Int. J. Nonlinear Anal. Appl. Volume 12, Special Issue, Winter and Spring 2021, 1639-1648 ISSN: 2008-6822 (electronic) http://dx.doi.org/10.22075/ijnaa.2021.5850



Machine learning based energy efficient multichannel resource allocation in cognitive radio networks

R. Vidhypriya^{a,}

^a PSG College of Technology, Peelamedu, Coimbatore 641004, India

(Communicated by Madjid Eshaghi Gordji)

Abstract

The growth of the Internet of Things and mobile devices highly rely on independent and distributed operation in wireless networks. A focus on the allocation of spectrum for effective communication, mitigation of interference and reduction in the energy consumption in the wireless environment is essential. Non-availability of the spectrum in a wireless network can be overcome by spectrum reuse in Cognitive Radio Femtocell networks (CRFN) which improves the indoor communication coverage. is mostly preferred. The spectrum is sensed at regular intervals by the secondary user (SU) to detect the presence of the primary user(PU). Sensing the spectrum reduces the performance and the throughput of the secondary users. To overcome the above in this research, a novel multichannel spectrum allocation (MSA) technique combined with a decode-and-forward (DF) based cooperative spectrum sensing scheme is proposed. The information rate that can be transmitted over a given bandwidth is greatly enhanced in the proposed multichannel resource allocation (MRA) technique It is evident from the simulation results, that the throughput of the SUs is boosted when compared over the established techniques.

Keywords: Terms–Cognitive radio femtocell network, Resource allocation, Cooperative spectrum sensing, Primary user, Licensed band, Secondary user allocation

1. Introduction

In real time wireless communication systems, the network is simultaneously used by multiple users and is in a shared state at any given point of time. The requirement of a bandwidth / spectrum for data transmission in a wireless network is achieved by dynamic allocation of resources [7]. With the advent of new devices, the number of users subscribing to the network increase from time to time, the

Received: August 2021 Accepted: Novamber 2021

Email address: rvp.bme@psgtech.ac.in (R. Vidhypriya)

need of radio spectrum is continuously in demand. Rather than increasing the number of macro cells, introducing femtocells in the traditional network will support in increasing the network capacity [4]. The unlicensed users defined as Secondary users (SU), operate in fallow licensed spectrum bands without interfering with the Primary / licensed Users (PU), by sharing the spectrum. Primary Users are given more priority to use the spectrum compared to that of the Secondary Users in such a shared network. The dynamic spectrum allocation approach enables the Cognitive Radio Femtocell Network to serve both the Primary and Secondary users. The secondary users have to continuously monitor the spectrum to identify the absence of any primary users so as to transmit the data to other secondary receivers. The DF approach is utilized to ensure that there is no interference to the PU [9].

The most important aspect of cognitive radio is spectrum sensing, which involves monitoring the frequency spectrum for empty bands. Spectrum sensing can be accomplished using a variety of methods, such as an energy detector or a matching filter. Only at larger signal to noise ratio (SNR) values can the energy detector function well, but the complexity of matched filters is very high. [12].

Due to these limits, the multichannel access technique was developed, which works better under low SNR conditions and has a lower complexity than the traditional algorithm. matched filter. Sensing throughput trade-off is experienced, with the enhancement in sensing reliability which causes a reduction in total throughput. Increase in throughput can be achieved by varying the sensing period interval [11]. In this research a cooperative cognitive radio environment is adopted as it provides higher spectrum sensing capacity and also to exploit the spatial diversity present in the wireless channel. The cooperative environment comprises of a centralized Fusion Centre (FC). The FC is synchronized with multiple secondary users, so as to enable the SUs to report the diagnosed sensing results to the FC at regular intervals [2]. FC identifies the presence of the PU based on the sensing data, and broadcasts this information to all the nodes.

Often, all SUs are required to sense the spectrum band and report the local sensing information to the FC during every slot period [5]. SUs spend a considerable amount of energy every time to sense the channel which decreases the performance and also the of total throughput of SUs is reduced. Thus it becomes imperative to consider the energy of the SUs. To warrant energy-saving for sensing operation as well as to improve the total throughput, a minimal number of SUs have to be identified and deployed.

In the proposed system, a multi-channel resource allocation scheme which enhances the total throughput of SUs and has better target detection performance is implemented. The enhancement in the total throughput of SUs is achieved based on the design of the time and energy spent in cooperative sensing. The energy required to operate the devices is more in wireless networks. As the blockage in the battery capacity still persists, optimization of battery power is another important concern that is addressed in this paper. The DF (decode and forward) methodology is utilized to reduce the interference, as interference is the major factor that reduces battery capacity of the devices.

This paper is organized as follows. In Section 2, presents a detailed overview of the related work, Section 3 elaborates on the system model. In Section 4 details the proposed work, with a brief discussion of the results in Section 5. And the conclusion is presented in Section 6.

2. Related work

The authors Rosouli et al [10] perform an improvement in throughput by optimizing sub-carrier pairing and power distribution. The concept of queueing was implemented at the SUs for the transmission of the data packets by the authors Wu and Min G [13]. Transmission of data using multiple paths with a path selection mechanism using DF method was implemented by Bhatnagar [3]. Ian F. Akyildiz, Brandon F. Lo, Ravikumar Balakrishnan [1] in their work presented a technique which detects the spectrum for data transmission efficiently and also safeguards the licensed users from harmful interference. The efficiency of detection is impaired with multipath fading, shadowing and receiver uncertainty issues. CSS has been found as an effective technique for mitigating the impact of these issues. While augmenting the detection performance, CSS can bring about a cooperation overhead. The overhead refers to any additional sensing time, delay, performance degradation. These overhead are the drawbacks in this system.Zhuo Li, Song Guo,DezeZeng, Ahmed Barnawi and Ivan Stojmenovic [8] proposed a joint resource allocation in multicell networks. A joint optimization across power control, channel allocation anduser association is considered. The optimization goal is to enhance the minimal throughput of cells. A simulated annealing based algorithm is used for solving user association and channel allocation problem. Branch and Bound algorithm is used for solving power control. The expected goal and efficiency has not been obtained.

Ghurumuruhan Ganesan and Ye Geoffrey Li [6] proposed a system with Cooperative Spectrum Sensing in Cognitive Radio Networks. This scheme utilizes the benefit of cooperation from the used spectrum sensing for obtaining improved detection time and increasing agility. The location of the primary transmitter is assumed in such a system. If the location of the primary transmitter is unknown, the benefit of cooperation cannot be utilized. This is the pitfall in such a system.

3. System model

A Cognitive Radio Femtocell network with a single PU node and multiple SU nodes are considered. The network is assumed to have a FC to identify whether the spectrum is in use by a PU or not. The nodes operate in half duplex mode with the DF scheme.

The SNR value is compared and if it found to be greater than the threshold value, the node is permitted to decode the received information.

The two dimensional CRFN with a PU is placed at the middle of F, denoted by k_c and N SUs are randomly located at $\{K_r \in F\}_{r=1}^N$. The complete frame design comprising of an initial sub-frame and M consecutive sub-frames for the sensing and broadcasting overhead [3] as represented in Fig. 1.

The network coherence time between PU and SUs is used to calculate the number of sub-frames M+1. At the initial sub-frame, the proposed joint RA approach is acknowledged. This is maintained for M sub-frames in a row. FC receives local sensing information from SUs in each sub-frame and makes an overall conclusion about the condition of the spectrum band, whether PU is present or not. SUs begin their own data transmissions to their secondary receivers, based on the ultimate decision of the SUs. vacancy by FC. The transmission of data by one SU is interfered by other SUs in such a system.

The discrete-time observation vector of the r-th SU is indicated by $x_r = [x_{r,1}, x_{r,2}, \ldots, x_{r,D}]$, where

$$\mathcal{H}_0: x_{r,n} = v_{r,n} \tag{1}$$

when the spectrum band is not presently being used by PU,

$$\mathcal{H}_1: x_{r,n} = g_r f_n + v_{r,n} \tag{2}$$

and when the spectrum band is presently being used by PU at the *n*-th time instant observation, and the positive integer D is the view size. Inequations (1) and (2), $v_{r,n}$ is denoted as an independent and identically distributed complex additive Gaussian noise with zero mean and variance $\sigma_v^2 g_r$ is denoted as a complex channel between PU and r-th SU and f_n is denoted as a transmitted complex signal of the PU. Assume that, each SU uses the energy detector, then the representation of the local test statistics of the r-th SU is given by

$$T(x_r) = \sum_{n=1}^{D} |x_{r,n}|^2$$
(3)

Assuming independent and identically distributed noise, $\chi^2(D)$ as the central chi-square distribution under \mathcal{H}_0 and $\chi^2(D, \eta_r)$ under \mathcal{H}_1 as the non-central chi-square distribution are followed by the local test statistics $T(x_r)$, where η_r is calculated as $b_0 ||k_c - k_r||^{-\alpha}$ with path gain at the unit distance b_0 and path-loss exponent α . The complex channel g_r is formed as an independent but not identically distributed channelin which SUs may experience a type of path loss or fading situations. Rayleigh fading with probability density function is represented as

$$f_{gr}(t) = \frac{t}{\eta_r} e^{-\frac{t^2}{2\eta_r}}, t \ge 0$$
(4)

Representing the general test statistic produced at FC byT(Z), where $Z = [z_1, z_2, \ldots, z_D]$ and the pre-determined decision threshold by λ , the spectrum sensing with detection performance is generally calculated by two indices: detection probability P_d and false alarm probability P_f are defined as follows

$$P_d = P_r\{T(Z) > \lambda | \mathcal{H}_1\} \text{ and}$$

$$P_f = P_r\{T(Z) > \lambda | \mathcal{H}_0\}$$
(5)

respectively. The upper bound of the spectral efficiency is determined as P_f , where minimum spectrum utilization is resulted by P_f .

The transmission of data for secondary networks is mentioned as per equation (5). Let the time spent when NSUs and FC sense the spectrum band cooperatively, be denoted by $D/f_s + N\tau_r$ and length of one sub-frame duration by T, where f_s represents samplingfrequency and τ_r represents reporting time for a SU. Then, the time taken fordata transmission of each SU becomes $T - D/f_s - N\tau_r$. Since P_d takes near to 1 while P_f near to 0 and the totalthroughput of SUs under \mathcal{H}_1 is very small, the total throughput of SUs can be estimated as:

$$E \approx P_{\mathcal{H}_0}(1 - P_f) \left(1 - \frac{D}{f_s^T} - \frac{N\tau_r}{T} \right) C_0 \tag{6}$$

where the probability that the spectrum is vacant is represented as $P_{\mathcal{H}_0}$ and C_0 represents the total throughput of SUs under \mathcal{H}_0 .

From equation 6, a maximization problem to enhance the totalthroughput of SUs over M subframes, without initial sub-frame, is represented as

$$max \left(1 - P_f\right) \left(1 - \frac{D}{f_s^T} - \frac{N\tau_r}{T}\right) C_0 \tag{7}$$

This is subjected to

$$P_d \ge \bar{P}_d \tag{8}$$

where P_d is target detection probability provided in CRFN and by using the same power of P, the power transmitted by each is assumed for each sub-frame. Then, C_0 is given by

$$\sum_{m=1}^{N} \log\left(1 + P|g_{m,m}|^2 / \left(\sigma_n^2 + \sum_{i=1,\neq m}^{N} P|g_{i,m}|^2\right)\right)$$
(9)

with the complex channel $g_{i,m}$ between *i*-th SU and *m*-th secondary receiver and noise variance σ_n^2 .

4. Proposed methodology

If a SU reduces the view size to have more transmission time for data, it results in a reduction in false alarm performance. This leads to a decrease in the total throughput of SUs as described in equation 7. From the works of Liang et. al., [12], the sensing time allocation (STA) scheme which determines the optimal view size of each SU for spectrum sensing, is calculated in reverse to the measured number of SUs used for sensing. From an energy saving point of view, the SU consumes a little amount of energy during acquisition of the PU's signal and broadcasting the local sensing information to the FC. Since the transmitting power of SU has been limited to be low value, the total throughput is considerably affected by the utilized energy. For optimizing the energy utilized for spectrum sensing, the broadcasting secondary user allocation (SUA) scheme as referred in [13] is opted. The proposed scheme decides the optimal number of SUs and the view size used for sensing in order to maximize the throughput performance. The goal of the system is to concurrently find the number of SUs, L out of N, involved in sensing and the view size, K, to maximize the network throughput satisfying target detection probability.

4.1. Problem methodology with RCOS based CSS

FC selects L broadcasting SUs using the local sensing information of all SUs at the initial subframe. Each SU accumulates K observations. The remaining (N - L)SUs awaits the global sensing decision from the FC to schedule their transmission of data. Here, the L sized set of SUs which help to CSS is indicated by S and their transmission power would be $P - \zeta$, where ζ indicates the power using for broadcasting. Using the joint RA strategy, the maximization problem can be formulated as

$$max_{K,L,S} (1 - P_f) \left(1 - \frac{K}{f_s^T} - \frac{\tau_r L}{T} \right) C_0\{L\}$$
(10)

where

$$C_{0}\{L\} = \sum_{r \in S} \log \left(1 + \frac{(P - \zeta)|g_{r,r}|^{2}}{\sigma_{n}^{2} + \sum_{i \in S \setminus r} (P - \zeta)|g_{i,r}|^{2} + \sum_{i \notin S \setminus r} P|g_{i,r}|^{2}} \right) + \sum_{r \in S} \log \left(1 + \frac{P|g_{r,r}|^{2}}{\sigma_{n}^{2} + \sum_{i \in S} (P - \zeta)|g_{i,r}|^{2} + \sum_{i \notin S \setminus r} P|g_{i,r}|^{2}} \right)$$
(11)

In the Fusion Center it is necessary to use the ample CSS scheme, which leads to save more resources than joint RA strategy with randomly selecting L reporting SUs. This will reduce the inconvenience by satisfying the target detection performance in equation 10. From the case that the larger local test statistics would have shown from the signal passed through a favorable network with a high probability, the RCOS based CSS scheme is adopted which selects the L broadcasting SUs with large local test statistics. The probability distribution function and cumulative distribution function of the local test statistics of the r-th SU under \mathcal{H}_1 are written as

$$f_r(z;K) = \int_0^\infty \psi\{z;K,t\} f_{\eta_r}\{t\} dt \ and$$
(12)

$$f_m(z;K) = \int_0^\infty \psi\{z;K,t\} f_{\eta_r}\{t\} dt$$
(13)

The ordering operation on the Nlocal sensing information $\{T\{X_r\}\}_{r=1}^N$ creates the order statistics $\{Tb_r\{X_{b_r}\}\}_{r=1}^N$, where $Tb_r\{X_{b_r}\}$ is the *r*-th order statistics in *X*. The global test statistics based on RCOS is created by directly combining with equal weights as $T_{RCOS} = \sum_{r=N-L+1}^N Tb_r\{X_{b_r}\}$. Then, the detection probability in 4 can be obtained as

$$P_{d} = 1 - \oint_{A} f_{T_{bL}}(z_{L}) dz$$

= $1 - \int_{0}^{\lambda} \frac{\lambda}{L} \cdots \int_{z_{N-1}}^{\lambda - \sum_{r=N-L+1}^{N-1} z_{r}} f_{T_{bL}}(z_{L}) dz_{N} \dots dz_{N-L+1}$

where $A = \{z_L : z_{N-L+1} + \cdots + z_N < \lambda, 0 < z_{N-L+1} < \cdots < z_N\}$ is denoted as integral region and the joint probability distribution function of $\{Tb_r\}_{r=N-L+1}^N$ is

$$f_{T_{bL}}(z_L) = \frac{N!}{(N-L)!} \left\{ \prod_{r=N-L+1}^{N} f_n(z_r;k) \right\} \left\{ \prod_{r=N-L+2}^{N} \times M_r(z_r;k) - M_{r-1}(z_{r-1};k) \right\} M_{N-L+1}(z_{N-L+1};K)$$
(15)

By substituting equation 15 in equation 14, the detection probability is mathematically obtained and the detection probability is declared using the function p_d as $P_d = p_d(K, L, \lambda)$.

4.2. Maximization problem with constraint relaxation

Based on the case that the results of the problem in equation 10, would be optimal and sustains equality in equation 8, as shown in [12], the problem in equation 10, can be represented only in terms of the variables K and L. Likewise, by replacing $f_{N-L+1}(.) = \cdots = f_N(.) = \varphi\{.\}$ and $M_{N-l+1}(.) =$ $\cdots = M_N(.) = \phi\{\cdot\}$ with pdf $\varphi\{z; K\}$ and cdf $\phi\{z; K\}$ of local test statistics $\chi^2\{N\}$ [1] in equation 15, conclusively. The false alarm probability P_f of RCOS based CSS in equation 10, can be obtained as

$$\stackrel{P_f}{=} 1 - \oint_A \frac{M!}{(M-L)!} \left\{ \prod_{r=N-L+1}^N \phi\{z_i; K\} \right\} \left\{ \prod_{r=N-L+2}^N \times \phi_r(z_j; k) - \phi\{z_{j-1}; k\} \right\} \phi\{z_{N-L+1}; K\}$$
(16)

Since the threshold λ is set to $p_d^{-1}\{K, L, \bar{P}_d\}$, P_f derived in equation 15, can be expressed as

$$P_f = p_{f_a}\{(K, L, p_d^{-1})(K, L, \bar{p}_d)\}$$
(17)

by introducing a function p_{f_a} . Here, the set of $\{K, L, \lambda\}$ satisfying $P_d = \bar{P}_d$ can be mathematically expressed. Finally, the maximization problem in equation 10, is rewritten as

$$max\left(1 - p_{f_a}\left((K, L, p_d^{-1})(K, L, \bar{p}_d)\right)\right) \left(1 - \frac{K}{f_s^T} - \frac{\tau_r L}{T}\right) C_0 L$$
(18)

The optimal solution set K^* , L^* is determined using the exhaustive search method, where K is an integer number and L is also an integer number constrained to the interval [1, N]. The best view size and number of SUs employed for CSS that improves the overall throughput of SUs while satisfying the target detection probability are determined by computing the reformulated issue in equation 18.

Note 1: When the overhead burden, and _r, are very minimal, the joint RA approach logically shows the same throughput as STA in equation (18). However, when f s grows, the joint RA strategy's throughput approaches that of SUA. In terms of the use of sensing-overhead resources, the proposed joint RA strategy makes a general statement from the existing RA schemes.

Note 2: The combined RA problem employing the RCOS based CSS improves the throughput performance as shown in Section V because the RCOS based CSS indicates local sensing information from more trustworthy SUs.

5. Performance analysis

This section compares the performance of suggested joint RA tactics to established RA strategies, such as STA and SUA. The performance is assessed in bit/s/Hz total throughput of SUs with different sampling rates. frequencies f_s , reporting times τ_r and power used ζ . Consider two dimensional CRFN with $\alpha = 2$ and target detection probability \overline{P}_d is set to 0.9. Assume that a sub- T is the frame period, and $P(\mathcal{H}_0)$ is the chance that the band is empty. The noise variance is 1, and the charged power P at each SU is set to 0 dB for each sub-frame. When $_r = 0.1 ms_s = 23$ dB, and M = 10, the throughput performance of STA, SUA, proposed joint RA with RS, and joint RA with RCOS is plotted as a function of the average received SNR from PU with varied f s in Fig. 2. SUA is sensitive tof s, i.e. for lowf s, whereas the STA scheme has less of an influence on the change off s.

Instead of using all of the SUs, the proposed technique makes proper use of the L number of SUs for sensing. The SUA and the proposed scheme are sensitive to changes in or rthan the STA. When and _rare are virtually zero, the throughput performance of the proposed joint RA and STA methods will be equal. CSS will consume less time and energy as a result of this. The proposed combined RA scheme's throughput will be similar to that of SUA during highf s, as noted in Note 1. In low received SNR, the joint RA strategy with RCOS reduces the amount of resources used for CSS. The improvement in joint RA performance with RCOS is depicted in Fig. 2.

The proposed approach maximises throughput performance, according to simulation results. In addition, Fig 3 depicts the throughput performance of the proposed joint RA scheme with RS and RCOS based on the number of sub-frames F + 1. Let $f_s = 2$ MHz, r = 0.1 ms, and = 23dB be the values. The joint RA plan with RS and RCOS makes utilisation of the reduced amount of resources by jointly scheming the time and energy for high average obtained SNR from PU. An initial sub-frame is used in the cooperative RA strategy with RCOS to monitor all of Sus' local test statistics. As a result, as the channel coherence time decreases, the throughput performance decreases. This results in a smaller M+1. The joint RA strategy with RCOS shows a significant performance maximization as the average received SNR from PU becomes low on account of the characteristic of RCOS based CSS as referred in Note 2. The joint RA strategy with RCOS or RS is chosen with appropriate channel coherence time and the average received SNR from PU. The proposed RA strategies is found to yield enhanced throughput performance than STA and SUA of which performance is considerably affected by f_s, τ_r, ζ .

6. Conclusion

The analysis is used to generalise the traditional RA techniques for CRFN in [12] and [13] that meet the target detection performance. The proposed joint RA strategy was designed to reduce the amount of time and energy spent on spectrum sensing, and its performance was compared to that of existing strategies. However, taking account of the practical i.n.i.d. channel model, the RCOS based CSS scheme which gives the criteria for selecting the set of broadcasting SUs. The ideal allocation approach was mathematically determined using the exhaustive search method. The simulation results reveal that the proposed combined RA scheme outperforms the existing RA schemes in terms of spectrum efficiency. When a substantial amount of reporting time and energy is required, or when a low sample frequency is used, the performance improvement becomes extremely significant. Initial Subframe {M consecutive subframes}



Figure 1: The complete frame structure of CRFN



Figure 2: Comparison of joint RA with RCOS, joint RA with RS, SUA and STA



Figure 3: Comparison of joint RA with RCOS and joint RA with RS

References

- I.F. Akyildiz, B.F. Lo and R. Balakrishnan, Cooperative spectrum sensing in cognitive radio networks: A survey, Phys. Commun. 4(1) (2011) 40–62.
- S. Atapattu, C. Tellambura and H. Jiang, Energy detection based cooperative spectrum sensing in cognitive radio networks, IEEE Trans. Wireless Commun. 10(4) (2011) 1232–1241.
- [3] M.R. Bhatnagar, Performance analysis of a path selection scheme in multi-hop decode-and-forward protocol, IEEE Commun. Lett. 16(12) (2012) 1980–1983.
- [4] V. Chandrasekhar, J. Andrews and A. Gatherer, *Femtocell networks: A survey*, Commun. Mag. IEEE. 46(9) (2008) 59–67.
- [5] W. Ejaz, G. Hattab, N. Cherif, M. Ibnkahla, F. Abdelkefi and M. Siala, Cooperative spectrum sensing with heterogeneous devices: Hard combining versus soft combining, IEEE Syst. J. 12 (2018) 981–992.
- [6] G. Ganesan and Y. Li, Cooperative spectrum sensing in cognitive radio networks, IEEE Trans. Wireless Commun. 6(6) (2007) 2204–2222.
- [7] X. Huang, S Liu, Y. Li, F. Zhu and Q. Chen, Dynamic cell selection and resource allocation in cognitive small cell networks, 2016 IEEE 27th Annual Int. Symp. Personal, Indoor, and Mobile Radio Commun. (2016) 1–6.
- [8] Zh. Li, S. Guo, D. Zeng, A. Barnawi and I. Stojmenovic, Joint resource allocation for Max-min Throughput in multi-cell networks, IEEE Trans. Vehicular Technol. 23(9) (2014) 4546–4559.
- S. Lee, K. Huang and R. Zhang, Cognitive energy harvesting and transmission from a network perspective, Proc. IEEE Int. Conf. Commun. Syst. (2012) 225–229.
- [10] H. Rasouli, H.Y. Kong and A. Anpalagan, Cooperative subcarrier allocation and power allocation in the downlink of an amplify-and-Forward OFDM relaying system, Wireless Pers. Commun. 79(3) (2014) 2271–2290.
- [11] A. Stovar and Z. Chang, Optimisation of cooperative spectrum sensing via optimal power allocation in cognitive radio networks, IET Commun. 11 (2017) 2116–2124.
- [12] Y.F. Wen and W. Liao, Spectrum section preallocation for cooperative sensing and transmission in cognitive radio ad hoc networks, IEEE Trans. Veh. Technol. 66 (2017) 8910–8925.
- [13] Y. Wu, G. Min A.Y. Al-Dubai, A new analytical model for multi-hop cognitive radio networks, IEEE Trans. Wirel. Commun. 11(5) (2012) 1643–1648.