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Convergence of mobile broadband and broadcast services: A cognitive radio sensing and sharing perspective

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Abstract: With next generation networks driving the confluence of multi-media, broadband, and broadcast services, Cognitive Radio (CR) networks are positioned as a preferred paradigm to address spectrum capacity challenges. CRs address these issues through dynamic spectrum access. However, the main challenges faced by the CR pertain to achieving spectrum efficiency. As a result, spectrum efficiency improvement models based on spectrum sensing and sharing models have attracted a lot of research attention in recent years, including CR learning models, network densification architectures, and massive Multiple Input Multiple Output (MIMO), and beamforming techniques. This paper provides a survey of recent CR spectrum efficiency improvement models and techniques, developed to support ultra-reliable low latency communications that are resilient to surges in traffic and competition for spectrum. These models and techniques, broadly speaking, enable a wide range of functionality ranging from enhanced mobile broadband to large scale Internet of Things (IoT) type communications. In addition and given the strong correlation between the typical size of a spectrum block and the achievable data rate, the models studied in this paper are applicable in ultra-high frequency band. This study therefore provides a good review of CRs and direction for future investigations into newly identified 5G research areas, applicable in industry and in academia.

Key words: cognitive radio; distributed networks; spectrum sensing and sharing; next generation networks

1 Introduction

The current trend towards Next Generation Networks (NGNs) seeks to provide a multitude of services, including telecommunication services, utilising broadband networks as well as Quality of Service (QoS) enabled transport services. In this way, end-users can be provided with high data rates, which satisfy their QoS requirements, at a lower cost of technology, thereby increasing user access to technology[1]. To achieve this, NGNs aim to integrate the spheres of wireless and fixed networks, namely, the traditional Public Switched Telephone Network (PSTN), terrestrial (broadcast) network, internet (including broadband) network, and the wireless network to form what is commonly referred to as 5G networks. NGNs separate service functions, control functions, and the underlying transport related technologies as a way to make it easier to maintain networks, and also adapt the service offering to the local environment[2].

Within the sphere of wireless networks, NGNs seek to enable the seamless integration of Radio Access Technologies (such as the Global System for Mobile communications (GSM), the Universal Mobile Telecommunications System (UMTS), and Long-Term Evolution (LTE)), Wi-Fi, and WiMAX. This is essentially an integration of the six 3GPP technologies with non-3GPP technologies (e.g., the IEE802.xx technologies)[2]. This integration has received a lot of research focus in recent years because (1) as observed in Ref. [3], wireless communication technologies enable the growth of several economic sectors in the world

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today and (2) the flexibility, convenience, and mobility capabilities offered by wireless networks make them driver for the adoption of technology across the globe including in low and middle income countries[4]. In fact, access to wireless networks is critical as the world increases its adoption of spectrum dependent technologies, such as machine-to-machine, Internet-of-Things (IoT), and internet-of-everything. This is evident in the increased number of devices with embedded communication capabilities, the exponential increase in internet addresses since the advent of the IP v6 protocol as well as the increased availability of cloud-based storage space and computing power. However, as widely reported in literature, the exclusive use of spectrum licensing model (commonly referred to as the static spectrum allocation model) hinders the adoption of spectrum-dependent technologies and results in the under-utilisation of spectrum (i.e., low spectrum efficiency) as access to spectrum is restricted to the licensed users[5,6].

To remedy this situation, the notion of Dynamic Spectrum Access (DSA) was developed. DSA enables non-licensed users to gain opportunistic access to licensed spectrum channels when such channels are not in use and vacate the same channels when the licensed user(s) resumes activities on the channels. This concept is considered a key enabler of NGNs as it enables multiple, dense, and distributed networks to co-exist harmoniously in the same frequency environment. In this way, the spectrum efficiency is increased. However, the realisation of this concept is dependent on the User Equipment's (UE's) ability to accurately and independently detect and utilise available spectrum channels in a way that enables the UE to maximise its own transmission requirements. The Cognitive Radio (CR) has been developed for such use[6,7].

The CR is the successor of the Software Defined Radio (SDR). The main difference between the SDR and the CR is that the SDR has a software defined physical (PHY) layer and is thus programmed to take specific actions, based on various triggers, whereas the CR is an intelligent communication system, comprising of transceiver-receiver pairs that are able to observe the operating environment, reason, decide, act, and learn from the radio environment[6,7] in order to improve the overall efficiency of radio communications. The primary objective of developing the CR is to enable licensed spectrum to be shared between licensed users and non-licensed users. This objective is similar to that of ultra-wide-band technology, however, the key difference between these two technologies is that the CR has cognitive abilities that enable it to reconfigure itself in order to opportunistically gain access to licensed spectrum, whereas the ultra-wide-band technology is an inflexible transmission technique restricted to low power and short range transmissions.

The CR periodically and independently observes the environment in which it operates, reasons rationally, learns from observations made, takes appropriate decisions regarding the transmission parameters required for successful transmission, and acts in accordance with the decisions made. It does this following the cognitive cycle depicted by Fig. 1[6].

The CR observes its environment in order to build its understanding of its environment and thereafter decides on appropriate action to take, in response to the observations made. This process is commonly referred to the CR's cognitive cycle and it comprises of the CR's cognitive tasks, namely, environmental awareness, re-configurability, and learning from experience[7]. Through these tasks, the CR is able to adjust a wide range of operating parameters (e.g., power control, frequency band selection, routing plan, duration of time slot, modulation and coding scheme selection, frame size, and interference control), and learn from the results of the decisions made. It is therefore through the cognitive cycle that the CR is able to maximise its current and

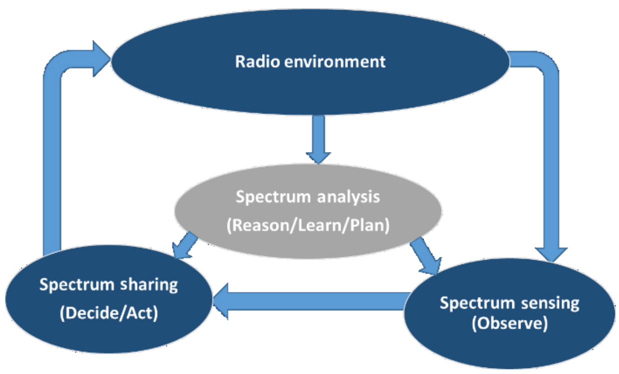

Fig. 1 Basic cognitive cycle[6].

future spectrum utilisation performance.

The contributions made in this paper are as follows:

• Review of the cognitive radio, its capabilities, and objectives.

• Review of narrowband and wideband sensing categories, techniques, and limitations.

• Review of spectrum sharing objectives, techniques, and challenges.

• Review of spatial spectrum reuse strategies and their application in CR networks.

• Review of joint sensing and sharing techniques and their challenges.

• Discussion of how joint sensing and sharing improve spectrum efficiency and challenges related to that.

• Discussion of future research opportunities in the field of spectrum efficiency improvement.

The remainder of the paper is organised such that in Section 2, narrowband and wideband spectrum sensing is discussed. Sections 3 and 4 explain spectrum sharing techniques and spatial spectrum reuse strategies, respectively. This is followed by Section 5 which discusses joint sensing and sharing approaches, advantages, and challenges. Section 6 provides an overview of open research directions while Section 7 concludes the paper.

2 Spectrum sensing

A challenge faced by CRs is how to balance conflicting goals, such as obtaining accurate sensing results and maximising throughput over available bandwidth, maximising throughput and minimising interference, or in broad terms, optimising the spectrum sensing and spectrum sharing processes[8]. These goals are summarised in Fig. 2[6–8]. They also provide the broad make-up of the spectrum sensing and sharing processes.

From the Shannon capacity theorem, it can be seen that the CR goals listed above impact the spectrum efficiency of a CR. That is, when these goals are optimised, then the CR is able to reach its channel capacity limit. The channel capacity is determined using Eq. (1) expressed below.

$$C = aB\log_2(1+\gamma) \tag{1}$$

where C is the channel capacity, a is the number of transmit antennae, B represents bandwidth (Hz), and γ represents SINR.

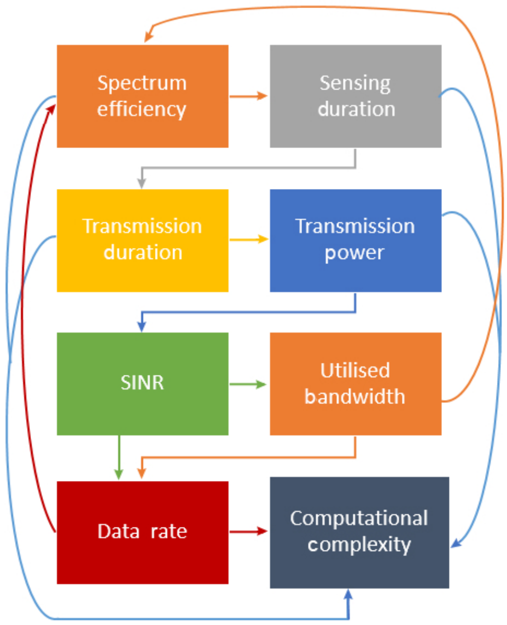

Fig. 2 Examples of CR goals that affect each other[6–8], where SINR represents the signal to interference noise ratio.

As such, spectrum efficiency is achieved when the decisions and actions taken by the CR succeed in preventing data packet collisions and enabling scalable data transmission. This is done through CR spectrum sensing and sharing techniques.

A CR's ability to improve spectrum efficiency hinges primarily on the effectiveness of its spectrum sensing techniques and thus the accuracy of its spectrum sensing results. In distributed non-cooperative CR networks, each CR relies on the accuracy of its individual spectrum sensing results to decide on the occupancy status of channels sensed. In doing this, the CR is required to address the following challenges:

(1) Consistently characterise the activity on a channel;

(2) Reliably identify spectrum opportunities that are best suited to satisfy the CR's data transmission requirements; and

(3) Minimise the amount of time spent sensing spectrum, in order to allow more time for data transmission.

This indicates that the CR must optimise its spectrum sensing techniques with due consideration of its environment and the presence of other CRs.

In literature, spectrum sensing techniques are categorised into two categories, namely, wideband and narrowband sensing. Narrowband sensing is applied when only one channel is analyzed at a time. Wideband sensing is applied when multiple frequencies are analyzed simultaneously. According to Ref. [9], a wideband signal can be categorized as a signal that has fractional bandwidth greater than 0.01, but smaller than 0.25. Narrowband sensing approaches have been widely studied and applied[8, 10–12]. These are discussed next.

2.1 Narrowband spectrum sensing

The narrowband spectrum sensing process is initiated when the CR collects sensing samples (statistical data) and performs spectrum sensing techniques over the collected samples to determine the channel availability status. The CR formulates this channel occupancy problem, in the frequency domain, as a binary hypothesis test wherein the signal received by the CR receiver on the sub-channel is given as follows: let x be a vector of length L as shown in Eq. (2):

$$x(t)=\begin{cases} n_0(t), & \text{if } H_0, \text{PU absent;} \\ Gy(t)+n_0(t), & \text{if } H_1, \text{PU present} \end{cases} \tag{2}$$

for $t = 1, 2, \ldots, L$. Here $x(t)$ is the samples of the signal received by the CR-receiver during time interval t, G is the Rayleigh channel gain, $y(t)$ is the samples of the signal transmitted by the PU using a randomly selected signaling strategy, and $n_0(t)$ is the noise sample which comprises of various types of noise (e.g., thermal noise, cross-band signal leakage, and interference noise), received at random from independent sources. These noise samples are considered to be Additive White Gaussian Noise (AWGN) samples that are symmetric, independent and identically distributed (i.i.d). This indicates that the values that the noise samples analyzed can take are Gaussian-distributed, have the same probability distribution, and are all mutually independent of each other.

The most common narrowband spectrum sensing techniques are the PHY-layer techniques, namely, the matched filter, the cyclo-stationary feature detection, the co-variance detection, and the Energy Detection technique. These techniques are discussed in more detail in the next section.

2.1.1 Spectrum sensing techniques

The matched filter method determines the presence of a PU on the spectrum by correlating a template of the PU's signal with the detected signal in order to determine if the detected signal is indeed the PU's signal. The cyclo-stationary feature detection method utilises the inherent cyclo-stationary features of a detected signal (e.g., periodic statistics and the spectral correlation of the modulated signals detected) to determine if the signal detected belongs to a PU or not[8]. The co-variance detection technique uses a sample co-variance matrix of the received signal and the Singular Value Decomposition (SVD) method to obtain the eigenvalues used to determine the channel occupancy status[10]. The Energy Detection method measures the energy (power) of a detected signal against a pre-set sensing decision threshold, τ, and if the energy of a detected signal is greater than the sensing decision threshold, τ, then it is said that there is an active user on the spectrum. The Energy Detector is, however, unable to detect spread spectrum signals or signals generated by PUs that use frequency hopping.

Machine learning techniques can be coupled with the other PHY-layer sensing techniques as a means of enhancing the performance of the sensing techniques and/or optimising the sensing parameters such as sensing duration and sensing detection threshold. In addition, machine learning techniques can be used to determine the order in which channels are to be sensed, the channels that the CR is most likely to be able to utilise successfully, and also predict the channels that are likely to attract the most competitors by predicting the channels that are most likely to offer the CR the highest channel capacity[1]. A successful application of machine learning results in the CR having learnt from its channel sensing and access experience with respect to its spectrum sensing tasks and applicable performance measure, if its spectrum sensing performance, as measured by the applicable performance measure, improves with the experience[13]. We focus on the Energy Detection technique for the remainder of this study because of its popularity, ease of use, and because it does not require apriori information about the PU.

To decide on the applicable channel occupancy hypothesis, H_0 or H_1, the CR applies the Energy Detection method which uses the energy estimation decision test, provided by Eq. (3). The H_0 decision indicates that the CR believes the channel is vacant, while the H_1 decision indicates that the CR believes the channel is occupied. That is

$$\lambda = \frac{1}{L}\sum_{t=1}^{L}|x(t)|^2 = \begin{cases} H_0, & \text{if } \lambda < \tau; \\ H_1, & \text{if } \lambda \geqslant \tau \end{cases} \tag{3}$$

The performance of the Energy Detector is evaluated using three main performance metrics, namely, the probability of false alarm denoted as P_{FA}, expressed as Eq. (4), the probability of misdetection, denoted as P_{MD}, expressed as Eq. (5), and the probability of detection, denoted as P_D, expressed as Eq. (6). The probability of false alarm, P_{FA}, indicates the probability of spectrum opportunities being missed by the CR. The probability of misdetection, P_{MD}, indicates the probability of occupied spectrum being used by the CR and thus causing undue interference to the licensed user/PU. The probability of detection, P_D, indicates the probability of a CR accurately detecting the presence of a PU on the identified spectrum.

$$P_{\mathrm{FA}} = P\,\{\text{decision} = H_1|H_0\} = P\,\{\tau > \lambda|H_0\} \tag{4}$$

$$P_{\mathrm{MD}} = P\,\{\text{decison} = H_0|H_1\} = P\,\{\tau < \lambda|H_1\} \tag{5}$$

$$P_D = P\,\{\text{decision} = H_1|H_1\} = P\,\{\tau > \lambda|H_1\} \tag{6}$$

In order to achieve consistently accurate (i.e., perfect) sensing results, perfect knowledge of the noise samples is required. This phenomenon is known as perfect sensing. However, in practice, this phenomenon is infeasible, because n_0 changes with time and as the location of the CR-receiver changes[14]. This change in n_0 is caused by the change in the noise power/variance, denoted as σ_v^2. As indicated in Ref. [14], various studies have proposed models to determine the distribution of n_0, with the most commonly applied model being that n_0 follows the distribution $n_0 \sim \mathcal{N}(0, \sigma_v^2)$. However, it is shown in Ref. [15] that there is always some residual uncertainties at most r dB, in estimating σ_v^2 because σ_v^2 changes in unsystematically. It is further shown that the residual uncertainty, r, can be approximated provided the CR-receiver can filter noise processes to a class of nominal noise distributions. From this, it can be shown that the noise variance of any Gaussian signal follows a distribution of $\sigma^2 \in \left(\frac{\sigma_v^2}{\alpha}, \alpha\sigma_v^2\right)$, where $\alpha = 10^{\frac{r}{10}} > 1$ represents the noise uncertainty factor. Quantifying the noise uncertainty factor enables the CR to reconfigure itself in a way that enables it to achieve its signal detection performance target. From this, it has been proven that there exists a certain Signal to Noise Ratio (SNR) threshold, which, if exceeded, causes at least one of the Energy Detector performance metrics (P_{FA}, P_{MD}) to become worse than 0.5, as depicted in Fig. 3. When this situation occurs then the Energy Detector is said to have failed due to a lack of robustness in the detector[16].

The SNR threshold phenomenon is discussed further in the next section.

2.1.2 Imperfect spectrum sensing

Spectrum sensing conducted in the presence of noise uncertainty is commonly referred to as imperfect sensing as it is expected that the CR may produce sensing results that contain errors. The performance of the CR in relation to spectrum sensing using the Energy Detector, in the presence of noise uncertainty, is measured by P_{FA}, expressed as

$$P_{\mathrm{FA}} = Q\left(\frac{\tau - \alpha\sigma_v^2}{\alpha\sigma_v^2\sqrt{\frac{2}{L}}}\right) \tag{7}$$

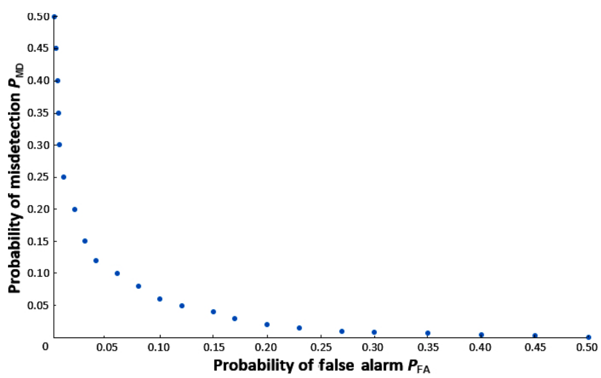

Fig. 3 Performance probabilities of the energy detector under noise uncertainty[16].

where $Q(\cdot)$ is the standard Gaussian complementary Cumulative Distribution Function (CDF).

From literature, it is noted that there exists an SNR wall below which the Energy Detector loses robustness and is unable to provide reliable sensing results despite an increase in the sensing duration. This threshold is commonly referred to as the SNR wall expressed by Eq. (8)[14–16]:

$$\text{SNR}_{\text{Wall}} = \frac{\alpha^2 - 1}{\alpha} \tag{8}$$

It is further noted that an increase in the noise uncertainty factor, α, increases the P_{FA}, and also increases the likelihood that the CR will encounter the SNR wall[14–16], this is illustrated by Fig. 4.

This is because an increase in the P_{FA} and in the SNR wall results in a decline of the CR's sensing performance. As such, if the P_{FA} increases such that $P_{\text{FA}} > 0.5$ then the CR should not conduct spectrum sensing in order to preserve its limited energy and avoid making channel access decision based on erroneous sensing results. Similarly, the CR should not conduct spectrum sensing if the SNR wall is higher than the SNR of the CR as the CR will fail to provide accurate sensing results despite an increase in the sensing time[16]. Therefore Eq. (9) must hold in order for the CR to obtain sensing results, in line with its P_{FA}.

$$\text{SNR} = \frac{\text{Signal}_{\text{power}}}{\text{Noise}_{\text{power}}} \geqslant \text{SNR}_{\text{Wall}} \tag{9}$$

Various studies that studied the SNR wall phenomenon have developed methods to approximate the noise, n_0, based on the distribution of the noise variance, σ_v^2, and introduced bounds on the noise uncertainty factor in order to enable the CR to avoid the SNR wall and thus yield reliable sensing results.

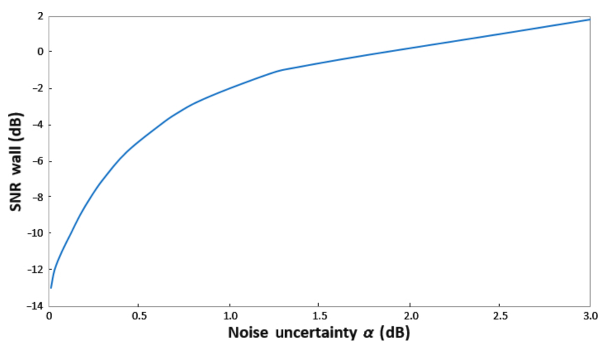

Fig. 4 Position of SNR threshold under noise uncertainty[16].

Examples of such studies include Refs. [17–20]. The main challenge with these methods is that they rely on the availability of the noise power and/or the noise variance distribution applied. Investigations to improve the residual noise uncertainty, r, are thus required in order to improve the approximation of the noise uncertainty factor and thus increase the reliability of the sensing results.

An alternative approach to identify the SNR wall and thus enable the CR to avoid the SNR wall entails the analysis of the sensing detection Threshold to the Noise variance Ratio (TNR). More specifically, if we assume that the sensing detection threshold is set to a suitable level and the noise variance distribution observed provides an acceptable approximation of the noise variance, then P_{FA} can be expressed as

$$P_{\text{FA}} = Q\left(\frac{\text{TNR} - \alpha}{\alpha\sqrt{\dfrac{2}{\text{Ts}}}}\right) \tag{10}$$

Furthermore, the utility that each CR aims to maximise through its sensing functions can therefore be expressed as

$$\text{Utility} = \left(1 - \frac{\text{Ts}}{N}\right)(1 - P_{\text{FA}}) \tag{11}$$

where Ts represents the number of times the CR senses the radio environment, and N represents the maximum number of times, in a single timeslot, that the CR can sense the radio environment in search of a vacant channel. The highest utility that a CR can achieve is represented by $U_{\max}$. The CR follows Algorithm 1 to optimise its spectrum sensing task and thus derive the optimal number of times it should try to find a spectrum opportunity, Ts*, based on the associated α^* and TNR*.

The outcome of Algorithm 1 provides an illustration of the effects that the TNR, α, and Ts have on the utility derived. Each colour line in Fig. 5 depicts a sensing exertion. From Fig. 5, we notice that the sensing exertions can be classified into 3 isolated imperfect sensing cases, namely,

Case 1: Optimal utility is reached within a relatively small number of sensing exertions.

Case 2: Utility is not optimized and therefore a large number of sensing exertions are required to increase the utility.

Algorithm 1 Spectrum sensing optimisation algorithm

Set the vectors $r = [0.001, 0.1, 1]$, $\mathrm{Ts} = [1 : 50]$, and $\mathrm{TNR} = [0.1 : 0.5 : 3.1]$
Set $U_{\max} = 0$, $N = 1000$, and $\alpha = 10^{\frac{r}{10}}$
 for $i = 1 :$ length(α)
  for $j = 1 :$ length(TNR)
   for $k = 1 :$ length(Ts)
    find $P_{\mathrm{FA}}^{*}(\mathrm{Ts}(k), \mathrm{TNR}(j), \alpha(i))$ using Eq. (10)
    if Utility$(\mathrm{Ts}(k), \mathrm{TNR}(j), \alpha(i)) > U_{\max}$
     $U_{\max} = $ Utility$(\mathrm{Ts}(k), \mathrm{TNR}(j), \alpha(i))$;
     $\mathrm{Ts}^{*} = \mathrm{Ts}(k)$;
     $\mathrm{TNR}^{*} = \mathrm{TNR}(j)$;
     $\alpha^{*} = \alpha(i)$
    end
   end
  end
end

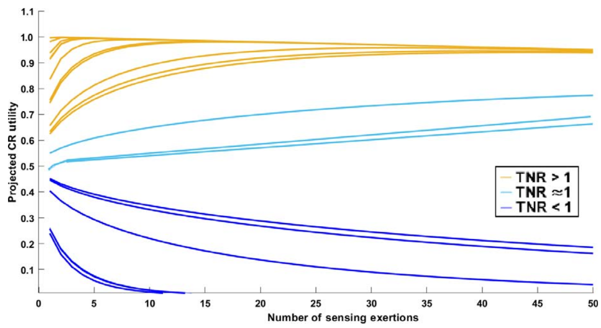

Fig. 5 Impact of sensing exertions on utility in the presence of noise uncertainty.

Case 3: The utility does not increase, despite the increase in the sensing exertions. This case depicts the same characteristics as the SNR wall.

It is further found that Case 1 occurs when TNR $>$ 1, Case 2 occurs when TNR $\approx$ 1, and Case 3 occurs when TNR $<$ 1 as depicted by Figs. 6 and 7. Case 1 is therefore depicted as the yellow region, Case 2 is depicted as the light blue region, and Case 3 is depicted as the dark blue region in Figs. 6 and 7.

Furthermore, it is observed that the impact of TNR on the utility is not directly dependent on α. This is because thesensing detection threshold, τ, is determined and set in view of the noise variance and its associated α. Thus a change in α will alter τ and the TNR. In this way, the CR is able to use the TNR alone to determine if it should immediately conduct spectrum sensing (Case 1), optimise its sensing task (Case 2) before beginning to sense, or opt to not conduct any sensing activities at all (Case 3) thereby reserving its energy instead.

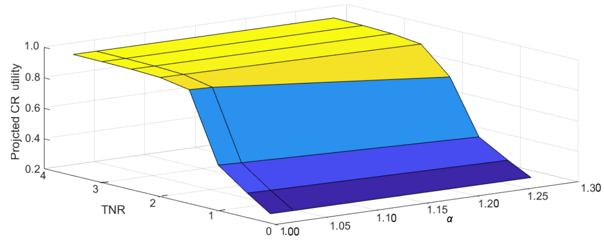

Fig. 6 Impact of TNR on the CR's utility.

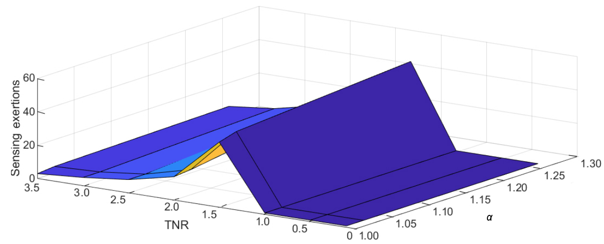

Fig. 7 Impact of TNR on the sensing exertions required.

2.1.3 Classification of spectrum sensing techniques

Narrowband spectrum sensing approaches can be classified based on their architecture (i.e., centralised or decentralised), behaviour (i.e., cooperative or non-cooperative), and/or access technique (i.e., overlay, underlay, or interweave)[18–20].

Decentralised architectures enable the formation of ad hoc networks when users require access to spectrum. They also enable the CR to take decisions independently, using their individual transmission requirements and the information observed from the operating radio environment. It is expected that there will be an increase in decentralised networks as the adoption of smart homes and smart cities increases. Non-cooperative approaches are approaches that do not require information sharing between nodes in order for the CR to decide on an action to take and thus be fit from a longer data transmission timeslot than cooperative approaches.

Cooperative approaches facilitate information sharing between CRs in a network, thereby improving the quality of the decisions made by CRs. These approaches, although effective in optimising the time required for sensing and also addressing the hidden user problem when it occurs, inherently require an allocation of time for such cooperation and data fusion techniques to process the data and reach a common view of the observed environment. The time allocated for cooperation is fixed and synchronised across all CRs, thereby causing possible inefficient use of time and a shorter data transmission timeslot. It is expected that the value derived from cooperative approaches, in cases where all the CRs sense the same set of channels and share their sensing results, will diminish as the adoption of small cell networks increases.

Interweave approaches enable the CR to use licensed spectrum when the PU is not using the spectrum, and also to configure its transmission power in a way that maximises the spectrum efficiency and addresses the transmission requirements of the CR. In such approaches, the CR is required to utilise the spectrum only when the PU is not using the spectrum and therefore does not have to adhere to an interference constraint to protect the PU from undue interference, instead it considers only the inter-cell interference constraints.

In contrast, the underlay and overlay approaches enable the CR to access licensed spectrum that is not fully utilised by the PU. However, the CR must ensure adherence to the interference constraints. In practice, it is difficult for CR networks to determine the interference thresholds required to ensure the PU does not experience harmful interference unless if the PU and CR know of each other and information sharing is enabled between them. Although many researchers have contributed to the development of practical interference constraints and interference temperature limits, this problem remains an open research problem.

Narrowband sensing approaches developed for distributed, non-cooperative, interweave-based CR networks offer the advantages of reduced traffic overhead in the network, eradication of the risk of the sink node/fusion centre being unavailable due to technical failure, and possible full access to idle spectrum.

2.2 Wideband spectrum sensing

As shown in Ref. [21], wideband spectrum sensing approaches can be categorised into three categories, based on the characterisation of the wideband. These categories are (1) approaches that consider the wideband spectrum as a set of sub-bands each having a fixed and known width, (2) approaches that consider the wideband spectrum as a set of sub-channels of an unknown fixed width; these approaches aim to estimate the partitions of the sub-bands and the associated power density level within the sub-bands, and (3) approaches that consider the wideband spectrum as a set of sub-bands each having a fixed and unknown width; these approaches aim to estimate the partition of each sub-band, but do not consider the power density level of the sub-bands. Examples of wideband sensing approaches used to characterise the spectrum band include Nyquist-based wideband sensing and compressive wideband sensing[22]. Once the spectrum band has been characterised, the sub-channels are then sensed by means of the narrowband sensing approaches discussed above[9].

In addition to the PHY-layer sensing process discussed above, the CR is also required to decide on various spectrum sensing parameters including the spectrum sensing detection threshold, sensing frequency, sensing duration, and channel sequence that the CR should follow when conducting spectrum sensing. These parameters are determined in the MAC-layer and therefore referred to as the MAC-layer sensing process[23].

A common assumption made in a CR network is that the time slots of all the PUs and CRs are synchronised and actions are taken at the beginning of a timeslot (e.g., sense/transmit). This means that all CRs would sense at the same time, so activity identified on a channel during the sensing timeslot is attributed to an active PU. This assumption may fail in practice as it is challenging for ad hoc distributed networks to (1) obtain the PU's timeslot information and (2) identify a CR in the network to whom all other CR's timeslots should be synchronised. Another assumption made is that the CRs have equal access to a common control channel which is always available to enable collision-free transmission, for the purposes of information sharing and collaboration, amongst the CRs. Further investigations are required in order to improve the practicality of these assumptions.

Once a CR has identified an idle channel, suitable for use, it then needs to reconfigure itself in a way that enables it to make the best use of the identified spectrum opportunity. This process is known as the sharing process and ranges from optimising the CR's transmission power and modulation scheme, to optimising its SINR. The spectrum efficiency of a CR is determined once this process has been completed. CR spectrum sharing techniques are discussed in the next section.

3 Spectrum sharing

In literature, Orthogonal Frequency Division Multiplexing (OFDM) is a widely applied spectrum access technique in distributed, non-cooperative, and interweave-based CR networks[23–25]. As such, the review of spectrum sharing techniques provided in this paper is based on OFDM. These techniques aim to optimise the spectrum efficiency of the n-th CR, E_n, using the objective function expressed as Eq. (12) below:

$$E_n = \begin{cases} \left(1-\frac{T_s}{T}\right)(1-P_{\mathrm{FA}})\sum_{k=1}^{K} P(H_0)B\log_2(1+\gamma), \\ \text{Channel is sensed available,} \quad \text{if } O_k = 1; \\ \text{Channels sensed unavailable,} \quad \text{if } O_k = 0 \end{cases} \tag{12}$$

where T_s is the time taken for sensing a wideband channel with K non-overlapping Additive White Gaussian Noise (AWGN) sub-channels, k is the sub-channel selected for use by the CR, $P(H_0)$ is the probability of the PU being absent, and O_k is the occupancy status of sub-channel k, determined from the sensing results. From Eq. (12), the optimal power transmission, SINR, and bandwidth that maximises the spectrum efficiency are determined based on the assumption that the CR is stationary or slow moving, the CR conducts Energy Detection sensing over its candidate channel, and the CR senses at most one channel at a time as it is equipped with a single antenna. Moreover, all channels have equal bandwidth, B.

The most common techniques applied to determine these parameters include classical optimisation approaches, such as linear programming and convex optimisation, heuristics, and game theory[23–27]. The challenge with these techniques is that they require information regarding the sensing parameters and the transmission power decisions of other CRs interested in the same spectrum opportunities. Without this information, the optimisation problem is reduced to an isolated capacity limit estimation problem. Many techniques have introduced constraints and pricing models to limit and/or penalise inter-CR interference and channel access decisions that cause spectrum inefficiency. However, these technique adaptations still require information about the sensing and sharing parameters. A more successful approach to resolve this challenge is the introduction of machine learning in spectrum sharing.

In recent years, machine learning in CR networks has attracted a lot of research attention as a tool to enable learning in spectrum sharing. It enables the CR to learn from past spectrum sharing experiences and to apply these lessons in its decision making processes in order to predict the behavior of the PU and the other CRs competing for the same spectrum.

The most widely applied algorithms are the Reinforcement Learning based approaches (e.g., Q-learning algorithm, threshold-learning) and the Neural Network based approaches (and the associated variations, e.g., Artificial Neural Network, Multi-layer Linear/Non-linear Perception Networks, Radial Basis Function Networks)[28–31]. The main drawback of Neural Network based learning approaches is that they require historical sensing information about the environment (e.g., channel usage patterns of the PU) in order for the CR to be trained prior to the execution of the approach. This disadvantage is exacerbated by the possibility of over-fitting the data. Overfitting occurs when the knowledge and the data captured are not sufficient to train the CR in a way that enables it to provide reliable results. In such a situation, the CR yields accurate results on training data, but far less accurate results in practice[29]. The main disadvantage of Reinforcement Learning based algorithms is that, although they learn through trial and error, they require many learning iterations to converge on an acceptable solution[30]. Recent studies of heuristically accelerated Reinforcement Learning approaches aim to address this[32].

A common shortfall of the Reinforcement Learning and the Neural Network learning approaches studied in the literature is that they assume that the operating environment is static during the learning process, thereby enabling convergence of the algorithm, however, in practice, the environment changes due to changes in the noise, mobility/the user location, user density/competition for scarce resources/spectrum, traffic load, and various other factors. Moreover, based on the No Free Lunch theorem which states that there is no universal learning algorithm that can succeed at all learning tasks, careful consideration is required to determine the learning approach best suited to maximise the spectrum efficiency of a CR, with due consideration of the prevailing environmental factors[29]. This is because the theorem implies that for every learning algorithm, there is a task at which the learning algorithm is not able to perform at a satisfactory level.

From the literature, it is clear that further research is required to develop spectrum sharing techniques specifically for distributed, non-cooperative CR networks. Spectrum sensing and sharing techniques can be overlaid over spatial spectrum sharing strategies to improve spectrum efficiency. The most commonly studied spatial spectrum sharing strategies are discussed next.

4 Spatial spectrum sharing

The two main spatial spectrum sharing strategies that have been identified for use in NGNs are the network densification architectures and the massive Multiple Input Multiple Output (mMIMO) techniques.

4.1 Network densification architectures

In recent years, there has been a trend of reducing cell sizes and cell coverage areas in a telecommunication network to form multiple small cell networks, which jointly depict a dense network architecture. This principle is commonly referred to as network densification and is a way of enabling the spatial reuse of spectrum to increase network capacity and coverage. Through network densification, it is expected that the pressure to provide access to wireless services and networks will be alleviated despite the increase in wireless users. It is for this reason that it is predicted that small cells will, by 2030, support ubiquitous device connectivity and expand network capacity, including 100 billion device connections, 20 000 fold mobile data traffic, and 1000 fold user experienced data rate, compared to 2010[33]. Examples of small cells include Micro, Pico, Femto, and Metro cells. These are made up of base stations or Wi-Fi access points. Each cell supports a set of users within a short range. These cells can be incorporated with each other through wireless technologies, such as point-to-point connections or connections to a Macro base station which uses terrestrial technologies for backhaul.

Small cells use low transmission power, and thus short transmission links, thereby enabling the reuse of spectrum without causing excessive interference to each other[34]. Interference management techniques are however required to manage the interference generated within the cells and between the cells as well, in order to ensure successful transmission of data across the small cell network. The most common interference management techniques applied in practice are the interference cancellation and interference coordination techniques[35]. Further, technologies, such as millimeter Wave (mmWave) when coupled with small cells, bring about further network capacity improvements required to deliver QoS based services[36].

CR network can adopt small cell network architectures and technologies (e.g., mmWave) as a way of optimising spectrum efficiency and providing reliable network services. This approach enables the CRs to sense available spectrum in small geographic ranges and establish a cell or a small cell network to ensure the spectrum opportunity is leveraged. The quality of the signal received by the n-th CR receiver, from its serving cell or CR transmitter, is denoted by $\varTheta_n$ and is expressed in terms of the SINR as

$$\varTheta_n = \frac{P_n}{I_n + N_0} \tag{13}$$

where P_n is the transmission power used by the CR, I_n is the sum of the transmission power of all other CRs in the serving cell, and N_0 is the additive white Gaussian noise. The spectral efficiency of a serving cell i is expressed as

$$E_i = \delta C \tag{14}$$

where δ is the network density, which is dependent on the channel power allocation across the small cells (serving cells) as well as the environmental factors that can influence the throughput achieved by each UE, e.g., shadowing, path-loss model applied in the near field region, and the noise level[8].

A major drawback of network densification is, consequently, that the optimal network density, and the transmission powers of all nodes in the serving cells must be known in order to determine if the spectrum efficiency of the network will be improved, prior to an actual deployment. This is because dense networks reach a density point beyond which they cease to achieve spectrum efficiency. In addition to this, a large number of small cells may be required in order to ensure vast coverage of a large geographic area thus requiring large capex outlays. Therefore, the inability to project the achievable spectrum efficiency of a small cell network during the planning phase can result in high operational cost inefficiencies in practice[35,37]. It is for this reason that current network densification approaches, and the associated interference management techniques are best suited for centralised network deployments rather than distributed network deployments. Further investigations are required to adapt network densification strategies for application in distributed and non-cooperative CR networks.

4.2 Massive MIMO

Massive MIMO, being an extension of traditional MIMO, offers added spectrum efficiency when coupled with a CR network. This is because mMIMO enables increased data rates, over spectrum holes identified by the CR, utilising a large number of antennae for transmission and receiving the signals transmitted in the CR network. These network deployments can comprise of a secondary base station with multiple antennae and multiple CR receivers, each with a single antennae or a secondary base station with multiple antennae and multiple CR receivers, each with multiple antennae[37,38]. A basic mMIMO network architecture is depicted in Fig. 8[39].

Through this massive deployment of antennae, the CR network is able to transmit and receive multiple data signals simultaneously, over the same channels, using beamforming technology[39], thereby enabling more users to gain access to wireless services[40] and

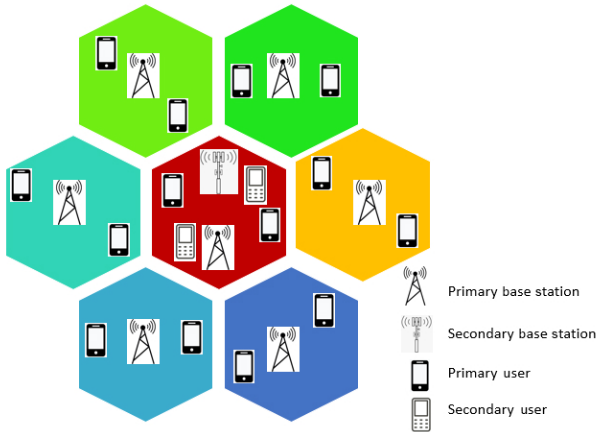

Fig. 8 System model for mMIMO-CR networks[39].

improving spectrum efficiency. Other benefits of mMIMO are that (1) antennae in mMIMO deployments are designed to consume low levels of power, (2) the quality of the sensing results (i.e., channel state information) is improved as an increased number of antennae sense/observe the same channel simultaneously, and (3) the technology can be integrated with small cell networks and various other spatial spectrum reuse strategies[41].

The CRs in the network further contribute to the performance achieved through their ability to reconfigure their transmit powers in order to optimise their SINRs and thus the channel capacity. However, the SINR of each CR and the path-loss propagation model applied affect the throughput achieved. Therefore, in order to optimise the spectral efficiency of an mMIMO-CR network, the CRs must know the physical positions and transmission powers of all other CRs in the network[42]. It is challenging to obtain this information in distributed and non-cooperative (ad hoc) networks. This makes current CR-mMIMO schemes best suited for centralised and/or cooperative networks.

5 Joint sensing and sharing

Spectrum sensing and sharing processes are executed in the same timeslot, sequentially. There is a direct trade-off between the time spent on these processes and the time available for data transmission. It is therefore, expected that jointly optimising the sensing and the sharing processes will result in the CR having optimal time for data transmission. This close relationship between the sensing and sharing processes motivates for the joint optimisation of these processes[30–32, 43–47].

Literatures indicate that the main spectrum sensing and sharing parameters that influence spectrum efficiency in distributed, non-cooperative, and interweave CR networks are sensing duration, sensing detection threshold, sensing order, probability of false alarm, probability of misdetection, transmission rate, transmission power, and interference[23–25]. Optimisation problems that aim to jointly optimise these parameters have been shown to be nonconvex NP-hard (i.e., computationally intractable) optimisation problems. To reduce the complexity of the optimisation problem, existing studies selected a subset of these parameters for optimisation. However, the problems remain non-convex. These problems are often solved using a two-step approach wherein the problem is reduced to a convex problem in the first step and solved in the second step using methods, such as non-linear optimisation, dynamic programming, bi-level optimisation, alternating optimisation, monotonic programming methods and Karush-Kuhn-Tucker (KKT) conditions, and game theory. Although effective, these methods' ability to produce an optimal solution is heavily dependent on the values used to reduce the problem to a convex problem.

The most common game theoretic approaches applied in the second step of the two-step joint sensing and sharing problems described above, are the potential games. This includes ordinal, weighted, exact, generalized ordinal, best-response, and pseudo potential games. In such games, each CR aims at maximizing its own objective which opposes the others' outcomes[48]. The general representation of a game, $\varGamma$, is expressed as

$$\varGamma = |(M\{S_i\}_{i\in M}, \{u_i\}_{i\in M})| \tag{15}$$

where M is the set of players (i.e., set of nodes that form the distributed CR network), S_i is the space of pure strategies of player i and u_i is the utility function of player i. All the players in the game have the same formulation of a utility function, known as a potential function, thus when each player maximises its utility function u_i, the overall network utility is also maximised[49].

Other game theoretic approaches applied included evolutionary games, Pareto optimality games, coalitional gams, and correlated equilibrium games[50–52]. However, potential games are preferred over these games because of their ability to address fairness in distributed networks as well as their ability to admit a pure strategy Nash Equilibrium (NE) which is represented by

$$U_i(s_i^*, s_{-i}^*) \geqslant U_i(s_i, s_{-i}^*) \tag{16}$$

where $\forall i, \forall s_i \in S_i$, $s_i \in S_i$ is the strategy chosen by player i, and s_{-i} represents the strategies adopted by the opponents of player i. However, this approach suffers from the same shortfalls as the two-step approach described above as the NE achieved in the second step is dependent on the quality of the parameters determined in the first step of the approach and used to reduce the non-convex problem to a convex problem and a potential game.

In recent years, a new class of games called non-convex games was introduced to enable game theoretic approaches to be used to solve non-convex problems without following the two-step approaches. These games have nonconvex strategy spaces and/or non-convex utility functions[42]. In Refs. [53, 54], it is shown that this new class of games can be used to solve joint sensing and sharing optimisation problems in distributed CR networks wherein there are global constraints that all the CRs must satisfy. This new class of games hinges of the concept of a relaxed Quasi-Nash Equilibrium, which unlike the traditional Nash Equilibrium might be a local equilibrium or stable point, and not necessarily a global equilibrium. As such, it is shown in Refs. [53, 54] that games that satisfy the criteria for this class of games will always converge to a stable point (i.e., a Quasi-Nash Equilibrium). However, these games, as in the case of the previously stated methods, aim to optimise only a subset of the sensing and sharing parameter that affect the spectrum efficiency of the CR. As such, further investigations are required to enable the joint optimization of all the sensing and sharing parameters that impact the achievable spectrum efficiency.

6 Future research directions

We have discussed many notable spectrum efficiency maximisation approaches and their associated limitations and challenges. In this section, we provide a brief overview of various open research areas that can be explored to further improve the spectrum efficiency of CR networks.

6.1 Dynamic spectrum access

Existing distributed sensing and sharing approaches consider single PU cases, however, in practice, we often find multiple PUs in a single geographic area having licences to different spectrum bands. As such, distributed spectrum sensing and sharing approaches suited for multi-PU and multi-CR environments are required in order to improve the overall spectrum efficiency (of all available spectrum) and foster the convergence of the different technologies (3GPP and 802.xx technologies).

Distributed schemes are preferred over centralised algorithms in large CR networks because of the robustness, maintainability, scalability, and modularity of the network as all of these factors aid in ensuring the fast convergence of the sensing and sharing approaches, relative to the network size. However, practical approaches to enable the identification of participating nodes require further investigation. In addition, the time impact of this activity should be incorporated into spectrum efficiency optimisation problem.

CRs are to increase spectral efficiency by optimising the time required to identify and utilise spectrum opportunities, and release the spectrum upon the return of the PU. Currently, this is achieved through the synchronisation of the CRs and PU timeslots such that CRs and PUs (if necessary) exit the spectrum at the end of their transmission slot. Approaches to protect PUs from interference caused by CRs in the case when their timeslots are not synchronised require further investigation.

Fair spectrum scheduling methods for ad hoc and distributed CRs are required to improve the spectrum efficiency achieved by co-existing CRs.

Further investigations into the relationship between the TNR and SNR are required as it is suspected that such a relationship can be used to determine if the sensing detection threshold is set at a suitable level. This is because preliminary studies conducted indicate that a TNR that is 3–5 dB higher than the SNR results in optimal sensing activities.

6.2 Resource management

CRs have an objective to optimise spectral efficiency despite being resource constrained radios and thus having limited energy to conduct all their tasks. It is therefore imperative that they utilise their energy efficiently so as to extend their life span. However, they are usually deployed in unattended environments (e.g., military, manufacturing, and agricultural environments) making them susceptible to security breaches. In such cases, data collected by CRs may be sniffed, destroyed, or altered (e.g., injection of false sensing data) causing a deterioration of the spectral efficiency of the CR. It is for this reason that energy efficient approaches to address security in distributed CR networks are required. These approaches must take into consideration the neighbour discovery processes followed in distributed CR networks and the flexibility available to CRs in such networks to enter and exit networks whenever the need arises.

Energy efficient joint sensing and sharing approaches to enable the transportation of multimedia and delay sensitive data over multiple channels in distributed CR networks will contribute to achieving spectrum efficiency, particularly in NGNs. Such approaches require further investigation.

Machine learning approaches require further optimisation in order to reduce their resource requirements, thereby making them more suitable for application in CR networks.

7 Conclusion

The concept of a CR first emerged in 1999[6] bringing with the promise to improve spectrum efficiency. In this paper, we provided an overview of the approaches introduced over the last two decades to achieve this promise. We proceeded to classify these approaches into spectrum sensing and the spectrum sharing approaches, and spatial spectrum reuse strategies. We provided an in-depth explanation of the architecture, behaviour, and spectrum access techniques supported by each of the stated approaches and strategies. We concluded the study by drawing attention to various open research questiones which are critical to the realisation of NGNs.

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