A Coalition Formation Game for Cooperative Spectrum Sensing in Cognitive Radio Network under the Constraint of Overhead

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Abstract: Cooperative spectrum sensing improves sensing performance of secondary users by exploiting spatial diversity in cognitive radio networks. However, cooperation of secondary users introduces some overhead also that may degrade the overall performance of cooperative spectrum sensing. The trade-off between cooperation gain and overhead plays a vital role in modeling cooperative spectrum sensing. This paper considers overhead in terms of reporting energy and reporting time. We propose a cooperative spectrum sensing based coalitional formation game model where the utility of the game is formulated as a function of throughput gain and overhead. To achieve a rational average throughput of secondary users, the overhead is to be optimized. This work emphasizes in optimization of overhead incurred. In cooperative spectrum sensing, participation of large number of cooperating users improve detection performance, on the contrary, it increases overhead too. So, to limit the maximum coalition size, we propose a formulation under the constraint of probability of false alarm. To reduce reporting overhead, an efficient fusion center selection scheme and an algorithm to select eligible secondary users for reporting are proposed. We also outline a distributed cooperative spectrum sensing algorithm using the properties of coalition formation game and prove that the utility of the proposed game has non-transferable properties. The simulation results show that the proposed schemes reduce the overhead of reporting without compromising the overall detection performance of cooperative spectrum sensing.

Keywords: Cognitive Radio Network, Cooperative Spectrum Sensing, Overhead, Reporting energy, Reporting time, Fusion Center.

1. Introduction

In the last couple of years, there has been an exponential growth of wireless users and mobile data traffic worldwide [1]. This demands high data rates that need an adequate amount of free spectrum. But the available radio spectrum is limited and not sufficient to fulfill such requirements. Spectrum scarcity is there, on the contrary, most of the licensed spectrum remains considerably underutilized. The concept of Cognitive Radio (CR) was first introduced by Joseph Mitola [2] as a solution to the conflict between spectrum scarcity and unutilized spectrum. A Cognitive Radio Network (CRN) allows licensed users (also known as primary users) and unlicensed users (also known as secondary users) to coexist in the same spectrum to share frequency bands without any harmful interference to the licensed users [3]. To avail unutilized spectrum, the Secondary Users (SU) sense the Primary User (PU) spectrum using a suitable spectrum sensing technique. But local spectrum sensing faces challenges like multipath fading, shadowing and receiver uncertainty problems [4], etc. that may degrade their sensing performance. To compromise such issues, the concept of Cooperative Spectrum Sensing (CSS) was developed. CSS has been proved as a significant scheme to improve the detection performance of spatially located SUs [4] by forming cooperation among them. The concept of CSS can be implemented through a parallel fusion model and game theoretic model, but in the state-of-the-art papers [5-10], the game theoretic model is regarded as a more appropriate approach for developing self-organized cooperation among SUs. Some of the research works that use game theoretic model as an efficient tool to access the spectrum dynamically are illustrated in [11]. Though CSS overcomes the issues that arise in non-cooperative sensing, however, cooperation of SUs incurs some overhead also. The overhead refers to any extra cost that arises due to the cooperation of secondary users and it limits cooperation gain. Several research papers [5-10] have formulated utility of the game as a trade-off between detection performance and probability of false alarm, some papers define utility as a function of throughput and total energy consumption during CSS. In literature, CSS-based game theoretic models normally concentrate on improvement of detection performance without considering the cooperation overhead counterpart. In CSS, cooperation of large number of SUs improves detection performance; on the contrary, it increases overhead too. So, to achieve a rational average throughput, the overhead incurred is to be compromised. Developing an efficient model for CSS under the constraint of cooperation overhead is not an easy task. Motivated by these facts, we propose a CSS-based coalition formation game model that considers the overhead of reporting energy and reporting time. In this work, we assume that the PU and the SUs coexist in an interweave CR environment where the SUs opportunistically utilize the spectrum hole with the least interference to the PU [3, 12]. The main contribution of this work is to design schemes to optimize overhead. The utility of the proposed game is formulated as a trade-off between throughput gain and overhead in terms of reporting energy and reporting time. As mentioned earlier, cooperation overhead increases along with the increase of coalition size, so we propose a formulation to compute the maximum feasible coalition size under a given false alarm constraint. To optimize the reporting energy overhead, an efficient Fusion Center (FC) selection algorithm is proposed. To reduce reporting overhead, we outline another framework that allows only the eligible SUs to report sensing information to the FC. We also design a distributed cooperative spectrum sensing algorithm under the framework of coalition formation game and prove that the utility of the proposed game has non-transferable properties. The performance of the proposed schemes is studied using MATLAB R2017a.

The rest of the paper is organized as follows: In Section 2, some of the related research works are mentioned. In section 3, we introduce the system model and some assumptions that are considered in the following sections. In Section 4, we set up the proposed model and present some schemes to optimize overhead parameters. A distributed cooperative spectrum sensing algorithm is also described in Section 4. The simulations and observations are discussed in Section 5. Finally, we conclude the paper with few plans in Section 6 and acknowledgment in Section 7.

2. Related work

In this section, we discuss some of the research works from the literature which are related to our current work. In CSS, reporting stage consumes considerable amount of energy and time which we consider as reporting overhead. The state-of-the-art research discusses many approaches that aim to optimize reporting overhead. We consider mainly two approaches: a) optimization of number of participating SUs and b) coalition head selection schemes with an objective to minimize reporting overhead. In [13,14], energy consumption is optimized by approximating optimal numbers of participating SUs under the constraints of detection probability and false alarm probability. In CSS, censoring is a significant approach for minimizing reporting overhead where SUs that satisfy some predefined censoring thresholds are only permitted to report sensing observations to the FC. The others are refrained from reporting and hence the number of reporting SUs are reduced. In [15], censoring thresholds are optimized to minimize reporting energy by satisfying some given detection probability constraint. [16] proposes a censoring scheme that decreases the number of sensing bits reported to the FC and thereby minimize the energy consumption during reporting. A confidence voting method has been suggested by [17] where the SUs whose confidence level is above a given threshold can only report sensing information to the FC. Each SU achieves a confidence level when it's sensing decision is identical to the cooperative decision taken by the FC. The SUs, whose confidence level is below the given threshold, keep on sensing the spectrum and comparing its decision with the cooperative decision until it gains a confidence level. This strategy minimizes reporting overhead by reducing number of reporting SUs in each round. Clustering is another approach that reduces reporting overhead significantly. In clustering, the SUs that fulfill some norms constitute clusters and one of the cluster SU is selected as the cluster head based on given criteria. The cluster head reports sensing observations to the FC on behalf of its cluster members. [18] considers a CRN with multiple clusters and proposes three different threshold based strategies to improve detection performance as well as to reduce reporting overhead between the cluster heads and the FC. In [19], concept of parallel reporting based on frequency division is adopted that reduces reporting time significantly. In [20], a multi level cluster based CSS scheme is proposed where some cluster heads are assumed to be located far away from the FC and in such scenario, they report their cluster decisions to the nearest cluster head instead of the FC and hence, the reporting overhead decreases. Coalition head or FC selection mechanisms play a vital role in minimizing reporting energy overhead since reporting energy mainly depends on the distance between the SUs and the FC. In [7], the coalition head selection algorithm formulates a function that considers mutual influence of mobility of each node and its energy on each other. The node that scores the highest function value is selected as the coalition head. In [21], the cluster head selection algorithm calculates net distance of each cluster member from the FC and the cluster member that scores the minimum net distance is considered as the cluster head and thus the reporting energy is minimized. They compute the net distance of each SU as the sum of its farness and the distance from the FC. In [22], an iterative cluster head selection scheme is proposed. The FC initiates the process and selects the cluster node which is closest to the FC as the cluster head. In the second round, the cluster head recursively executes the process and selects a new cluster head which is closest to the earlier cluster head and generates its members. This process executes recursively until the final cluster head is selected. The related research in [23, 24] considers the distance between the FC and cluster nodes as one of the influencing parameter in selecting cluster head.

3. Assumptions and system model

The current work considers a CR network consisting of N numbers of SUs and one PU where PU and SUs are assumed to be synchronized in a time frame T. We presume that the SUs sense the PU spectrum using the energy detection method due to its low computational complexities [4]. In the energy detection problem, let $\mathcal{H}_1$ and $\mathcal{H}_0$ be the two binary hypotheses that represent the presence of PU and spectrum hole in the frequency band respectively and it can be expressed as [4]:

$$y(t) = \begin{cases} x(t) + n(t), & \mathcal{H}_1: when\ PU\ is\ present \\ n(t), & \mathcal{H}_0: when\ PU\ is\ absent \end{cases} \tag{1}$$

Where, $y(t), n(t)$ and $x(t)$ represent the received signal by SU_i, zero-mean additive white Gaussian noise(AWGN) with variance σ_n^2 and PU signal received with variance σ_x^2. In any spectrum sensing technique, P_d and P_f are two parameters that are used to evaluate sensing performance. P_d is the probability of correct detection of PU under $\mathcal{H}_1$ and P_f is the probability of false detection of PU under $\mathcal{H}_0$ in the channel and they are expressed as [4] :

$$P_d = Prob(Y > \lambda/\mathcal{H}_1) \tag{2}$$

$$P_f = Prob(Y > \lambda/\mathcal{H}_0) \tag{3}$$

Where Y and λ are the energy of the received signal and decision threshold. Spectrum sensing schemes target high P_d and low P_f. We consider that to perform CSS, the SUs in a cooperation footprint area [4], cooperate to constitute coalitions in such a way that their utility improves. We presume, all cooperating SUs of a coalition sense a channel at the same time and takes a local decision which is reported to the FC through a common control channel using the Time Division Multiple Access (TDMA) approaches. We consider, the time frame T is fixed and finite [25] and T consists of sensing time T_S, reporting time T_R and transmission time T_T. So, T can be expressed as $T = T_S + T_R + T_T$. In literature, some papers consider variable sensing, reporting, and transmission time [25], others regard transmission time as fixed and variable sensing and reporting time to achieve a fixed throughput [26]. To study the tradeoff between throughput gain and overhead of reporting energy and time, we consider variable reporting and transmission time keeping the sensing time fixed. If $T_{r,i}$ be the reporting time slot of SU_i of coalition S, then the total reporting time T_R can be given by:

$$T_R = |S| * T_{r,i} \tag{4}$$

Where $|S|$ is the size of coalition S. The transmission time T_T can be expressed as:

$$T_T = T - T_S - T_R \tag{5}$$

We consider that during CSS, the SUs spend mainly sensing energy and reporting energy. Let $E_i = E_{s,i} + E_{r,i}$ be the energy spend by SU_i in time slot T, where $E_{s,i}$ and $E_{r,i}$ are the sensing energy and reporting energy of ith SU. Inspired by [27], we express $E_{s,i}$ and $E_{r,i}$ as follows:

$$E_{s,i} = T_{s,i} * \delta_s \tag{6}$$

$$E_{r,i} = d^{\alpha}_{su_i-FC} * (\delta_r * T_{r,i}) \tag{7}$$

Where δ_s, δ_r are the sensing energy and reporting energy spend by SU_i per unit time, $T_{s,i}, T_{r,i}$ are the sensing and reporting time slot of SU_i, d_{su_i-FC} is the distance between SU_i and the FC, α is the path loss exponent. Generally, α ranges between 1.6 and 6.5, and in free space propagation α equal to 2 [28]. Accordingly, the total sensing energy and reporting energy spend by the coalition are given by:

$$E_S = \sum_{i=1}^{|S|} E_{s,i} \tag{8}$$

$$E_R = \sum_{i=1}^{|S|} E_{r,i} \tag{9}$$

The individual probability of detection $P_{d,i}$ under $\mathcal{H}_1$ and the probability of false alarm $P_{f,i}$ under $\mathcal{H}_0$ of SU_i within a coalition S is given by [10]:

$$P_{d,i} = Q\left(\left(\frac{\epsilon}{\sigma_n^2} - snr - 1\right)\sqrt{\frac{m}{2snr+1}}\right) \tag{10}$$

$$P_{f,i} = Q\left(\left(\frac{\epsilon}{\sigma_n^2} - 1\right)\sqrt{m}\right) \tag{11}$$

Where Q is the complementary distribution function, ϵ denotes detection threshold for SUs, σ_n^2 is Gaussian noise variance, m is the time-bandwidth product, and snr stands for the signal-to-noise ratio. We consider that the FC uses OR hard decision fusion rule to result in a cooperative decision about the presence or absence of the PU in the frequency band and then forwards the decision to all the SUs of S. If the cooperative decision is in favor of $\mathcal{H}_0$ i.e., the channel is not occupied by the PU, then SUs are allowed to transmit data through the channel. The cooperative probability of detection P_D and the probability of false alarm P_F of coalition S is given by [10]:

$$P_D = 1 - \prod_{i=1}^{|S|}(1 - P_{d,i}) \tag{12}$$

$$P_F = 1 - \prod_{i=1}^{|S|}(1 - P_{f,i}) \tag{13}$$

It can be observed from (12) and (13) that as the coalition size increases, the P_D and P_F also increases.

Let P_{H_1} be the probability that PU is present under $\mathcal{H}_1$ and P_{H_0} be the probability that PU is absent under $\mathcal{H}_0$ in the frequency band at any time slot T, then $P_{H_0} + P_{H_1} = 1$ [29]. The SUs try to transmit through the PU frequency band when 1) it is not occupied by the PU and no false alarm is generated by the SUs and 2) the PU is present but the SUs can't detect it [29]. The probability of the first scenario is $P_{H_0}(1 - P_F)$ and the probability of the second scenario is $P_{H_1}(1 - P_D)$.

4. Proposed Model

Let $(N_C, \mathcal{V})$ be the proposed coalition formation game, where $N_C (N_C \le N)$ is the number of cooperating SUs in coalition S and $\mathcal{V}$ is the utility function of the game. We define the utility $\mathcal{V}(S)$ of $S(S \subseteq N, S \neq \varphi)$ as a transaction between throughput gain and cost and is devised as follows:

$$\mathcal{V}(S) = Th\_Gain(S) - Cost(S) \tag{14}$$

Where $Th\_Gain(S)$ is the cooperation gain in terms of throughput and $Cost(S)$ is the overhead incur in terms of reporting energy and reporting time. We formulate $Th\_Gain(S)$ [27] and $Cost(S)$ as follows:

$$Th\_Gain(S) = P_{H_0}(1 - P_F) * T_T * r_t \tag{15}$$

$$Cost(S) = P_{H_1}(1 - P_D) * T_T * E_R \tag{16}$$

Here, r_t represents data transmission rate in the frequency band when the PU is absent and we define r_t using Shannon's formula as $r_t = B\ \log_2(1 + snr)$, where B is the bandwidth of the channel. In CSS, throughput can be achieved successfully when the sensing channel is not occupied by the PU and is correctly identified as free. We define the achievable average throughput of SU_i as:

$$Th_i = \frac{P_{H_0}(1 - P_F) * T_T * r_t}{|S|} \tag{17}$$

Property 1: The utility of the proposed coalition formation game is non-transferable.

Proof: The utility function as shown in (14) is a trade-off between throughput gain and overhead. The cooperative decision taken by the FC is a probability of the presence or absence of the PU in the frequency band. So, it can not be apportioned among the cooperating SUs. The FC forwards the final cooperative decision to all the SUs of S. As a result, the $P_{d,i}$ and $P_{f,i}$ of SU_i becomes identical to the P_D and P_F of coalition S and hence, the utility of SU_i is identical to the utility of coalition S. Since the utility of coalition S is not distributed among the cooperating SUs, it proves that the utility of the proposed coalition formation game is non-transferable.

4.1 Optimization of overhead parameters

In the proposed model, the improvement of average throughput depends on the optimization of overhead parameters T_R and E_R. However, the throughput of the game is also influenced by P_F and the coalition size $|S|$. Conversely, as mentioned in (4),(9), and (13), the values of T_R , E_R and P_F increases along with the increase of $|S|$. The increase of false alarms reduces the spectral efficiency [4]. So, to avail optimal performance, we consider a false alarm constraint $P_{F,max}$ such that no coalition exceeds it i.e. $P_F \leq P_{F,max}$. If $|S|$ keep on increasing even after reaching the $P_{F,max}$, the values of T_R and E_R increases further causing overhead. So, to optimize the values of T_R and E_R, it is essential to limit the maximum coalition size that eventually depends on the false alarm constraint. Inspired by [5] and [6], we propose a formulation that approximates the maximum feasible size of a coalition under a given false alarm constraint through *Theorem1*.

Theorem1: For a given false alarm constraint $P_{F,max}$, of any coalition S, the maximum feasible coalition size $|S_{max}|$ can be approximated as :

$$|S_{max}| \approx \frac{\log\left(1 - P_{F,max}\right)}{\log\left(1 - P_{f,avg}\right)} \tag{18}$$

Where $P_{f,avg}$ is the average probability of false alarm of cooperating SUs in S.

Proof: Let us assume that in the CRN, the SUs are arranged very close to each other in such a way that coalition S can accommodate all N numbers of SUs in it i.e., $|S| = N$. As SUs are closely grouped in S, we presume that they experience the same probability of false alarm i.e., $P_{f,i} = P_{f,j}$ $\forall i,j \in S,\ i \neq j$. In such an ideal situation, the probability of false alarm as defined in (13) can be expressed as:

$$P_{F_N} = 1 - \left(1 - P_{f,i}\right)^N \tag{19}$$

And the average probability of false alarm $P_{f,avg}$ is computed as:

$$P_{f,avg} = \frac{N * P_{f,i}}{N} \ or\ P_{f,avg} = P_{f,i} \tag{20}$$

Let $P_{f,max}$ be the false alarm constraint for S. Replacing $P_{f,i}$ by $P_{f,avg}$ and P_{F_N} by $P_{f,max}$ in (19) we get,

$$P_{f,max} = 1 - (1 - P_{f,avg})^N$$

$$\text{Or } 1 - P_{f,max} = (1 - P_{f,avg})^N \tag{21}$$

Taking log on both sides of (21) we get,

$$N \approx \frac{\log\left(1 - P_{f,max}\right)}{\log\left(1 - P_{f,avg}\right)} \tag{22}$$

Equation (22) approximates the maximum size of coalition S in the perfect scenario that we have considered.

Now, let us consider that coalition S can accommodate maximum $|S_{max}| \leq N$ numbers of SUs and all cooperating SUs experience different $P_{f,i}$ i.e., $P_{f,i} \neq P_{f,j} \forall i,j \in S, i \neq j$ based on their snr values. In this scenario we compute P_{avg} as:

$$P_{f,avg} = \frac{\sum_{i=1}^{|S_{max}|} P_{f,i}}{|S_{max}|} \tag{23}$$

Now, considering (23) in (22) we get,

$$|S_{max}| \approx \frac{\log\left(1 - P_{F,max}\right)}{\log\left(1 - P_{f,avg}\right)} \tag{24}$$

Equation (24) depicts that in any coalition S, for a given false alarm constraint $P_{F,max}$, the maximum feasible coalition size $|S_{max}|$ can be approximated as a function $P_{F,max}$ and $P_{f,avg}$ where all SUs practice different $P_{f,i}$.

4.1.1 Optimization of energy spent by SUs during reporting.

As defined in (7), the energy spent by SU_i to report its sensing decision to the FC is directly proportional to the distance between SU_i and the FC. Therefore, the longer the d_{su_i-FC}, the more $E_{r,i}$ will be spent. If the FC is positioned at an optimum distance from all other SUs of S then d_{su_i-FC} will be reduced and accordingly $E_{r,i}$ will be optimized. Using the concept of closeness centrality measure, we propose a FC selection algorithm.

a) *Algorithm1: Fusion Center Selection Algorithm [FCSA]*

Let coalition S consists of $N_C (N_C \leq N)$ numbers of cooperating SUs represented by $\{SU_1, SU_2, \cdots, SU_{N_C}\}$. Let d_i be the distance between SU_i and the PU and $d_{i,j}$ be the distance of SU_i from SU_j $\forall i,j \in S$ and $i \neq j$. We presume that $d_{i,j} \ll d_i$ and express $d_{i,j}$ as follows:

$$d_{i,j} = \left|d_i - d_j\right| \tag{25}$$

It is considered that during coalition formation, the SUs organize themselves in a topological structure based on the way they merge or split. The closeness centrality(C) of SU_i defines how short the shortest paths are from SU_i to all other SUs. It can be expressed as the normalized inverse of the sum of the distances from SU_i to all other SUs of S. and is given by:

$$C(SU_i) = \frac{|S| - 1}{\sum_{j\in S} d_{i,j}} \tag{26}$$

Where $|S| = N_C$ and $\sum_{j\in S} d_{i,j}$ is the sum of the distances from SU_i to all other SUs of S.

Let $C = \left\{C(SU_1), C(SU_2), \cdots, C\left(SU_{N_C}\right)\right\}$ be a vector consisting of closeness centrality values of each SU of S. The maximum closeness centrality score CC_{max} is expressed as:

$$CC_{max} = max\{CC\} \tag{27}$$

Equation (27) defines that any SU_i having $C(SU_i) = CC_{max}$ is selected as the FC of S as it is the most central and connected SU in S. If more than one SU score CC_{max}, then any one of them can be declared as the FC of S.

Algorithm1: FC selection for Coalition S

Input	:	$\|S\| = N_C$, d_i.
Output	:	FC of S, vector d^*_{su-FC}.
Begin		
Step 1	:	Set $d_{sum} = 0$ and $CC_{max} = -1$.
Step 2	:	For $i = 1$ to $\|S\| - 1$

For $j = 1$ to $|S| - 1$

Compute $d_{i,j}$ $\forall$ $i,j \in S, i \neq j$ using(25)

Store $d_{i,j}$ in vector d^*_i

Compute $d_{sum} = d_{sum} + d_{i,j}$

End for

Vector $d_i^* = [d_{i,j}, d_{i,k}, d_{i,l}, \cdots]$

Set $f_i = d_{sum}$

Compute $C(SU_i) = \frac{|S|-1}{f_i}$

If $C(SU_i) > CC_{max}$ then

Set $CC_{max} = C(SU_i)$

Else

Continue

End if

End for

Step 3	:	The SU_i, scoring the maximum closeness centrality value CC_{max} is considered as the FC of coalition S.
Step 4	:	Select the distance between SU_i and the FC from d_i^* and store it in the vector $d_{su-FC}^* = [d_{su_i-FC}, d_{su_j-FC}, \ldots\ldots]$ where $d_{su_i-FC}\ \forall\, i \in S$ is the distance between SU_i and the FC

End

Algorithm1 optimizes the reporting energy $E_{r,i}$ of SU_i by selecting the most centrally located SU as the FC of S. Accordingly, the total reporting energy E_R which is the sum of $E_{r,i}$ of all SUs of S also become minimum. Thus, the overhead of reporting energy is optimized.

4.1.2 Selection of qualified SUs for reporting.

Equation (17) defines that the improvement of the average throughput of each SU depends on the maximization of transmission time. On the other hand, as mentioned in (5), for a time frame T, the transmission time T_T can be increased by reducing the reporting time T_R , since we consider sensing time T_S as fixed. Again, according to (4), in the TDMA approach, for a reporting time slot $T_{r,i}$, the T_R can be reduced by decreasing the number of reporting SUs in S. Eventually, maximization of average throughput depends on the optimization of reporting SUs in S. Here, we propose an algorithm that allows only the qualified SUs to report sensing decisions to the FC and thus the number of reporting SUs can be reduced.

a) Algorithm2: Qualified SU Selection Algorithm (QSA)

This algorithm allows only qualified SUs to report its sensing decision to the FC by applying a qualifying criterion. We assume that before reporting, every cooperating SU has to forward it's $d_{su_i-FC}\ \forall i \in S$ to the FC and the FC calculates the average, f_{avg} as:

$$f_{avg} = \frac{\sum_{i=1}^{N_{C-1}} d_{su_i-FC}}{(N_C - 1)} \tag{28}$$

The FC permits only those SUs to report whose $d_{su_i-FC} \leq f_{avg}$. In other words, the SUs whose $d_{su_i-FC} > f_{avg}$ are refrained from reporting their sensing decision to the FC. Accordingly, the number of reporting SUs in S reduces. Let $N_R (N_R < N_C)$ be the numbers of SUs in S that are qualified for reporting. Now, the T_R and E_R as defined in (4) and (9) can be redefined as $T_R = N_R * T_{r,i}$ and $E_R = \sum_{i=1}^{N_R} E_{r,i}$. Since $N_R < N_C$, the T_R and E_R reduces further.

Algorithm 2: Qualified reporting SU selection algorithm of coalition S of size $|S| = N_C$.

Input	:	N_C , d_{su-FC}^*
Output	:	N_R : number of SUs qualified for reporting, Q_{su}: list of qualified SUs.
Begin		
Step1	:	SU_i of S reports it's d_{su_i-FC} to the FC
Step2	:	FC computes f_{avg} using (28) and forwards it back to the SUs of S

Step3	:	For $i = 1: N_C$
		If $d_{su_i-FC} \leq f_{avg}$ then
		SU_i reports its sensing decision to the FC
		Send SU_i to vector Q_{su}
		Else
		Continue
		End if
		$Q_{su} = [Q_{su_i}, Q_{su_j}, \cdots\cdots]$
		End for

Step4	:	Calculate $N_R = count(Q_{su})$
End		

4.1.3 Distributed cooperative spectrum sensing.

We propose a distributed CSS algorithm using the properties of the coalition formation game. The algorithm consists of five phases: a) local spectrum sensing performed by the SUs of CRN, b) adaptive coalition formation using merge and split rule, c) selection of the FC, d) selection of qualified SUs that report sensing decision to the FC e) the FC makes a cooperative decision and forwards it to the SUs of the coalition.

At the beginning of time frame T, we consider all SUs in the CRN as singleton coalitions. To carry out CSS, multiple singleton coalitions merge to structure larger coalitions if their utility improves and a coalition splits into smaller coalitions if splitting results in coalitions with improved utilities[7]. Let us assume that in the cooperation footprint area, k numbers of coalitions, represented by $\{S_1, S_2, \cdots\cdots\cdots, S_k\}$, are formed using simple merge and split rules. The merge and split operations using Pareto order as defined in [7] are as follows:

Definition 1:	Merge any set of mutually disjoint coalitions $\{S_1, \ldots, S_k\}$ where $\{\bigcup_{i=1}^{k} S_i\} \rhd \{S_1, \cdots, S_k\}$, so $\{S_1, \ldots\ldots, S_k\} \rightarrow \{\bigcup_{i=1}^{k} S_i\}$
Definition 2:	Split any coalition $\{\bigcup_{i=1}^{k} S_i\}$ into smaller coalitions where $\{S_1, \ldots\ldots, S_k\} \rhd \{\bigcup_{i=1}^{k} S_i\}$, so $\{\bigcup_{i=1}^{k} S_i\} \rightarrow \{S_1, \ldots\ldots, S_k\}$

a) Algorithm3: Distributed Cooperative Spectrum Sensing Algorithm (DCSSA)

Algorithm 3: Distributed Cooperative Spectrum Sensing Algorithm

Input	:	$P_{F,max}$: Given false alarm constraint, N: number of SUs in the CRN

Output : Cooperative spectrum sensing decision

Begin

Step 1 : Each singleton coalition senses the PU channel using the energy detection method

Step 2 : Begin coalition formation using merge and split rule through Pareto order

a. Merge coalitions using definition 1

b. Split a coalition into multiple coalitions using definition 2

Repeat a. and b. until the merge-and-split process terminates with stable coalitions

Step 3 : Select the FC using algorithm1

Step 4 : Select qualified SUs using algorithm2 and report sensing decision to the FC.

Step 5 : a) The FC fuses reported decisions using OR hard decision fusion rule and take a cooperative decision about the presence or absence of the PU in the channel.

b) The FC reports the cooperative decision to all SUs of S and accordingly SU decides whether to transmit through the channel or not.

End

(b) Stability of coalition

During the process of coalition formation, the coalitions attain a stable state if they maintain the following conditions.

1. The probability of false alarm of each coalition should not exceed the given false alarm constraint i.e., $P_F \leq P_{F,max}$.
2. The maximum numbers of cooperating SUs that can be accommodated in a coalition S under a given false alarm constraint $P_{F,max}$ should not go beyond $|S_{max}|$.

5. Simulation

We study the performance of the proposed model using MATLAB R2017a. For simulation, we set up a CRN of 200 x 200 m^2 area where the PU is located at the center and SUs are scattered randomly in the area. Some of the parameters that we consider for simulation are listed in table1. Figure1 plots the scenario of energy required to report sensing information versus the distance between SU_i and the FC. It can be observed in the figure that as the distance between SU_i and the FC increases, the reporting energy of each SU also increases. So, to reduce the reporting energy, it is essential to select the FC in such a way that it is positioned at the optimum distance from all other SUs of the coalition.

Table 1: Parameters and their values used in simulation

Parameters	Value
$\mathbf{P_{H_0}}$	0.20
$\mathbf{P_{H_1}}$	0.80
T	100 milliseconds
$\mathbf{T_S}$	10 milliseconds
$\mathbf{T_r}$	0.1 millisecond
snr	−20dB to 1dB
B	1MHz
$\mathbf{r_t}$	80 bits per second
$\mathbf{\delta_r}$	0.0013mJ per bit per second [30]

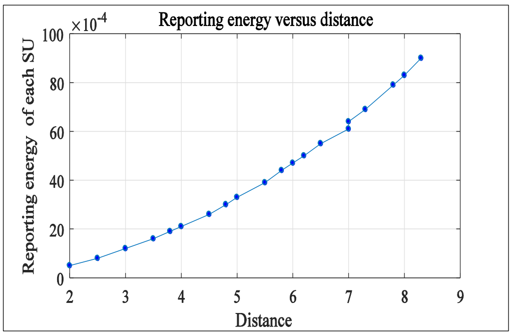

Figure 1: Reporting energy versus distance to the FC

The fusion center selection scenario using algorithm1 is presented in figure 2. Here, we consider 15 numbers of SUs and assume that their distances from the PU are generated randomly. The closeness centrality value of each SU is calculated using (26) and are plotted. It is noted in the figure that SU_4 scores the maximum closeness centrality value, so it is considered as the FC of the coalition. Since the FC is the most central and connected SU in the coalition, the distance between SU_i and the FC decreases and hence, the reporting energy of each SU reduces. The total reporting energy, which is the sum of individual reporting energies, also decreases, and as a result, the overhead of reporting energy optimizes.

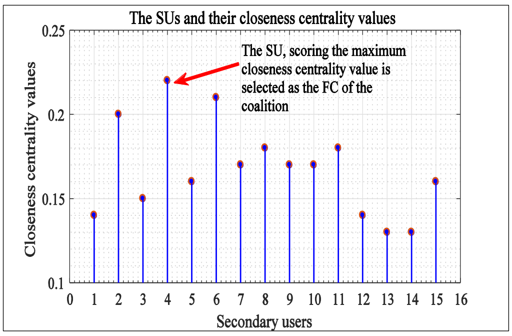

Figure 2: The SUs and their closeness centrality values

Figure 3 presents the scenario of total reporting energy versus fusion center. In the figure, it is observed that if SU_4 having the maximum closeness centrality value is considered as the FC, then the total reporting energy spent by that coalition will become minimum and the overhead of reporting energy is optimized.

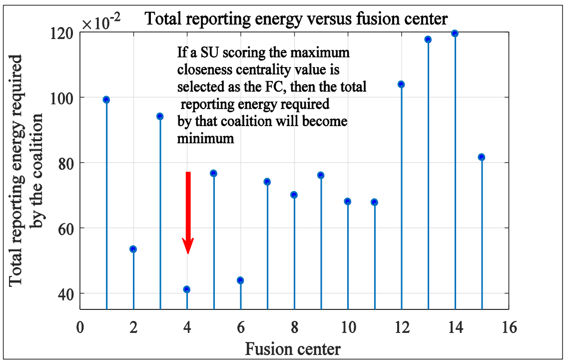

Figure 3: The FCs and total reporting energy spent by the corresponding coalitions.

The trade-off between throughput and transmission time is presented in figure 4. It plots the average throughput versus transmission time for three different reporting time slots. In the figure, it is observed that as transmission time increases, the average throughput improves. It is also noted in the figure that for a given coalition size, the smaller the reporting time slot, the longer the transmission period, and hence

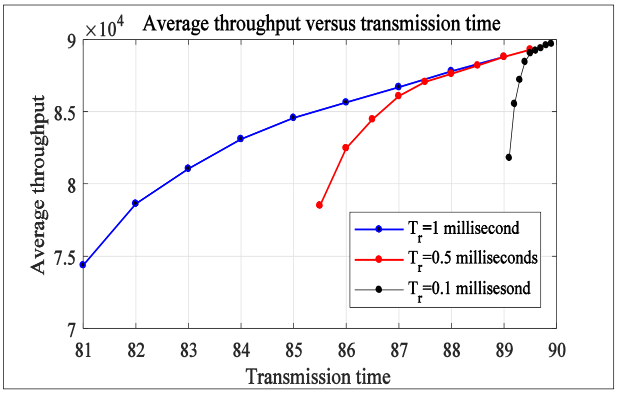

Figure 4: Average throughput versus transmission time

throughput improves. Figure 5 presents the scenario of false alarm constraint and the respective maximum feasible coalition size. The figure portrays that as the value of $P_{F,max}$ increases, the $|S_{max}|$ of coalition S also rises and as a result, the probability of occurring overhead of E_R and T_R increases too. From the figure, we can conclude that to reduce the overhead in terms of reporting energy and reporting time in the proposed model, it is preferable to consider a lower value of false alarm constraint.

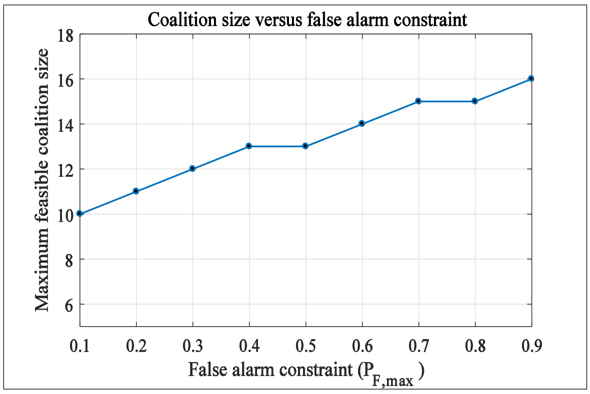

Figure 5: Maximum feasible coalition size for different false alarm constraints

6. Conclusion and future work

In this paper, we have devised a coalition formation game for cooperative spectrum sensing in interweave cognitive radio networks under the constraint of cooperation overhead in terms of reporting energy and reporting time. The objective of this work was to design schemes to reduce overhead to improve throughput gain. To limit overhead we propose theorem1 that approximates the maximum number of cooperating SUs that can be accommodated in a coalition under a given false alarm constraint. Theorem1 describes that the lower the false alarm constraint, the lesser the overhead incurred. For better performance, IEEE 802.22 recommends false alarm constraint to be less than 0.1[31]. Algorithm1 is a better choice of solution for optimization of reporting energy overhead and similar type of overhead that depends on the distance between SUs and the FC. On the other hand, algorithm2 is another scheme that permits only eligible SUs to report sensing decisions to the FC and thereby minimizes reporting time overhead. The outline of algorithm2 can be a choice for similar kinds of problems where it is required to reduce the overhead of reporting time. In conclusion, we can say that the proposed model can be referred by any CSS-based problems that consider reporting overhead. In future work, we would like to explore other cooperation overhead constraints and design efficient schemes to optimize them for better performance of cooperative spectrum sensing in cognitive radio networks.

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