A spectrum sensing approaches in cognitive radio network by using cloud computing environment

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ABSTRACT
A spectrum agreement has failed to meet the demands of new applications due to the fixed spectrum allocation (FSA) concept. But current efforts are targeted towards the utilization of cognitive radio as a way of addressing the issue of resources deficiency. The number of radio spectrum users keeps increasing daily owing to the advancement in technology in all aspects of life; even the licensed band users are currently demanding for extension of their radio spectrum and to balance the congestion in radio spectrum, some users may have to be placed on other bands. This article focused on voids detection (via spectrum sensing) in radio spectrum and secondary user assignment in cloud computing. Spectrum sensing was approached in two ways in this study-underlay and interweave spectrum allocation. Both approaches are evaluated using certain performance metrics, such as throughput enhancement and queuing time minimization.

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1. INTRODUCTION
Radio spectrum utilization is currently on the increase due to the impact of digital communication on our daily lives. Hence, efforts are being made towards ensuring efficient spectrum utilization as it is a great challenge facing communication experts. The concept of cognitive radio was developed to ensure optimum spectrum utilization; it relies on the dynamic use of spectrum without any form of interference. The available frequency on the electromagnetic spectrum (EMS) ranges from 2.5 Hz-3.5 GHz, meaning that radio spectrum is an aspect of the EMS. Telecommunication relies on electromagnetic signals that are commonly known as radio wave in this field; such signals can be propagated using different physical mediums. The regulation of the usage of this spectrum is responsibility of organizations, such as the international communication union (ITU); this regulation is to ensure no interference(s) between different users at a time. Furthermore, there could be local regulations enforced by different local authorities in each region to ensure proper utilization of radio spectrum [1]-[4]. About 50 communication service channels have been established by ITU as given by [5]; however, some radio channels can be leased to some operators to enable them to use a particular channel (they are called the licensed users). Similarly, broadcasting and TV bands are allotted in the same manner to the licensed users (called the working bands). Hence, cellular application relies on the cellular spectrum while TV broadcasting make use of television spectrum.

Radio spectrum has recently been congested due to the increasing demand for radio resources by the users [6]-[10] and the limited available radio resources. This has called for the optimal utilization of the
available radio resources. Various techniques are currently ben proposed to address these challenges; some of these techniques include frequency pooling, spread spectrum, spectrum reuse, & cognitive radio. This requires the involvement of two major players: the licensed user (those that have been allotted a fixed band for uninterrupted transmission) and the unlicensed user (those that needed access to a licensed band belonging to other networks before transmitting their content). A licensed band is also defined as the range of radio spectrum currently used by the licensed users. The concept of cognitive radio allows unlicensed users to share radio resource with the licensed users without any harmful effect on either side [11]-[15]. This paper considered a cognitive radio network (CRN) as a way of optimizing the average throughput of the secondary spectrum candidates by using cloud computing environment.

2. IEEE 802.22

The IEEE 802.22 standard developed WRAN to support digital TV broadcasting, especially in small regions where the number of users is limited [16]. The first CRN was simulated on this protocol owing to its capability of reusing the white spectrum in small areas with low interference [17]. The CRN technology has been detailed in previous studies where it was referred to as “wireless regional area networks” that facilitates sharing of spectrum between licensed users (LUs) & unlicensed users (UUs) without any interference to the LUs. But this standard only supports small power applications, such as TV broadcasting (digital and analogue) and wireless microphone. This standard was later published by IEEE late in the year 2011 [18]-[21]. The development of IEEE 802.22.1 and IEEE 802.22 WG was aimed at reducing the interference of low power apps and to improve the previous standard in a manner that allows some WLAN apps to participate in this technology. At first, IEEE 802.22 began with point-to-multiple-point communication (P2MP) [22] which is mainly applicable to digital TV network and formed by the installation of “premises attached equipment” (PAE) that is directly connected to the network base station using wires. The role of the BSS is the formation of the network traffic and initiation of spectrum management. WRAN-based digital TV broadcasting with CR capabilities works by relying on PAE for gathering channel status information status (also called spectrum sensing); the sensed information is channelled to the BSS for onward decisions on user mobility & channel allocations [23]. Note that user assignment to a new channel is done by the BS in a cauterized manner; however, the user must be within the coverage range of the network to participate in this facility. The users are only allowed to sense the spectrum and forward the sensed data to the higher layer [24]-[27].

3. SPECTRUM UTILIZATION

The aim of the CRN is to facilitate sharing of spectrum between licensed and unlicensed users without any harmful effect on both sides. As per previous studies, spectrum sensing is an important aspect of the cognitive cycle [28]-[30] because the unlicensed users have to first sense the channel periodically to identify vacancies. Radio spectrum is partitioned into smaller bands for different applications; such applications are referred to as the licensed users and are licensed to make use of those bands allocated to them at any time to broadcast their content freely; however, they must ensure there is no harm on their neighborhood. Being that CRN aims at ensuring the availability of the licensed spectrum bands to unlicensed users at the time with the licensed users (especially when the LUs are idle), CRN must always know the condition of the channels before assigning any UU to the vacant band to ensure no interference with the LUs [31],[32]. Spectrum sensing provides the needed channel information to the higher CRN layer; such channel information may be in the form of full channel with LUs or vacant channel. In other word, the channel may be prone to “Additive White Gaussian Noise” and fading effects; the undesired channel participants may be listed as AWGN, fading. [33]-[35]. These channel disturbances can negatively affect the performance of the channel when existing in the radio bands. Spectrum sensing may also detect when a channel is currently being used by a licensed user or not such that the following hypothesis can be satisfied:

**H0: Procedure may produce this result if the channel is vacant, else, only noise components are present.**

\[
H_0 = n(t)
\]  

(1)

Otherwise, H1 hypothesis will be satisfied which states that the channel is being demanded by a licensed user, so, hypothesis may return both noise and signal detection components as:

\[
H_1 = n(t) + S(t)
\]  

(2)

Where n(t) is the noise component, s(t) is the signal from the licensed user indicating its presence on the radio band. This information is important to avoid interference between the licensed and unlicensed users.

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Energy detection is one of the available ways of investigating radio spectrum as it relies on the power spectrum density (PSD) of the channel that contains all the frequency components. The PSD output can be forwarded to the decision-making circuit for the validation of the status of the channel in terms of vacancy or the presence of noise components. So, the results will likely become H₀, else, H₁ may be satisfied. The mathematical expression of the outcome of this paradigm is as:

\[ H_x[l] = \sum_{l=\pm\infty} X[l] \cdot H[n - 1] \]  

This phase focused on three perspectives: the working bandwidth, the number of required LUs, and the simulation time. Here, bandwidth is equally partitioned among the LUs to arrive at the following assumption: \((\text{PU-BW} = \text{total BW} / \text{total PUs})\) \([36]-[39]\). The focus on the simulation time is to study the random behaviors of the licensed user in terms of band occupancy; later, a program will be used to compute the frequency of each licensed user, followed by the preparation of the frequency modulation that will be forwarded to all the users in the radio spectrum. Figure 1 shows DFT of noisy transmitted signal. The outcome of this phase is the provision of frequency bands as a public variable in vector form for usage in the subsequent procedures. The transmitted signal was prepared for a bandwidth of 800 Hz, 8 LUs, and 80 secs of simulation time; the program is expected to produce F-bands=[100 200 300 400 500 600 700 800]. The addition of AWGN to the above set is to ensure the realization of the ground network constraints.

4. **BEHAVIORS MODELLING**

The licensed users are known to occupy the channel 100% all time; however, the proposed approach infers that some licensed users will vacate the channel at any time to return after some time. Hence, the unlicensed user can take over the available channel for a time (Tw) and may reoccupy the same channel after Tw second. Therefore, these factors are considered uncontrolled random variables. The license band can be used by each user for Tw and exit after the stipulated time; note that Tw is never the same for any two users except there are other criteria. Based on the time constraint, the program can initiate a matrix known as behaviors matrix which contains the binary information regarding the availability of channels per time slot during the simulation period. The user behaviors modelling process is depicted in Figure 2.
4.1. Cognitive users modeling

This step begins with the determination of the number of cognitive users, followed by feeding a double of the number of licensed users as cognitive users. The FSS regulations provides that a white band can only be used by cognitive users if and only if the band is vacant. Hence, a new matrix that corresponds to the activity of the unlicensed user may be established based on the behaviors of the licensed user. The activity matrix is determined as the inverse of the behavior matrix as shown in Figure 3.

5. RESULTS AND DISCUSSION

Having continuously sensed the available bands, the network may be tested on the manner of assigning unlicensed users to the white band. For every number of unlicensed users, the availability of spectrum is a function of the activities of the licensed users. Hence, the unlicensed users can only share the portion of the white band permitted by the base station of the licensed user. The constrains that may be considered in this phase of the system include throughput and time delay. Time delay results from the mobility of the users and the number of candidates interested in the band. The unlicensed user must wait to be allowed to participate in the band; if there are few candidates that want to share the band, the unlicensed users may have chance to use the band briefly. Two techniques were proposed in this paradigm for spectrum sharing between the licensed and unlicensed users; these are underlay spectrum sharing and interweave spectrum sharing.
The outcome of this process are the throughput and the transmission delay; Transmission delay is the time used by each unlicensed user during the functional time before reaching its transmission turn. On the other hand, throughput is the number of unlicensed users that successfully delivered to the destination after certain numbers of iteration. Being that network is functional, the licensed users are normally being activated; so, their behavior and activity are constantly been monitored by the unlicensed users who are waiting to exploit any free band/spectrum. Transmission delay is noted for each user while throughput is monitored per iteration. The results of the processes are computed and checked for trade-off between the examined techniques in terms of throughput and time.

5.1. Queuing time monitoring

The sharing of the white band by the licensed and unlicensed users depend on the spectrum sharing techniques that governs the process. Underlay spectrum sharing (USS) requires that the licensed and unlicensed users are simultaneously transmitting but the activity of the unlicensed users is restricted to a certain level to keep off interference with the licensed users (this can lead to the unlicensed users forming queues). As shown in Figure 4, whenever two users are sharing the same licensed slot, it is expected that one of the users will start transmitting first before the other; this means that the second user must wait for the first user to vacate the channel.

The interweave spectrum sharing (ISS) technique is shown in Figure 5; this technique allows transmission only when the band has been vacated. This technique reduces the number of unlicensed users waiting to share the band, thereby eliminating the possibility of queues. The users must sense the spectrum periodically to exploit its free periods before the return of the licensed user. Hence, the transmission rate is higher while the transmission delay is lower under the ISS technique.
5.2. Throughput

Considering 18 unlicensed users, ISS permits that they simultaneously transmit with the licensed users but must not interfere with the activities of the licensed users; so, there may be time delay before the transmission though throughput is improved. This means that the actual number of users sharing the band is more than the total available unlicensed users. The throughput for each iteration (8 iterations of 10 secs each) and 18 unlicensed users is shown in Figure 6. The ISS techniques achieved lesser throughput than USS for similar traffic patterns as seen in Figure 7.

![Throughput counted for cognitive users (underlay) sharing](image1)

Figure 6. Throughput of the cognitive network when underlaying spectrum technique is used

![Throughput counted for cognitive users (interwave) sharing](image2)

Figure 7. Throughput of the ISS technique in CRN

6. CONCLUSION

Cognitive users participate in the white band via either simultaneous transmission with the licensed users or by waiting for a channel to be vacated. The behavior of the licensed users during active transmission is monitored by the unlicensed users to detect spectrum occupancy status. The activity of licensed users is simulated as random variables owing to their uncertain behaviors with respect to time. Spectrum sensing can be interrupted by issues like fading effects and channel noise, leading to spectrum gaps appearing busy due to such incidents. In this study, CRN was modelled in Matlab; both licensed and unlicensed users can sense the channel using energy detection method; they can also share the channel using the waiting time estimator approach which provides the activity and behavior matrixes. The simulation allows the participants to share the spectrum, followed by determination of the throughput and transmission delay when using either USS or...
ISS. The use of the time estimator algorithm reduced the latency and computation cost to ensure a balance between transmission delay and throughput.

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