transmission rate $R_{i,j}$ depends on $W_{t,i,j}$

according to (2.3). During one time slot, the value of T, τ and D_i are constant. Thus, both the throughput and energy consumption for transmission are functions of $W_{t,i,j}$. We first consider the throughput maximization problem as follows

$$\begin{aligned} \underset{W_{t,i,j}}{\text{maximize}} \quad & U_{i,j}(W_{t,i,j}) \\ \text{subject to} \quad & W_{t,i}^{min} \leq W_{t,i,j} \leq W_{t,i}^{max}. \end{aligned} \tag{3.15}$$

Note that the objective function in problem (3.15) is a piecewise function. We can rewrite $U_{i,j}(W_{t,i,j})$ by substituting (2.3) to (3.5) and obtain the objective function as follows

$$U_{i,j}(W_{t,i,j}) = \begin{cases} \frac{B_j \log_2\left(1+|g_i|^2 \frac{W_{t,i,j}}{\sigma_n^2}\right)(T-\tau)}{T}, & \text{if } W_{t,i,j} \leq W_{t,i,j}^h, \\ \frac{D_i}{T}, & \text{otherwise,} \end{cases} \tag{3.16}$$

where $W_{t,i,j}^h > 0$ is the threshold and satisfies that $B_j \log_2\left(1+|g_i|^2 \frac{W_{t,i,j}^h}{\sigma_n^2}\right)(T-\tau) = D_i$. Combining problem (3.15) and equation (3.16), different transmission power range leads to different optimal solution results to problem (3.15). We denote the set of optimal solutions to problem (3.15) as $\mathcal{W}_{t,i,j}^* = \{W_{t,i,j} \mid W_{t,i,j}$ is an optimal solution to problem (3.15)$\}$. We have

$$\mathcal{W}_{t,i,j}^* = \begin{cases} \{W_{t,i}^{max}\}, & \text{if } W_{t,i}^{max} \leq W_{t,i,j}^h, \\ \{W_{t,i,j} \mid W_{t,i,j}^h \leq W_{t,i,j} \leq W_{t,i}^{max}\}, & \text{if } W_{t,i}^{min} \leq W_{t,i,j}^h \leq W_{t,i}^{max}, \\ \{W_{t,i,j} \mid W_{t,i}^{min} \leq W_{t,i,j} \leq W_{t,i}^{max}\}, & \text{otherwise.} \end{cases} \tag{3.17}$$

According to (3.17), the number of solutions to problem (3.15) depends on the relations between $W_{t,i,j}^h$ and the range of the transmission power. In other words, SUs set their transmission power to a certain value or within a range to obtain the maximum throughput. In order to save energy spent on transmission while guaranteeing the maximum throughput, we consider an optimization problem that minimizes the energy consumption for data transmission under the constraint that the highest throughput is obtained. This optimization problem is formulated as follows

$$\begin{aligned} \underset{W_{t,i,j}}{\text{minimize}} \quad & E^t_{i,j}(W_{t,i,j}) \\ \text{subject to} \quad & U_{i,j}(W_{t,i,j}) \geq U^{max}_{i,j}, \end{aligned} \tag{3.18}$$

where $U^{max}_{i,j}$ is the maximum value of $U_{i,j}(W_{t,i,j})$, which can be achieved only when the transmission power $W_{t,i,j}$ is an optimal solution to problem (3.15) ($i.e.$, $W_{t,i,j} \in \mathcal{W}^*_{t,i,j}$). In other words, the solution to problem (3.15) serves as the constraint in problem (3.18). In this way, the requirement for throughput can be guaranteed when we minimize the energy consumption for data transmission. As we discussed above, the number of solutions to problem (3.15) depends on the range of transmission power. Therefore, for problem (3.18), the optimal solutions are obtained based on the following three cases.

In Case 1, where $W^{max}_{t,i} \leq W^h_{t,i,j}$, the only solution to problem (3.15) is the optimal solution to problem (3.18), which is $W^{max}_{t,i}$. It means SU i has to perform data transmission over channel j with its maximum transmission power in order to achieve the highest throughput. In this case, the energy consumption for transmission during one time slot, which is the objective function value of problem (3.18), is $W^{max}_{t,i}(T-\tau)$.

In Case 2, we have $W^{min}_{t,i} \leq W^h_{t,i,j} \leq W^{max}_{t,i}$. The optimal solution to problem (3.15) is $\{W_{t,i,j} \mid W^h_{t,i,j} \leq W_{t,i,j} \leq W^{max}_{t,i}\}$, which is a constraint in problem (3.18). We express

$E_{i,j}^t$ by substituting (2.3) and (2.5) to (3.7) and obtain the objective function as follows

$$E_{i,j}^t(W_{t,i,j}) = \frac{W_{t,i,j} D_i}{B_j \log_2\left(1 + |g_i|^2 \frac{W_{t,i,j}}{\sigma_n^2}\right)}. \tag{3.19}$$

Proposition 1. *Function $E_{i,j}^t(W_{t,i,j})$ in (3.19) is a monotonically increasing function.*

Proof. We take the first derivative of function $E_{i,j}^t(W_{t,i,j})$ with respect to $W_{t,i,j}$ and obtain

$$E_{i,j}^{t\,\prime}(W_{t,i,j}) = \frac{\frac{\ln 2 D_i \sigma_n^2}{B_j |g_i|^2}}{\left(\ln(1 + |g_i|^2 \frac{W_{t,i,j}}{\sigma_n^2})\right)^2} \left(\ln(1 + |g_i|^2 \frac{W_{t,i,j}}{\sigma_n^2}) - \frac{|g_i|^2 \frac{W_{t,i,j}}{\sigma_n^2}}{1 + |g_i|^2 \frac{W_{t,i,j}}{\sigma_n^2}} \right). \tag{3.20}$$

Since $\frac{\frac{\ln 2 D_i \sigma_n^2}{B_j |g_i|^2}}{\left(\ln(1+|g_i|^2 \frac{W_{t,i,j}}{\sigma_n^2})\right)^2} > 0$, to prove the monotonicity of function $E_{i,j}^t(W_{t,i,j})$, we need to show that $\ln(1 + |g_i|^2 \frac{W_{t,i,j}}{\sigma_n^2}) - \frac{|g_i|^2 \frac{W_{t,i,j}}{\sigma_n^2}}{1+|g_i|^2 \frac{W_{t,i,j}}{\sigma_n^2}} > 0$ for $\forall\ W_{t,i,j} > 0$. Assume that $y = \ln(1+|g_i|^2 \frac{W_{t,i,j}}{\sigma_n^2}) - \frac{|g_i|^2 \frac{W_{t,i,j}}{\sigma_n^2}}{1+|g_i|^2 \frac{W_{t,i,j}}{\sigma_n^2}}$. We calculate the first derivative of y with respect to $W_{t,i,j}$, which is

$$\begin{aligned} y' &= \frac{|g_i|^2}{\sigma_n^2} \left(\frac{1}{1 + |g_i|^2 \frac{W_{t,i,j}}{\sigma_n^2}} - \frac{1}{(1 + |g_i|^2 \frac{W_{t,i,j}}{\sigma_n^2})^2} \right) \\ &= \frac{|g_i|^4 \frac{W_{t,i,j}}{\sigma_n^4}}{(1 + |g_i|^2 \frac{W_{t,i,j}}{\sigma_n^2})^2}. \end{aligned}$$

We have $y' > 0$, $\forall\ W_{t,i,j} > 0$. Thus, y is monotonically increasing with respect to $W_{t,i,j}$ and $y(W_{t,i,j}) > y(0) = 0$. Therefore, $E_{i,j}^{t\,\prime}(W_{t,i,j}) > 0$ and $E_{i,j}^t$ is monotonically increasing with $W_{t,i,j}$. □

According to Proposition 1, the value of $E_{i,j}^t(W_{t,i,j})$ increases with $W_{t,i,j}$ when $W_{t,i,j}^h \leq W_{t,i,j} \leq W_{t,i}^{max}$. Thus, the optimal solution to problem (3.15) is $W_{t,i,j}^h$, which satisfies $B_j \log_2\left(1 + |g_i|^2 \frac{W_{t,i,j}^h}{\sigma_n^2}\right)(T - \tau) = D_i$ and $W_{t,i}^{min} < W_{t,i,j}^h < W_{t,i}^{max}$.

In Case 3, we have $W^h_{t,i,j} \leq W^{min}_{t,i}$, problem (3.15) has multiple solutions in the set $\{W_{t,i,j} \mid W^{min}_{t,i} \leq W_{t,i,j} \leq W^{max}_{t,i}\}$. The objective function is the same with that in Case 2. According to Proposition 1, the optimal solution to problem (3.18) is $W^{min}_{t,i}$.

The optimal solution to problem (3.18) changes with the relation between the $W^h_{t,i,j}$ and transmission power range. When the range of the transmission power of SU i is fixed, the value of $W^h_{t,i,j}$ determines the number of solutions to (3.15), and thus affects the solution to problem (3.18). According to the definition of $W^h_{t,i,j}$, the value of $W^h_{t,i,j}$ depends on the traffic demand of SU i. When SU i has very few data bits to transmit (i.e., D_i is very small), $W^h_{t,i,j}$ is relatively small. In this case, $\frac{D_i}{T-\tau}$ is equal to $R_{i,j}$, and $R_{i,j}$ is monotonically increasing with $W_{t,i,j}$. Thus, $W^h_{t,i,j}$ is smaller than $W^{min}_{t,i}$, which corresponds to Case 3. Therefore, SU i saves energy by setting its transmission power as $W^{min}_{t,i}$. On the contrary, when D_i is very large, $W^h_{t,i,j}$ is greater than $W^{max}_{t,i}$. In order to obtain the highest throughput, SU i performs transmission with a transmission power of $W^{max}_{t,i}$. In this way, the transmission power is adaptively controlled according to the traffic demand of SU. Also, the energy spent on data transmission is minimized under the constraint that SU achieves the highest throughput.

3.4 Performance Evaluation

In this section, we compare the performance of the OCF algorithm, SCF algorithm, and disjoint coalition formation (DCF) algorithm from the perspective of aggregate throughput. In DCF algorithm, each SU can only join at most one coalition instead of multiple coalitions, and SUs form a disjoint coalition structure by implementing this algorithm. DCF algorithm is similar to the algorithm proposed in [15].

Unless stated otherwise, we consider a CRN with N SUs and M PUs (i.e., M licensed channels). SUs are randomly placed in a 100 m $\times$ 100 m square region. The base station is placed at the center of the square region. Each channel has a bandwidth of 100 kHz and the probability that a channel is idle is randomly chosen between $[0.5, 1]$. The CRN works in a time slotted manner. The slot duration T is 100 ms and the sensing duration is 5 ms. We model the channel gain of the link of SU i as $|g_i|^2 = 1/d_i^n$, where d_i is the distance between SU i and the base station, and n is the path loss exponent. We set n to 2. We set the target detection probability at each channel as 0.99. The received PU's SNR at each SU $\gamma_{i,j}$ is set to -15 dB. The noise power σ_n^2 is set to 0.01 mW. The threshold of transmission power of each SU $W_{t,i}^{min}$ is 50 mW and the upper bound $W_{t,i}^{max}$ is 150 mW. The sensing power at each SU $W_{s,i,j}$ is 50 mW. The number of sensing samples during the sensing stage in a time slot N_s is 5000, which is similar to the parameters setting in [31]. The number of packets generated by each SU during a time slot follows Poisson distribution with an average rate of $\lambda = 0.5$ packet per time slot, and each packet is 20 kb. The buffer size of each SU is set to 200 kb. The energy efficiency threshold η_{min} is 500 kb/J.

Fig. 3.1 shows a snapshot of a stable overlapping coalition structure obtained by implementing OCF algorithm. There are seven SUs and three PUs (*i.e.*, three licensed channels) in the network. The base station (BS) is located in the center of the square area.

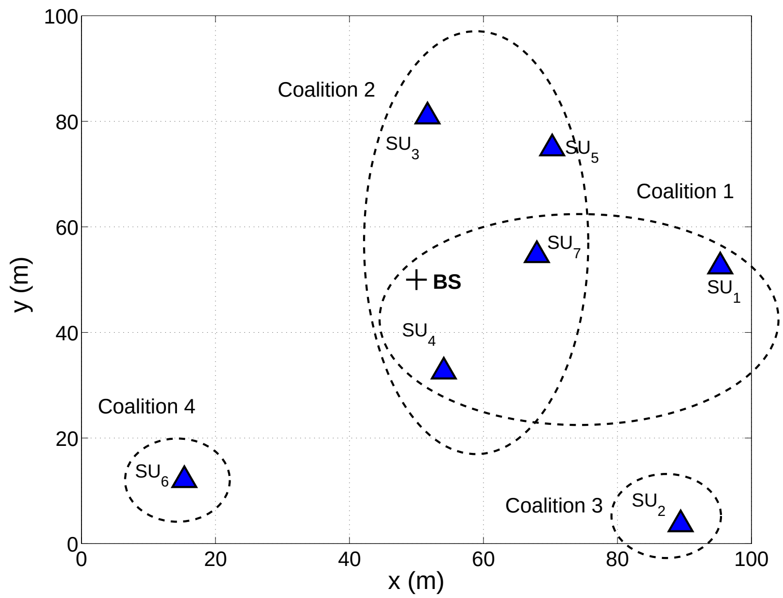

Figure 3.1: An example of a stable overlapping coalition structure ($M = 3, N = 7$) by OCF algorithm.

Seven SUs are randomly distributed in the area. All the SUs in the same ellipse form a coalition to sense and access a channel. Results in Fig. 3.1 show that SUs 1, 4 and 7 belong to coalition 1, which corresponds to channel 1. SUs 3, 4, 5 and 7 form a coalition to sense and access channel 2. SU 2 forms a singleton coalition to use channel 3. SU 6 joins the coalition 4, which is the coalition of quit sensing. Thus, the overlapping coalition structure $\Pi = \{\{1, 4, 7\}_1, \{3, 4, 5, 7\}_2, \{2\}_3, \{6\}_4\}$. In this stable coalition structure, coalitions 1 and 2 are overlapped with each other. SUs 4 and 7 contribute to both coalitions at the same time. While SU 6 chooses not to cooperate with other SUs due to the fact that it has no traffic demand during the current time slot. Therefore, SU 6 is in quit sensing coalition.

Fig. 3.2 shows the aggregate throughput of SUs when the number of SUs N increases

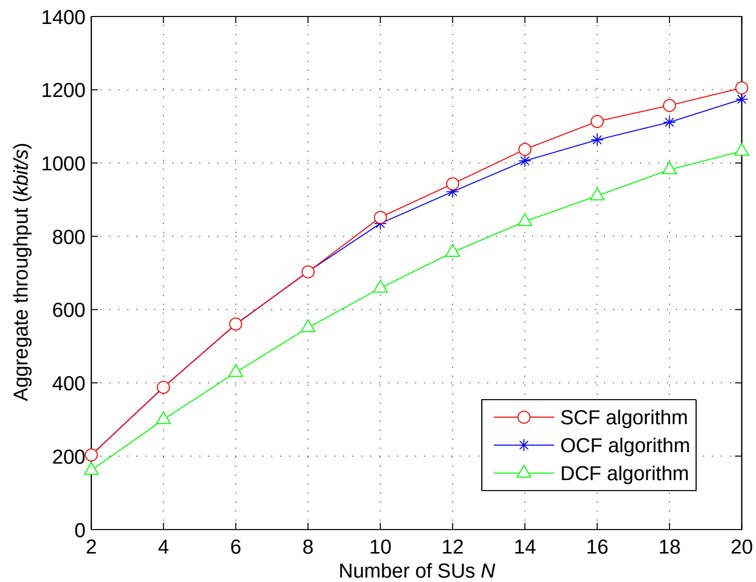

Figure 3.2: Aggregate throughput versus the number of SUs (N) in CRN for $M = 6$.

from 2 to 20. As it shows in this figure, both OCF and SCF algorithms outperform DCF algorithm in terms of aggregate throughput. This is because in OCF and SCF algorithms, SUs can join multiple coalitions, which increase their chances to access channels and improve their throughput. However, in DCF algorithm, an SU can only join one coalition and share one channel with other SUs, its chance of obtaining the use of channel is limited. This result shows that overlapping coalitional game strategy improves spectrum efficiency.

Fig. 3.3 shows the aggregate throughput of SUs when the number of PUs M (i.e, the number of channels) increases from 1 to 10. Results show that OCF and SCF algorithms have similar performance. When M is small, the performance gap between these two algorithms and DCF algorithm is small. This is because in OCF and SCF algorithms, SUs can sense very few channels to improve their chance of transmitting data when channel

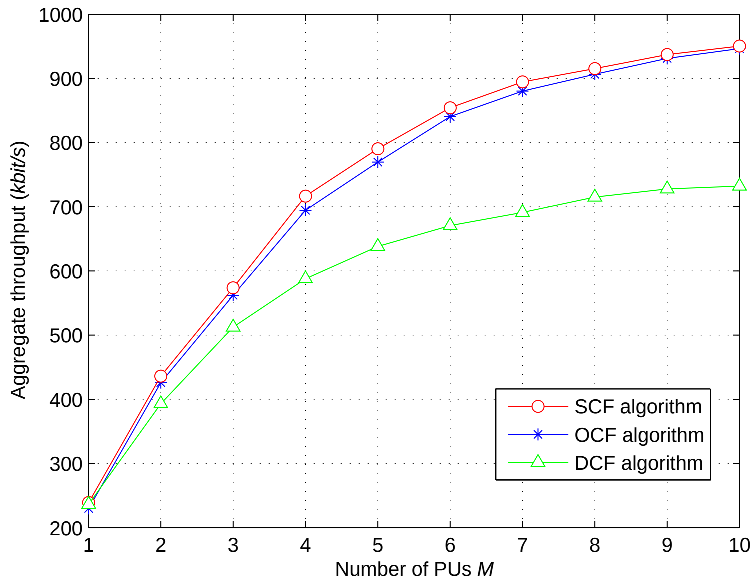

Figure 3.3: Aggregate throughput versus the number of PUs (M) in CRN for $N = 10$.

resources are limited. The gap of performance becomes larger when M increases. When more channels become available, SUs in OCF and SCF algorithms obtain higher throughput by joining multiple coalitions. However, SUs in DCF obtain limited improvement of throughput due to the constraint that it can choose to sense and access only one channel.

Fig. 3.4 shows the aggregate throughput when increasing the average generated packet rate λ. Both OCF and SCF algorithms outperform DCF algorithm in terms of throughput when λ changes from 0.1 to 1. The throughput increases with traffic demand when λ is small for all algorithms. Larger value of λ means more data information generated at each SU during each time slot, which encourages SUs to join in coalition and obtain higher throughput. When $\lambda \geq 0.7$, the throughput does not increase significantly with traffic demand. This is due to the fact that the increase of throughput is constrained by

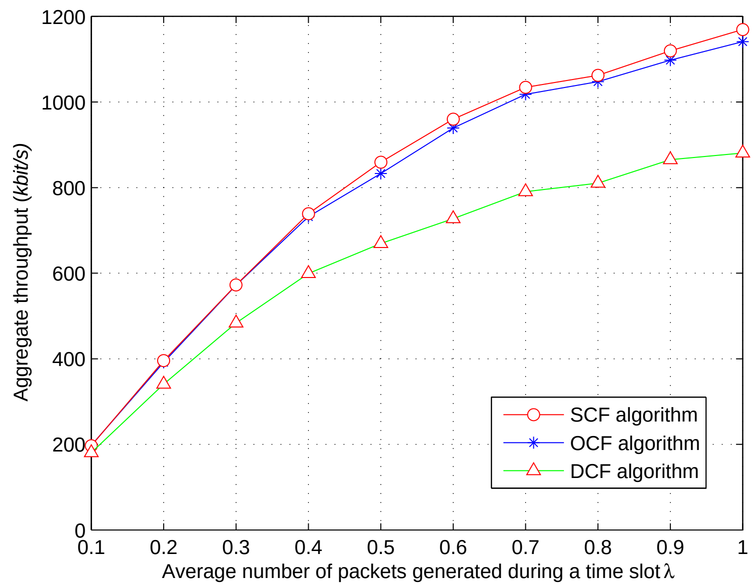

Figure 3.4: Aggregate throughput versus the average generated packets rate λ.

spectrum resources.

In Fig. 3.5, it shows the aggregate throughput for various energy efficiency threshold η_{min}. When η_{min} is smaller than 1500 kbit/J, the energy efficiency threshold has little effect on the number of coalitions that an SU can join. Therefore, SUs are able to join enough coalitions to satisfy their traffic demand. In this case, the increase of η_{min} has little effect on SUs' throughput. However, when $\eta_{min} \geq 1500$ kbit/J, the number of coalitions that an SU is allowed to join is limited. SUs are refrained from transmitting data in their buffer until the expected energy efficiency becomes greater than the threshold. This leads to the decrease of throughput. Moreover, OCF and SCF algorithms still outperform DCF algorithm in this scenario.

Fig. 3.6 shows the number of iterations when running OCF and SCF algorithms as

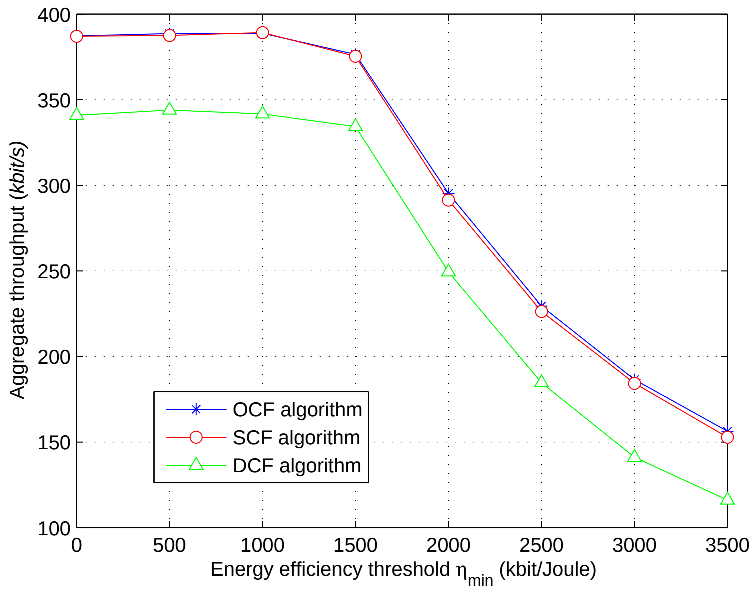

Figure 3.5: Aggregate throughput versus the energy efficiency threshold η_{min}.

the number of SUs in network increases. When N is small, the number of iterations for these two algorithms are similar. This is because when there are only a few SUs, the cooperation possibilities are limited. The number of iterations that OCF algorithm needs to converge is not very large. However, when $N > 10$, the performance gap between these two algorithms becomes larger. In SCF algorithm, an SU checks each new coalition only once when it is active. However, in OCF algorithm, all SUs try to form new coalitions whenever there is a change in coalition structure until the process converges. The number of possible coalition structures increases exponentially with N. Therefore, OCF algorithm requires more iterations to reach a stable coalition structure than SCF algorithm when N is large.

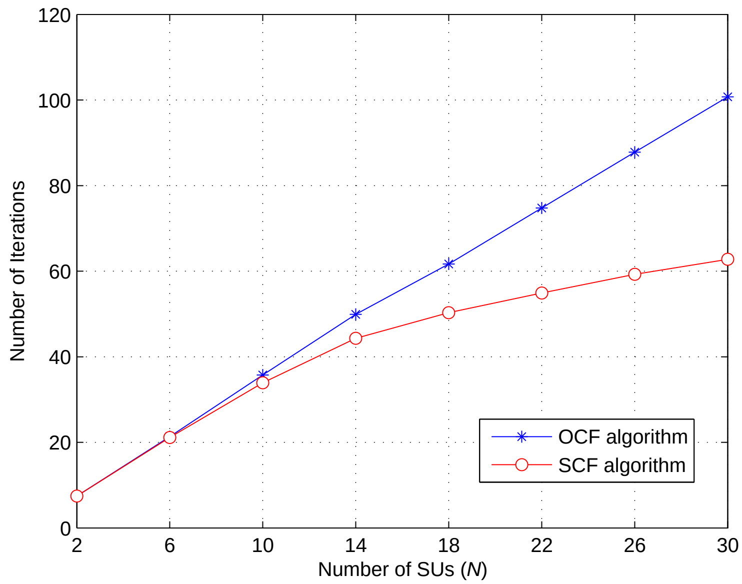

Figure 3.6: Number of iterations versus the number of SUs N.

3.5 Summary

In this chapter, we studied a traffic-demand based cooperation strategy in CRNs with multiple channels. We proposed a joint cooperative spectrum sensing and access scheme to enable energy-constrained SUs to obtain a high throughput while maintaining a high energy efficiency. An overlapping coalitional game was formulated to solve this problem, in which each SU makes its own decision to form overlapping coalitions with other SUs to sense and access multiple channels cooperatively. To reach a stable coalition structure, we proposed an OCF algorithm based on three move rules, which captures both individual payoff and social welfare. We proved that our proposed OCF algorithm converges to a stable coalition structure. We also proposed a modified SCF algorithm, which has a lower computational complexity and requires less information exchanges. Moreover, an adaptive transmission power control scheme is proposed. Simulation results show that the OCF algorithm and modified SCF algorithms have similar performance in terms of throughput. Both of these two algorithms outperform the DCF algorithm.

Chapter 4

Conclusions and Future Work

In this chapter, we conclude the thesis by summarizing the research work and contributions that we have made. We discuss the limitation of our current work and suggest possible extensions for future research.

4.1 Conclusions

In the thesis, we developed a traffic demand-based joint cooperative spectrum sensing and access strategy in CRNs. In our proposed strategy, each SU can choose to perform cooperative sensing when it has high traffic demand, or simply quit sensing when it has no data to transmit. In this way, the energy can be conserved for future transmission. We first considered the case that each SU senses at most one channel during sensing stage. Then, we extended the problem by taking into account multiple-channel sensing ability of each SU. We applied coalitional game theory to analyze two different situations respectively, and proposed several coalitional formation algorithms. Specifically, our contributions are as follows:

- In Chapter 2, we considered a cooperation strategy in CRNs from the perspective of individual SU, which can only sense one channel at a time. We formulated the problem as a disjoint coalitional game. Each SU serves as a player to implement a cooperation strategy that can maximize its own utility, which captures expected throughput and traffic demand. We proposed a sequential coalition formation (SCF) algorithm to obtain a final coalition structure. For performance evaluation, we compared our proposed SCF algorithm with switch rule-based coalition formation (SRCF) algorithm in terms of throughput and algorithm running time. Simulation results show that our proposed algorithm achieves a higher throughput than SRCF algorithm and requires less running time.

- In Chapter 3, we extended the problem by allowing each SU to sense multiple channels during the sensing stage. It provides SUs more opportunities to utilize spectrum resources. We applied overlapping coalitional game theory to solve our problem in the new system model. During the process of coalition formation, each SU not only considers its own individual payoff, but also takes into account social welfare, which is defined as the value of coalition structure. We proposed an overlapping coalition formation (OCF) algorithm to reach a stable coalition structure. It is proved that the OCF algorithm converges after a finite number of iterations. Moreover, a modified SCF algorithm is proposed to reach a final coalition structure. The modified SCF algorithm has similar performance with OCF algorithm, but with lower number of iterations and less information exchange among SUs. We also proposed an adaptive transmission power control scheme for each SU to minimize the energy consumption spent on transmission while guaranteeing the maximum throughput. For performance evaluation, we analyzed several different factors that may affect the performance of the algorithms, such as the number of SUs and PUs, the traffic demand of SUs and energy efficiency lower bound. We also presented the snapshot of overlapping coalition structure and studied the number of iterations when implementing different algorithms. Simulation results show that our proposed algorithms outperform disjoint coalition formation (DCF) algorithm in terms of aggregate throughput of SUs.

4.2 Future Work

Our current work can be extended in the following directions:

- In our system model, we fixed the sensing duration and sensing power during the sensing stage, which can affect the sensing performance and expected throughput of SUs. Therefore, it would be interesting to explore the relation between the sensing parameters and throughput when we study the CSSA strategy in CRNs. In this case, the system model setting would be more general, as each SU will be able to adjust its sensing duration and sensing power to fit its individual traffic demand. However, considering the uncertainty of the sensing parameters will increase the computational complexity of the problem. Also, if each SU uses adaptive sensing control when making cooperation decisions, it requires more information exchange among SUs, which may increase the overhead. Therefore, developing a cooperation strategy that involves sensing uncertainty, but has relatively low computational complexity is a possible extension to our current work.

- In our proposed algorithms, each SU makes the decision of spectrum sensing and access jointly. This limits the possible cooperation among SUs and may constrain the improvement of throughput. Therefore, letting each SU make separate cooperation decisions during sensing stage and data transmission stage is another possible extension to our current work. We can divide the problem into two parts: cooperative sensing problem and spectrum allocation problem, which can be formulated as two different coalitional games, respectively. That is, SUs first perform cooperative sensing according to a coalition structure that can optimize the sensing performance. Then, SUs access the channels based on another coalition structure that makes the most use of spectrum resources. Therefore, it would be interesting to explore the relation between these two games, and study a cooperative strategy that can optimize the decisions of an SU in both games.

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