Adaptive Assignment of Heterogeneous Users for Group-Based Cooperative Spectrum Sensing

Lamiaa Khalid and Alagan Anpalagan, *Senior Member, IEEE*

***Abstract*—In this paper, we consider a multichannel cognitive radio network, where cooperative secondary users have heterogeneous sensing ability in terms of their sensing accuracy. We employ a group-based cooperative spectrum sensing (CSS) scheme in which cooperating secondary users are grouped such that different groups are responsible for sensing different channels. In this group-based CSS scheme, channels sharing the same cooperating users are scheduled to sense in different sensing rounds. In this work, we propose adaptively assigning the heterogeneous cooperating secondary users to different groups to maximize the throughput efficiency while maintaining a predefined sensing accuracy. To this end, we analytically derive a closed-form expression for the throughput efficiency in terms of the average opportunistic throughput and average sensing overhead. We also formulate the throughput efficiency maximization problem for heterogeneous secondary users as a nonlinear binary programming problem, which is computationally intractable. We then propose three efficient adaptive assignment heuristics that perform the assignment of users to groups and the assignment of those groups to the sensing rounds such that the throughput efficiency is maximized. Simulation results demonstrate that our proposed assignment heuristics can achieve near optimal performance with low computational complexity and can also improve the throughput efficiency significantly compared to the existing nonadaptive assignment and sequential CSS schemes.**

***Index Terms*—Cognitive Radio, Cooperative Spectrum Sensing (CSS), Sensing Accuracy, Sensing Overhead.**

I. Introduction

COGNITIVE radio (CR) technology offers a possible solution to improve utilization efficiency of the existing radio spectrum. In a cognitive radio network, secondary users (SUs), equipped with cognitive radios, access the wireless spectrum opportunistically without interfering with the licensed primary users. To reliably identify the vacant licensed bands, some methods that SUs can employ are: geolocation combined with access to database, beacons, spectrum sensing or a combination of any of those methods [1], [2]. With the geolocation method, primary users register the relevant data such as their location and transmit power as well as expected duration of usage at a centralized database. SUs then have to access this database to determine the availability of vacant licensed bands at their location. With the beacon method, SUs only transmit if they receive a control signal (beacon) identifying vacant channels within their service areas. Without reception of this control signal, no transmissions are permitted by SUs. With the aforementioned methods, secondary devices will need additional connectivity in a different band in order to be able to access the database [1] or a dedicated standardized channel will be needed to broadcast the beacons [2]. With the spectrum sensing approach, SUs autonomously detect the presence of the primary signals and only use the channels that are not used by the primary users. In this paper, we consider that SUs employ spectrum sensing to determine vacant licensed frequency bands and restrict their secondary transmissions to those empty bands. The energy detection approach is mostly used in spectrum sensing since it has low computational and implementation complexities and prior knowledge of the primary users' signal is not needed [3].

The unreliability in individual secondary user's sensing results gives rise to sensing errors which affect the sensing accuracy. Spectrum sensing performance can be improved using network cooperation where SUs share their spectrum sensing measurements [4]. When each SU has only one transceiver, it is difficult for SUs to transmit their data and sense at the same time. Due to this hardware limitation, SUs employ a periodic sensing-transmission structure in which the sensing and transmission are performed periodically in separate periods [5]. An alternative to the periodic sensing-transmission structure is to take advantage of dedicated sensors that perform cooperative spectrum sensing and report decision to SUs as a service. However, energy efficiency is a critical issue in sensor-aided CR networks. In [6], the authors proposed a cooperative schedule of each sensor node's on/off time and an optimal scheduling order to extend the network lifetime and minimize the node switch frequency.

In centralized cooperative spectrum sensing (CSS), SUs send their sensing information to a centralized unit, called a fusion center, for making a combined decision. In practice, when an SU transmits the local decision to the fusion center, errors may occur over the reporting channel [7]. In [8], the authors proposed an efficient data fusion technique combining power control and phase shifting techniques to enhance the detection performance of CSS based on OR fusion rule. For the case of multiple input multiple output reporting channels, where

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The authors are with the Department of Electrical and Computer Engineering Ryerson University, Toronto M5B 2K3, ON, Canada (e-mail: lamiaa_khalid@yahoo.com).

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the fusion center is equipped with multiple antennas, it was shown in [9] that the impact of orthogonal transmissions among SUs on the reporting channel is significant in the case of non-cooperative communication, while it becomes negligible in the case of cooperative communication considering decode and forward protocol.

In sequential CSS, all the cooperating SUs sense an identical channel in each sensing period and channels are sensed one by one sequentially. This CSS scheme exploits the multiuser diversity leading to improved sensing accuracy. In [10], it was proven that, for sequential CSS, the optimal sensing order that maximizes the system throughput can be achieved by sorting the channels in descending order of the ratio of the achievable throughput on the channel to the sensing time. In [11], a sensing-period optimization mechanism and an optimal channel-sequencing algorithm were developed to maximize the discovery of spectrum access opportunities and minimize the delay in discovering an available channel when all SUs participate in sensing a channel simultaneously. In [12], the authors studied the CR technology from a cyber physical system (CPS) perspective focusing on actively applying spectrum sensing to improve communication reliability and state estimation performance in CPS for the single and multiple licensed channels cases. For the case of multichannel sensing, sequential CSS was applied in which SUs only sense a subset of all the channels in each sensing round.

In addition to the sensing accuracy, the throughput efficiency, which can be represented by the metrics of sensing overhead and opportunistic secondary throughput, has a significant impact on the performance of spectrum sensing. However, there is a fundamental trade-off between sensing accuracy and throughput efficiency in spectrum sensing. To increase the cooperation gain (i.e., sensing accuracy), more cooperating SUs should perform the sensing. However, using more cooperating users will lead to an increase in the amount of overhead traffic in the secondary network [13] which decreases the throughput efficiency. In sequential CSS, only one channel could be sensed by the cooperating SUs during each sensing period which leads to a delay in the discovery of available channels and consequently, a degradation in the throughput efficiency.

In [14], two different channel sensing policies, the random sensing policy and the negotiation-based sensing policy, were proposed to discover the available channels. In both policies, different users are allowed to sense different channels, that are selected either randomly or through negotiation, which enables SUs to identify and utilize the maximum number of vacant channels. The authors assumed that each SU is equipped with two transceivers. One transceiver is tuned to the dedicated control channel, and another transceiver is used to periodically sense and dynamically use the identified unused channels. The authors in [15] proposed full parallel cooperative sensing, where each user senses a distinct channel, with the aim of discovering multiple spectrum opportunities in a single sensing period. To maximize the achievable throughput, the authors optimized the number of sensing SUs and adaptively changed the stopping threshold in searching for available channels by considering the wireless channel dynamics. In [16], the authors proposed a group-based CSS scheme in which the cooperative SUs are divided into several groups and each group senses a different channel during a sensing period while SUs in the same group perform the joint detection on the targeted channel. The sensing process will not stop unless an available channel is discovered. Assuming that all SUs have equal probabilities of detection and false alarm, they formulated the achievable throughput maximization problem to determine the number of groups and number of users in each group in time varying channels.

It was shown in [16] that by varying the number of groups and the number of cooperative SUs in each group, the trade-off between the sensing accuracy and the sensing efficiency, which was defined in terms of the transmission opportunities discovered by SUs and the sensing overhead due to cooperation, could be adjusted. However, similar to most existing work on CSS, it was assumed that all SUs have the same energy detection threshold and identical average signal-to-noise ratio (SNR) to the primary user [17]. In reality, however, the average SNR will vary since SUs are at different distances from the primary user. Also, the cost of using multiple sensing rounds to find the desired channel on the performance of the group-based sensing scheme was not considered in [16]. In this work, we design novel adaptive user-group assignment algorithms for group-based CSS to achieve a trade-off between the throughput efficiency and sensing accuracy. In contrast to the work in [16], we consider that the cooperating SUs have heterogeneous sensing ability in terms of the sensing accuracy which introduces new challenges to the group-based CSS. We analyze the scenario when channel state information is available and SUs can adapt their transmission rate according to the channel quality. In our prior work [18], we considered an adaptive grouping scheme for CSS in the absence of channel state information.

The contributions of this work can be summarized as follows:

- We analytically derive closed form expressions for the average opportunistic throughput and average sensing overhead for the group-based sensing scheme over additive white Gaussian noise (AWGN) channels when SUs have heterogeneous sensing ability and adaptive transmission rate. We incorporate in our analysis the cost of using multiple sensing rounds to find a vacant channel.
- We formulate the throughput efficiency maximization problem for non-identical SUs as a non-linear binary programming problem which is generally NP hard.
- We propose three efficient heuristic assignment algorithms to solve the formulated optimization problem in which the non-identical SUs are adaptively assigned to groups based on their probabilities of detection.
- Using extensive simulations, we show that our proposed algorithms can achieve comparable performance to the optimal solution with much lower computational complexity and can outperform the existing non-adaptive grouping and sequential sensing schemes.
- We examine the effect of different parameters such as the number of groups, the number of SUs, the sensing duration and imperfect reporting channel conditions on the performance of the three proposed algorithms as well as the the existing non-adaptive grouping and sequential sensing schemes.

The rest of the paper is organized as follows. We present our system model in Section II. In Section III, we describe the group-based cooperative sensing scheme and formulate our throughput efficiency maximization problem. We present our proposed adaptive user-group assignment algorithms and analyze their complexity in Section IV. We evaluate the performance of our proposed assignment algorithms in Section V. We discuss some related issues in Section VI and conclude the paper in Section VII.

II. System Model

In this paper, we consider a cognitive radio network with K SUs and L licensed channels. We assume that all the considered SUs utilize the licensed channels used by the same set of primary users. Therefore, the licensed channel availability information sensed by each SU is consistent among all SUs [19].

A. Primary User Channel Usage Model

We consider the alternating ON/OFF model for the primary user channel usage pattern as studies have shown that it approximates the spectrum usage pattern at public safety bands [20]. In this model, each channel alternates between two modes: ON mode, in which the channel is occupied by a primary user and OFF mode, in which the channel is idle. The SUs can utilize the OFF period of the primary user channel to transmit their own data. We consider the operation of SUs on a frame by frame basis. Each frame duration, T, consists of a sensing period, T_s, and a transmission period, T_t, for data transmission in case the primary user is absent. During data transmission within a frame, if the transmission time, T_t, is relatively short, it is reasonable to assume that the spectrum state does not change during T_t [15].

B. Discrete Rate Adaptive Modulation

To utilize the time-varying feature of the channels, an SU can adapt its transmission rate according to the channel quality using adaptive modulation. In this work, we consider secondary user pairs with low mobility; therefore, the channel gain of each transmission link can be estimated accurately via pilot symbols or training sequences [21]. Assuming the channel is idle, using the background noise and transmit power, the achievable transmission rate of a secondary user pair over this channel can be determined based on the physical layer model and parameters [22]. According to Shannon theory, the channel rate and the received SNR have a one-to-one mapping relationship, i.e., $R_m = W\log_2(1+SNR_m)$, where W refers to the channel bandwidth. In adaptive modulation with continuous rate adaptation, the set of signal constellations is unrestricted. In this work, we consider the more practical scenario where only a discrete finite set of M constellations is available [23]. For the discrete rate case, the rate region boundaries $\{SNR_m\}_{m=1}^{M}$ define the range of SNR over which the different constellations are transmitted. More specifically, for each channel, $M-1$ thresholds divide the SNR range $(0,\infty)$ into M regions and assigns a corresponding achievable rate R_m to each region $[SNR_m, SNR_{m+1})$. Therefore, when the SNR falls within a given region, the associated signal is transmitted with the corresponding data rate.

C. Energy Detection

Considering that there is no information exchange between the primary and SUs, each SU needs to perform spectrum sensing non-cooperatively. We employ the computationally efficient and widely used energy detection technique [24] for spectrum sensing. Energy detection requires no information about the primary user's signal which is more practical. In the energy detection model, the problem of detecting the presence of primary users is equivalent to distinguishing between the two following hypotheses [3],

$$x_k(n) = \begin{cases} v_k(n), & H_0 \\ h_k s(n) + v_k(n), & H_1 \end{cases} \tag{1}$$

where $x_k(n)$ is the received signal of the k^{th} secondary user at the n^{th} time instant, h_k is the k^{th} user channel gain which is assumed to be constant during the detection interval. The primary user's transmitted signal, $s(n)$, is an independent identically distributed (i.i.d.) random process with zero mean and variance σ_s^2 and is assumed to be a binary phase-shift keying signal. The noise, $v_k(n)$, is a real-valued Gaussian variable with zero mean and variance σ_v^2. Without loss of generality, $s(n)$ and $v_k(n)$ are assumed to be independent. The goal of the spectrum sensing is to decide between two hypotheses, H_0 and H_1, the hypothesis that the primary user is absent and present, respectively.

The test statistics for the energy detector for the k^{th} user, Y_k, is computed as the sum of the received signal energy over an interval of $N = T_s f_s$ samples, where f_s is the sampling rate, and is given by [17]:

$$Y_k = \sum_{n=1}^{N} |x_k(n)|^2. \tag{2}$$

For a large number of samples, N ($N \geq 10$ [21]), using the central limit theorem [25], the distribution of the test statistics, Y_k, can be approximated by a Gaussian distribution with mean [17]

$$\mu_k = \begin{cases} N{\sigma_v}^2, & H_0 \\ N\left(\frac{|h_k|^2{\sigma_s}^2}{{\sigma_v}^2}+1\right){\sigma_v}^2, & H_1 \end{cases} \tag{3}$$

and variance

$$\sigma_k^2 = \begin{cases} 2N\sigma_v^4, & H_0 \\ 2N\left(\frac{2|h_k|^2{\sigma_s}^2}{{\sigma_v}^2}+1\right){\sigma_v}^4, & H_1 \end{cases} \tag{4}$$

We assume that the channels between the primary transmitter and secondary receivers change slowly such that they can be assumed to be constant during each operation period of interest. The noise variance, σ_v^2, can be estimated by measuring the power level of a channel which is known to be idle and the channel gain, h_k, can also be obtained a priori when the primary

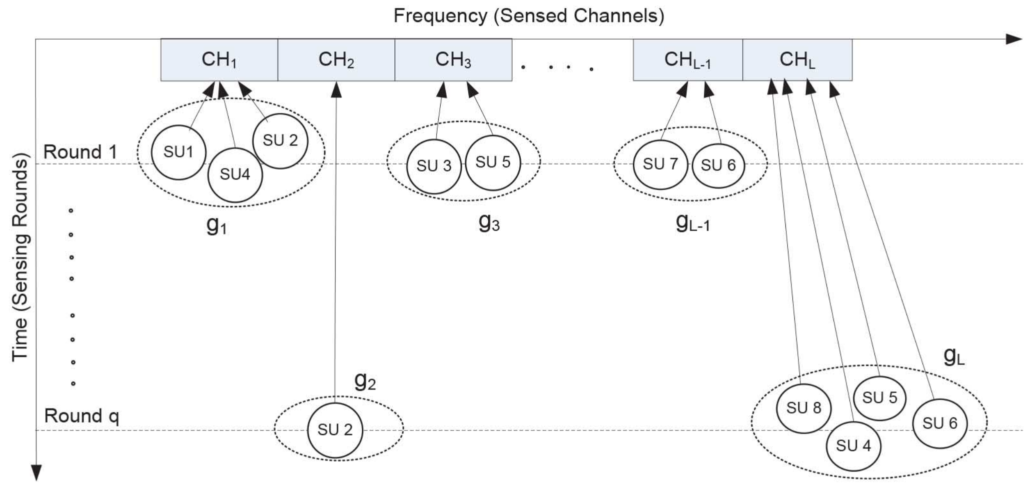

Fig. 1. Illustration of the group-based cooperative sensing scheme.

transmitter is known for sure to be active [26]. This a priori information about the channel condition is attainable since pilot signals are transmitted periodically in the primary system for this specific purpose.

In this paper, we consider SUs with heterogeneous sensing abilities that are represented by different probabilities of detection and false alarms, $p_{d,k}$ and $p_{f,k}$, that are, respectively, given by

$$p_{d,k} = P(Y_k > \gamma_k|H_1) = Q\left(\frac{\gamma_k - N(\sigma_v^2 + |h_k|^2\sigma_s^2)}{\sqrt{2N(\sigma_v^2 + 2|h_k|^2\sigma_s^2)\sigma_v^2}}\right), \tag{5}$$

and

$$p_{f,k} = P(Y_k > \gamma_k|H_0) = Q\left(\frac{\gamma_k - N\sigma_v^2}{\sqrt{2N\sigma_v^4}}\right). \tag{6}$$

where γ_k is the decision threshold for the k^{th} secondary user.

III. Group-Based Cooperative Spectrum Sensing

Suppose a secondary user, k', wants to find an idle channel to initiate data transmission. To find an idle channel, SUs will cooperatively sense the licensed channels using the group-based CSS scheme. In this proposed sensing scheme, the cooperative SUs are grouped into several groups and each group senses a different channel during a sensing period. SUs in the same group cooperate together to sense the targeted channel using energy detection. Cooperative SUs, with heterogeneous sensing abilities represented by non-identical probabilities of detection and false alarm, will be adaptively assigned to groups to achieve a trade-off between the throughput efficiency and the sensing accuracy. Groups sharing the same cooperating SUs will perform sensing in different sensing rounds. An illustrative example of the proposed adaptive group-based CSS scheme is shown in Figure 1.

A. Problem Formulation

In this work, we define the total number of groups to be equal to the number of licensed channels, i.e., $|G| = L$, where $G = \{g_1, \cdots, g_{|G|}\}$ is the set of all groups and $|G|$ is the cardinality of set G. The "group" in this work refers to a set of cooperating SUs sensing a certain channel from the set of licensed channels. According to the above definition, each group, $g_i (i = 1, \cdots, |G|)$, will sense a distinct channel such that, for example, sensing by group 1 is equivalent to sensing channel 1 and sensing by group 2 is equivalent to sensing channel 2 and so on. However, the number of groups used in each sensing round (the number of licensed channels that can be sensed in each sensing round) will differ based on how the cooperating SUs are assigned to the different groups. After each sensing period, the sensing results are sent back to the fusion center that makes the final decision about the occupancy of a certain channel by fusing the decisions made by the cooperating SUs in each group. The choice of the fusion scheme will affect the achievable throughput of the cognitive radio system [27] but it will not alter the conceptual way the user-group and group-sensing round assignments are performed which is the main objective of this work. In order to minimize the communication overhead, we consider that each secondary user, k, sends a single one-bit hard decision, d_k, to the fusion center on the absence or presence of the primary signal. One of the simplest suboptimal data fusion strategies is the counting rule in which the fusion center counts the number of secondary users' decisions which are in favor of the hypothesis H_1. In the case when SUs have heterogeneous sensing ability, the counting rule reduces the required system knowledge and complexity and it has been shown in [28] that the counting rule provides remarkable robustness properties in such scenario. Using the counting rule, the fusion center makes the final global decision, d_0, as follows:

$$d_0 = \begin{cases} \text{Decide } H_1, & \text{if } \sum_{k=1}^{K} d_k \geq n' \\ \text{Decide } H_0, & \text{if } \sum_{k=1}^{K} d_k < n' \end{cases} \tag{7}$$

where n' represents the minimum number of users that needs to decide in favor of the presence of a primary user's signal in order for the fusion center to decide globally that a primary user's signal is present.

If no idle channel is found in the first sensing round, more sensing rounds are performed until an idle channel is discovered or all the available L channels are sensed. Therefore, the total number of sensing rounds, Q, is less than or equal to the number of channels to be sensed (this is equal to the total number of groups, $|G|$). In the worst case, all the cooperating SUs are assigned to each group to sense each channel in a separate sensing round. This results in the total number of sensing rounds Q being equal to the total number of groups, $|G|$ (i.e., sequential CSS). When an idle channel is discovered, the SU that reserved the channel can access the discovered channel and transmit its data. The average transmission time for an SU using an idle channel is equal to the average duration of the channel idle time.

Let $\mathbf{R} = \{R_1, R_2, \cdots, R_M\}$ represent the achievable channel rate vector of length M where region m corresponds to an achievable rate R_m and $m = 1, \cdots, M$. Therefore, each secondary transmitter can select a rate according to its SNR on the channel [29]. Since the total number of groups, $|G|$, is equal to the number of licensed channels, L, and each group, g_i, is assigned to sense a distinct channel, l, in the analysis that follows, sensing by group g_i is equivalent to sensing channel l. If channel l (sensed by group g_i) is discovered using q sensing rounds, the achievable throughput of the secondary user k' that uses this channel for secondary transmission during the transmission time, T_t, is given by

$$C(q) = R_{i,k'} \frac{T_t}{qT_s + T_t}, \tag{8}$$

where T_s is the duration of the sensing period in each frame and the rate, $R_{i,k'}$, is the channel rate achievable on the channel sensed by group g_i for user k' when the sensed channel is free and is chosen for transmission and $R_{i,k'} \in \mathbf{R}$.

Therefore, we can express the average opportunistic throughput in each channel, F, by,

$$\begin{aligned} F &= E[C(q)] \\ &= \sum_{q=1}^{Q} C(q) P_q(g(i)) \\ &= \sum_{q=1}^{Q} P_q(g_i) R_{i,k'} \frac{T_t}{qT_s + T_t}, \end{aligned} \tag{9}$$

where $E[.]$ is the expectation operator, q is the index of the sensing round and Q represents the total number of sensing rounds needed to sense the licensed channels until an idle channel is found where $1 \leq Q \leq |G|$. The term $P_q(g_i)$ is the probability that at least one group, g_i, was successful in discovering an idle channel in the q^{th} sensing round which we will derive later in this section. For a given T_s and T_t, the average opportunistic throughput will decrease as the delay in finding a vacant channel, which is represented by the number of sensing rounds, increases.

Since SUs use a periodic sensing-transmission structure as mentioned earlier, they do not sense and transmit their data at the same time. Therefore, there will be a throughput cost incurred as a result of the cooperative sensing which we refer to in this paper as sensing overhead. The sensing overhead will depend on the number of cooperating SUs and the rates of the channels that they were using for transmission. We define the average sensing overhead incurred by the group-based CSS scheme, O, as

$$O = \sum_{q=1}^{Q} P_q(g_i) \sum_{h=1}^{q} \sum_{g_i \in G^{(h)}} \sum_{k \in g_i} R_{i,k} \frac{T_s}{T_t}, \tag{10}$$

where $G^{(h)} = \{g_i | 1 \leq i \leq |G|\}$ is the set of groups that perform sensing in the h^{th} sensing round and $R_{i,k}$ is the rate with which the cooperating user k was transmitting on its selected channel and $R_{i,k} \in \mathbf{R}$. If the cooperating user was not transmitting, we set $R_{i,k} = 0$.

Let $P_s(g_i)$ represent the probability that a channel is successfully discovered by group g_i. Then, we have

$$P_s(g_i) = (1 - P_F(g_i)) P_I, \tag{11}$$

where $P_F(g_i)$ is the probability of false alarm of the final decision by the fusion center on the channel sensed by group g_i and P_I is the probability of a channel being idle.

Due to non-identical probabilities of false alarm for SUs and the variable number of SUs in each sensing group, the probability, $P_s(g_i)$, will be different for different groups. Therefore, the probability that at least one channel is discovered by the adaptive group-based sensing scheme in the q^{th} sensing round, p_q, is modelled by Poisson binomial distribution which describes this probability of obtaining at least one success in $|G^{(q)}|$ non-identical Bernoulli trials, where $|G^{(q)}|$ is the cardinality of set $G^{(q)}$, as [30], [31]:

$$p_q = \sum_{x=1}^{|G^{(q)}|} \sum_{J_{|G^{(q)}|} \in A^{(x)}} \prod_{c=1}^{|G^{(q)}|} (P_s(u_{c,q}))^{j_c} (1 - P_s(u_{c,q}))^{1-j_c} \tag{12}$$

where $J_{|G^{(q)}|} = (j_1, \cdots, j_{|G^{(q)}|})$ is a vector of length $|G^{(q)}|$ and $A^{(x)}$ is a set of vectors where all elements are either 0 or 1 and the sum of the elements is equal to x, i.e., $Y = (y_1, \cdots, y_b) \in A^x$ if $y_r \in \{0, 1\}, \forall 1 \leq r \leq b$ and $\sum_{r=1}^{b} y_r = x$. The vector $U^q_{|G^{(q)}|} = (u_{1,q}, \cdots, u_{|G^{(q)}|,q})$ is a vector of length $|G^{(q)}|$ and $u_{c,q} \in G^{(q)}$ such that $1 \leq c \leq |G^{(q)}|$ and $u_{c,q} \neq u_{d,q}, \forall q, c, d, c \neq d$. The probability that channel l is successfully discovered by group $u_{c,q}$, $P_s(u_{c,q})$, is given by (11).

We calculate the probability that at least one channel is discovered after q sensing rounds as

$$P_q(g_i) = \frac{p_1}{1 - \prod_{w=1}^{|G|}(1 - p_w)}, \quad q = 1 \tag{13}$$

and,

$$P_q(g_i) = \frac{p_q \prod_{u=1}^{q-1}(1 - p_u)}{1 - \prod_{w=1}^{|G|}(1 - p_w)}, \quad q = 2, 3, \cdots, |G| \tag{14}$$

where p_q is given by (12) for $1 \leq q \leq |G|$.

Following the decision rule in (7), due to the non-identical probabilities of false alarm and detection for SUs, the global probabilities of detection and false alarm are modelled by

Poisson binomial distribution of obtaining at least n' successes in $|K_i|$ independent non-identical Bernoulli trials, where $K_i = \{k \in g_i | 1 \leq k \leq K\}$ is the set of users in group g_i and $|K_i|$ is the cardinality of set K_i. Therefore, using the same formula as in (12), the global probabilities of false alarm and detection of the final decision on the channel sensed by group g_i are, respectively, given by

$$P_F(g_i) = \sum_{x=n'}^{|K_i|} \sum_{J_{|K_i|} \in A^{(x)}} \prod_{k=1}^{|K_i|} (p^i_{f,k})^{j_k} (1 - p^i_{f,k})^{1-j_k}, \tag{15}$$

and

$$P_D(g_i) = \sum_{x=n'}^{|K_i|} \sum_{J_{|K_i|} \in A^{(x)}} \prod_{k=1}^{|K_i|} (p^i_{d,k})^{j_k} (1 - p^i_{d,k})^{1-j_k}, \tag{16}$$

where $p^i_{f,k}$ and $p^i_{d,k}$ denote the probabilities of false alarm and detection of the k^{th} user on the channel sensed by group g_i, respectively, $J_{|K_i|} = (j_1, \cdots, j_{|K_i|})$ is a vector of length $|K_i|$ and $A^{(x)}$ is a set of vectors where all elements are either 0 or 1 and the sum of the elements is equal to x as defined in (12).

From (5) and (6), the target probability of false alarm for the channel sensed by group g_i, $p^i_{f,k}$, is related to the probability of detection, $p^i_{d,k}$, as follows:

$$p^i_{f,k} = Q\left(\left(\sqrt{\frac{2|h^i_k|^2\sigma_s^2}{\sigma_v^2} + 1}\right) Q^{-1}(p^i_{d,k}) + \sqrt{\frac{N}{2}}\frac{|h^i_k|^2\sigma_s^2}{\sigma_v^2}\right), \tag{17}$$

where h^i_k is the channel gain of the k^{th} user on the channel sensed by group g_i.

Using the adaptive group-based sensing scheme, it is possible to sense more than one channel at each sensing period. This possibility can increase the throughput efficiency which we define as the ratio of the average opportunistic throughput over the sum of the average opportunistic throughput and the average sensing overhead. Our objective is to optimally assign the non-identical cooperating SUs to groups and then assign those groups to the sensing rounds such that the throughput efficiency is maximized. We define the throughput efficiency, Γ_{eff}, to be

$$\Gamma_{eff} = \frac{F}{F + O}. \tag{18}$$

To formulate the throughput efficiency maximization problem, we introduce the user assignment indicator, $\xi_{i,k}$, and the group assignment indicator, $\eta_{i,q}$, where i, k and q are the indices of the groups, users and rounds, respectively. The user assignment indicator $\xi_{i,k}$ is equal to 1 if user k is assigned to group i and $\xi_{i,k} = 0$, otherwise. Similarly, the group assignment indicator $\eta_{i,q}$ is equal to 1 if group i is sensing in round q and $\eta_{i,q} = 0$, otherwise. Therefore, we can express the average opportunistic throughput and the average sensing overhead incurred by the adaptive group-based sensing scheme as follows

$$F = \sum_{q=1}^{|G|} P_q(g_i) \frac{T_t}{qT_s + T_t} \max_i (R_{i,k'}\eta_{i,q}), \tag{19}$$

and

$$O = \sum_{q=1}^{|G|} P_q(g_i) \sum_{h=1}^{q} \sum_{i=1}^{|G|} \sum_{k=1}^{K} \xi_{i,k}\eta_{i,h}R_{i,k}\frac{T_s}{T_t}, \tag{20}$$

where $P_q(g_i)$ is given by (13) for $q = 1$ and by (14) for $2 \leq q \leq |G|$.

We can express the probability that at least one channel is discovered in the q^{th} sensing round, p_q, as

$$p_q = \sum_{x=1}^{|G|} \sum_{J_{|G|} \in A^{(x)}} \prod_{i=1}^{|G|} (\eta_{i,q})^{j_i} (P_s(g_i))^{\eta_{i,q} j_i} (1 - P_s(g_i))^{\eta_{i,q}(1-j_i)}. \tag{21}$$

The probability of false alarm for each group is

$$P_F(g_i) = \sum_{x=n'}^{K} \sum_{J_K \in A^{(x)}} \prod_{k=1}^{K} (\xi_{i,k})^{j_k} (p^i_{f,k})^{\xi_{i,k} j_k} (1 - p^i_{f,k})^{\xi_{i,k}(1-j_k)}. \tag{22}$$

Similarly, the probability of detection for each group is

$$P_D(g_i) = \sum_{x=n'}^{K} \sum_{J_K \in A^{(x)}} \prod_{k=1}^{K} (\xi_{i,k})^{j_k} (p^i_{d,k})^{\xi_{i,k} j_k} (1 - p^i_{d,k})^{\xi_{i,k}(1-j_k)}. \tag{23}$$

We can now formulate the throughput efficiency maximization problem as follows:

$$\max_{\xi_{i,k}, \eta_{i,q}} \quad \Gamma_{eff} \tag{24}$$

subject to

$$\xi_{i,k} \in \{0, 1\} \qquad 1 \leq i \leq |G|, 1 \leq k \leq K \tag{25}$$

$$\eta_{i,q} \in \{0, 1\} \qquad 1 \leq i \leq |G|, 1 \leq q \leq |G| \tag{26}$$

$$\sum_{i=1}^{|G|} \xi_{i,k}\eta_{i,q} \leq 1, \qquad 1 \leq q \leq |G|, 1 \leq k \leq K \tag{27}$$

$$\sum_{q=1}^{|G|} \eta_{i,q} \leq 1, \qquad 1 \leq i \leq |G| \tag{28}$$

$$|\eta_{i,q} - \eta_{j,q}| = \min\left(1, \sum_{k=1}^{K} \xi_{i,k}\xi_{j,k}\right), 1 \leq i, j, q \leq |G|, i \neq j \tag{29}$$

$$P_D(g_i) \geq P_{Dth}, \qquad \forall g_i \in G \tag{30}$$

Constraints (25) and (26) are to ensure proper values for the user and group assignment indicators, respectively. Since each user can sense at most one channel at a time, constraint (27) restricts the assignment of each user to only one group in each sensing round. However, to allow for more flexibility in the assignment, we do not restrict the assignment of the same user to a different group in another sensing round as shown in the example in Figure 1. Constraint (28) ensures that, at each sensing round, any group that did not sense yet will be given the chance to sense if it meets its sensing requirement. This constrain also restricts each group to sense in only one sensing round to ensure that each channel is sensed at most once during all sensing rounds. Constraint (29) indicates that the groups that do not share any users should be assigned to sense in the same sensing round. This constraint tends to maximize the number of groups in each sensing round in order to decrease the number of rounds needed to sense all the available channels which in turn reduces the delay in finding a vacant channel. Constraint (30) puts a limit on the probability of detection for each group g_i, $1 \le i \le |G|$ to guarantee an adequate level of sensing accuracy.

B. Sensing Duration

In this section, we investigate the effect the sensing duration, T_s, on the maximum throughput efficiency when the sensing threshold for user k lies between the mean noise power and the primary signal power such that $\sigma_v^2 \le \gamma_k \le \sigma_v^2 + |h_k|^2\sigma_s^2$. This implies that the secondary transmitter can effectively distinguish between the noise power and the primary signal power. Therefore, as the sensing duration increases (the number of samples N increases), the false alarm probability, $p_{f,k}(\gamma_k, T_s)$ decreases monotonically, while at the same time the detection probability, $p_{d,k}(\gamma_k, T_s)$ increases monotonically [32]. For a certain user-group assignment, according to (22) and (23), $P_F(g_i, T_s)$ and $P_D(g_i, T_s)$ are monotonically increasing in $p^i_{f,k}(\gamma_k, T_s)$ and $p^i_{d,k}(\gamma_k, T_s)$, respectively. Therefore, if a certain sensing duration, $T_{s,0}$, is able to guarantee an adequate level of sensing accuracy, $P_D(g_i, T_{s,0}) = P_{Dth}$, any other sensing duration, $T_{s,1}$, which is greater than $T_{s,0}$, is able to satisfy constraint (30) for the same γ_k and the same user-group assignment, since $P_D(g_i, T_{s,1}) > P_D(g_i, T_{s,0})$.

The throughput efficiency in (18) decreases as the ratio between the average sensing overhead and the average opportunistic throughput, O/F, increases which is given by

$$\frac{O}{F} = \frac{T_s \sum_{q=1}^{|G|} P_q(g_i) \sum_{h=1}^{q} \sum_{i=1}^{|G|} \sum_{k=1}^{K} \xi_{i,k}\eta_{i,h} R_{i,k}}{T_t^2 \sum_{q=1}^{|G|} \frac{1}{qT_s+T_t} P_q(g_i) \max_i (R_{i,k'}\eta_{i,q})} \tag{31}$$

Both the average sensing overhead, O, and the average opportunistic throughput, F, are dependent on the variation of T_s through the term T_s and the probability $P_q(g_i)$ which is a function of T_s. The truncated geometric distribution $P_q(g_i)$ in (13) and (14) has a maximum at $q = 1$ and decreases monotonically with increasing q for a certain T_s. Note that, the effect of changing T_s will be most dominant when $q = 1$ and since the term $P_q(g_i)$ appears on both the nominator and denominator of (31) this will in turn diminish the effect of changing $P_q(g_i)$ with T_s on the throughput efficiency Γ_{eff}. Therefore, from (18) and (31), as T_s increases, for a certain user-group and group-round assignment, the ratio O/F increases and the throughput efficiency Γ_{eff} decreases. Based on the above discussion, in order to prevent performance degradation in terms of the throughput efficiency, the secondary network should reduce the sensing duration to the minimum sensing duration that satisfies the sensing accuracy constraint. In this work, we generally do not restrict the number of users assigned to a certain group; therefore, we design T_s such that it satisfies the sensing accuracy constraint for the case of a single user.

C. Imperfect Reporting Channel

In this section, we incorporate the effect of imperfect reporting channels between the heterogeneous SUs and the fusion center in our group-based CSS scheme. We consider that the secondary users communicate to the fusion center over a dedicated binary symmetric channel (BSC). The BSC model arises when separation between sensing and communication layers is performed in the design phase, namely a decode-then-fuse approach [33]. Reporting channel errors are assumed to be i.i.d and we denote the probability of error of sending the one-bit decision from the k^{th} user to the fusion center by $p_{e,k}$. For the case of binary information, the received probabilities of detection and false alarm at the fusion center from the k^{th} user are, respectively, given by:

$$p^{fc}_{d,k} = p_{d,k}(1 - p_{e,k}) + (1 - p_{d,k})p_{e,k}, \tag{32}$$

and,

$$p^{fc}_{f,k} = p_{f,k}(1 - p_{e,k}) + (1 - p_{f,k})p_{e,k}. \tag{33}$$

Therefore, we can express the probability of false alarm for each group as

$$P_F(g_i) = \sum_{x=n'}^{K} \sum_{J_K \in A^{(x)}} \prod_{k=1}^{K} (\xi_{i,k})^{j_k} (p^{fc_i}_{f,k})^{\xi_{i,k} j_k} (1 - p^{fc_i}_{f,k})^{\xi_{i,k}(1-j_k)}. \tag{34}$$

Similarly, we can express the probability of detection for each group as

$$P_D(g_i) = \sum_{x=n'}^{K} \sum_{J_K \in A^{(x)}} \prod_{k=1}^{K} (\xi_{i,k})^{j_k} (p^{fc_i}_{d,k})^{\xi_{i,k} j_k} (1 - p^{fc_i}_{d,k})^{\xi_{i,k}(1-j_k)}. \tag{35}$$

where $p^{fc_i}_{f,k}$ and $p^{fc_i}_{d,k}$ denote the probabilities of false alarm and detection received at the fusion center from the k^{th} user on the channel sensed by group g_i, respectively.

IV. Adaptive Assignment Algorithms

The optimization problem in (24)–(30) is a non-linear binary programming problem. This problem is computationally hard as it is more general and harder to solve than binary programming which is known to be NP hard [34]. In this section, we propose three assignment heuristics to solve the problem given in (24)–(30) with low computational complexity.

In order to achieve our objective of maximizing the throughput efficiency with a guaranteed sensing accuracy on each channel, we need to maximize the opportunistic throughput while minimizing the sensing overhead. Both the opportunistic throughput and sensing overhead depend on the total number of sensing rounds needed to discover an idle channel and the number of cooperating users in each group. In our proposed group-based CSS scheme, each sensing round has a subset of channels (all channels have equal probability of being idle, P_I) and the channel subsets in different sensing rounds are sensed in a sequential manner.

A. Channel Selection then Best User Assignment (CSBUA) Algorithm

We first propose a greedy heuristic algorithm with the objective of assigning the maximum number of groups (channels) to each sensing round. Each channel is then sensed with the best subset of the available cooperating users such that the sensing accuracy is achieved with minimum number of users. Algorithm 1 shows the pseudo code of the proposed Channel Selection then Best User Assignment (CSBUA) algorithm. In CSBUA algorithm, the channels are first sorted in descending order of the achievable rates of user k' on those channels. Therefore, for $i < j$, $R_{i,k'} \geq R_{j,k'}$, $\forall i, j$. At the start of each sensing round, the best channel is selected and the user (chosen from the set of all candidate users for this round) with the best probability of detection $p^i_{d,k}$ on this channel is assigned to the channel and removed from the set of all candidate users for this round. Intuitively, the user with the best detection probability on a certain channel should necessarily be one of the cooperating users sensing this channel. Therefore, by assigning available users with the highest probability of detection to sense each channel, the sensing accuracy for each channel is increased with fewer number of users which will in turn decrease the average sensing overhead. User k can sense only one channel in each round but can be assigned to sense another channel in a different round, i.e., the set of all candidate users is initialized with all cooperating SUs at the beginning of each sensing round. In the example shown in Figure 1, SU1 is assigned to sense channel 1 (highest channel rate for k' in this round), therefore, SU1 cannot be assigned to sense channel 3 even if it has the best probability of detection on it. On the other hand, channel 3 must still be sensed in this round if its sensing requirement can be achieved using a subset of the unassigned SUs (SU3 and SU5 in this example).

Once a channel is selected, CSBUA algorithm will assign users to a group (channel) until the probability of detection on this channel reaches a certain target value, P_{Dth}; then, this group is removed from the set of all groups. This group will then be assigned to this sensing round and so the equivalent channel will be sensed in this round (following that, the algorithm continues assigning users to the next group in the same fashion and so on). To maximize the number of groups in each sensing round, the algorithm will try to place any unassigned users in the remaining groups. For example, assume $\mathcal{M}$ is the set of cooperating SUs and that CSBUA algorithm assigns the set of users K_1 to group 1 and the set of users K_2 to group 2 such that the sensing requirement (i.e., $P_{D_{th}}$) for each of those groups is achieved. If the remaining unassigned users (i.e., the set of users $\mathcal{M} - K_1 - K_2$) cannot meet $P_{D_{th}}$ for group 3, then before going to the next sensing round, CSBUA algorithm will try to place those unassigned users in group 4 to meet $P_{D_{th}}$. As long as there are unassigned users remaining, the algorithm will continue in the same manner until P_{Dth} is achieved for a group or it is determined that no more groups can be sensed in this sensing round. This is possible since each user has a different probability of detection for each group, $p^i_{d,k}$. The rationale behind this group assignment is that by maximizing the number of groups in each round, we will in turn minimize the number of rounds needed to sense all available channels which will increase the average opportunistic throughput and accordingly increase the throughput efficiency.

Algorithm 1. Algorithm for Channel Selection then Best User Assignment (CSBUA)

$G = \{g_1, g_2, \ldots, g_{|G|}\}$
$V = \{1, 2, \ldots, |G|\}$
$\mathcal{M} = \{1, 2, \ldots, K\}$
$q \leftarrow 1$ /*Initialize the rounds*/
Sort the channel rates $R_{channel} = \{R_1, R_2, \ldots, R_{|G|}\}$ in a descending order
for $i = 1$ to $|G|$ **do**
    for $k = 1$ to K **do**
        $\xi_{i,k} \leftarrow 0$ /*Initialize the user assignment indicators*/
    end for
    for $q = 1$ to $|G|$ **do**
        $\eta_{i,q} \leftarrow 0$ /*Initialize the group assignment indicators*/
    end for
end for
while $G \neq \emptyset$ & $q \leq |G|$ **do**
    $\acute{M} \leftarrow \mathcal{M}$
    for $i \in V$ **do**
        while $\acute{M} \neq \emptyset$ **do**
            $k^* = \arg\max_{\forall k \in \acute{M}} \{p^i_{d,k} | k \in \acute{M}\}$ /*Choose one user with maximum $p^i_{d,k}$ for each channel (group)*/
            $\xi_{i,k^*} \leftarrow 1$ /*Assign user k^* to group g_i*/
            $\acute{M} \leftarrow \acute{M} \backslash \{k^*\}$ /*Remove user k^* from the set of all candidate users $\acute{M}$*/
            calculate $P_D(g_i)$ according to (23) for a given n'
            if $P_D(g_i) \geq P_{Dth}$ **then**
                $\eta_{i,q} \leftarrow 1$ /*Assign group g_i to sense in round q*/
                $G \leftarrow G \backslash \{g_i\}$ /*Remove group g_i from the set of groups G*/
                $V \leftarrow V \backslash \{i\}$ /*Remove index i from the set of group indices $V = \{1, 2, \ldots, |G|\}$*/
                break;
            end if
        end while
        if $\eta_{i,q} = 0$ **then**
            for $k = 1$ to K **do**
                if $\xi_{i,k} = 1$ **then**
                    $\acute{M} \leftarrow \acute{M} \cup \{k\}$
                end if
                $\xi_{i,k} \leftarrow 0$ /*Initialize the user assignment indicators for the unassigned groups*/
            end for
        end if
    end for
    $q \leftarrow q + 1$ /*Go to the next sensing round*/
end while

B. Best User Assignment then Channel Selection (BUACS) Algorithm

Next, we propose a heuristic algorithm that assigns the best set of users from all the cooperating users to each group (channel) such that the sensing accuracy on each group is achieved with the minimum possible number of users. The channels are then sensed in a sensing order that maximizes the average opportunistic throughput. Algorithm 2 shows the pseudo code of the proposed Best User Assignment then Channel Selection (BUACS) algorithm. In BUACS algorithm, for each group (channel) i, the user k (chosen from the set of all cooperating SUs) with the highest $p^i_{d,k}$ is assigned to the group. BUACS algorithm then continues assigning more users in descending order of their probability of detection on group i until the probability of detection on this channel reaches a certain target value, P_{Dth}. For every other group, BUACS algorithm assigns the optimal subset of users chosen from the set of all cooperating users (candidate users set will not be reduced for each group). The groups, with their assigned optimal user sets, are then sorted in descending order based on a sorting factor for each group g_i, $\Delta_{g_i}, i = 1, \cdots |G|$. Later in this section, we will discuss two different sorting factors in details.

For each sensing round, after selecting the group, g_i, that has the maximum Δ_{g_i} from the set of unassigned groups, any other unassigned group g_j whose optimal set of users is not a subset of the optimal set of users for the selected group (groups) is assigned to sense in the same sensing round. All these groups will then be assigned to this sensing round and removed from the set of all groups. Following that, the algorithm continues assigning groups to the next sensing round in the same manner until all groups are assigned. In the example shown in Figure 1, SU2 is assigned to sense channel 1 and channel 2, therefore, channel 1 and channel 2 must be sensed in different sensing rounds. On the other hand, channel 1 and channel 3 are sensed by different SUs and therefore can be sensed in the same sensing round.

It is clear from the above discussion that the performance of the BUACS algorithm will depend on the sorting factor, $\Delta_{g_i}, i = 1, \cdots |G|$. We consider two variants of this algorithm by using two different sorting factors as follows:

1) BUACS1: This algorithm sorts the channels based on the achievable rates of user k' on those channels, i.e., $\Delta_{g_i} = R_{i,k'}, i = 1, \cdots |G|$, which is the same sorting factor used in CSBUA algorithm.

2) BUACS2: This algorithm makes use of the knowledge of the optimal subset of users for each channel and use a sorting factor to sort the channels based on the maximum achievable throughput for each channel if it is sensed by its optimal set of users, $R_{i,k'} P_s(g_i), i = 1, \cdots |G|$, divided by the number of users in the optimal user set for this channel, $|K_i|, i = 1, \cdots |G|$ i.e., $\Delta_{g_i} = \frac{R_{i,k'} P_s(g_i)}{|K_i|}$. The rationale behind choosing this sorting factor is that Δ_{g_i} is now proportional to the throughput efficiency. Therefore, by choosing the channels with the highest Δ_{g_i} to be sensed first, whenever possible, the throughput efficiency can be maximized.

Algorithm 2. Algorithm for Best User Assignment then Channel Selection (BUACS)

$R_{channel} = \{R_1, R_2, \ldots, R_{|G|}\}$
$G = \{g_1, g_2, \ldots, g_{|G|}\}$
$V = \{1, 2, \ldots, |G|\}$
$\mathcal{M} = \{1, 2, \ldots, K\}$
$q \leftarrow 1$ /*Initialize the rounds*/
for $i = 1$ to $|G|$ **do**
  for $k = 1$ to K
    $\xi_{i,k} \leftarrow 0$ /*Initialize the user assignment indicators*/
  end for
  for $q = 1$ to $|G|$ **do**
    $\eta_{i,q} \leftarrow 0$ /*Initialize the group assignment indicators*/
  end for
end for
for $i = 1$ to $|G|$ **do**
  $\acute{M} \leftarrow \mathcal{M}$
  while $\acute{M} \neq \emptyset$ **do**
    $k^* = \arg\max_{\forall k \in \acute{M}} \{p^i_{d,k} | k \in \acute{M}\}$
    $\xi_{i,k^*} \leftarrow 1$ /*Assign user k^* to group g_i*/
    $\acute{M} \leftarrow \acute{M} \backslash \{k^*\}$ /*Remove user k^* from the set of all candidate users $\acute{M}$*/
    calculate $P_D(g_i)$ according to (23) for a given n'
    if $P_D(g_i) \geq P_{Dth}$ **then**
      calculate $\Delta(g_i)$
      break;
    end if
  end while
end for
while $G \neq \emptyset$ & $q \leq |G|$ **do**
  $\alpha \leftarrow$ sorted indices of $\Delta_{g_i}, \forall i \in V$ /*sort indices of the groups according to the descending order of the values of Δ */
  $\eta_{\alpha(1),q} = 1$ /*Assign the channel with highest value of the function Δ to sense in round q*/
  if $|G| > 1$ **then**
    for $i = 2$ to $|G|$ **do**
      $\sigma \leftarrow 0$
      for $j = 1$ to $i - 1$ **do**
        for $k = 1$ to K **do**
          $\sigma \leftarrow \sigma + (\xi_{\alpha(i),k} \cdot \xi_{\alpha(j),k})$
        end for
      end for
      if $\sigma = 0$ **then**
        $\eta_{i,q} = 1$
        $G \leftarrow G \backslash \{g_{\alpha(i)}\}$ /*Remove group g_i from the set of groups G*/
      end if
    end for
  end if
  $G \leftarrow G \backslash \{g_{\alpha(1)}\}$ /*Remove the first assigned group from the set of groups G*/
  $q \leftarrow q + 1$ /*Go to the next sensing round*/
end while

C. Complexity Analysis

The main motivation of the proposed suboptimal algorithms is their reduced computational complexity. The exhaustive search which enumerates all possible solutions has an exponential time complexity of $O(2^{(K|G|+|G|^2)})$ which is very high, where $O(.)$ is the big O notation. In this section, we quantify the time complexity of our heuristic algorithms. For Algorithm 1, namely CSBUA, we first sort the channels according to their rates, as shown in line 5, which requires time $(|G|\log(|G|))$. For each group, we need to sort the users according to their maximum probability of detection for this group which requires time $(K\log(K))$ in line 18. Since we will have to return to line 17 until the condition on the probability of detection of the group in line 22 is satisfied, therefore, the complexity of the internal while-loop in lines 17-28 is $(K\log(K)+K)$. In the first sensing round, $q=1$, the internal while-loop (lines 17-28) is repeated for $|G|$ groups. In each subsequent sensing round, this internal while-loop will be repeated for all the remaining unassigned groups. In the worst case, the complexity will be the sum of the finite series $[|G|(K\log(K)+K)+(|G|-1)(K\log(K)+K)+(|G|-2)(K\log(K)+K)+\ldots]$ which is equal to $(\frac{|G|}{2})(|G|+1)(K\log(K)+K)$. Therefore, the complexity of CSBUA algorithm is $O(|G|^2K\log(K))$.

Similarly, for Algorithm 2, namely BUACS, the complexity for the for-loop (lines 14-26) is $|G|(K\log(K)+K)$. In the first sensing round, $q=1$, the complexity of the internal while-loop in lines 28-42 is $(|G|\log(|G|)$ (channel indices sorting) $+K(|G|-1)(|G|-2)$ (three for-loops lines 30-41). Following the above analysis for Algorithm 1, the worst case complexity for the while-loop (lines 27-46) is $(\frac{|G|}{2})(|G|+1)\,((|G|\log(|G|)+K(|G|-1)(|G|-2)))$. Therefore, the complexity of BUACS algorithm is $O(|G|^4K)$. In most practical cases, the computational complexity of BUACS algorithm will be higher than that of CSBUA algorithm.

V. Performance Evaluation

In this section, we evaluate the performance of the proposed adaptive assignment algorithms. The length of the sensing period, T_s, is set to 1 ms and the length of frame, T, is 10 ms. The threshold on the probability of detection, P_{Dth}, is set to 0.9 and the probability that the primary user is absent P_I is set to 0.3. The probability of detection for each user and channel, $p_{d,i}^k$, is randomly generated from a uniform distribution between [0.5,1] and the number of samples $N=100$. For each $p_{d,i}^k$, the probability of false alarm $p_{f,i}^k$ is calculated according to (17). The channel bandwidth is 6 MHz, the number of transmission modes $M=5$ and the rate vector $\mathbf{R}=\{4.54, 6.05, 7.56, 9.08, 12.10\}$ Mb/s [35]. The results are obtained by averaging over 1000 simulation runs.

We compare the three proposed assignment algorithms, CSBUA, BUACS1 and BUACS2, with the non-adaptive grouping and sequential CSS schemes. In the non-adaptive grouping scheme, SUs are randomly assigned to sense the channels, not based on their probability of detection on each channel, and the channels are randomly sorted with no specific sorting order. In the sequential CSS scheme, all SUs sense the same channel in each sensing period with the aim of improving the sensing accuracy of the primary user's activity. Therefore, in sequential sensing, we assign all the users to each group, i.e., $\sum_{k=1}^{K}\xi_{i,k}=K\ \forall i$ and assign only one group to each sensing round.

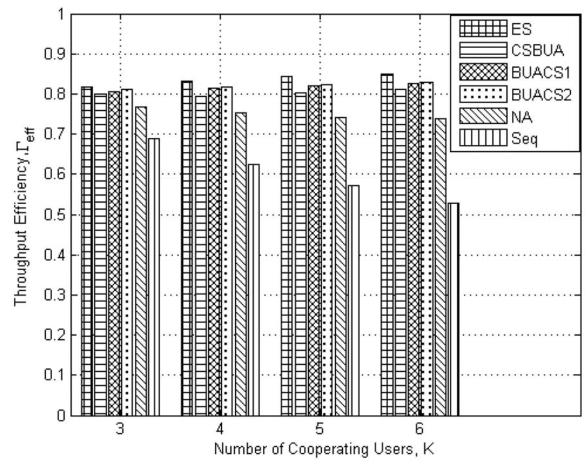

Fig. 2. Throughput efficiency versus number of cooperating users for $|G|=2$.

In Figure 2, we compare the throughput efficiency of CSBUA, BUACS1, BUACS2, non-adaptive grouping (NA) and sequential sensing (Seq) algorithms with the optimal solution obtained by the exhaustive search (ES) when $|G|=2, 3\le K\le 6$ and the OR rule is employed by the fusion center ($n'=1$ in (23)). The main drawback of the exhaustive search is that its complexity increases exponentially with the number of SUs, K, and number of groups, $|G|$. Due to this high time complexity, an exhaustive search could only be used in a domain where K and $|G|$ are small. We observe from the figure that the throughput efficiency of CSBUA, BUACS1 and BUACS2 algorithms are close to the optimal throughput efficiency obtained through exhaustive search with a relative difference bounded by 4.7%, 2.9% and 2.6%, respectively. On the other hand, the relative difference between the exhaustive search and the non-adaptive scheme is bounded by 13%. BUACS2 algorithm, that uses a sensing factor proportional to the throughput efficiency, gives better performance (closer to optimal value) for all the considered values of K compared to CSBUA and BUACS1 algorithms. However, BUACS2 algorithm has higher computational complexity compared to CSBUA algorithm as discussed in Section IV-C. We also observe from the figure that all the proposed assignment algorithms outperform both the non-adaptive grouping and sequential sensing algorithms for all the considered values of K.

Next, we investigate the impact of different counting rules on our proposed adaptive assignment algorithms. In Figure 3, we compare the average global probabilities of detection and false alarm for group i (averaged over 1000 simulation runs) when different number of users is assigned to the group for the OR and Majority Voting (MV) fusion rules. The global probabilities of false alarm and detection for group i are obtained from (15) and (16), respectively, where $n'=1$ for the OR rule and $n'=\lceil\frac{|K_i|}{2}\rceil$ for the MV rule with $|K_i|$ denoting the number of

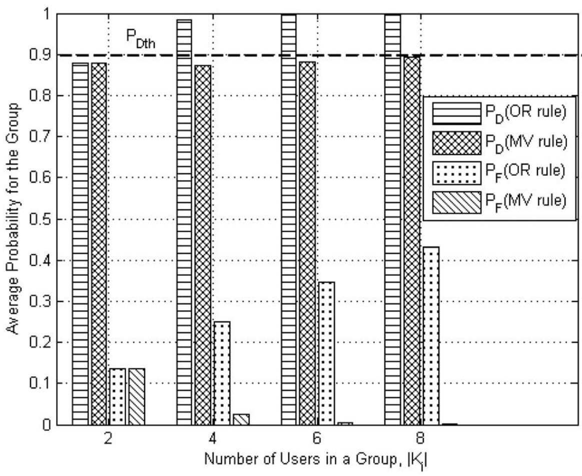

Fig. 3. Average probability of detection for group i versus the number of users assigned to group i for the OR and MV fusion rules.

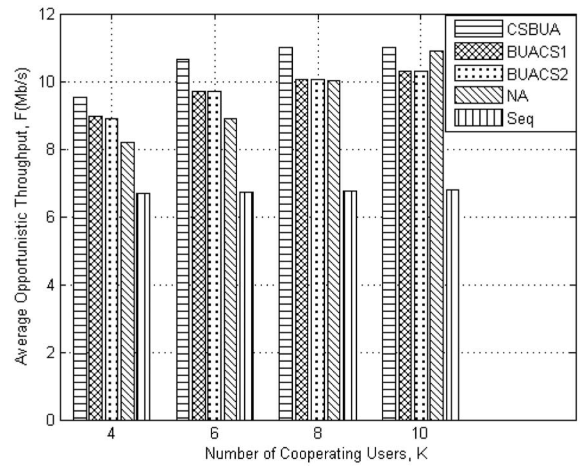

Fig. 5. Average opportunistic throughput versus number of cooperating users for $|G| = 4$.

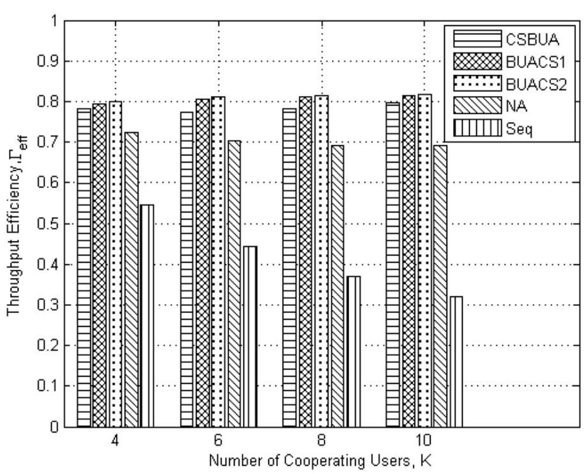

Fig. 4. Throughput efficiency versus number of cooperating users for $|G| = 4$.

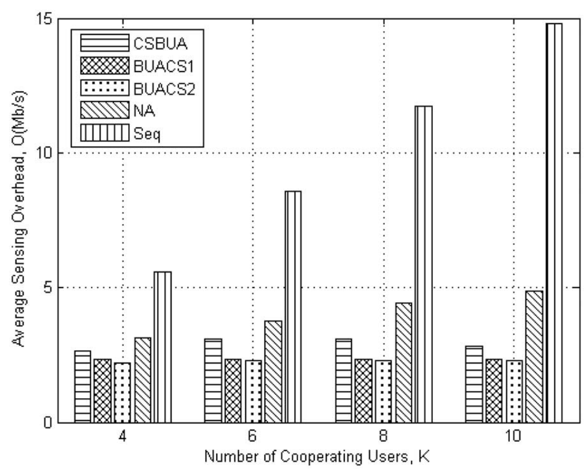

Fig. 6. Average sensing overhead versus number of cooperating users for $|G|$=4.

users in group i and $\lceil x \rceil$ is the smallest integer greater than x. Since CSBUA, BUACS1 and BUACS2 algorithms assign users to a group in descending order of their probability of detection on this group, we observe from the figure that, using the OR fusion rule, we can achieve higher probability of detection compared to the MV rule for the same number of users in a group on the expense of higher probability of false alarm. The figure also shows that in order to achieve the desired sensing accuracy, P_{Dth}, for the group using MV rule, we need to considerably increase the number of cooperating users in this group (provided sufficient number of users K are available for cooperation) compared to the OR rule ($|K_i| = 4$ for OR rule compared to $|K_i| > 8$ for MV rule) which will in turn result in more number of sensing rounds and higher average sensing overhead. Therefore, for the rest of this section, we consider that the fusion center uses the OR fusion rule to combine the decisions from the set of cooperating SUs in each group.

In Figure 4, we plot the throughput efficiency versus the number of cooperating users K with $|G|$=4 for the proposed assignment algorithms, non-adaptive grouping and sequential sensing schemes. We observe from the figure that BUACS2 algorithm consistently provides the best performance, in terms of throughput efficiency, among all considered algorithms. We also observe that the throughput efficiency for CSBUA, BUACS1 and BUACS2 algorithms increase as the number of users increases with respect to the number of groups (channels) since this provides more degrees of freedom in the user assignment, which results in better performance, in terms of the average opportunistic throughput and average sensing overhead, of the proposed algorithms compared to the non-adaptive and sequential schemes. For the sequential scheme, the throughput efficiency decreases as the number of users increases since the sequential scheme uses all the users to sense a single channel which largely increases the average sensing overhead and accordingly degrades the throughput efficiency. Since the throughput efficiency depends on both the average opportunistic throughput and average sensing overhead, we can see from the figure that the change in the throughput efficiency of the non-adaptive scheme as the number of users increases will depend on the change in the average opportunistic throughput compared to the change in the average sensing overhead.

Figures 5 and 6 show the average opportunistic throughput and average sensing overhead versus the number of cooperating

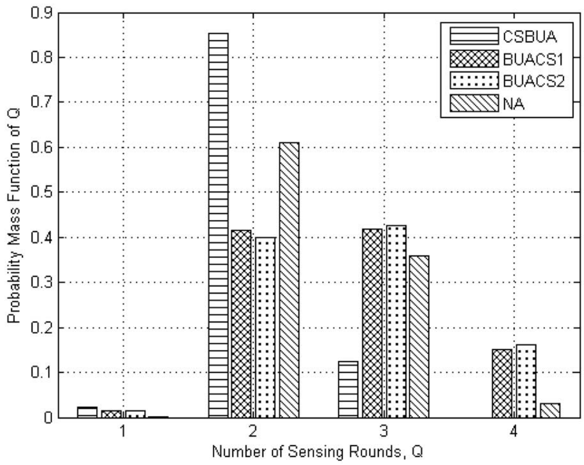

Fig. 7. Probability mass function of the number of sensing rounds for the proposed and non-adaptive schemes for $|G| = 4$ and $K = 4$.

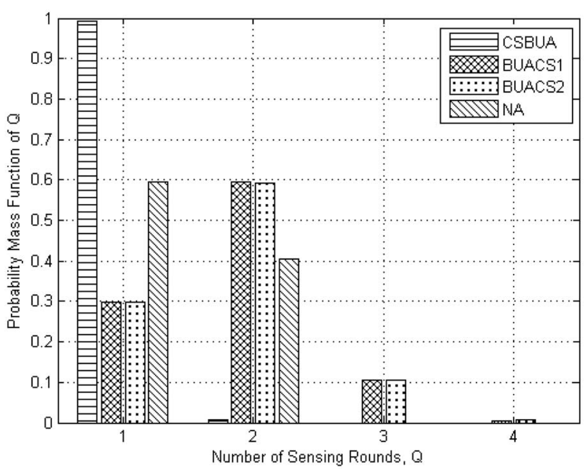

Fig. 8. Probability mass function of the number of sensing rounds for the proposed and non-adaptive schemes for $|G| = 4$ and $K = 8$.

users with $|G| = 4$, respectively. We observe that, for CSBUA, BUACS1 and BUACS2 algorithms, when the number of users compared to the number of channels is small ($K < 8$ in the considered case), the average opportunistic throughput and the average sensing overhead increase with the number of users. However, when $K \geq 8$, there is a slight increase in the average opportunistic throughput while the average sensing overhead starts to decrease as more users are available. The availability of more users allows for the best users (with higher probability of detection for the channels) to be chosen for cooperation. Therefore, on average, less number of rounds are needed to discover the available channel. For the non-adaptive grouping scheme, increasing the number of users increases the average opportunistic throughput. However, increasing the number of users will also increase the sensing overhead as the users are randomly assigned. Therefore, on average, more sensing rounds may be needed to discover the available channel as compared to the proposed assignment algorithms. We also notice that CSBUA algorithm provides the highest opportunistic throughput compared to the other considered algorithms since the algorithm tends to minimize the number of sensing

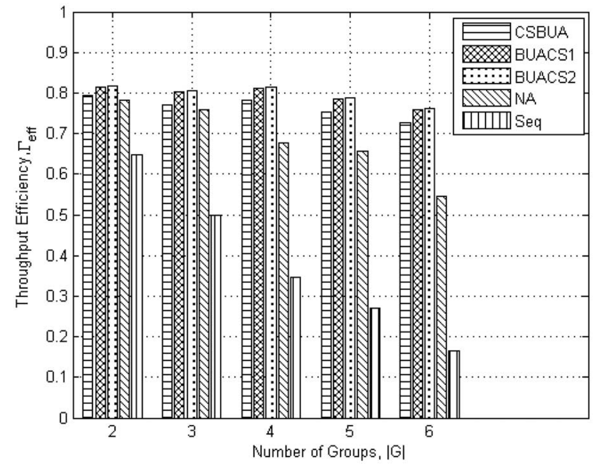

Fig. 9. Throughput efficiency versus number of groups for $K = 2|G|$.

rounds needed to sense the available channels as explained in Section IV-A. On the other hand, BUACS2 algorithm provides the lowest sensing overhead since the algorithm tends to minimize the number of users needed to achieve the desired sensing accuracy as explained in Section IV-B. To illustrate those facts, in Figures 7 and 8, we plot the probability mass function of the number of sensing rounds needed by each of the proposed assignment algorithms and the non-adaptive grouping algorithm for $K = 4$ and $K = 8$, respectively. We compare the average number of sensing rounds needed by each algorithm to sense the available channels and show the effect of changing the number of users K on the average number of sensing rounds for the different algorithms as explained above. For the sequential scheme, the number of sensing rounds is fixed and is equal to the number of available channels (groups).

Figure 9 shows the comparison of throughput efficiency for CSBUA, BUACS1, BUACS2, non-adaptive grouping and sequential sensing algorithms with different number of groups when fixing the number of users to twice the number of available groups. The comparison indicates that the proposed CSBUA, BUACS1 and BUACS2 algorithms are consistently able to achieve higher throughput efficiency compared to the non-adaptive grouping and sequential sensing schemes with BUACS2 algorithm providing the best performance among all the considered algorithms for all the considered cases of K and $|G|$. We also notice that, when the number of groups and users increase, the relative difference between the proposed assignment algorithms and the non-adaptive grouping scheme also increases. This is because by increasing the number of group and users, we have more degrees of freedom in assigning the users to the groups which is better exploited by the adaptive assignment algorithms. For $|G| = 6$ and $K = 12$, the relative difference between BUACS2 algorithm and the non-adaptive grouping scheme is approximately 28.5% compared to a relative difference of approximately 4.5% when $|G| = 2$ and $K = 4$. For $|G| = 6$ and $K = 12$, the relative difference between BUACS2 algorithm and the sequential sensing scheme is approximately 78%.

To evaluate the impact of the sensing duration, T_s, in Figure 10, we plot the throughput efficiency versus the number

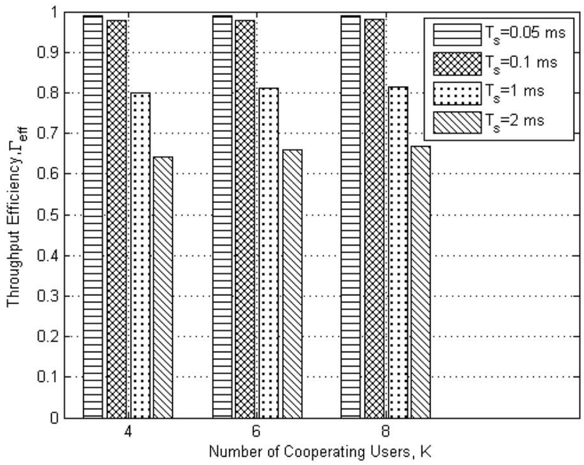

Fig. 10. Throughput efficiency for BUACS2 algorithm versus number of cooperating users with different T_s for $|G| = 4$.

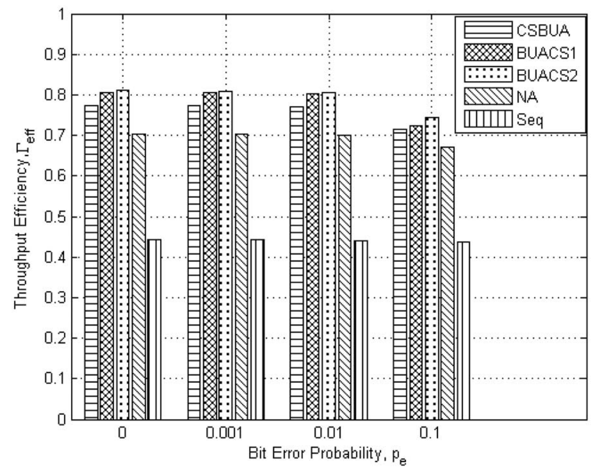

Fig. 11. Throughput efficiency versus probability of bit error for $|G| = 4$ and $K = 6$.

of cooperating users K for BUACS2 algorithm with different values of the sensing duration, T_s, when $|G| = 4$ (similar results are obtained for CSBUA and BUACS1 algorithms which are omitted due to space limitation). We can see from the figure that as the sensing duration increases, for fixed number of users, the throughput efficiency decreases which agrees with the analysis in Section III-B. Therefore, the maximum throughput efficiency will be obtained when T_s is set to the minimum sensing duration that satisfies the sensing accuracy constraint in (30).

Next, we evaluate the effect of imperfect reporting channel conditions on the performance of CSBUA, BUACS1, BUACS2, non-adaptive grouping and sequential sensing algorithms. To this end, in Figure 11, we compare the throughput efficiency of all considered schemes for different values of the probability of bit error p_e for $|G| = 4$ and $K = 6$. The figure shows that CSBUA, BUACS1 and BUACS2 algorithms outperform the non-adaptive and sequential algorithm, in terms of throughput efficiency, for all the considered values of p_e and that BUACS2 algorithm provides the best performance among all the considered algorithms. We also notice that as p_e increases, the throughput efficiency decreases for all the considered algorithms. This decrease in throughput efficiency is due to the increase in transmission errors which causes the global false alarm probability in (34) to increase. Therefore, the average opportunistic throughput for all the considered schemes will decrease while increasing the average sensing overhead.

VI. Discussion

A. Stopping Strategy

In this work, we considered that sensing will stop when an idle channel is found. If all the channels are sensed busy, SUs will need to wait for a short period of time then resume sensing till finding an idle channel to utilize. Using this stopping strategy, the proposed group-based CSS scheme may incur a large sensing overhead if the number of sensing rounds needed to find a vacant channel is large. In our proposed scheme, the sensing overhead depends on the number of sensing rounds used until a vacant channel is found which is in general less than the number of available channels to be sensed. For a certain number of available channels, the number of sensing rounds (sensing overhead) decreases as the number of cooperating users increases. Therefore, the sensing overhead maybe significantly large if and only if the number of cooperating users is small relative to the number of channels to be sensed and the probability of the channels being idle is low. To address this issue, another stopping strategy may be employed. For example, we can limit the number of sensing rounds used by the algorithm by placing an upper bound on the average sensing overhead. In the proposed algorithms, after each sensing round, we can calculate the expected sensing overhead (it depends on number and rates of SUs assigned to the this specific round and the probability of successfully finding an idle channel in this specific round), when the accumulated overhead over the previous rounds exceeds the upper bound, sensing is stopped and may be allowed to resume after a certain wait period.

B. Primary Transmitter Detection Model

While studying the performance of the proposed group-based cooperative scheme, it has been assumed that a spectrum access opportunity for secondary users exists when the primary transmitter is inactive. However, secondary users can still share the spectrum when the primary user is transmitting provided that the amount of interference generated at the primary receiver is not harmful. To protect the primary receiver, a guard area can be defined around each receiver where the secondary transmission is not permitted. The spectrum sensing problem can then be viewed as deciding whether or not the secondary transmitter is within the guard area. In the case where the secondary user can detect the primary user's transmitter but can still be allowed to transmit, the hypotheses may need to be modified in some reasonable way that accounts for those spatial spectrum opportunities. The probabilities of detection and false alarm will need to be computed using this modified formulation. The proposed user-group assignment algorithms in this work depend on the values of those probabilities and not on their specific distributions. This suggests that the proposed algorithms can still be applied to improve the group-based CSS performance. However, further performance analysis and evaluations need to be carried out in future work to assess this performance improvement.

VII. Conclusion

In CR networks, a key objective is to maximize the spectrum efficiency without degrading the sensing accuracy. In this paper, we considered an adaptive group-based CSS scheme where the secondary users have heterogeneous sensing abilities and derived a closed form expression for the throughput efficiency that takes into account both the average opportunistic throughput and the average sensing overhead. We formulated the throughput efficiency maximization problem subject to a predefined limit on the sensing accuracy as a non-linear 0-1 integer programming problem and proposed three efficient heuristic adaptive assignment algorithms, namely CSBUA, BUACS1 and BUACS2 algorithms, to solve the formulated problem. The proposed algorithms adaptively perform user-group and group-sensing round assignments with the aim of minimizing the number of sensing rounds and number of cooperating users needed to discover an available channel while satisfying a predefined sensing accuracy requirement and thus increasing the throughput efficiency. The proposed assignment algorithms have low computational complexity and their performance is within 2.6%–4.7% of that of the exhaustive search for $|G| = 2$ with BUACS2 algorithm providing the best performance and CSBUA algorithm providing the lowest computational complexity. The simulation results demonstrated that the proposed assignment algorithms can provide throughput efficiency improvement of up to 28.5% and 78% when compared to non-adaptive grouping and sequential sensing schemes, respectively, for $|G| = 6$ and $K = 12$. We examined the effect of several parameters such as the number of cooperating users and channels, sensing duration and imperfect reporting channel conditions on the proposed assignment algorithms. The proposed assignment algorithms were consistently able to outperform the non-adaptive grouping and sequential sensing schemes for the different parameters examined with the BUACS2 algorithm consistently providing superior performance compared to the other considered algorithms for all the considered cases.

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Lamiaa Khalid received the B.Sc. degree in electrical engineering from the Ain Shams University, Cairo, Egypt, and the M.Sc and Ph.D degrees in electrical engineering from the Ryerson University, Toronto, ON, Canada. Since 2014, she has been a Postdoctoral Researcher with the Ryerson University, working in the area of cognitive radio networks and spectrum sensing solutions. Her research interests include cognitive radio networks, cooperative spectrum sensing, energy harvesting, and optimization for wireless communication systems.

Alagan Anpalagan (S'98–M'01–SM'04) received the B.A.Sc., M.A.Sc., and Ph.D. degrees in electrical engineering from the University of Toronto, Toronto, ON, Canada. He joined with the ELCE Department, Ryerson University, Toronto, ON, Canada, in 2001, and was promoted to Full Professor in 2010. He served the Department as Graduate Program Director (2004–2009) and the Interim Electrical Engineering Program Director (2009–2010). During his sabbatical (2010–2011), he was a Visiting Professor at Asian Institute of Technology, Pathumthani, Thailand, and Visiting Researcher at Kyoto University, Kyoto, Japan. His industrial experience includes working for three years with Bell Mobility, Nortel Networks, and IBM. He directs a research group working on radio resource management (RRM) and radio access and networking (RAN) areas within the WINCORE Laboratory. He also completed a course on Project Management for Scientist and Engineers at the University of Oxford CPD Center, Oxford, U.K. He has coauthored three edited books: *Design and Deployment of Small Cell Networks* (Cambridge University Press, 2014), *Routing in Opportunistic Networks* (Springer, 2013), *Handbook on Green Information and Communication Systems* (Academic Press, 2012). His research interests include 5G wireless systems, energy harvesting and green communications technologies, cognitive radio resource management, wireless cross layer design and optimization, cooperative communication, M2M and sensor communication, small cell, and heterogeneous networks. He is a Registered Professional Engineer in the province of Ontario, Canada. He is a Fellow of the Institution of Engineering and Technology (FIET). He served as an Editor for the IEEE COMMUNICATIONS SURVEYS AND TUTORIALS (2012–2014), IEEE COMMUNICATIONS LETTERS (2010–2013), *Springer Wireless Personal Communications* (2011–2013), and *EURASIP Journal of Wireless Communications and Networking* (2004–2009). He also served as Guest Editor for three special issues: EURASIP SI in Radio Resource Management in 3G+ systems and SI in Fairness in Radio Resource Management for Wireless Networks, and MONET SI on Green Cognitive and Cooperative Communication and Networking. He served as TPC Co-Chair, IEEE Globecom'15: SAC Green Communication and Computing, IEEE WPMC'12 Wireless Networks, IEEE PIMRC'11 Cognitive Radio and Spectrum Management, IEEE IWCMC'11 Workshop on Cooperative and Cognitive Networks, and IEEE CCECE'04/08. He served as Vice Chair, IEEE SIG on Green and Sustainable Networking and Computing with Cognition and Cooperation (2015), IEEE Canada Central Area Chair (2012–2014), IEEE Toronto Section Chair (2006–2007), ComSoc Toronto Chapter Chair (2004–2005), and IEEE Canada Professional Activities Committee Chair (2009–2011). He was the recipient of the Dean's Teaching Award (2011), Faculty Scholastic, Research and Creativity Award (2010 and 2014), Faculty Service Award (2011 and 2013) from the Ryerson University. He was also the recipient of Exemplary Editor Award from IEEE ComSoc (2013) and Editor-in-Chief Top10 Choice Award in Transactions on Emerging Telecommunications Technology (2012).