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Recent Paradigms for Efficient Spectrum Sensing in Cognitive Radio Networks: Issues and Challenges

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Abstract. Rapidly advancing technological advancements in the recent past has made the life of consumers at ease through innovation of sophisticated and state of the art gadgets. The consumers are able to access data at high speeds at their own free will irrespective of time and location. With increasing benefits of these wireless gadgets and technologies working on well-known and efficient radio frequency spectrum, an increasing scarcity in availability of radio frequency spectrum is found to be a rising consequence in recent times. With ever increasing number of wireless gadgets, increasing burden on spectrum allocation is emerging to be a prevalent research topic in recent times. Cognitive radio networks (CRNs) have been found to be effective and intelligent solutions, which by a sequence of intelligent sensing, aggregation of sensed information and decision making, provide an optimal method of allocation of spectrum to demanding users. This paper provides a detailed insight into various methods used in cognitive spectrum sensing, their classifications and methodologies. A vast survey of literature has been systematically provided in this paper with the issues and challenges forming the concluding parts of this survey. Knowledge of existing methods described in the literature with their merits and limitation help in developing and improving the performance of existing spectrum sensing methods to a great extent.

Keywords: Cognitive radio networks, spectrum sensing and allocation, received signal strength, false alarm detection, primary users, and secondary users.

1. Introduction

In recent times, there has been a rapid increase in the utility of state of the art devices and gadgets powered by cutting edge technologies. There has been an ever increasing demand for efficient methods of data processing, their handling mechanism and storage requirements. Fast computing has been the demand from the side of consumers, who require high rates of data transfer with communications reaching their location in the shortest time possible. This has been witnessed by the sudden boom in development of hand held gadgets where users are able to communicate and access whatever information they require irrespective of time and location. Wireless communication technologies have gained significant research interests and ground, with the increasing utility of such handheld gadgets by consumers. Wireless communication technologies have evolved a long way but in the shortest time possible due to this rapidly increasing demand for fast communication rates across the globe. Remote monitoring and surveillance, remote monitoring in health care sector, industrial automation through sensors, surveillance of hostile territories are some of the most significant utilities being put in practice today, using concepts of high speed wireless data transfer [62]. A simple chart illustrating the growth of such wireless technologies in the past two decades is illustrated in figure 1 shown below.

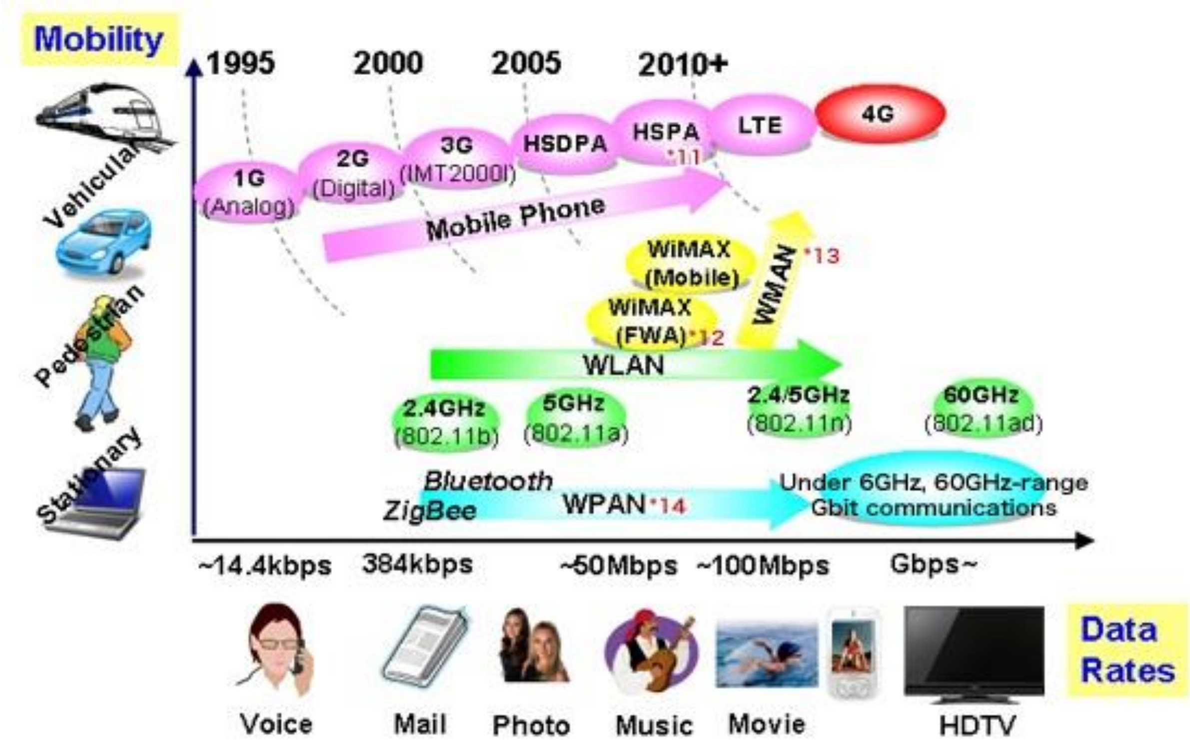

Fig. 1 Illustration of evolution of wireless communication technologies.

It is quite evident from the above illustration, that, the evolution of communication technologies starting from conventional dial up networks which are characteristic of 1G technologies have come up to high speed wireless methods [29] [35] with 4G and 5G technologies in the shortest time possible. On the other hand, an essential point to be noted, from the evolution graph, is that, technological advancements have been a blessing in disguise, as improvement in wireless communication technologies leading to increased number of wireless devices/gadgets, have put a high volume of overhead on the electromagnetic spectrum. Since, all these wireless devices operate on the radio frequency spectrum (RF), the availability of radio frequency spectrum is becoming scarce day by day. Higher speeds of transmission demand higher bandwidths, which, is quite a challenging blockade with respect to allocation of scarcely available RF spectrum [63]. In spite of alternate technologies to RF spectrum being research in recent times, like light fidelity technology, it is to be noted that, these researchers are very much in their infant stages. Moreover, they are hindered by a line of sight communication challenge which is a limiting feature in case of long distance wireless communication. Hence, in view of all the above mentioned facts, there has been an increasing need for an effective and intelligent method of allocating the available radio frequency spectrum among users/consumers for their device operation. This growing interest and research activities in the related field has led to concept of cognitive radio networks (CRNs) [4]. Cognitive radio networks [43 – 44] could be simply defined as intelligent components which help to allocate scarcely available radio frequency spectrum to demanding users/consumers based on a sequence of operations namely, sensing, aggregation and decision making [52]. This process of three activities is commonly referred to as the cognitive cycle [55]. A typical cognitive cycle is depicted in figure 2 shown below.

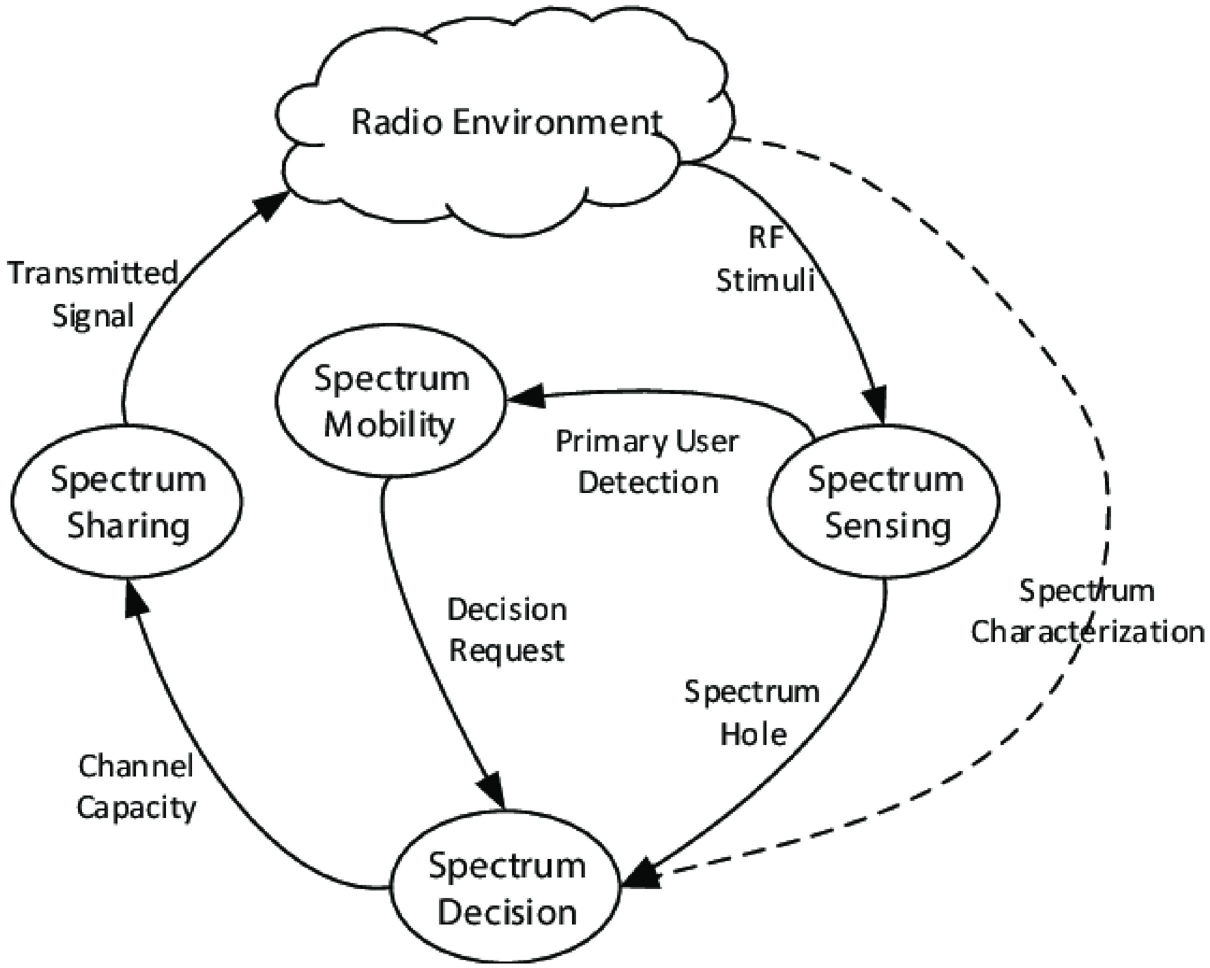

Fig. 2 Illustration of cognitive cycle in CRNs.

It could be observed from figure 2, that, a systematic sequence of sensing followed by aggregation of sensed information [16] evidently leading to decision making based the sensed information, form the complete cognitive cycle [46]. Beforehand, it is to be noted that, the cognitive radio network system categorizes the users/consumers into two major groups' namely primary users (PU) and the secondary users (SU) [32]. While primary users reflect the licensed group of users, secondary users represent the unlicensed band of users. Based on spectrum availability, the cognitive network allocates the available bandwidth in an intelligent manner to the users demanding access. It is to be noted that, the licensed band of users (PUs) have complete access to bandwidth while SUs have to find a way to access bandwidth only when available. Hence, the entire problem of cognitive radio network converges to a detection or classification process, where, the channel is continuously sensed for presence of PU activity [108] [80]. In case, PU activity is not detected, a requesting SU is given access to the RF spectrum. In other words, the problem definition of CRNs is concisely stated to be a binary hypothesis problem related detection of presence or absence of PU activity in the channel. Mathematically it could be formulated as

$$S = \begin{vmatrix} 1 & if\ y(t) = p(t) + \delta \\ 0 & if\ y(t) = \delta \end{vmatrix} \qquad (1)$$

In equation (1), y(t) represents the output signal or the received signal on the channel, δ represents the channel noise while CS represents cognitive sensing. Equation (1) could be interpreted as the detector output to be a one when the primary user activity is detected in the channel while a 0 is interpreted as the presence of just channel noise with no primary user activity, thus reflecting availability of bandwidth.

With the preliminary insights into cognitive sensing using CRNs, this review paper is organized into two section henceforth with the first briefing about the various conventional models of efficient spectrum sensing [2] using concepts of CRNs [26] [58]while the second phase elaborates on the role of soft computing models to achieve the prescribed objective.

2. Conventional spectrum sensing models in CRNs

As mentioned in previous sections, CRNs are all about intelligent allocation of available bandwidth to users requesting access to the EM spectrum. The efficiency of CRNs in doing the same, is largely dictated by presence of a powerful and effective cognitive cycle, which involves sensing, aggregation and decision making [105]. A continuous method of sensing the channel for any presence of primary user is to be done the CRN model [9]. At the outset, CRNs are found to operate in two major schemes, namely non-cooperative [19] [69] and cooperative methods [10] [25]. In the former scheme, the SUs requesting access to the spectrum have their own individual objectives of getting access to the spectrum without any due consultation with other SUs. This vacancy otherwise known as spectrum hole or white space can be detected only with efficient and continuous sensing of channel [3].

Non- cooperative methods are also termed as local sensing methods as there is no coordination and communication between the SUs in the network. In the latter, the existing SUs gain access to the channel in a cooperative manner, which is achieved by total coordination and communication between existing SUs requesting access to the channel [27] [114]. Information from all sensing units are gathered, analyzed and then a decision is arrived on the allocation of bandwidth to the most deserving SU. Amongst cooperative sensing [90], a distributed sensing [87] ensures that each SU in the network takes its own decision based on information sensed while a centralized sensing ensures that a specialized infrastructure based fusion center makes the decision after complete analysis of the sensed information [24]. However, since, the objective of this survey is related to the various sensing methods [112][118] employed in the CRN model, a review of various methods of information sensing is discussed in this section

2.1. Energy detectors

A well-known simple yet effective method is the energy detection model. Its operation is quite straight-forward in the sense that presence or absence of PU in the channel is detected based on comparing the received signal energy with a standard threshold. The energy statistic is obtained through a fast Fourier analysis followed by squared magnitude of the average energy [91]. The threshold in this case to a great extent depends on the estimation process of noise, which is also quite challenging. The challenges related to noise estimation arises from the fact that, noise magnitude is not static and highly unpredictable [89]. Hence, dynamic methods of noise estimation have also been used in the literature. Most of energy detection methods make the detector to sense for primary user activity over a specific time window [11]. However, in case of fading channels [49] like Nakagami and Rayleigh models [106], the fixed time window based detection may not work and hence, may result in drastic increase in false alarm detections. Hence, these scenarios are considered equivalent to detection of unknown signals [24] where specialized square law combiners and selectors are used to improve the probability of detection. This scenario arises even in case where the transmitter power drops down drastically thus making incorrect detections. Noise limitations have also been carried out using a band pass filter – square law device mechanism [71]. Detection of presence of PU is done by threshold comparison technique. Probability of false alarm has been used an efficient metric to validate the performance of the proposed technique. Effects on false alarm performance through varying levels of signal to noise ratios (SNRs) in ranges of -10dB has also been performed. However, limitations like vulnerability of threshold towards varying levels of noise intensities tend to increase the probability of false alarm [99 – 100].

2.2. Matched filter techniques

The Increasing interference of noise in channel making detection of PU activity makes it a cumbersome process in case of simple energy detection models [84]. Hence, concepts of matched filtering which exhibits phenomena of linearity have been used to enhance the SNRs of the receive signal, thus making the detection process much easier. Matched filters [30, 93] operate on the same lines of energy detectors by utilizing a threshold comparison process. On the contrary to energy detectors which do not require any prior knowledge, the statistics required for generating the threshold is taken from pilot signals obtained from the same transmitter. They are simple in structure and exhibit optimal performances. However, requirement of prior knowledge for extraction of samples for the pilot signal prove to be a limiting factor. Moreover, advances in matched filter detection methods have been investigated in the literature [42] [81] where dynamic threshold assignments have been invoked to accommodate continuously changing noise characteristics. Knowledge of prior information regarding the received signal with matched filters include parameters like bandwidth, modulation technique used, the format of the transmission frame used etc.

Further, matched filters are divided into coherent and non-coherent methods. While in the former, the magnitude and phase of received signal is known, a replica of the received signal is used to compute either power or magnitude of received signal for comparison with the predefined threshold value. Method of improvement in spectrum utilization has been reported using matched filtering techniques in the literature [23] where the problem of SU requiring a spectrum space in 5 Gaussian channels with zero mean and variance is experimented. Effects of modulation have been studied in this method where BPSK modulation schemes report a lower detection rate of 0.43 over AM schemes which report a 0.8 detection rate. However, with increasing false alarm rate scenario, AM and BPSK schemes are found to converge on their detection rates. SNR computations are critical to matched filter methods and computed as

$$SNR\ (dB) = \frac{|R(t)|^2}{|N(t)|^2} \qquad (2)$$

Where R(t) represents the magnitude of received signal and N(t) reflects the magnitude of noise on the Gaussian channel. Other essential parameters for modeling the efficiency of the spectrum sensing process include probability of detection computed as

$$P_D = Q(\sqrt{2(SNR)}, \sqrt{\frac{T}{\sigma^2}}) \qquad (3)$$

and probability of false alarm detection computed through

$$P_{FAD} = 1 - ({}^{T}/_{\sigma}, 2) \qquad (4)$$

In equations (3) and (4), T represents the threshold for comparison and σ the variance of noise. Qdenotes the branch of the matched filter also referred to as the Q function of the matched filter. A detailed investigation in the literature related to performance comparisons of matched filtering techniques against energy detectors have been presented [81]. Findings from the work indicate non requirement of prior knowledge of receiver characteristics, simple scheme of detection as the meritorious points while unstable nature of threshold, capability to operate in low SNR environments to be limitations [72]. On the other hand, matched filter techniques are characterized by increased robustness to noise, ability to dynamically adapt to changing noise patterns [68]. However, requirement of prior knowledge of channel and signal characteristics, need for different receivers for varying signals are observed to be the limiting features of MF methods.

2.3. Cyclo-stationary feature detection schemes

These methods of cognitive spectrum sensing through feature detection of sensed channel requires prior information of the received signal. They are found to be more robust towards noisy channels when compared over energy detector models with the consequence of being relatively complicated.

They work on the principle of identifying repeated patterns from the sensed signals analogous to periodic signal detection [85]. Based on the computation of integral of the periodically detected feature signal with a threshold, the presence or absence of PU is detected [104]. Experimental results in the literature prove that they work better even at lower levels of SNRs. Conventional cyclic feature detection methods exhibit a high degree of computational complexity due to excessive computations of FFTs and periodograms. Reduction in complexity is observed in a sub section average cycostationary feature detection proposed in the literature [107]. This is accounted for, by segmenting the input features into subsets and computing FFTs for each of the subset. This method requires partial prior information on the channel characteristics and received signal. Spectral correlation factor (SCF) have been used as a parameter to identify the periodic feature set [33] using window functions such as Hanning, Hamming etc.CyclostationarySpectral Function (CSF) and CyclostationaryAutocorrelation Function (CAF) have been used in the literature [79] to estimate the periodicity of the sensed received signal. Optimal spectral efficiency in presence of fading channels are notable findings of this experimental work. A sequential method of cyclostationary feature detection [20] is found to reduce the computation time to a great extent when compared over conventional cyclostationary detection methods. This in turn is found to improve the sensing efficiency

Other methods of spectrum sensing using cognitive networks observed in the literature present an Eigen value computation based method of presence of PU. These techniques do not require prior knowledge regarding the channel or signal characteristics [47]. Either ratio of maximum to minima of Eigen value or ratio of average to minima of Eigen value [70] is used to detect the presence of PU activity. Markov models [65] [101] have been successfully implemented in literature for effective spectrum sensing based on analysis of spectrum sensing time interval.Cooperative sensing schemes using single and double relay models [77] have been investigated in the literature. In the first model, namely, amplify and relay (AR), the relay unit senses the received signal, amplifies and relays to the sensing unit located outside the local coverage area during the first time slot. In the double relay model, namely, detect and relay, the sensed signal is analyzed for presence of PU and then relayed over to the decision making unit. Complexity in the sensing process and prevention of fading effects [67] on sensing reports are reduced by invoking concepts of clustering [94] [12] [39] where local sensing [57] methods are employed to gather energy information and sent to the cluster heads. These cluster heads analyze these reports and make a preliminary decision. Following this, the reports of all cluster heads are sent to the receiver module which ultimately decides upon allocation of spectrum based on availability. Similar clustering schemes have been made noise resistant by integrating with Eigen value decomposition methods [61] [28].Advances in cluster based spectrum sensing methods have been done in the literature [64]. High sensing efficiency, reduction in reporting time of sensed reports to the fusion center and reduced energy consumption are notable findings from this experimental work.

3. Machine learning models in CRN spectrum sensing

Machine learning methods have been found to be rapidly emerging areas of interest in recent times. Machine learning methods are based on learning based approaches followed by training to detect and converge upon the desired point of optimization [88]. A review of various intelligence based techniques for cognitive spectrum sensing is summarized below in table 1.

Technique	Principle of working	Merits	Limitations
Fuzzy based methods [40][6][13][7]	Rule based fusion for detection of presence/absence of PU in the channel	Improved probability of detection and reduced false alarm detection	Increased time consumption Accuracy depends on efficient spectrum sensing using energy detection method
Fuzzy C means spectrum sensing [21]	Soft decision based PU detection [95]	Increased detection probability and utilizes less number	Depends on efficiency of energy detector

		of samples	
Neural Network based spectrum sensing [17] [96] [86] [48] [102]	Training of feature vectors from the received signal [73]	Improved energy detection and capable to self-adapt to dynamically varying conditions Weights are trained using historical sensed information Better performance over AND and OR based rules	Efficiency depends on effective feature extraction process [78].
Deep learning based spectrum sensing [103] [31]	Extended versions of NNs for handling unstructured and complex data	Superior performance even at low SNRs [60] Increased gain [56] over conventional methods	Computational complexity tends to increase with increasing layers
Game theory based spectrum sensing [15][34][83][8][38]	Derivatives of evolutionary algorithms allowing users to choose between two strategies [66]	Optimal resource allocation [59] [110] Optimal power allocation to users [92] [113] [116]	Computational complexity overhead with increasing number of users.

Apart from the above mentioned machine learning methods, concepts of optimization have been playing a major role in recent time to optimize essential components towards convergence of optimal solution. Nature inspired algorithms [75] like ant colony optimization [37], bee colony [53], particle swarm optimization [82] [117], genetic algorithm [22] [45], cat swarm algorithm [76] have been effectively used to optimize essential constituents like feature vector sensed by the sensing units. This in turn help in providing precise decisions related to presence/absence of primary users in the received signal. They also play vital roles in optimizing the number of SUs and assigning their priorities towards channel assignments [50]

4. ISSUES AND CHALLENGES

An extensive survey of literature related to various methods of efficient spectrum sensing has been studies in this paper and findings have been summarized in this section.

1. Rapid advances in communication technologies have seen an enormous growth in utility of various gadgets which are handheld and portable. These devices provide state of the art services to the consumer. Most of these devices utilize radio frequency for their operation hence making it a very scarce quantity. Hence, the need for cognitive radio systems, which allocate spectrum in an intelligent manner, has become an emerging area of interest in recent times.
2. Energy detector schemes are simple yet efficient schemes of detecting the presence/absence of PU in the received signal. However, most of the schemes observed in the literature suffer from a fixed threshold problem, as noise prevalent in such channels tend to vary with time in a random manner.
3. An essential finding from energy detection scheme is that, it does not require any aprior knowledge [36] regarding the channel characteristics. However, it does come with a consequence of not being able to differentiate between various signal types. These schemes could be used for mere detection purposes.

4. Matched filter detection methods are similar to ED models except that they require aprior knowledge of the received signal which is not possible at all times. Better noise handling capabilities are yet another finding of these matched filter methods.
5. Cyclostationary feature detection methods exhibit optimal performances even in presence of noise but require full or partial prior information. Process of cyclostationary feature detection are found to exhibit increase computational complexity.
6. Cluster based methods are found to reduce the network complexity and thereby reduced energy consumption.
7. Opportunistic methods [18] is one of the most widely sought after technique for CRN models where allocation of bandwidth to SUs during idle times of PUs is the primary logic.
8. Another challenging issue found from literature involves reduction in interferences of SUs and PUs which if left unattended may result in drastic degradation of system throughput. Hence appropriate methods of noise estimation and interference estimation is to be carefully studied and examined before implementation.
9. Channel Estimation is one of the major issue and challenges in CRN models as effective sensing is reflected through a precise channel estimation technique and amount of information gathered through channel state information (CSI) [5].
10. Machine learning methods have been investigated to a great extent in the literature and have been able to provide precise decisions on presence and absence of PUs in the sensed signal [1]. The preciseness in most of the case is dependent on efficient feature detection and efficient non-cooperative techniques like energy detectors, matched filters etc.
11. Optimization methods [74] [111] have been effectively used in the literature to provide optimal spectrum allocation, distribution of resources [97] [109] and power allocation to users [51] [54].

This survey paper has provided an exhaustive study of various research contributions and presented findings of each technique with their prospects and limitations for spectrum sensing through cognitive radio networks. The paper has systematically discussed various techniques related to cooperative and non-cooperative methods of spectrum sensing. The findings of this paper would be an eye opener to researchers working in the relevant field of spectrum sensing using cognitive radio networks.

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