Chapter 3

A Constraint based Cooperative Spectrum Sensing Technique

3.1 Introduction

Recently, to fulfil the ever-increasing demand of wireless communication, research interests have grown towards opportunistic spectrum allocation using cognitive radio (CR) technique, which can utilize the unused holes in licensed spectrum. Spectrum sensing is the key function in CR technique to detect the availability of spectrum holes and to make opportunistic access to these holes, provided licensed users are protected from harmful interference [2]. The factors due to spatial diversity like multipath fading, shadowing and receiver uncertainty problem [3, 17–20, 43] make primary signal weak, which affects the individual spectrum sensing performance of secondary users (SUs). The Cooperative Spectrum Sensing (CSS) [3, 17, 32, 33] is proven to be an emerging scheme, which significantly improves detection performance by exploiting the spatial diversity of the SUs. The cooperation among SUs enable them to share their local sensing information to make a combined decision more accurate compared to their individual decisions [17]. Implementing the collaboration involves additional overheads due to cooperation, which pose as constraints in the effectiveness of CSS scheme. Reporting time and reporting energy are two dominant sources of overhead in cooperation, incurred to share the individual sensing information among the SUs. During cooperation, the reporting time determines how quickly the individual spectrum sensing results be made available for cooperative decision making. It is important because spending extra time for reporting will leave less time for transmission and hence is an overhead. Again, the reporting energy determines the amount of extra energy needed to report the sensing information. This is important because it leads to significant overhead if operations involved in reporting is too much energy consuming. Therefore modeling of a CSS scheme is to take into account of the above constraints to achieve efficiency in spectrum sensing, which is a challenging task. The two most common approaches [3] of modeling cooperation are: *parallel fusion model* and *game theoretic model*. The Parallel Fusion (PF) model, which does not analyze the strategic interactions among multiple decision makers dynamically and can not address the optimization issues on run. From the literature review [3], it is found that the game theoretical modeling offers capability to incorporate dynamic change in behavior.

The cooperative spectrum sensing schemes discussed in the literature [3, 32, 33, 61–68] mostly address to overcome the problem due to multipath fading, shadowing and hidden node problem by means of modeling the framework for cooperation and proposing techniques to perform efficient fusion operation. Works in [34, 45] model CSS framework by means of game theoretic approach. The method in [46] models a throughput-efficient sensing as either selfish or altruistic coalition formation game depending on SUs individual gain, which takes into account the sensing duration and reporting delay of SUs as cooperation overhead. But the cooperation overhead due to constraints like reporting time, reporting energy and delay required for computing a decision by the fusion center play important roles in CSS performance, which are challenging to be considered. To the best of our knowledge, no CSS technique with consideration of above cited constraints has been reported in the literature.

In this chapter, we formulate the problem of CSS as a non-transferable coalition game [23, 24], where SUs organize themselves into disjoint partitions (also called coalitions) based on optimization of a utility function. The utility function of each coalition takes into account both detection accuracy and cooperation overhead. The utility/payoff function of the game collects the total revenue to be optimized, while considering the cost due to reporting time and reporting energy as constraints. The revenue is collected in terms of average throughput per SU (that is, transmission rate) by means of minimizing the probability of false alarm of a coalition. The game eventually establishes that with the increase in size of a coalition the average throughput of the coalition also increases upto a certain coalition size, beyond that the throughput start decreasing due to extra overhead from reporting time. Cost due to reporting time there after exceeds the throughput gain from increased size of coalition. The cost of reporting energy is minimized by adopting a policy for selecting the head of a coalition while playing the game. A scheme for dynamic selection of head of a coalition is proposed, which is based on selecting an SU as head having its position at the minimum average distance from all other SUs. The distributed Cooperative Spectrum Seinsing (DCSS) algorithm finds the optimal partition that maximizes the overall utility of all the coalitions in the network. The condition to achieve the coalition stability is established through mathematical analysis. Further, simulation based study is carried out to demonstrate how SUs can organize themselves into stable partitions with optimal utility and convergence property of the proposed scheme.

The rest of this chapter is organized as follows. Section 3.2 formally defines the problem. The assumptions taken and symbols and notations used throughout this chapter are also presented. The system model is presented in section 3.3. Section 3.4 presents the proposed game theoretic model for CSS and the distributed CSS algorithm for its realization. In that section, the optimization of cost parameters and the head selection scheme are described. The stability of coalition is also studied and evaluated in that section. Section 3.5 evaluates the performance of the proposed model through simulation based studies. Finally, section 3.6 concludes this chapter.

3.2 Problem Statement

The main objective is to model the cooperative spectrum sensing for CR network incorporating the interaction behavior of SUs for higher detection performance while minimizing the cooperation overhead and hence to improve average throughput of the network. The cooperation overheads considered are the reporting time and reporting energy.

3.2.1 Assumptions

- At a given time slot, both PUs and SUs are synchronized [2, 69] and only one PU can transmit at a given slot
- The SNR value of each SU depends on it's position from the PU
- Energy Detector(ED) [3, 15, 70] based approach is used for local/individual spectrum sensing by the SUs because of its low computational and implementation complexity
- Reporting channel is considered to be ideal or error free
- The noise present in the wireless channel is Circular Symmetric Complex Gaussian (CSCG) [46]

3.2.2 Notations and Symbols Used

For the remainder of this chapter, the notations and symbols used are summarized in Table 3.1.

Table 3.1: Notations and symbols used

Notations/Symbols	Comments
N	Number of SUs in the network
$\mathcal{K}$	Number of PUs in the network
S	Represents a coalition
K	Number of SUs in a coalition
T	Duration of a time slot
T_S	Sensing duration
T_R	Sum of the reporting times by all the SUs in a coalition
$T_{r,i}$	Time required to report local sensing information to the coalition head by the i^{th} SU

T_C	Total time taken by the coalition head to compute and disseminate the final results to every SU in a coalition
T_T	Time duration available for data transmission within a time slot
E	Energy consumed by an SU within a time slot
E_S	Energy consumed during sensing by an SU
E_R	Energy consumed for reporting the local sensing information to coalition head by an SU
E_{RC}	Energy consumed for receiving the final sensing result from the coalition head
E_T	Energy consumed for data transmission within a time slot
e_s	Sensing energy per bit
e_l	Energy consumed by the reception circuitry per bit
e_d	Energy dissipated per bit per $metre^2$
e_t	Energy spent by transmission circuitry per bit
d	Distance between transmitter and receiver
μ	Path loss exponent
b	Number of bits to be transferred/received/sensed
$P_{f,i}$	Probability of false alarm of the i^{th} SU
$P_{d,i}$	Probability of detection of the i^{th} SU
$P_{m,i}$	Probability of miss detection of i^{th} SU
$P_{f,S}$	Probability of false alarm of a coalition S
$P_{f,td,S}$	Target probability of false alarm for a coalition S
$\hat{P}_d$	Target probability of detection of a coalition
$P_{f,avg}$	Average probability of false alarm of all the SUs in the network
λ_i	Energy Detection (ED) threshold for the i^{th} SU
γ_i	Received SNR from the PU to the i^{th} SU
P_i	PU signal power received at i^{th} SU
u	Time bandwidth product
σ^2	Noise variance/power
$Q(.)$	Complementary distribution function of the standard Gaussian
P_{PU}	Signal power from PU
κ	Path-loss constant
d_i	Distance between the i^{th} SU and the PU
R_i	Average throughput of the i^{th} SU
P_{H_0}	Probability of the PU being absent in a time slot
r_i	Transmission rate of the i^{th} SU
S_{op}	Optimal size of a coalition
$d_{avg,i}$	Average distance between the i^{th} SU and the other SUs in a coalition
$d_{avg,min}$	Minimum average distance between the i^{th} SU and the other SUs in a coalition

V_{avg}	Vector consisting of average distances of SUs from all other SUs in a coalition S

3.3 System Model

An ad-hoc CR network consisting of N numbers of SUs and $\mathscr{K}$ numbers of PUs is considered which works in a slotted time system with T as the duration of a time slot. T is subdivided into four sub slots as shown in the Figure 3-1 and can be

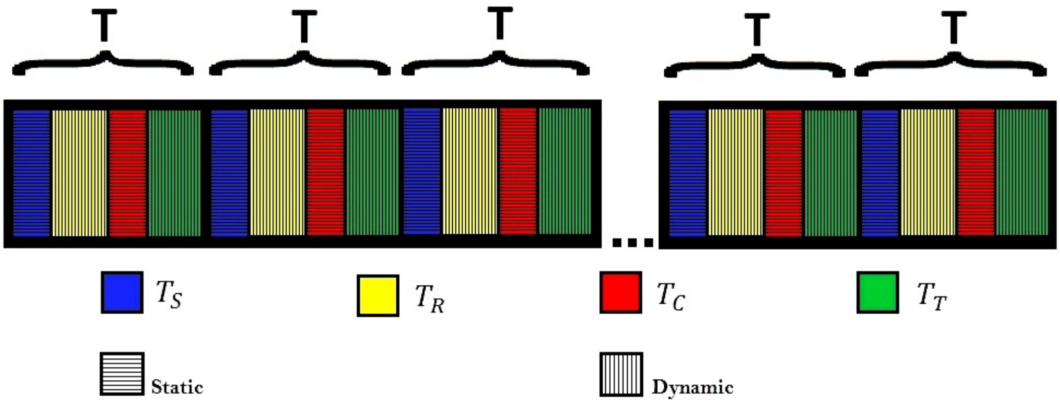

Figure 3-1: Time Slot Structure

expressed as $T = T_S + T_R + T_C + T_T$, where T_S is the sensing duration, T_R is the sum of reporting times taken by all the SUs within a coalition S, T_C is the time taken by the coalition head to compute the final sensing result and disseminate it to the members of the coalition, and T_T is the time duration available for data transmission. T_R and T_T varies dynamically according to the number of SUs in coalition S. Through a coalition game with the given optimization criteria, SUs form coalitions among themselves. As shown in the Figure 3-2, each SU performs energy detection independently and sends its local sensing data to the coalition head, which combines the sensing data from the members of the coalition and makes the final decision on presence or absence of PU. Finally, the decided final sensing result is reported to the members of the coalition. The total energy spent by an SU in a time slot, denoted by E is the sum of the energy spent during sensing, reporting local sensing data to coalition head, receiving the final sensing result from the coalition head and data transmission. Therefore, E can be expressed as $E = E_S + E_R + E_{RC} + E_T$, where E_S, E_R, E_{RC} and E_T represent the energy spent during the four major sub slots within a time slot as stated above (also defined in Table 3.1).

The values of E_S, E_{RC} and E_T can be obtained using the formulas given

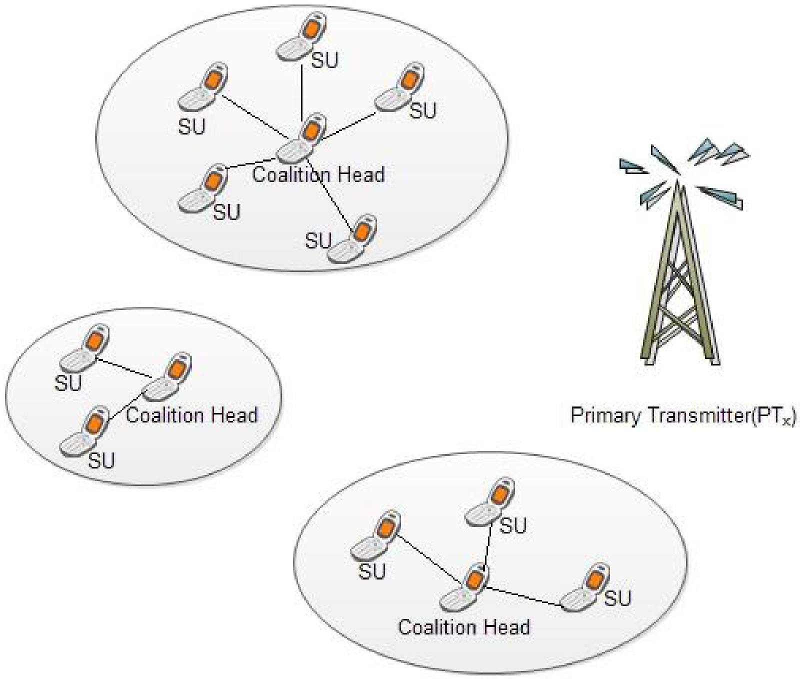

Figure 3-2: Coalition formation by SUs

in [71] which are stated by Eq.(3.1), Eq.(3.2) and Eq.(3.3) respectively.

$$E_S = e_s b \tag{3.1}$$

$$E_{RC} = e_l b \tag{3.2}$$

$$E_T = e_d b d^{\mu} + e_t b \tag{3.3}$$

Thus, the energy required for reporting the sensing information, E_R can be computed using the equation of energy for transmission given in Eq.(3.3). In presence of CSCG noise in wireless channel, the probability of false alarm and the probability of detection for the i^{th} SU with a given ED threshold λ_i are computed using the Eq.(3.4) and Eq.(3.5) respectively [72]. Similarly, for a given target probability of detection and the ED threshold, the probability of false alarm for the i^{th} SU is computed using Equation Eq.(3.6) [46].

$$P_{f,i}(\lambda_i) = Q\left(\left(\frac{\lambda_i}{\sigma^2} - 1\right)\sqrt{u}\right) \tag{3.4}$$

$$P_{d,i}(\lambda_i, \gamma_i) = Q\left(\left(\frac{\lambda_i}{\sigma^2} - \gamma_i - 1\right)\sqrt{\frac{u}{2\gamma_i + 1}}\right) \tag{3.5}$$

$$P_{f,i}(\hat{P}_d, \gamma_i) = Q(\sqrt{2\gamma_i + 1}Q^{-1}(\hat{P}_d) + \sqrt{u}\gamma_i) \tag{3.6}$$

where $\gamma_i = \frac{P_i}{\sigma^2}$ with $P_i = \frac{\kappa P_{PU}}{d_i^{\mu}}$. From the Eq.(3.6), it is observed that for the i^{th} SU, the probability of false alarm $P_{f,i}$ increases with the increase in target probability of detection $\hat{P}_d$. Therefore, in order to minimize the $P_{f,i}$ for a given $\hat{P}_d$, SUs need to perform CSS and may form coalitions to make a collaborative decision about detection. The coalition head, collecting the local sensing results from the SUs in the coalition, combines the received information and makes a decision using AND fusion rule. With strict primary protection requirement, to obtain the accuracy of the collaborative decision making, a variant of soft data fusion technique using AND fusion rule is applied for its simplicity. Coalitions are assumed to be non-overlapping, that is, all the SUs are members of at most one coalition [46]. SUs in a coalition are assumed to be fair and trustworthy. It is also assumed that all the SUs within a coalition S have their own SNR values depending on their distances from the PU. Hence, the probability of false alarm of any coalition S of size $|S|$ can be given by the Eq.(3.7), which states that for a given $P_{f,i}$, the value of $P_{f,S}$ decreases as the number of SUs increases.

$$P_{f,S} = \prod\nolimits_{i=1}^{|S|} P_{f,i} \tag{3.7}$$

3.4 Game Theoretic Formulation of the Proposed CSS

3.4.1 CSS using Game Theory

To model the CSS framework with incorporation of the dynamic behavior of SUs during cooperation, the interaction among the SUs plays critical role, which can be analyzed using game theory [23,24]. Out of the two categories of game theoretic approaches namely non-cooperative and cooperative game theory; the cooperative game theory takes into account the behavior of rational players when they have mutual benefit via cooperation. Since, SUs aim to improve the sensing performance via cooperation among themselves considering their mutual benefit with other SUs, the framework of CSS can be modeled efficiently using the cooperative game theoretic approach.

3.4.2 The Proposed Coalitional Game Model

Using game theory [23, 24], the CSS has been modeled as a non-transferable coalition game and is named as distributed CSS or DCSS in short. The game is represented by $(\mathcal{N}, \nu)$, where $\mathcal{N}$ is the finite set of players (SUs) and ν is the utility or payoff associated with each of the players in a coalition.

3.4.2.1 Design of Utility Function

In coalitional game, the utility function $\nu(S)$ for a coalition S can be expressed by using Eq.(3.8), which collects the total revenue to be optimized.

$$\nu(S) = Rev(S) - (C_{T_R}(S) + C_{E_R}(S)) \tag{3.8}$$

where $Rev(S)$ represents the revenue, which is collected in terms of average throughput per SU and $(C_{T_R}(S) + C_{E_R}(S))$ represents the cost due to cooperation overhead in terms of reporting time and reporting energy.
Inspired by [72] and [46], the average throughput R_i of the i^{th} SU, while considering the cost due to reporting time as constraint can be stated as

$$R_i = P_{H_0}\left(1 - \frac{T_S}{T} - \frac{T_R}{T} - \frac{T_C}{T}\right)(1 - P_{f,S})\, r_i \tag{3.9}$$

The constraint due to reporting energy is indirectly considered in $\nu(S)$ through selecting the head of the coalition S in such a way that the average distance between every SU and the coalition head is minimized.

Property 1: The proposed coalition game has a non-transferable utility.

Proof: The utility function given by Eq.(3.8) for coalition S is a function of $Rev(S)$, $C_{T_R}(S)$ and $C_{E_R}(S)$. Since the final decision of any SU within a coalition is based on the decision of the coalition head, the probability of false alarm and probability of detection of any SU within S is identical to the probability of false alarm and probability of detection of the S. Thus the throughput of the i^{th} SU (any arbitrary SU) within S is equal to the throughput of the coalition, i.e. $\nu_i(S) = \nu(S)$. Therefore, the throughput generated by the coalition S cannot be arbitrarily distributed among the members of the coalition S, establishing that game has the non-transferable utility.
This completes the proof of *Property 1*. □

3.4.3 Optimization of Cost Parameters

The maximization of throughput of coalition S depends on optimization of cost parameters in terms of time and energy spent during reporting.

3.4.3.1 Optimization of Cooperation Overhead due to Reporting Time

The cost of reporting time (i.e. $C_{T_R}(S)$) is minimized by means of minimizing the probability of false alarm of a coalition S. From Eq.(3.7) and Eq.(3.9), it can be stated that while the number of SUs in the coalition S increases, the value of $P_{f,S}$ decreases and eventually the value of T_R increases. On the other hand, the value of average throughput R_i mainly depends on T_R and $P_{f,S}$, which are determined by the size of the coalition S. For a coalition S with size $|S|$, the value of R_i

becomes optimal when the value of $P_{f,S}$ reaches close or equal to the target value of $P_{f,S}$ denoted by $P_{f,td,S}$ (i.e. $P_{f,S} \approx P_{f,td,S}$). Now, if the size of S keeps on increasing even after reaching the $P_{f,td,S}$, the value of T_R further increases, which causes extra overhead. Therefore, the size of S depends on $P_{f,td,S}$ and decides the optimal value of T_R, leading to the following *Theorem 1.*

Theorem 1: For a given value of $P_{f,td,S}$, if the $P_{f,avg}$ is the average probability of false alarm of all the SUs in the CRN, the optimal size of any coalition S can be approximated as:

$$S_{op} \approx \frac{log(P_{f,td,S})}{log(P_{f,avg})} \tag{3.10}$$

where $P_{f,avg}$ can be expressed by Eq.(3.11).

$$P_{f,avg} = \frac{\sum_{i=1}^{|S|} P_{f,i}}{|S|} \tag{3.11}$$

Proof: Let us assume a coalition S, which accommodates all the $|S|$ number of SUs of a CRN. Now, by using the Eq.(3.7), the probability of false alarm of the coalition S can be expressed by Eq.(3.12)

$$P_{f,S} = \prod_{i=1}^{|S|} P_{f,i} \tag{3.12}$$

Let us assume that each SU within the coalition S has same probability of false alarm i.e. $P_{f,i} = P_{f,j}, \forall i, j \in S$, then the average probability of false alarm of the coalition can be given by Eq.(3.13).

$$P_{f,avg} = \frac{|S|P_{f,i}}{|S|} \quad \text{Or} \quad P_{f,i} = P_{f,avg} \tag{3.13}$$

Also, if $P_{f,i} = P_{f,j}, \forall i, j \in S$ then

$$\prod_{i=1}^{|S|} P_{f,i} = (P_{f,i})^{|S|} \tag{3.14}$$

Let $P_{f,td,S}$ be the given target probability of false alarm for the coalition S. By using Eq.(3.13) and Eq.(3.14) and replacing $P_{f,S}$ with $P_{f,td,S}$ for the coalition S, we can rewrite the Eq.(3.12) as Eq.(3.15).

$$P_{f,td,S} = (P_{f,avg})^{|S|} \tag{3.15}$$

Now, taking *log* on both side of the Eq.(3.15), we get

$$\begin{aligned} log(P_{f,td,S}) &= |S| log(P_{f,avg}) \\ \text{Or} \quad |S| &\approx \frac{log(P_{f,td,S})}{log(P_{f,avg})} \end{aligned} \tag{3.16}$$

Thus, Eq. (3.16) represents the approximate optimal size of the coalition S in which each SU within the coalition has the same probability of false alarm.
Again, let us assume that the probability of false alarm of each SU within the

coalition S is varying according to its SNR value, and then the average probability of false alarm can be computed by the formula given in Eq.(3.17).

$$P_{f,avg} = \frac{\sum_{i=1}^{|S|} P_{f,i}}{|S|} \tag{3.17}$$

Now, for a given value of $P_{f,td,S}$, for any coalition S, the optimal size of that coalition S, in which the probability of false alarm of each SU is varying according to its SNR value, can be approximated by using Eq.(3.16) and (3.17) as follows:

$$|S| \approx \frac{log(P_{f,td,S})}{log(P_{f,avg})} \quad \text{Or} \quad S_{op} \approx \frac{log(P_{f,td,S})}{log(P_{f,avg})} \tag{3.18}$$

where S_{op} represents the optimal size of the coalition S.
This completes the proof of *Theorem 1.* □

3.4.3.2 Optimization of Cooperation Overhead due to Reporting Energy

The cost of reporting energy of a coalition S (i.e. $C_{E_R}(S)$) is minimized by adopting a policy for selecting the head of a coalition while playing the game. Eq.(3.8) states that the utility $\nu(S)$ of a coalition S is a decreasing function of $C_{E_R}(S)$, i.e. the value of $\nu(S)$ decreases with the increase of $C_{E_R}(S)$. Again, the equation of E_R states that the value of E_R is directly proportional to d^{μ} i.e. the value of E_R increases with the increasing value of d. The value of d decides the optimal value of E_R, which is dependent on selection of the coalition head. The coalition head is selected in such a way that the average value of d for all the SUs in the coalition becomes the minimum and eventually optimizes the value of $C_{E_R}(S)$.

Let S is a coalition which consists of K number of SUs denoted by $\{1, 2, \ldots, K\}$ and $D = \{d_1, d_2, \ldots, d_K\}$ is a distance vector where d_i represents the distance of SU i from a PU, $\forall i \in S$. Now, the average distance of SU i from SU j, $\forall j \in S$ and $i \neq j$ can be given by using Eq.(3.19).

$$d_{avg,i} = \frac{\sum_{j=1, j\neq i}^{K} |d_i - d_j|}{K-1} \tag{3.19}$$

Let $d_{avg} = \{d_{avg,1}, d_{avg,2}, \ldots, d_{avg,K}\}$ be a vector consisting of average distances of each of the SUs from the all other SUs in coalition S. Then, the minimum average distance of each of the SUs from all the other SUs in the S can be expressed as:

$$d_{avg,min} = min\{d_{avg,i}, \forall i \in S\} \tag{3.20}$$

From the Eq.(3.20), any SU i within the coalition S having $d_{avg,i}$ equal to $d_{avg,min}$ will be chosen as the coalition head. If more than one SU is present in the coalition having same $d_{avg,min}$, then any one of them is chosen at random as the coalition head. The steps of the proposed algorithm for head selection is given in Algorithm 1.

Algorithm 1: Coalition head selection for a coalition S of size K

Input: Distance vector, $D = \{d_1, d_2, \ldots, d_K\}$ for a coalition S
Output: Head of coalition S

Step 1: Calculate the average distance $d_{avg,i}$ of SU i from SU j, $\forall j \in S$ and $j \neq i$ of the coalition using Eq.(3.19).

Step 2: Set $d_{avg,i}$ as a minimum average distance i.e. $d_{avg,min} = d_{avg,i}$.

Step 3: Calculate the average distance $d_{avg,l}$ of SU l from SU j, $\forall j \in S$, $l \in S$, $j \neq l$ and $l \neq i$ of the coalition.

Step 4: If $d_{avg,l} < d_{avg,min}$ then $d_{avg,min} = d_{avg,l}$.

Step 5: Repeat the Step 3 and Step 4 for all $\forall l \in S$.

Step 6: The value $d_{avg,min}$ gives the minimum average distance and the SU associated with $d_{avg,min}$ i.e. any SU l within the coalition having $d_{avg,l}$ equal to $d_{avg,min}$ will be considered as coalition head.

Time complexity analysis of Algorithm 1 (Coalition head selection)

For a coalition S with size K, the determination of $d_{avg,i}$ for an arbitrary SU i will take at most $O(K)$. At most $O(K^2)$ will be taken to form the vector average distances of each of the SUs from all the other SUs in coalition S i.e. d_{avg}. Because, the formation of d_{avg} will be carried out by broadcasting the value $d_{avg,i}$, $\forall i \in S$ by each SU i to all other SUs within the coalition S. The determination of $d_{avg,min}$ will take maximum of $O(K)$, which involves the computation to find a smallest number among K numbers. Therefore, the complexity of the algorithm is $T(K) = O(K) + O(K^2) + O(K)$, which implies that $T(K) = O(K^2)$. Since for a CRN, the value of K is reasonably smaller for any coalition, the time required for head selection will also be reasonable in terms of overhead. Moreover, once the coalition reaches its stability state, no more computation is required for the head selection.

3.4.4 The Distributed CSS Algorithm

The proposed game model is realized by a distributed algorithm. The algorithm consists of four main phases - (i) Individual local sensing by SUs, (ii) Adaptive coalition formation by an iterative merge and split operation for maximizing coalition utility, (iii) Selection of coalition heads in the resultant coalitions, and (iv) Performing coalition based sensing for making cooperative decision per coalition. The algorithm for distributed CSS assumes that at any time slot T_l ($l \neq 0$), the CRN with N SUs is constituted by M number of coalitions given by $\{S_1, S_2, S_3, \ldots, S_M\}$ except at the first time slot T_0. At T_0, there is no coalition and each SU performs non-cooperative spectrum sensing. The steps of the proposed CSS algorithm is given in Algorithm 2.

Algorithm 2: Distributed CSS (DCSS)

Input: $\hat{P}_d$ (Target detection probability)
Output: Final/cooperative sensing decision

Step 1: Each SU senses the PU channel individually using non-cooperative sensing technique (energy detection).

Step 2: Start coalition formation considering individual SUs as coalitions with single SU and go to Step 3.

Step 3: Two coalitions S_i and S_j can merge to form a large coalition $S_{i,j}$ if

- the average throughput of each SU in the resulting coalition gets improved i.e. for all member $x \in S_i$ and $y \in S_j$, $\nu_x(S_{i,j}) > \nu_x(S_i)$ and $\nu_y(S_{i,j}) > \nu_y(S_i)$, where ν_x represents the payoff of x and ν_y represents the payoff of y.

Step 4: A coalition $S_{i,j}$ can split to form two sub-coalitions S_i and S_j if

- the average throughput of each SU in the resulting sub-coalitions gets improved i.e. for all member $x, y \in S_{i,j}$, $\nu_x(S_i) > \nu_x(S_{i,j})$ and $\nu_y(S_j) > \nu_y(S_{i,j})$, where ν_x represents the payoff of x and ν_y represents the payoff of y.

Step 5: Repeat Step 3 and Step 4 until the coalition(s) becomes stable.

Step 6: Select coalition head using Algorithm 1.

Step 7: Each SU sends its local sensing information to their coalition head within the coalition.

Step 8: Coalition head combines all information received from SUs of the coalition and fuses to makes a final decision.

Step 9: Finally, coalition head transmits the final sensing decision to each of the SUs within the coalition via some broadcasting mechanism.

Time complexity analysis of Algorithm 2 (Distributed CSS)

The time complexity of the DCSS algorithm can be estimated by approximating the number of comparisons (attempts) for merge and split operation during coalition formation. Considering the worst case scenario of convergence, where there exist n singleton coalitions[1] in the network, denoted by $\{S_1, S_2, \ldots, S_n\}$, the complexity can be estimated as follows.

To approximate the number of merge attempts, let there be n number of singleton coalitions in $\mathcal{N}$. In the first iteration of the algorithm, any coalition $S_i, \forall S_i \in \mathcal{N}$ will attempt to form coalition with any other coalition $S_j, \forall S_j \in \mathcal{N}$ and $i \neq j$. In worst case, S_i attempts to merge with S_j, requires at most $(n-1)$ comparisons. Similarly the merge attempts will be repeated for all members of $\mathcal{N}$,

[1]In game theory [23], a coalition having only one player is called a singleton coalition.

since each singleton coalition may try to form a larger coalition requiring $n(n-1)$ number of comparisons. At the end of the first iteration, in worst case, only one coalition will be formed consisting of only two members of $\mathcal{N}$. The rest of the members of $\mathcal{N}$ will fail to form any more coalitions and will remain singleton. In the second iteration, all the member of $\mathcal{N}$ except those members whoever have already formed a larger coalition during the first iteration, will try to merge with the previously formed larger coalition. This may take at most $(n-2)$ number of comparisons. At the end of second iteration, in worst case, only one coalition will be formed consisting of three members of $\mathcal{N}$. Similarly, the iteration process continues until the coalitions are formed and become stable. Therefore, in the worst case scenario the total comparisons required for all the merge attempts can be given as follows.

$$T(n) = n(n-1)+(n-2)+(n-3)+\ldots+1 = n(n-1)+(n(n-1))/2 = O(n^2) \quad (3.21)$$

To approximate the number of split attempts by any coalition S with size n, the game will try to form all possible disjoint subsets of coalition S. Since the power set of any set of size n contains all the possible subsets of that set, finding any two disjoint subsets from that power set will take at most 2^n number of comparisons. Therefore, in worst case scenario, for any coalition S of size n, the time complexity for split attempts will be at most $O(2^n)$.

However, in practice the worst case time complexity of the proposed DCSS algorithm is not encountered. Since in most of the instances in practice, the number of SUs in a coalition is reasonably small, the number of merge attempts required is significantly less compared to the worst case scenario. In such an instance, instead of going through all possible merge attempts with every coalition, whenever a coalition finds a partner satisfying the condition for merge it merges. Therefore, in all cases it does not require to go through all the possible merge attempts. Similarly, once a coalition is heading towards split, the search for further split is not necessary until the previous split attempt leads the coalition unstable.

3.4.5 Stability of Coalition

The stability of a coalition S, depends on the following two conditions, which ensure that a coalition S neither tries to form a larger coalition by merging with other coalitions nor splits into smaller sub-coalitions. During the process of coalition formation, the SUs can operate in self-organizing way.

Condition 1: $P_{f,S} \approx P_{f,td,S}$, i.e. probability of false alarm of the coalition S is approximately equal to the target probability of false alarm of the coalition S.

Condition 2: Number of SUs in the coalition is approximately equal to the S_{op} i.e. the optimal size of the coalition S.

Once the above two conditions get satisfied, a coalition S achieves its optimal throughput and becomes stable.

3.5 Simulation Results and Observations

In this section, we first present the results to show how average probability of false alarm varies with number of SUs for different values of P_d both using non-cooperative and cooperative techniques. The results to show how the average throughput (spectral efficiency) per SU gets improved with increase in number of SUs for the given value of $\hat{P}_d$ using both the techniques are presented next. Comparison of our proposed CSS technique with basic cooperative sensing is not feasible since in the basic cooperative sensing method dynamic parameters are not considered. Our method considers dynamic parameters such as adaptive interaction behavior of the SUs, dynamic coalition formation through merge and split, distance adaptive SNR value consideration, dynamic coalition head/fusion center selection, considering reduction of reporting time and reporting energy consumption criteria. The importance of considering dynamic parameters is discussed in first paragraph of section 3.1. We present the results to show how the maximum throughput can be achieved when a coalition reaches its optimal size. Then we present the results to show how the coalition size varies to maintain different target probability of false alarms. The results to demonstrate how the distance between transmitter and receiver impacts to consume extra energy during reporting in a coalition is presented next. Further, we present the results to show the process of coalition head selection and how the selection of the head affects the reporting energy consumption.

MATLAB based numerical simulation has been carried out to study the behavior and the efficacy of the proposed model. There is no CRN simulator available to simulate the L1 and L2 level schemes/techniques so far. The available simulators (ns2 CRCN [73] patch and Omnet++) support the CRN setup allowing the MAC schemes and higher layer protocol simulation only. Actual testbed setup using USRP devices has been left out in this thesis since it is very challenging because of the practical viabilities in deployment environment, and requires separate research. In our MATLAB based simulation the parameters taken for simulation are listed in Table 3.2. For simulation, a network is setup with a single PU such that it is placed at the center of a circular area with $100m$ radius and the SUs are placed randomly within the range. The results of the experiments using the proposed model are compared with the non-cooperative spectrum sensing technique. Figure 3-3 and Figure 3-4 show the results of experiments conducted to evaluate the performance of the proposed model in terms of average probability of false alarm and compared with the non-cooperative spectrum sensing technique. Figure 3-3 shows that the average probability of false alarm does not depend on number of SUs in non-cooperative spectrum sensing, whereas, it decreases with increase in number of SUs. The proposed cooperative model gives enhanced performance with reduced probability of false alarm. Figure 3-4 shows that for different given values of $\hat{P}_d$, the probability of false alarm decreases with increase in number of SUs.

Parameter	Value
R (radius of PU coverage)	100m
u (time-bandwidth product)	0.3
P_{H_0} (probability of PU being absent)	0.8
T (period of time slot)	100 milliseconds
T_S (sensing period)	5 milliseconds
T_C (total time taken by the coalition head to compute and transmit the final results to every SU)	5 milliseconds
T_r (time period required for SU to send it's sensing information to the coalition head)	0.5 milliseconds
r_i (transmission rate of the SU_i to its receiver when the PU is absent)	80 bits/sec/Hz
e_d (energy dissipated per bit per $metre^2$)	0.0013 $pJ/bit/m^2$ as taken by Zheng *et al.* [74]
e_t (energy spent by transmission circuitry per bit)	5 $nJ/bit/signal$ as taken by Zheng *et al.* [74]
μ (path loss exponent)	4
$\hat{P}_d$ (target probability of detection)	0.9
SNR range	-15 to -1dB

Table 3.2: Values of different parameters used in simulation

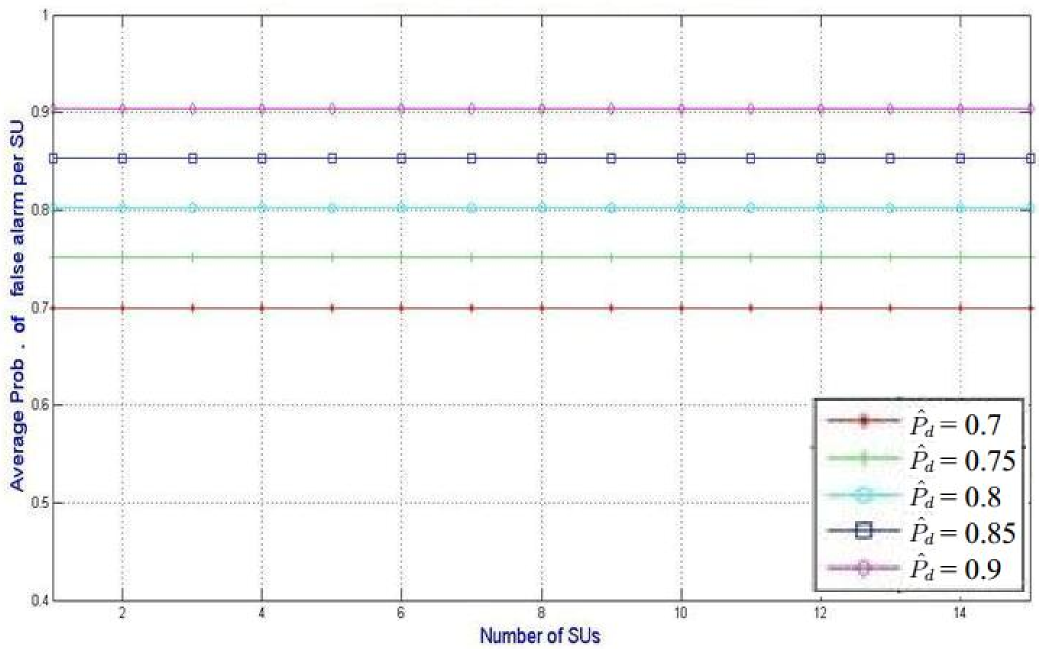

Figure 3-3: Average Probability of False Alarm vs. Number of SUs (Non-Cooperative)

To demonstrate the achieved throughput (spectral efficiency) by the proposed CSS model compared to the non-cooperative technique, an experiment is carried out for a coalition with 30 nodes, while the given target probability of

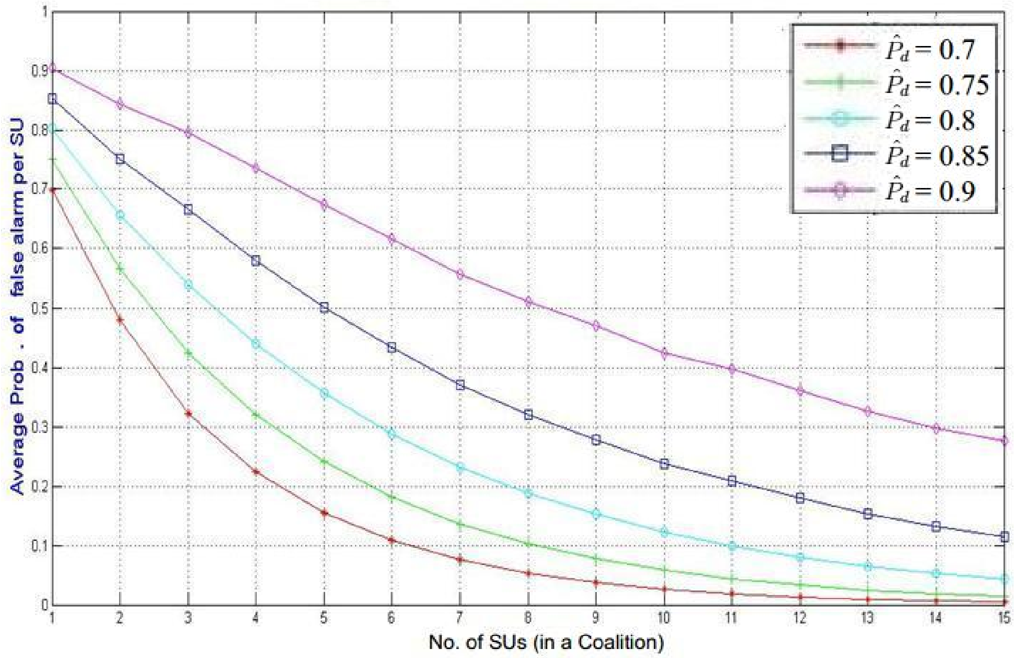

Figure 3-4: Average Probability of False Alarm vs. Number of SUs (Proposed Cooperative Model)

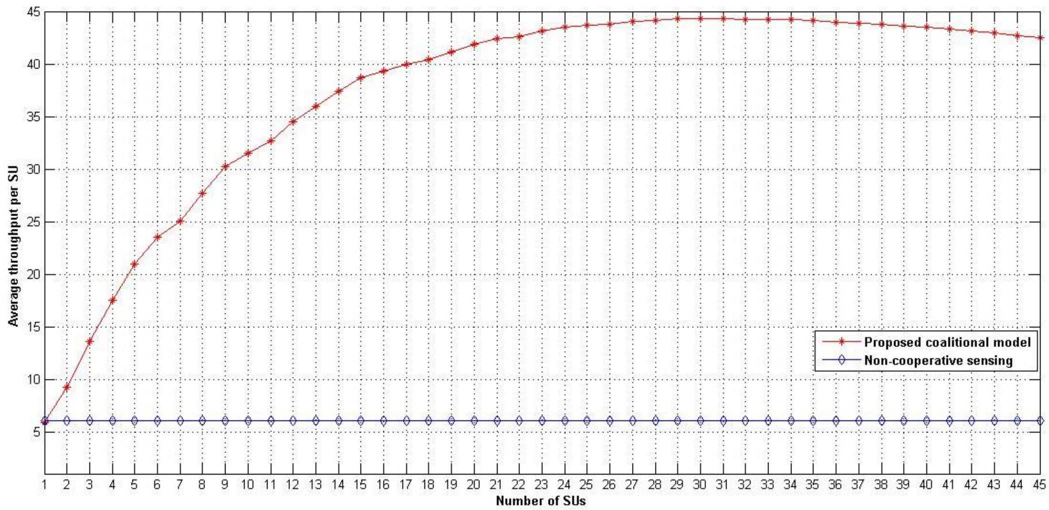

Figure 3-5: Throughput vs. SUs with $\hat{P}_d = 0.9$

detection ($\hat{P}_d$) being considered is 0.9. For non-cooperative sensing, we set the SNR value to be -15 dB, and for the proposed model it is considered within the range from -15 to -1 dB randomly for 30 SUs. In case of non-cooperative sensing since the SUs perform sensing activity independently, $P_{f,S} = P_{f,i}$. So, even on considering the random SNR values they do not have any impact at all as shown in Figure 3-6. Figure 3-5 and Figure 3-6 show that the proposed model enhances the spectral efficiency significantly by increasing the average throughput per SU with increase in the number of SUs compared to the non-cooperative approach. It is due to the reduction of probability of false alarm, achieved through cooperation among SUs within a coalition.

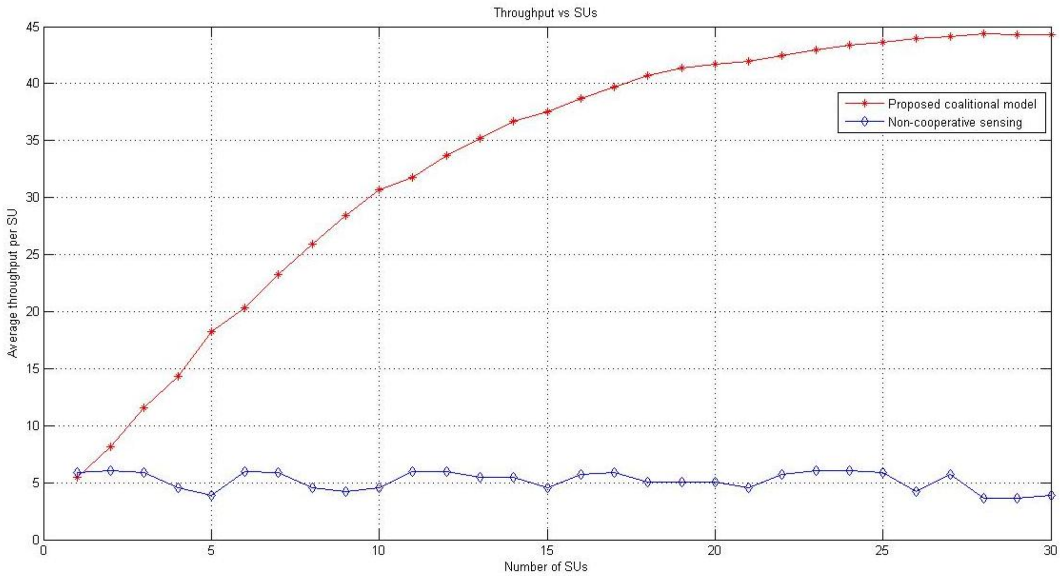

Figure 3-6: Throughput vs. SUs with $\hat{P}_d = 0.9$ (With random SNR for both the techniques

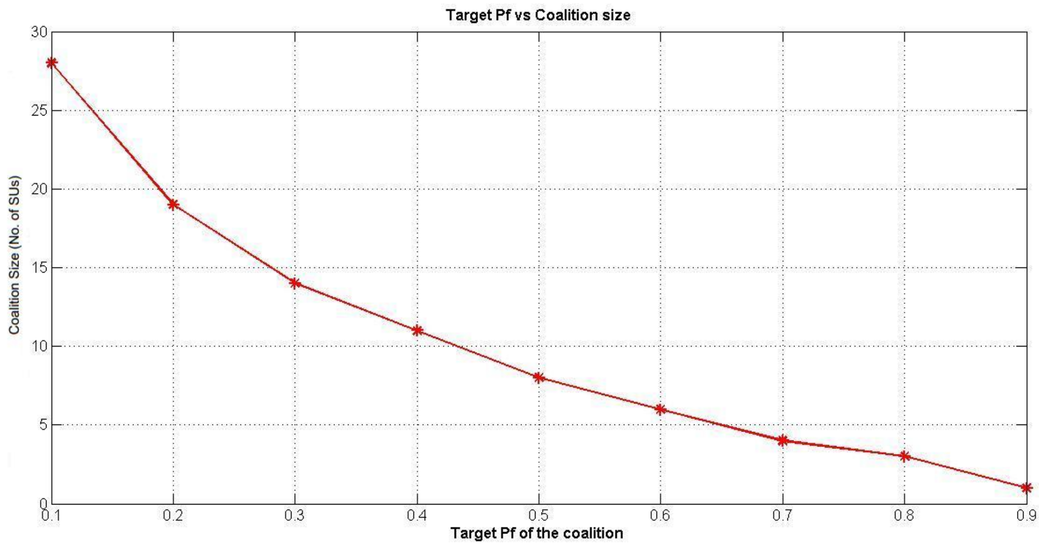

Figure 3-7: Target Probability of False Alarm vs. Optimal Coalition Size

Figure 3-7 shows how to determine the number of SUs, which forms the optimal sized (i.e. S_{op}) coalition in order to tolerate different target probability of false alarm (i.e. $P_{f,td,S}$). The experiment is conducted taking the $\hat{P}_d = 0.9$ and the SNR which ranges from -15 dB to -1 dB for a coalition S. The optimal size of the coalition is found to be 28 numbers of SUs. It also shows that when the value of target probability of false alarm (i.e. $P_{f,td,S}$) is required to be maintained at lower level for a coalition S, the number of SUs needed to form the coalition becomes higher. Therefore, depending on requirement to tolerate the given target probability of false alarm, the optimal size of a coalition is decided. Using the Eq.(3.10), the optimal number of SUs required can be computed to maintain the given $P_{f,td,S}$. This will aid in reducing the overhead of T_R spent by the coalition, while optimizing the size of the coalition.

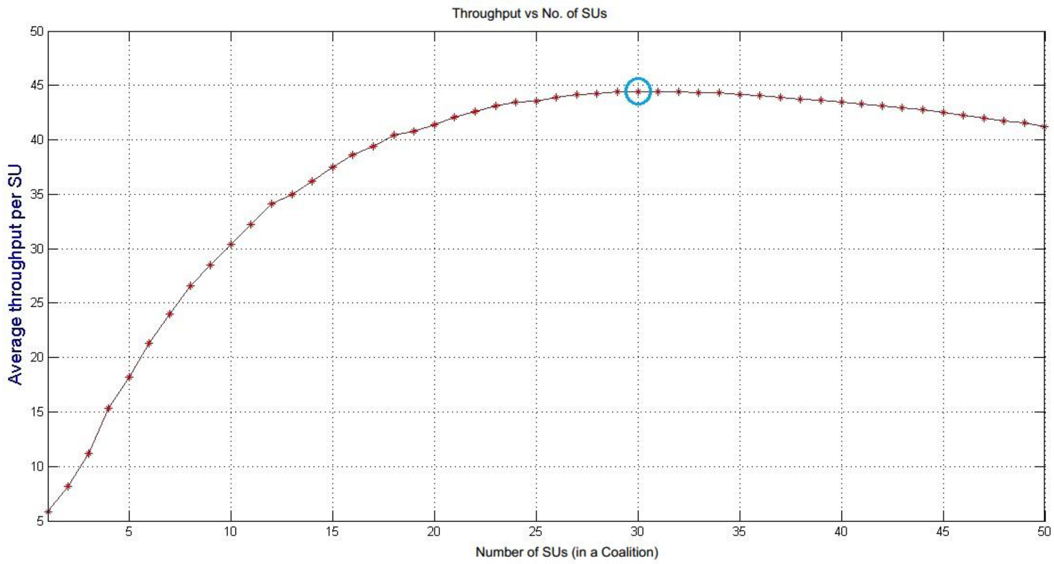

Figure 3-8: Throughput vs. Number of SUs (Impact of reporting time)

Figure 3-8, shows the average throughput improvement with the increase in number of SUs in a coalition beyond optimal size. It can be seen that after a point the achieved throughput starts decreasing with further increase in the number of SUs in the coalition. This indicates that at this point, the coalition can achieve the maximum throughput and the coalition is formed with maximum size beyond the optimal number of SUs, which is found to be 30 in our experimental setup. But, while more numbers of SUs get added into the coalition beyond the optimal size, the throughput of the coalition starts decreasing. It is due to the increase in reporting time by the SUs to transmit their individual sensing information to the coalition head. Therefore, the number of SUs in a coalition beyond the optimal size becomes redundant.

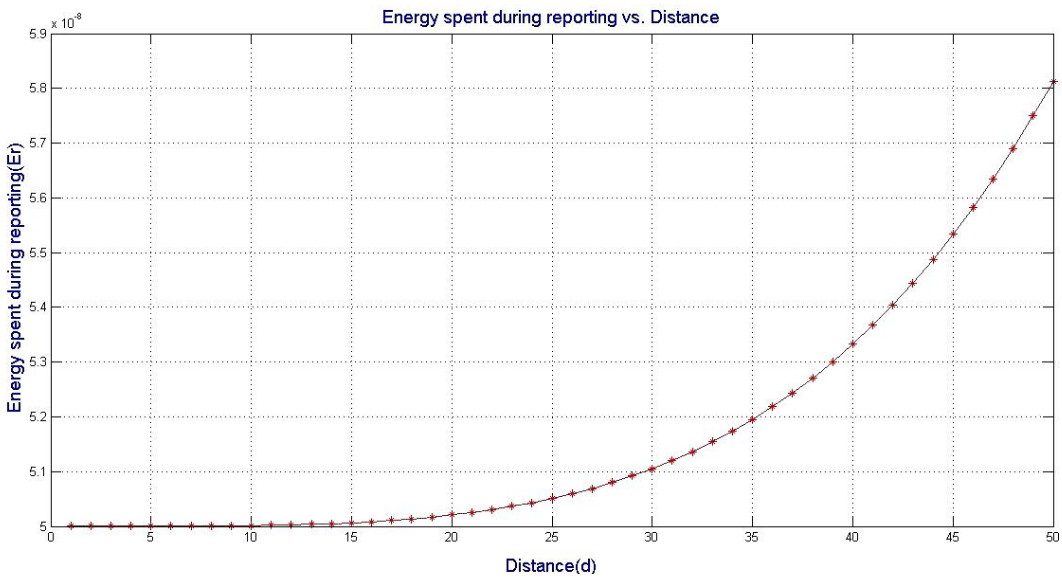

Figure 3-9: Energy Spent (during reporting) vs. Distance (between transmitter and coalition head)

Figure 3-9 shows that how the distance between transmitter and receiver affects extra energy spent during reporting in a coalition. It shows that with the increasing distance between the coalition head and the SUs, the amount of energy required for reporting by the SUs increases. It can be observed that for an SU in coalition of 30 nodes, the amount of energy consumption starts increasing while it's distance increases beyond 15m from the coalition head and the amount of energy spent is drastically high when the SU goes further away close to 50m in our experimental setup.

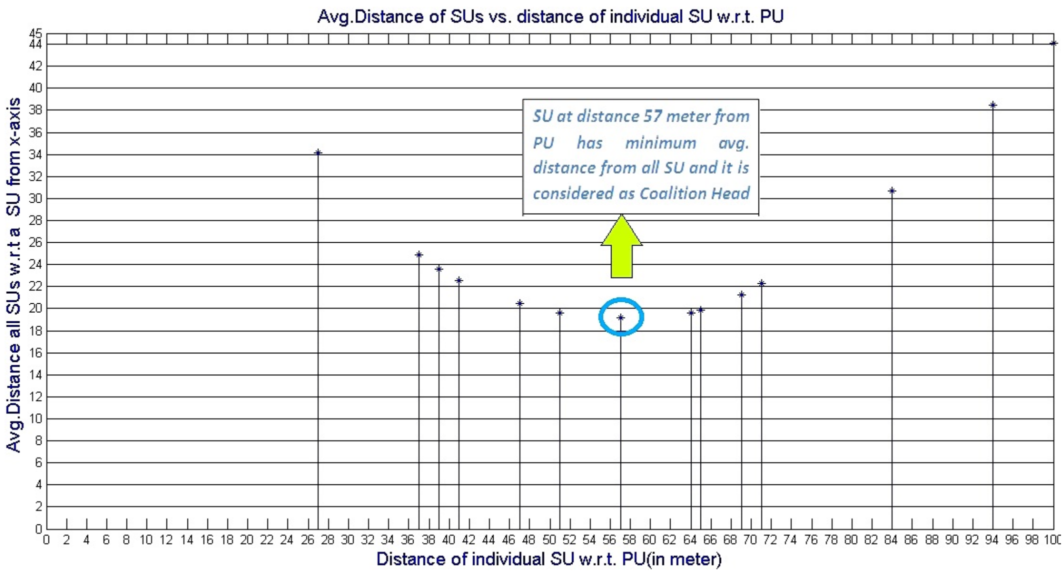

Figure 3-10: Coalition Head Selection (Avg. distances of the SUs vs. Distance of individual SU w.r.t. PU)

Figure 3-10 demonstrates the process of coalition head selection. For the sake of simplicity, the experiment is carried out considering a coalition of 15 numbers of SUs. Further, the distances where the SUs locate from the PU are generated randomly during the experiment. The average distance of each of the SUs from all other SUs in the coalition is calculated using Eq.(3.19). It shows that the SU at a distance of 57m from the PU has the minimum average distance from all other SUs and is selected as the coalition head.

Figure 3-11 shows how the coalition head selection affects the reporting energy consumption, which eventually reduces the overhead due to reporting energy. It shows that when the SU locates itself with a minimum average distance from all other SUs, and at a distance of 57m from the PU in the coalition, it is selected as the coalition head. The energy spent by the coalition becomes minimal with this SU as the head, which eventually reduces the overhead of reporting energy of the coalition.

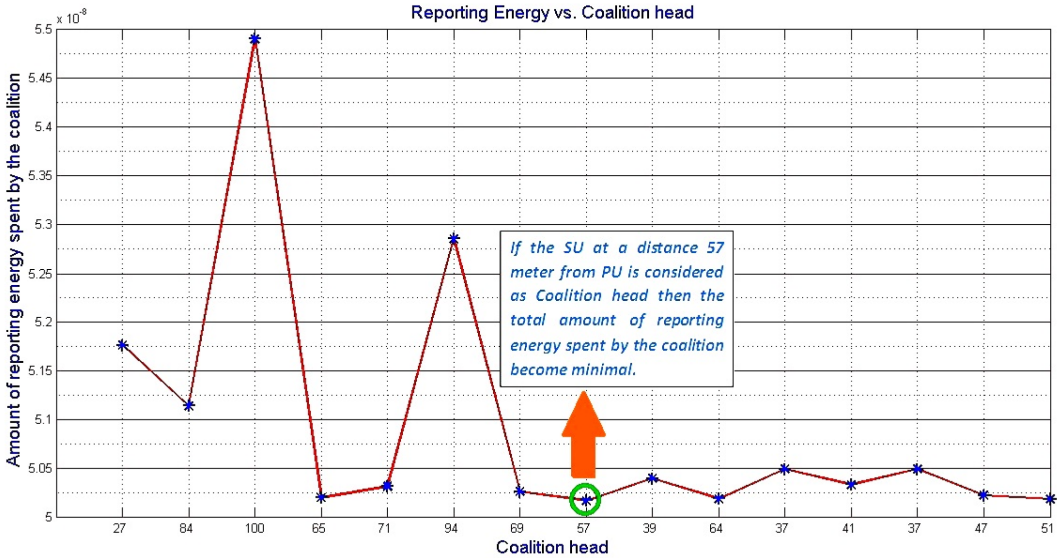

Figure 3-11: Reporting Energy vs. Coalition Head Selection

3.6 Conclusion

In this chapter, the cooperative spectrum sensing problem in CRN to improve spectral efficiency while maintaining a given level of detection accuracy is investigated. Spectral efficiency is improved through minimizing the average probability of false alarm which in turn is determined from the cooperation overhead. The cooperation overhead considered are the reporting time and reporting energy. The proposed CSS scheme is modeled as a cooperative game where the SUs organize themselves into disjoint partitions while maintaining the overall utility function. Game dynamics handles the reporting time - coalition size trade-off and reporting energy - selection of coalition head trade-off. The proposed scheme is shown to reach stable partition analytically. Simulation results further validate the claim.

Sensing performance of CSS can further be enhanced if SUs use adaptive energy detection threshold based on their position/location, which will be addressed in the next chapter.