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SURVEY ARTICLE

A Survey on Soft Computing Techniques for Spectrum Sensing in a Cognitive Radio Network

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Abstract
The need for faster wireless connectivity is increasing rapidly in all the sectors of the technologies. Whether it is a patient monitoring system, military application, entertainment services, streaming services, or global stock markets, there is a tremendous increase in the need for enhanced wireless telecommunication services. The wireless telecommunication consumers rely on bulk data, and massive growth in the number of users has resulted in the spectrum congestion. To avoid such spectrum congestion and to satisfy the data hunger of the wireless telecommunication users, the possible solution is Cognitive Radio Network (CRN). A CRN, therefore, plays a significant role in the field of wireless communication, and an efficient spectrum sensing enhances the effectiveness of the CRN. In this paper, complete research carried out so far in the field of spectrum sensing for CRN is discussed. Different soft computing techniques (GA, PSO, ABC, ACO, FFA, FSS, Cuckoo Search, ANN, FIS, GFIS) are surveyed in this paper, along with a detailed comparative analysis between conventional and soft computing techniques for spectrum sensing. In addition to that, the challenges faced in the implementation of CRN and its requirements is also addressed. Different spectrum sensing elements and requirements are presented and road map of spectrum sensing with soft computing techniques towards 5G is discussed. Furthermore, the paper also suggests the future prospects, research challenges and open issues associated with soft computing techniques for spectrum sensing in CRN.

Keywords Cognitive radio network · Spectrum sensing · Soft computing techniques · Metaheuristic techniques

Motivational Background

The tremendous demand for wireless applications has lead to the enormous growth of wireless communication. The existing radio spectrum is a finite natural resource, and it is getting jampacked continuously. And with the advancement towards 5G, there is a 1000 times increase in the demand of the radio spectrum because of the rise in demand of higher capacity, higher spectral efficiency and higher connectivity [142]. Therefore, the requirement for a robust and flexible wireless communication has become more evident. The conventional approach via electromagnetic spectrum licensing and re-utilizing it was not manageable. It was rather static and caused inefficient use of the available spectrum. This raised the need for efficient spectrum utilization, which creates possibilities for spectrum access dynamically, called dynamic spectrum access (DSA). Federal Communication Commission (FCC) published a report prepared by the Spectrum Policy Task Force (SPTF) [17]. In which specific rules and regulations recommended for using the radio spectrum more efficiently and improving the existing spectrum usage. The report illustrated that the problem of inefficient spectrum utilization is more critical than the spectrum scarcity. From the measurement of 0–6 GHz spectrum utilization at Berkeley Wireless Research Center (BWRC) and frequency utilization table shown in Fig. 1, it is clear that allotted channels are mostly unused, some are partial while the others heavily used. The higher frequency regions were inadequately utilized and termed as spectrum holes or white space.

FCC confirmed about the underutilized spectrum bands. Later FCC issued the notice for proposed rule making (NPRM) [17], that aimed at making efficient spectrum management by using cognitive radio (CR) technology.

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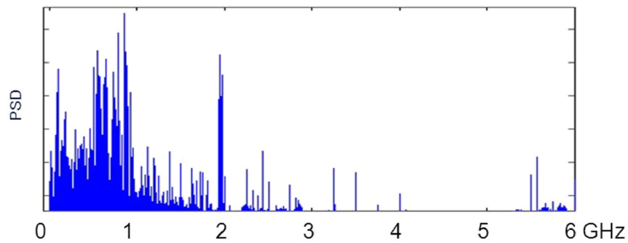


Freq (GHz)	0~1	1~2	2~3	3~4	4~5	5~6
Utilization(%)	54.4	35.1	7.6	0.25	0.128	4.6

Fig. 1 Measurement figure and frequency table of 0–6 GHz spectrum utilization of BWRC [22]

In the current scenario, with the evolution of 5G technology, there will be demand for cooperation and coordination-based spectrum access. In the 5G heterogeneous network, to improve the spectral efficiency while maintaining the quality of service of a system, there is the need for an efficient dynamic spectrum access technology. There is development in the field of millimeter-wave (mmWave) technology, in which 5G technology planned to deploy in the millimeter wave frequency band (30–300 GHz) and this frequency spectrum is abundantly available. But the 5G technology used in the mmWave suffers from the drawbacks associated with the high mmWave frequency bands. As the path loss is directly proportional to the square of the frequency, so mmWave suffers from high path loss, in addition to that is also suffers from high losses due to penetration, attenuation, rain, etc. Due to this, it has a shallow coverage area and supports only Line of Sight (LoS) propagation [145]. At mmWave frequencies, there is high foliage loss. The power requirement for mmWave technology is relatively very high [148]. With these disadvantages of mmWave, it is difficult to establish 5G technology solely based on mmWave techniques. The CR, with its cognitive abilities, can provide more flexibility to 5G technology and can enhance the spectrum utilization [138]. Therefore, the CR-enabled wireless technology can efficiently utilize the spectrum and thus feeds on the bandwidth and data rate hunger of the wireless telecommunication service users. In this way, CR technology considered one of the critical enablers of 5G as well as upcoming 6G technologies.

The important factor that makes a CRN "cognitive" is its spectrum awareness or spectrum sensing technique. Spectrum sensing performs spectrum hole detection, and these spectrum holes utilized to avoid spectrum congestion. Therefore, spectrum sensing is a vital part of the CR technology [10, 13]. In this paper, an effort made to cover all the aspects of the spectrum sensing for cognitive radio networks with the primary focus on the survey on soft computing techniques employed for efficient spectrum sensing along with their pros and cons.

The organization of this entire survey paper is as follows: "Cognitive Radio: Introduction" gives a brief about the cognitive radio network, its attributes, functions, implementation of soft computing techniques for CRN, design challenges. "Introduction to Spectrum Sensing" introduces spectrum sensing and provides a summary of research work and surveys carried out in the field of spectrum sensing involving conventional techniques. "Introduction to Spectrum Sensing" also briefs out about the requirements and components of spectrum sensing. After forming a base about cognitive radio and spectrum sensing, the survey paper explains about conventional spectrum sensing techniques, and complete classification of all existing spectrum sensing techniques in terms of Fig. 8 in "Conventional Spectrum Sensing Methodologies". The section gives a brief about all the conventional spectrum sensing techniques. Energy detection technique is one of the popular spectrum sensing technique over which soft computing techniques are developed [69, 72, 85, 110, 113, 121–124, 127, 128] as its least complex. "Conventional Spectrum Sensing Methodologies" gives accuracy and complexity analysis between existing conventional spectrum sensing techniques, the time complexity analysis of the spectrum sensing methods is also done in "Complexity Analysis of the Spectrum Sensing Methods". In "Soft Computing-based Approaches for Spectrum Sensing", different soft computing techniques employed for spectrum sensing is surveyed, explained, and compared based on the performance metrics. In addition to that, research challenges associated with it have briefed out. The cognitive radio network is an essential paradigm for 5G wireless communication, and spectrum sensing being the vital part of the cognitive radio network; the road map of spectrum sensing towards 5G is detailed in "Road Map of Spectrum Sensing Towards 5G" showing how spectrum sensing optimization and soft computing techniques plays a crucial role in forming the building blocks for efficient spectrum sensing-based CRN for 5G. The future scope and ventures for the soft-computing-based spectrum sensing are mentioned in "Future Scope for the Soft-Computing-Based Spectrum Sensing", followed by the future research challenges and open issues in "Future Research Challenges and Open Issues". This survey is aimed at explaining all the details associated with the cognitive radio network, spectrum sensing with prime focus on the soft computing techniques which is having an enormous scope for enhancing the efficiency of the spectrum sensing, thus increasing the effectiveness of the cognitive radio network employed for the wireless communication.

The prime contributions of this survey paper are:

1. Survey works in the area of the spectrum sensing in CRN were mainly focused on the pros and cons of associated with the conventional spectrum sensing tech-

nique, along with their brief description [33, 35, 80, 89, 150]. Through this survey work, attempt is made on the complete exploration of the soft computing techniques for the spectrum sensing in a CRN. Also, conventional spectrum sensing techniques have drawbacks of poor and complex performance [33]. To overcome this, soft computing techniques are employed for spectrum sensing [71, 101, 103, 148]. Therefore, major motivation of this survey work is to provide complete insight into the researchers working in the area of implementing cognitive radio network for 5G and 6G with soft computing-based spectrum sensing.
2. Detailed comparative analysis is made between conventional and soft computing techniques for spectrum sensing.
3. Comparison is also made among the different soft computing techniques employed for spectrum sensing.
4. In addition to that, the challenges faced in the implementation of CRN and its requirements have also been addressed.
5. Different spectrum sensing elements and requirements are presented.
6. Road map of spectrum sensing with soft computing techniques towards 5G is discussed.
7. Hybrid soft computing techniques for the efficient spectrum sensing is proposed for future 5G/6G technologies.
8. Based on this survey paper, the reader would get direction towards soft computing implementation of spectrum sensing in CR wireless sensor network/CR-based 5G/6G heterogeneous inter operability network and for applications in body area networks.
9. Future research challenges and open issues associated with the spectrum sensing are addressed in this paper.

Cognitive Radio: Introduction

In communication engineering for increasing demand of RF spectrum and apparent scarcity of the bandwidth caused by fixed frequency allocation, CR is a sure solution [17].

The CR technology is wireless communication with transceiver and intelligence technique for detecting channel status like whether its in use or not, after that moving into unoccupied ones keeping avoidance with the occupied ones [14]. The CR technique helps in utilizing the unused frequency spectra while minimizing the interference with the other users. A CRN comprises secondary users (SUs) or the unlicensed users, which opportunistically access the primary users (PUs) or the licensed users' radio spectrum. The main challenge for the secondary user is to detect spectrum holes within frequency bands, which can only be achieved by efficient spectrum sensing. The spectrum holes are noninterfering multidimensional areas within frequency time and space. Relevant keywords dealing with CRN are spectrum sensing, spectrum handoff [131], rendezvous [140], multicasting [118].

Major performance criterion defining cognitive radio systems are:

- Spectrum hole's authentication and PU's detection.
- Precise estimation of links in between the nodes.
- Frequency control in a speedy and precise manner.
- Precise methodology for controlling power with assurance of proper communication between CR nodes without interfering the PU's transmission.

A detail on CR types, challenges and its elementary parts have been discussed in the proceeding sections.

Attributes of CRN

Main attributes of CR are described as:

- Cognitive capability: It is defined as the capability of CR to sense or capture the information from the radio environment of its radio technology. Joseph Mitola via basic cognitive cycle explained about cognitive capability to observe the Scenario (*Spectrum Sensing*), adjust itself (*Spectrum Analysis*), design plans, take decisions and then perform action (*Spectrum Decision*). The "Basic Cognitive Cycle" in Fig. 2 briefly describe about the actions involved in Cognitive capability
- Adaptability: It is referred as CR's ability to alter the functions and dynamically program itself according to its radio environment(modulation scheme, communication protocol, transmitting frequency and power).

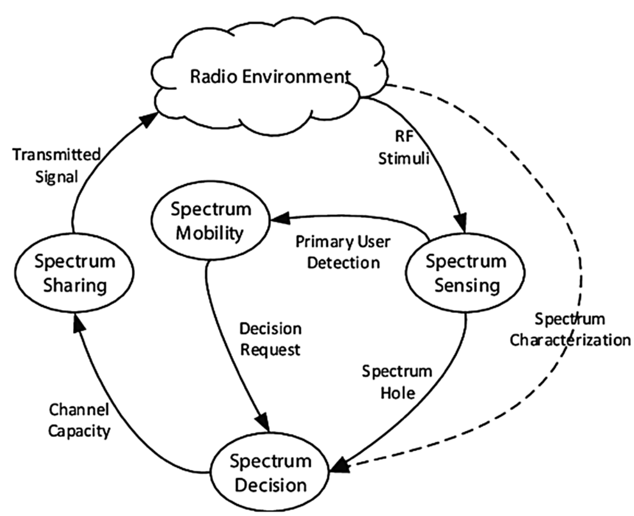


Fig. 2 Basic cognitive cycle [13]

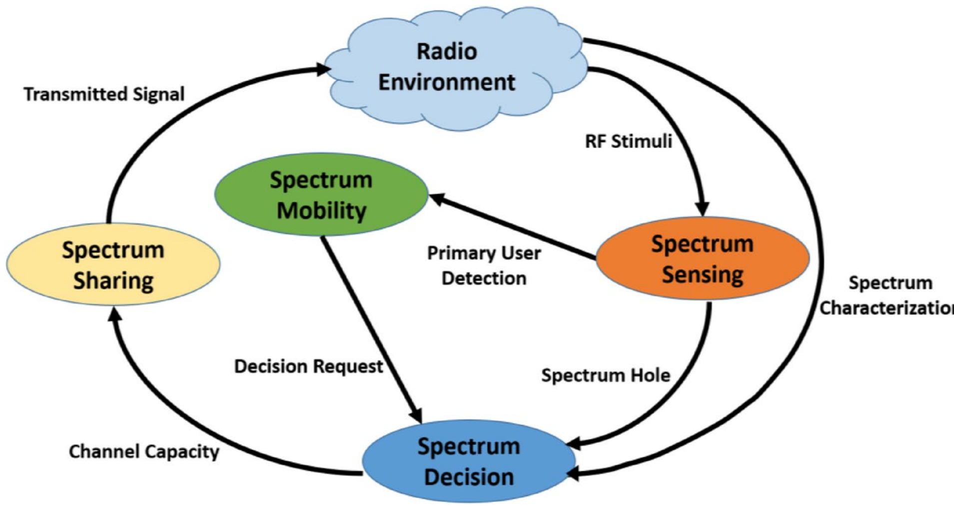


Fig. 3 CR network cycle

CR Functions

Basic CR involves four major functions as shown in Fig. 3.

- Spectrum sensing: Through spectrum sensing a CRN firstly estimates the presence of primary user (PU) on a particular channel. After that, CRN can share its detection result with other cognitive radios (CRs) [45]. Main aim of the Spectrum sensing is to obtain the spectrum status and its activity, for that purpose it periodically scans the target frequency band. Basically, a CR transceiver detects spectrum holes and decides a method to access w/o interfering licensed transmission.
- Spectrum management: For proper scheduling of spectrum, CR performs spectrum management within the existing users. Once the spectrum holes being found it is then selected by CR. This characteristic of CR is termed as spectrum management. Spectrum Management comprises of sensing of the spectrum, analyzing it and taking a decision on it. Spectrum analysis means characterizing separate bands of spectrum, so as to get proper spectrum band as per the wants of the user. When CR choose data rate and decides transmission bandwidth transmission mode, it is then referred to as spectrum decision. CR selects a suitable spectrum band which is in accordance with spectrum characteristics and user requirements.
- Spectrum Sharing: CR allocates vacant spectrum to SU's until the PU don't has the use of it. This is termed as spectrum sharing and it's an essential feature of CR.
- Spectrum mobility: When a PU needs back it's allotted channel, then CR withdraws and hand it over to PU. This process is called as spectrum mobility or hand-off [99] which lets CR user to alter the operating frequency. And during this process, CR transits to another better available spectrum. CR tries to maintain the requirements for smooth communication during this process.

Among above-discussed four functions of CR spectrum sensing is extremely vital, because if spectrum sensing is not efficient then SU can cause interference to the PU data transmission. Thus, affecting the QoS of the PU and that is a critical issue. Therefore, if the spectrum sensing is performed efficiently then the rest of the process involved in the CRN can be performed effectively.

Implementation of Soft Computing Techniques in Cognitive Radio

The core of CR is its capacity to enhance its execution process via learning. It is accomplished by the Soft Computing techniques related to cognitive radio. The Domain of Soft Computing is concerned with the outline and advancement of a calculation for empowering CR to learn. This is suited for conditions in light of understanding, because, by examples Soft Computing techniques learn, and by comparisons, they act.

The Soft Computing-based Cognitive engine is considered very vital for CR [46, 78]. And this led to the introduction of various intelligence algorithms for CR. Few examples are, Genetic Algorithm-based work was advanced for Cognitive Engine (CE) at Virginia Tech. Performance of GA-based CE showed that certain changes were imparted to transmission parameters which changed to different settings [21, 26]. Some other methods that were applied to CE are "Rule Based System" [48], "Case Based Learning" [57], "Fuzzy Logic" [59] and "Neural Network" [46]. The CR learning algorithm based on AI can be called as a Radio Environment Map (REM) enabled situation aware learning algorithm. REM can be categorized as global and local REM, where the former present the CR environment as the comprehensive view and latter gives the local view of the environment around CR. The network structure is the source of global REMs. At the same time, the radio capable

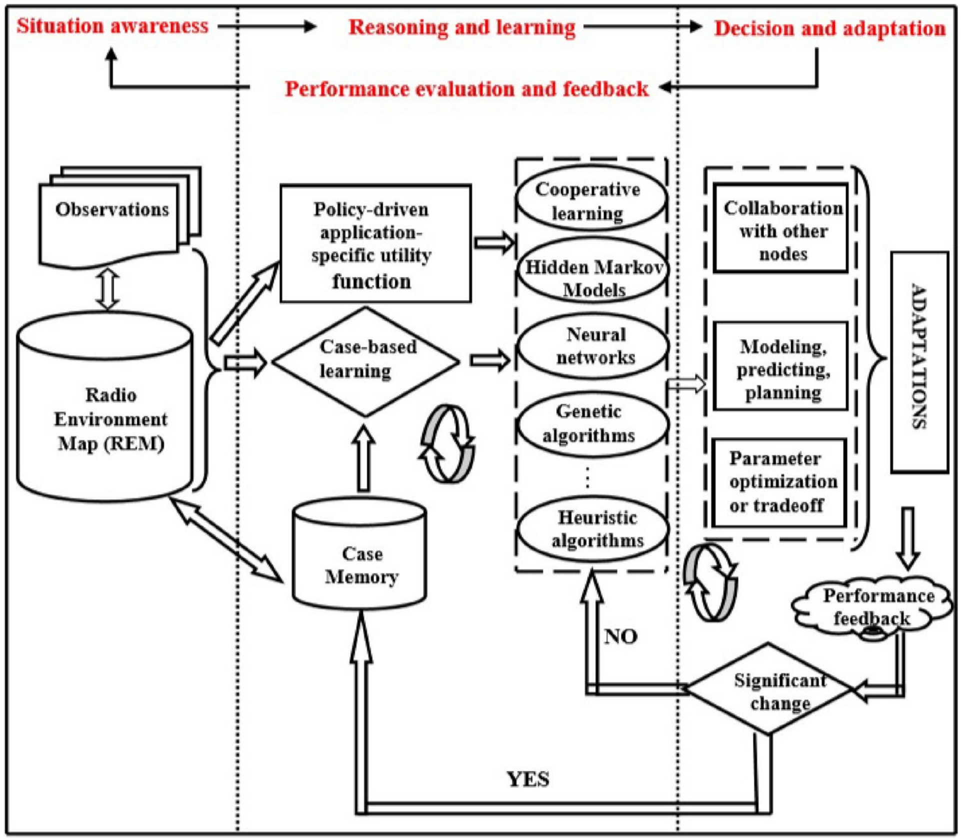


Fig. 4 System flow and framework of REM enabled CRN [34]

of performing spectrum sensing and monitoring transmissions of CR and Primary Users (PUs) within the range forms the Local REM. Diagrammatic description of the AI-based CR-learning algorithm by Zhao et al. [34] is shown in Fig. 4 via which it can be visualized that CE forms the basis of CRN. CE is an intelligent system with three fundamental processes sense, learn, and optimize the CR network. CR, based on its experience, forms the knowledge base and makes decisions on the current situation and also predicts future behavior. The environmental and operational information is represented and stored in CR's databases. Such databases are a kind of representation of REMs. In REMs, the database contains information such as spectral regulations, geographical features and the locations and activities of radios which are used in characterizing the environment of a given geographical area [34].

The CR covers a wide range of opportunities with various research works. Therefore, while dealing with CRN, one should not only be concerned about its advantages and opportunities but also about the issues related to it. In the next section, various research and implementation issues associated with CRN are dealt with.

Design Challenges for Cognitive Radio

The design hurdles associated with CRN are decisiveness (the ability to make quick and proper decisions and strategy for proper channel selection), training methodologies to be employed, security (protection against malicious users) [61], cross-layer design (Designing of networks within CRS is itself a difficult task, so the designing of higher layers such as MAC, Network layer, Spectrum management within different layers of the network is a humongous challenge) [35, 37], Geolocation, RF front end challenges (Maintaining high adaptability to multiple access methods and multiple modulations, Design should be such that RF Front End should have high switching ability and also should be able to communicate more than two points at a time), Baseband issues.

Spectrum sensing issues: Considered as the backbone of the CRS, spectrum sensing is one of the most critical and difficult task carried out by the CR. Major issues associated with spectrum sensing include accuracy of spectrum sensing decision, sensing time, implementation of spectrum sensing algorithm along with the consideration of noise uncertainty, multi-path fading, and shadowing effect. A computational and algorithmic implementation of spectrum sensing is a challenge in terms of maintaining precision while deciding the occupancy of the spectrum, its sensing time, and also concerning the malicious users. Spectrum

Table 1 Design hurdles in CRN and spectrum sensing

MAC layer issue	One of the prime issue associated with CRN is the spectrum management. CRN needs a MAC system than efficiently adapt itself to allocate transmission power and spectrum among SUs [35]
Spectrum licensing	Improvement is required in spectrum licensing strategy for efficient and flexible spectrum access [33]
Spectrum sensing challenges	1. Measuring techniques to calculate the interference caused to the nearby PUs are yet to be deviced [35]
	2. Need for developing spectrum sensing techniques that can coexist with the other operating CRN [35]

sensing computation and algorithm should also consider the noise interference, uncertainty due to multi-path fading and shadowing effect, and even hidden primary user problems. Table 1 gives a brief detail on the design hurdles in CRN and Spectrum Sensing .

Introduction to Spectrum Sensing

Spectrum Sensing is a process by which CR periodically observes a particular frequency spectrum, intending to recognize the primary users' presence or absence. Through spectrum sensing, CR can learn, measure, and get aware of its environment. Spectrum sensing is one of the two major processes involved in CR's dynamic spectrum access operation. When a particular frequency band is available (i.e., it is not in use by the PU at that specific instant of time in a particular position), then SU can avail that spectrum. Therefore, if a PU is not communicating via all channels, then spectrum opportunity can be developed for SU in the channel, which is not in use. Spectrum sensing not only means detection of the unused spectrum but also involves the determination of spectral resolution of each spectrum hole, estimating the direction of incoming interfering signals and signal functions. Table 2 gives the brief summary on previous survey in the field of spectrum sensing. Mostly, CR system co-exist with other radio frameworks, utilizing similar channel yet not causing any undue interference. While sensing the spectrum occupancy, the CRN must undergo following considerations:

- Nonstop spectrum detection: It is fundamental for the CRN to ceaselessly detect the spectrum occupancy. Regularly, a CR framework will use the spectrum on a non-obstruction premise to the PU. Appropriately, it is essential for the CR framework to constantly detect the spectrum in the event that the PU returns.
- Monitoring available vacant spectrum: There are possibilities that PU might be needing back the spectrum that being utilized by CR user, in such cases, CR user must immediately vacant the spectrum and it must have

Table 2 Summary on spectrum sensing surveys

S.No	Year	Authors	Prime contribution
1	2006	Akyildiz [35]	Brief review on cognitive radio technology and xG Network
2	2009	Yucek [61]	Surveyed spectrum sensing methodologies, spectrum sensing problems and proposed multidimensional spectrum sensing concepts
3	2009	Zeng [80]	Surveyed spectrum sensing methods namely energy detector, cyclostationary detection, matched filter detection, robust sensing, Likelihood ratio test, joint space time sensing and Eigen value-based sensing
4	2010	Akyildiz [89]	Addressed the issues of cooperative spectrum sensing in terms of cooperation overheads, method, and cooperation gain. Cooperation method is studied with respect to its fundamental elements such as sensing techniques, hypothesis testing, control channel and reporting, data channel. Survey has been done with following factors under consideration- sensing time, delay, energy efficiency , cooperation efficiency, security , mobility and wide band sensing issues
5	2011	Subhedar and Birajdar [94]	Spectrum sensing techniques have been surveyed, addressed the challenges and issues in spectrum sensing implementation. Comparative analysis of different sensing methodologies has been done
6	2012	Dhope and Simunic [98]	Surveyed cluster-based cooperative spectrum sensing and their role in improving the overall performance of cooperative spectrum sensing with low computational cost
7	2013	Khan and Nakagawa, [112]	Surveyed spectrum sensing techniques for PU detection. Techniques investigated are for cooperative spectrum sensing namely fuzzy logic, asynchronous cooperative spectrum sensing, network coding and relay diversity
8	2016	Muchandi and Khanai [132]	Surveyed spectrum sensing methods and schemes for the CRN and also addressed associated challenges in it
9	2016	Cichon, [133]	Presented novel ideas to implement energy efficient cooperative spectrum sensing algorithm and classified various energy efficient cooperative spectrum sensing techniques

an elective spectrum accessible to which it can switch as the need arises.

- Monitoring the types of transmission: CR should be able to detect the transmission type of PU so as to avoid false transmissions and interference.

The stability of the entire system is an important factor to be considered before designing a spectrum sensing technique. As the CR framework moves from one channel to another, then there are chances that spectrum occupancy will increase, which can reduce the spectrum efficiency and also affects the overall cognitive framework. If for a circumstance, channels are highly occupied by the PUs, and only a few numbers of channels are assigned or are accessible, then the first CRN settles at a particular channel. And when it recognizes another client, it proceeds to the following channel. The next channel might also be used by another client, so CRN needs to identify the new channel occupancy and it proceeds further. This process continues till the last client, thereafter it jumps to the first channel, and then the entire process is repeated. This situation if happens, then the cognitive radio spectrum detecting calculations must be capable of tackling these types of problems and guarantee the utilization of the available spectrum in the best possible manner. In the CR, spectrum detection is an important computational algorithm associated with its entire field. With experience, the CR spectrum detecting method gets improved. It will be intended to suit the expanding utilization of the spectrum in addition to any malevolent attacks that could be introduced to CRN.

Requirements of an Efficient Spectrum Sensing

As spectrum sensing is the key factor in a CRN, it is important to carry out spectrum sensing efficiently. The Essential requirements associated with the spectrum sensing are depicted through Fig. 5 “The taxonomy of spectrum sensing requirements”.

The main challenge for an engineer developing a CR framework is to design the spectrum sensing technique meeting the requirements mentioned in Fig. 5. Results obtained after detection have a considerable effect on the CR in terms of its accuracy. Therefore, spectrum sensing is an important issue to be considered while designing a CRN and has pulled attention among many researchers.

Components of Cooperative Spectrum Sensing

Components of cooperative spectrum sensing is shown in Fig. 6 is been discussed as follows:

- Cooperative Model: Here, emphasis is given on how the spectrum sensing is carried out by the secondary users. Game theory models and parallel fusion model have already been developed for obtaining Optimal decision performance [65]. These models are based on cooperative gain.
- Sensing Techniques involving Energy detection, Compressed sensing and cyclo-stationary feature detection are one of the most important element of cooperative spectrum sensing. Spectrum sensing is a method of detecting the primary users based on which inference is made whether the channel is vacant or occupied. The type of

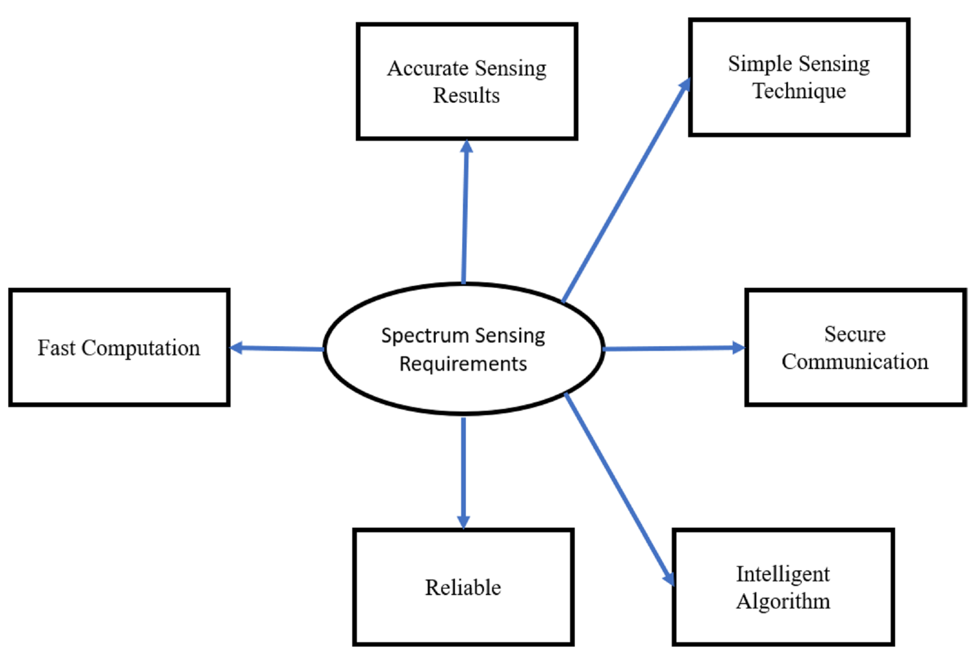
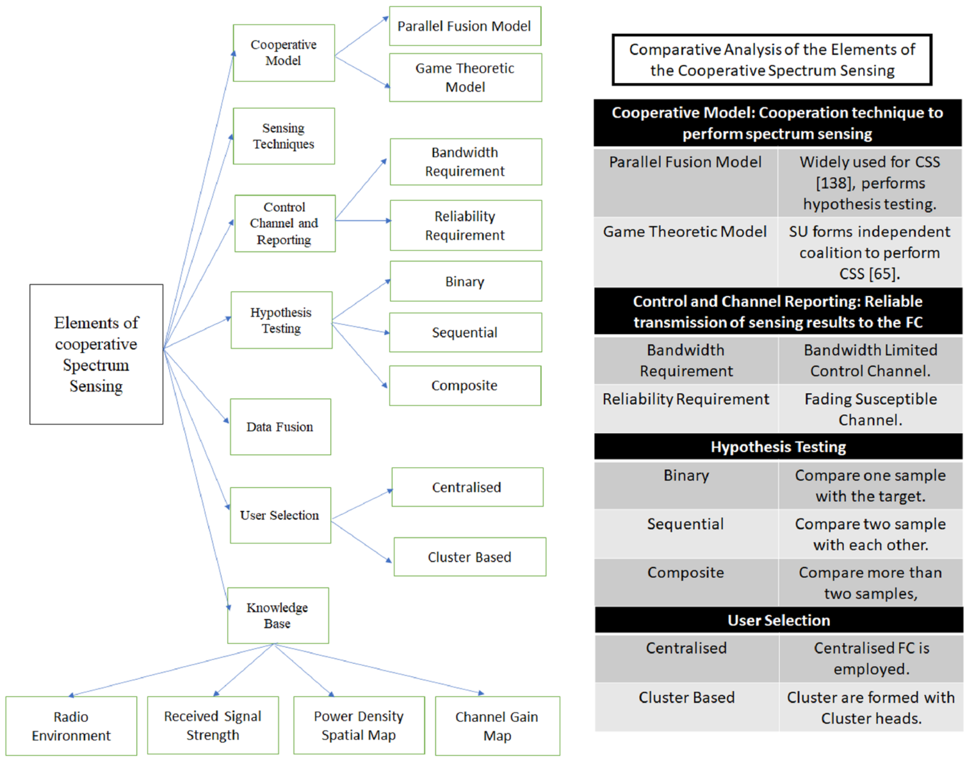


Fig. 5 Taxonomy for spectrum sensing requirements [139]

Fig. 6 Elements of spectrum sensing [139]



sensing technique selected affects the cognitive radio users (CRUs) undergoing cooperative spectrum sensing. For cooperative spectrum analysis, sensing primary signals and then sampling and processing of these signals plays very important role, because without proper sensing and sampling there might be chances that weak primary signals goes undetected with respect to the strong signals and its a big sensing challenge.

- Control and reporting section: It deals with the efficient and reliable reporting and sensing data to the Fusion Center, Data which is obtained by the cognitive secondary users while doing cooperative spectrum sensing. This sensing data are also shared with the other cognitive users via control channel which is fading, susceptible and band limited. This control channel is referred as Common Control Channel(CCC) [35, 75] and it is accessed via MAC scheme. In cooperative spectrum sensing, perfect control channel is impractical but current research shows that flawed control channel can be seen as the option for influencing cooperative sensing scheme.

Designing of control channel is a tough task because it has to consider various aspects such as:

- Recovering quickly to channel flaws.
- Robust to primary users.
- Bandwidth Efficiency.
- Dedicated data reporting.
- Dynamic in accordance to Primary User activity.

- Hypothesis Testing: To determine the presence of primary users, statistical tests of survey data are performed and it is termed as Hypothesis testing. Individual cooperative users perform hypothesis testing to reach a local decision,for a cooperative decision hypothesis testing is done by FC. In a hypothesis testing for getting an optimum decision, large number of samples are required and that makes the process of hypothesis testing difficult.
- Data Fusion: Sensing data (reported and shared one) is combined to make a cooperative inference, thus process of merging is termed as Data Fusion. There are three divergent methods via which data fusion is carried out. These are mentioned in descending order of their performance with respect to control channel and bandwidth:

  - Soft Decision: Here, all sensing data obtained by cognitive user are combined together to get soft decision.
  - Optimized soft decision: Here, optimization of all local sensing data is performed and only optimized data is sent for soft combining.
  - Hard decision: One bit decision is transmitted by cognitive user for Hard Combining.

- User Selection: It helps in optimizing the selection of cooperative cognitive user and deciding the absolute cooperation range which in turn facilitates in maximizing cooperative gain and minimizing cooperative overhead. It also help in determining the performance of cooperative spectrum sensing by emphasizing on improving the cooperative gain and addressing the overhead issues. In a cooperative spectrum sensing, if cognitive user faces the problem of correlated shadowing then by selecting independent cooperative cognitive users for sensing can help in obtaining a better sensing results. This shows that user selection is an important factor in implementing an efficient cooperative spectrum sensing model.
- Knowledge base keeps the record of the previous experiences and information so as to improve the overall spectrum sensing. Information stored in the knowledge base are the deductive knowledge or the knowledge gained via user experience. Knowledge base comprises information regarding Primary user and CR user location, Primary user activities, signal strength profiles. Performance of cooperative spectrum sensing is highly influenced by the knowledge of primary user characteristics such as transmission power, location and traffic patterns. The knowledge base forms the essential part of cooperative spectrum sensing system, because if primary user information are properly updated in the knowledge base then it enables efficient PU detection. Therefore, in this manner, it assists CRN in spectrum detection.

Conventional Spectrum Sensing Methodologies

In the literature survey, a number of spectrum sensing methodologies have been identified. In this section, some of the widely used spectrum sensing techniques have been discussed with respect to their characteristics, working, merits and demerits.

Based on the signal detection techniques, spectrum sensing techniques have been broadly classified into four different categories [89]. Figure 7 shows the basic spectrum sensing techniques.

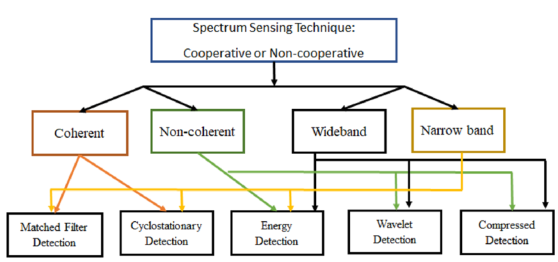
First type of classification is named as Coherent and Non Coherent detection. In the coherent detection technique prior information of primary users is required which is then evaluated with respect to the received signal so as detect the primary signal coherently, where as in non-coherent detection, there is no requirement of prior knowledge of primary signal for the detection. Second half of the classification is based on the bandwidth of the spectrum to be sensed, and its classified as narrow band and wide band. Spectrum sensing classification can be visualized in Fig. 7.

Existing methodology had drawbacks with respect to spectrum sensing which in turn had negative impact on overall efficiency of the CR model. Therefore, these basic methods were incorporated with some optimization methodologies to increase the spectrum sensing efficiency. Now, the classification of spectrum sensing can be made comprising of popular traditional methods, some basic methods and various optimization methodologies that have been used for spectrum sensing. Based on above discussion, a broader classification of the works carried out in spectrum sensing is depicted in Fig. 8.

For detailed description, each methodology is described individually as under:

4A. Energy detection-based spectrum sensing-Energy detection technique, also known as radiometry or periodogram, is a low computational, most commonly used technique having fewer implementation complexities [22, 27, 32, 73]. Energy detection technique works basically by measuring only the received signal, it is basically a non-coherent-based detection device. One

Fig. 7 Basic spectrum sensing techniques [35]



Spectrum Sensing Technique: Cooperative or Non-cooperative	
Coherent	Based on signal detection [35]. Priori knowledge of the primary signal is required.
Non-Coherent	Based on signal detection. Priori knowledge of the primary signal is not required.
Wideband	Based on the bandwidth of the spectrum of interest (Wideband)
Narrowband	Based on the bandwidth of the spectrum of interest (Narrowband)

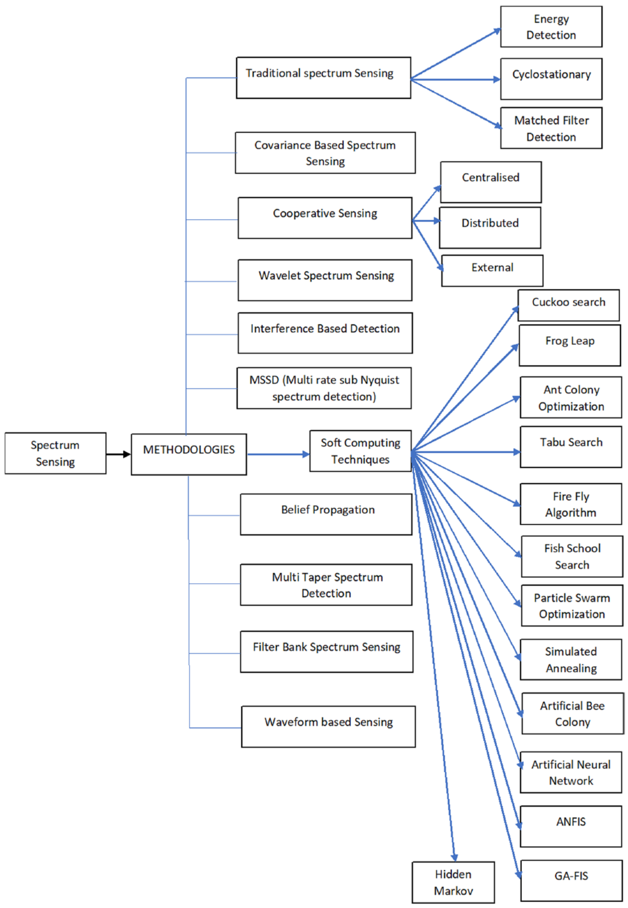


Fig. 8 Taxonomy of existing spectrum sensing methodologies

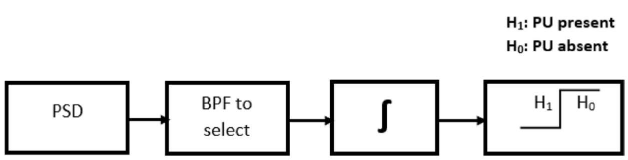


Fig. 9 Working model of energy detection [33]

of the drawbacks associated with energy detection technique is that it performs poorly in low signal-to-noise ratio and also the estimation error due to noise may degrade detection performance significantly [60]. Another challenges associated with the energy detection are the selection of threshold for detecting primary users and inability to differentiate interference from primary user and noise [73]. In addition to that energy detector's efficiency lags while detecting the spread spectrum signals [22, 33]. Figure 9 depicts the basic block diagram of energy detection technique. From the figure, it can be seen that its important elements consist of first the Power spectral Density estimation, secondly Band Pass Filter to select channel, then the Integrator and lastly estimating the presence or absence of primary user is done based on inferences obtained from previous blocks. For better understanding about the working of energy detection, consider *x(n)* as the primary signal transmitted through a channel of gain *h*. Then, the received can be written as in Eq. 1 [151]:

$$y(n) = hx(n) + w(n), \tag{1}$$

where *w(n)* is the Additive white Gaussian Noise(AWGN) sample and *n* represents the sample index.For no transmission by primary user *x(n)* takes the value 0. The decision metric for the energy detector can be written as in Eq. 2.

$$M = \sum_{i=0}^{N} |Y(i)|^2 \tag{2}$$

here *N* is the size of the observation vector. The band occupancy can be known by comparing the decision metric *M* against a fixed threshold: λ_T. Function *y(n)* follows a binary hypothesis shown in Eq. 3.

$$\begin{aligned} y(n) &= w(n) &&: H_0\{\text{Signal is Absent}\} \\ y(n) &= hx(n) + w(n) &&: H_1\{\text{Signal is Present }\} \end{aligned} \tag{3}$$

The probabilities of false alarm (P_f) and detection (P_D) can be evaluated as ($P_r(M > \lambda_T | H_0)$) and ($P_r(M > \lambda_T | H_1)$), respectively. Since P_f is the probability of false alarm which implies that the energy detector has done missed detection, though the channel is vacant its been inferred as busy. Therefore, a minimized value of P_f is preferred to prevent the under utilization of transmission opportunities, since P_f is the probability that the system incorrectly decides that the considered frequency is occupied when it is actually not. Where as P_D detection probability is desired, since it is the probability of detecting signal when it is actually present. From the flowchart in Fig. 10, it can be seen that first secondary user (SU) collects the information with respect to PU, and the energy of the signal is estimated. Then, the probability of detection and probability of false alarm are computed to analyze the effect of fading channel on the detection performance. To maximize the probability of detection, lowered value of threshold is desired. Final value of energy detector is the average or total of all the energy detection values from N samples. The major issue associated with energy detector is its degraded performance at low SNR values [124], to have improved performance a spectrum sensing technique should be able to perform in low SNR values as channel condition deteriorates the PU signal.

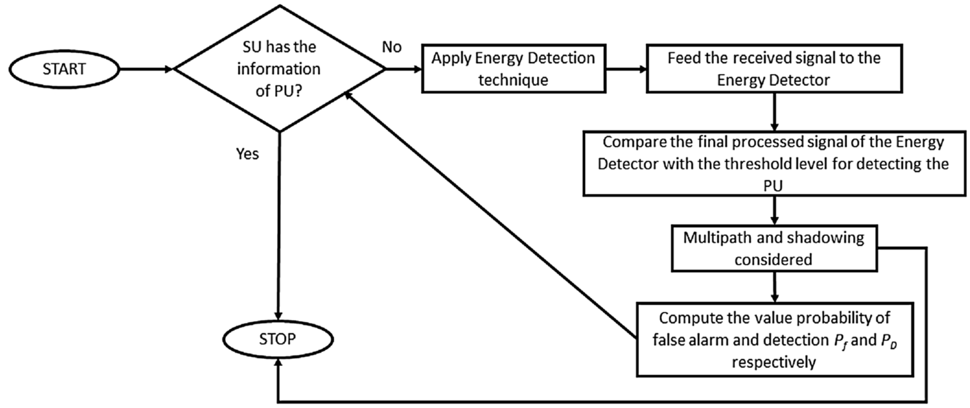


Fig. 10 Flowchart of energy detection technique

4B. Cyclostationary-Based Spectrum Sensing: Cyclostationary is the process where the statistical properties vary periodically with time. And the method which employs the cyclostationarity attributes of the received signal for detecting the primary user transmission is termed as cyclostationary feature detection [22, 27, 32, 73]. Signals which are modulated using sine wave carrier or any cyclic prefixes shows periodicity despite the data being the stationary random process. The modulated signals are described as cyclostationary because their statistics, mean and auto-correlation shows periodicity [22]. Wireless communication signals are mostly cyclostationary where as the noise is wide sense stationary having no correlation, so the cyclostationary of the primary signals can be used to detect its presence. In this process for detecting the presence of signals in a given spectrum, cyclic correlation function is used instead of power spectral density. For calculating cyclic spectral density function $S(f,\alpha)$ of a received signal referred in Eq.(1), following functions depicted in Eq. 4 is used [5, 61]:

$$S(f,\alpha) = \sum_{T=-\infty}^{\infty} R_y^{\alpha}(\tau)e^{-j2\pi f\tau} \tag{4}$$

$$R_y^{\alpha}(t) = E[y(n+\tau) * y(n-\tau)e^{j2\pi\alpha n}] \tag{5}$$

Here, $R_y^{\alpha}(\tau)$ shown in Eq. 5 represents cyclic auto-correlation function (CAF) and α is referred as cyclic frequency. Peak value of cyclic spectral density function is obtained when the cyclic frequency has values equivalent to that of fundamental frequencies of signal *x(n)*. Cyclostationary feature detector can be implemented for very low SNR detection using the information embedded in the primary user signal which does not exist in the noise. This technique is robust and performs better than energy detection technique. But computational complexity and longer observation time adds to its disadvantage. And also cyclostationary technique has the difficulty of exploiting cyclostationary feature in weak voice signal [56]. Figure 11 shows the basic block diagram of cyclostationary feature detector and its working sequence is explained with the help of flowchart shown in Fig. 12.

4C. Waveform-based sensing: It is applicable to systems with known signal patterns. With the knowledge of a known pattern, sensing can be performed by correlating the received signal with a known copy of itself [28, 36, 43]. Mathematical model of waveform-based sensing can be expressed as shown in Eq. 8 [28]:

$$T = \Re e\left[\sum_{n=1}^{N} y(n)x^*(n)\right]$$

$$T = \sum_{n=1}^{N} |x(n)|^2 + \Re e\left[\sum_{n=1}^{N} w(n)x^*(n)\right] \quad \text{(when PU is present)}$$

$$T = \Re e\left[\sum_{n=1}^{N} w(n)x^*(n)\right] \quad \text{(when PU is absent)} \tag{6}$$

here:

$$y(n) = x(n) + w(n) \tag{7}$$

Based on the comparison between the metric value of T and a fixed threshold λ_e , decision is made whether PU signal is present or absent. Waveform-based sensing has better reliability and convergence time as

Fig. 11 Working model of cyclostationary feature detector [33, 94]

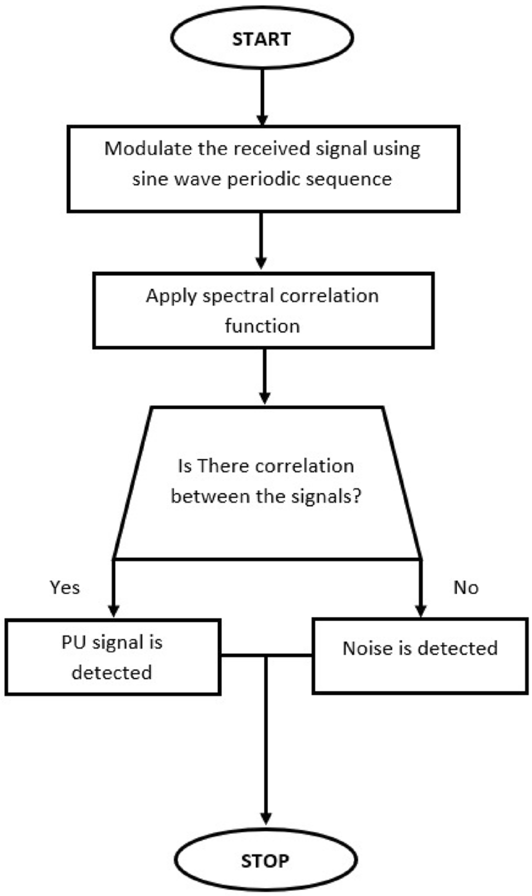


Fig. 12 Flowchart of cyclostationary feature detection technique

compared to energy detector-based sensing [28]. In addition to that, the performance of the sensing algorithm increases as the length of the known signal pattern increases [33]. But for to have increased length of the known signal, it is required have high sensing time which eventually decreases the transmission time and thus the overall throughput of the system, moreover waveform-based sensing is susceptible to synchronization error [33].

4D. Matched Filter: Basic feature of matched filter(MF-Linear Filter) is to increase the output signal to noise ratio for a particular input signal, so it is designed in that manner. Matched filter detection is applied when secondary user has a priori knowledge of primary user. Working principle of matched filter is like correlation. It correlates the unknown signal with mirror and time shifted version of the reference signal. Equation for the matched filter operation can be expressed as in Eq. 6 [94]:

$$T = \sum_{k=-\infty}^{\infty} h(n-k)x(k) \tag{8}$$

Which is governed by two hypothesis stated in Eq. 7:

$$\begin{aligned} y(t) &= w(t) && : H_0\{\text{PU Absent }\} \\ y(t) &= x(t) + w(t) && : H_1\{\text{PU Present }\} \end{aligned} \tag{9}$$

Here, $x(n)$ is the signal to be detected which is convoluted with matched filter's impulse response $h(n)$ which is the equivalent to the reference signal to be detected. Basic block diagram of matched filter and its work flow is explained in Figs. 13 and 14. Matched filter's impulse response which is matched to the reference signal to have the maximum signal to noise ratio. One of the advantages of matched filter is that it requires less detection time, since it need only $O(1/SNR)$ samples to meet the required probability of detection [35]. Matched filter detection is the best way of detecting

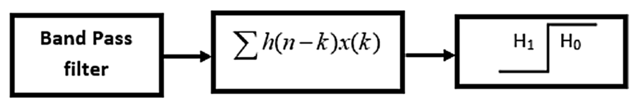


Fig. 13 Block diagram of matched filter [94]

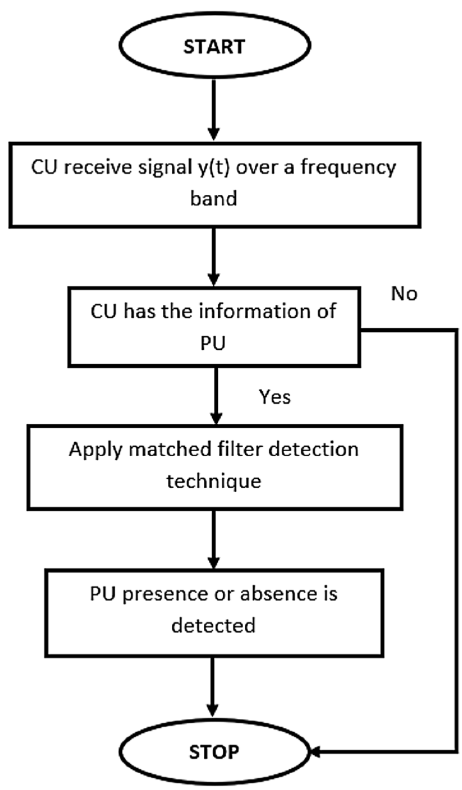


Fig. 14 Flowchart of matched filter

in stationary gaussian noise, provided that the information of the PU signal is already known to the user. But for cognitive user with matched filter detection, it is required that it is fully synchronized with the PU, which is very difficult to achieve in the cases of low SNR [55, 102]. In addition to that to perform coherent detection, matched filter requires receiver for all type of signals and their corresponding algorithm is to be executed resulting in high implementation complexity and power consumption [33].

4E. Multi-Taper spectrum sensing: Before the introduction of cognitive radio, multi-tapper concept was proposed in the year 1982 [94] and multi-taper was first used for spectrum estimation in Haykin et al. [29]. An estimate of the periodogram can be referred as the filter banks' output. And the power spectrum estimate's each points correspond to filter's output. With the help of modulation of single prototype filter, the filter bank is constructed. Multi tapper spectrum sensing works in a similar way but it uses multiple orthogonal prototype filter so as to improve the variance of estimated power and reduce the leakage [62]. Here, received samples are collected in vector form and represented as a set of slepian base vectors. By utilizing the feature that slepian vectors have maximum energy concentration in the band width $f_c - w$ and $f_c + w$ under finite sample size, CR user can easily identify the spectrum opportunities in given bands. Multi-Tapper is preferred for small sample space as it uses multiple prototype filter, and with the increase in the number of samples the computational complexity also increases [94].

4F. Spectrum sensing based on filter bank technique: Farhang-Boroujeny in [47] proposed spectrum sensing based on filter bank technique for a CRN. A pair of matched root nyquist filter has been used to implement the proposed technique. Filter-based spectrum sensing can be considered simplified version of Multi-Tapper-based spectrum sensing in which for each band there is a prototype filter. On comparing Filter bank with multi-tapper, it can be inferred that the best prototype filter used in multi-tapper has its magnitude response comparable to the magnitude response of root nyquist filter proposed by Farhang in [47]. In terms of variance over frequency band with low-power spectral density, Filter bank spectrum sensing has better performance than multi-tapper. Filter bank has lower leakage compared to multi-tapper and it also performs better for a large number of samples while multi-tapper spectrum sensing has better estimation index with small sample space. Multi-tapper spectrum sensing is faster than filter bank spectrum sensing, because smaller window size for a particular sampling rate [62].

4G. Covariance-based Spectrum Sensing: Here, PU signal is detected based on the diagonal elements of covariance matrix. Diagonal elements take the value 0 in the absence of PU signal and its 1 when PU signal is present [55]. Basically, covariance-based spectrum sensing works on the principle that PU signal at the CR user is correlated due to these factors:

- Over sampling
- Dispersive channels
- Using multiple receive antennas

CR user utilizes this correlation factor to distinguish between PU signal and white noise. Covariance-based spectrum sensing performance depends on the statistics of received PU signal. If PU signal and white noise are non distinguishable then covariance method fails. A brief about above-discussed method is shown

Table 3 Accuracy and complexity analysis of the basic spectrum sensing methods

Sensing methods	Accuracy ratings (1–10)	Complexity ratings (1–10)	Remarks
Energy detector(ED)	2	2	It is the least complex system but with low accuracy and at low SNRs the Energy Detection techniques is not suited to obtain a high detection probability [22] Energy Detector with proper soft computing techniques, can effectively optimize the spectrum sensing parameters and thus, can efficiently predict the PUs [124]
Cyclostationary detector(CSD)	3	4	It is slightly more accurate than energy detector but with higher complexity [69]. With Soft Computing techniques the complexity of CSD can be optimized and further can improve its performance on detecting the PUs [125]
Filter bank detector	4	6	Accuracy wise its better compared to ED and CSD, but it is more complex with respect to the ED and CSD [62]
Multi-tapper	4	7	Same level of accuracy as that of filter bank but its slightly more complex [62]
Covariance method	7	5	High in accuracy with comparable complexity
Matched Filter	8	7	Highly accurate but increased level of complexity, requires priori knowledge of PU signal [62]

in Table 3 which depicts the ratings of the basic spectrum sensing techniques with respect to accuracy and complexity. The ratings have been done based on the surveyed paper. The complexity is analyzed based on time complexity of the sensing methods. The time complexity associated with the Conventional Energy Detector is $O((N_s))$, where N_s is the number of energy samples sensed [33]. The complexity of cooperative spectrum sensing depends on the number of SUs within a Fusion Center, Spectrum sensing technique employed by the each SUs and the complexity associated with the evaluation at the fusion center. So the complexity associated with the cooperative spectrum sensing is higher than the conventional energy detector [148]. The Matched filter complexity is analyzed based on its requirement of dedicated receiver for every primary user $Dp * N_s$, where Dp is the dedicated receivers for each primary users [22]. The accuracy of each sensing methods is evaluated based on the performance remarks in [22, 33, 62, 69, 124, 125] for obtaining the probability of detection (Pd) and probability of false alarm (Pfa) in different SNR conditions. The ED has the least accuracy for Pd and Pfa, whereas Matched Filter with dedicated PU receiver has the highest accuracy level.

4H. Wavelet-based Spectrum Sensing: Han et al. 2013 [115] proposed Wavelet-based energy detection for spectrum sensing. The author described about the scheme in which wide band signal is fed to the filters and then the corresponding output is used to detect the presence of PU signal with the help of wavelet based edge detector. Proposed scheme is also applicable to multiple CRN and it proved beneficial for high compressive ratio and sparsity level. Capriglione et al. [126] proposed wavelet-based spectrum sensing for low SNR scenarios. With the help of simulation results, it was shown that proposed method performed better than other conventional spectrum sensing in low SNR scenarios

4I. Belief Propagation: Zhang et al. [90] proposed belief propagation-based spectrum sensing to deal with the issues of wide band spectrum sensing. Issues such as acquisition of spectrum for limited sampling capability and method to collaborate secondary users. With the proposed technique, authors are able to deal with these issues of wideband spectrum sensing via graphical model based on probability. The graphical model showcase the technique for combining secondary users based on multi-prior information. And Belief propagation infers the occupancy of the spectrum based on statistical details. Simulation results showed that proposed method can efficiently implement cooperative compressed spectrum sensing for low SNR and sampling rate with high performance in terms of cooperation among the secondary users even in diverse conditions.

4J. Multirate SubNyquist Spectrum Detection:MSSD known as Multi rate SubNyquist Spectrum Detection proposed by Sun et al. 2011 [91] for spectrum sensing in CRN. Seeing the significant challenge faced by CRN in fading environment author proposed MSSD-based method spectrum sensing method for both non fading and Rayleigh fading channels. In MSSD, each CRUs has a wideband filter, a sampler and an FFT which determines the energy of the signal in frequency domain, proposed system model also consist of fusion center which channelize separate subnyquist sampling rates for CRUs and each CRUs performs asynchronous subnyquist sampling followed by FFT. From CRUs, quantized energy is transferred to FC. FC fuses the received signal and chooses a threshold for testing the binary hypothesis and distributes the result to al CRUs. Simulation results depicted in the paper has proven that Proposed method performed well in fading environment with low complexity level for computation and implementation.

4K. Interference-Based Detection: In this technique, CRUs operate in spectrum underlay similar to ultra wide band (UWB). Basic methodology of UWB technique is that the system can communicate with high bandwidth over large portion of communication spectrum but with a condition that it should maintain a very low energy level with short range communication. Interference-based detection can be classified into two categories as under:

a. *Interference Temperature-based management*: Here, basic idea is to fix an upper threshold for interference in a particular frequency band for a specific geographic location such that the CRUs will not cause any problematic disruption while using a particular band in that specific area. For controlling the interference, Transmission power of the CRUs is regulated depending on the location of CRU with respect to primary users [50]. Interference measurement at receiver side is the main focus of the this method. Similar to UWB technology, in this method also the CRUs can co-exist and trans-

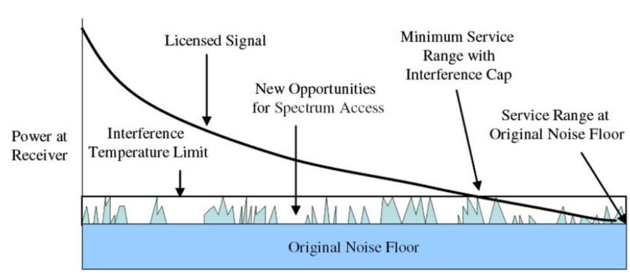


Fig. 15 Interference temperature model [63]

mit parallelly with PUs while keeping the transmitting power very low so as not cross interferrence temperature threshold as set by the system which prohibits any harmful interference to PUs by CRUs [94]. Figure 15 shows the basic model of interference temperature-based detection. Power limit is one of the disadvantage associated with this method, because the CRUs are not permitted to transmit data at high power even if the PU is completely idle. To constrict the interference caused to PUs, CRUs should have their power range confined within the threshold power limit. For this, CRUs should always keep the track of the location and the equivalent threshold level of permitted transmit power of that location, otherwise interference could be caused to PU transmissions.

b. *Primary Receiver-based detection*: In this method leakage power from the RF Front of primary receiver's local oscillator (LO) is been detected. This type of power leakage usually happens when primary receiver receives data from primary transmitter. For detecting this power leakage, a sensor node low in cost is mounted near to a PU's receiver within the range of communication of CRUs. The sensed information is passed on to CRUs which make the final decision regarding spectrum occupancy status. In this manner the spectrum detection is carried out via this technique.

4L. Cooperative Spectrum Sensing: Many problems were associate with the non-cooperative spectrum sensing like noise uncertainty, fading, shadowing and hidden terminal problem. As a solution, cooperative spectrum sensing is introduced in [22, 25]. Cooperative spectrum sensing performs better in terms of detection as compared to non-cooperative spectrum sensing since it exploits diversity gain provided by associated radios. It overcomes loss due to building penetration, it imposes high sensitivity requirements inherently limited by cost and power requirements, improves agility, reduces interference to PU, improved detection probability and reduced deduction time. Cooperative spectrum sensing working can be described as follows [40]:

- Each CR device performs local sensing and make a binary decision.
- CRUs' binary decisions are then forwarded to a fusion center(common receiver) which can be an WLAN access point or a cellular network's base station.
- Fusion center then make a cumulative decision based on the binary decisions obtained from CRUs. From the decision of the fusion center presence or absence of the PU in a specific band is inferred.

Based on the architecture following classification can be made for cooperative spectrum sensing [88, 89]:

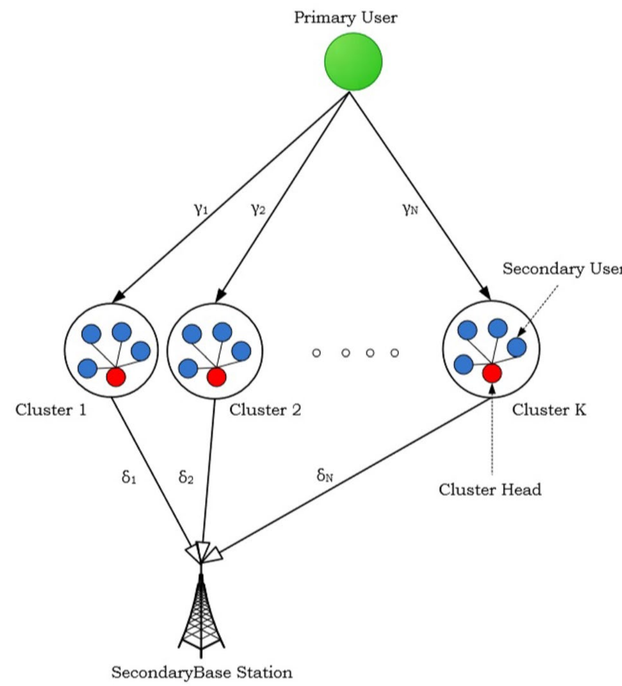


Fig. 16 Centralized cooperative spectrum sensing [94]

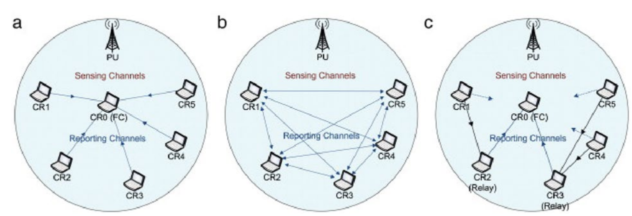


Fig. 17 **a** Centralized, **b** Decentralized coordinated, **c** Decentralized uncoordinated [89]

a. *Centralized cooperative spectrum sensing*:In this the sensing information from CRUs are collected to a central unit. Central unit identifies the available spectrum and broadcast this information to other CRUs or it can directly control CR traffic. Here, CRUs group together to form clusters and each cluster have cluster head/central unit, which forward the cumulative decision of CRUs to a fusion center.Centralized cooperative spectrum sensing is shown in Fig. 16.

b. *Decentralized cooperative spectrum sensing*:Decentralized cooperative spectrum sensing is further classified into two groups (i)Decentralized Coordinated (ii)Decentralized Uncoordinated [89] as shown in Fig. 17.

- Decentralized Uncoordinated:In this technique CRU detect channel by themselves and if PU is detected then the channel is vacated without informing other CRUs of the cluster.Because of this Decentralized Uncoordinated Technique is more error prone as compared to Coordinated technique. And there is more probability that CRU detect that the channel incorrectly and, therefore, causing interference to the PU.
- Decentralized Coordinated:In this type of cooperative spectrum sensing technique, CR clusters do not have a cluster head [152]. Cooperation between the CRUs is done via gossiping algorithm or clustering schemes in which CRUs within the clusters auto coordinate themselves [31]. Cooperative spectrum sensing in all turns out to be very beneficial, however, there are certain challenges associated with cooperative spectrum sensing like increased overhead traffic, increased power consumption due to heavy communications, increased complexity and the need for control channels.

4M. Eigen value-Based Spectrum Sensing: Variation in autocorrelations of signal and noise is the basic working principle of eigen value-based spectrum sensing. Similar to energy detection technique, eigen value-based spectrum sensing also do not require priori knowledge of primary signal but energy detection technique is not handy for correlated signal. Such shortcomings of energy detector method is overcome by eigenvalue-based spectrum sensing [49, 54]. In this method, eigen values of the covariance matrix of received signal is estimated for signal detection.

Guimaraes et al. in [108] proposed eigenvalue-based centralized cooperative spectrum sensing for detecting OFDMA and wideband signal. For binary hypothesis testing, author proposed four test statistics which are Generalized likelihood radio test, maximum minimum eigenvalue detection, maximum eigenvalue detection and the energy detection and made a comparison between eigenvalue fusion, decision fusion and sample fusion, the simulation results showed that eigenvalue fusion-based detection techniques outperformed the other schemes.

Soft Computing-based Approaches for Spectrum Sensing

Spectrum Sensing Optimization

The challenging aspect of spectrum sensing is mainly all about accurately detecting the presence and the absence of PU in a particular frequency spectrum. This detection process is characterized by the probability of detection (the measure of accurately detecting the presence of PU) and the probability of false alarm (the measure of inaccurately or falsely detecting the presence of PU). For an efficient spectrum sensing technique, it is required to have high detection probability and low false alarm probability. But these two terms maintain a trade off governed by the spectrum sensing parameters such as sensing time, detection threshold, transmission power, sensing power, and fusion weights. The longer span of spectrum sensing, i.e. longer sensing time results in high detection probability and low false alarm probability. But for the fixed frame length, longer sensing time decreases the transmission time which eventually reduces the SUs' throughput [124]. Therefore, sensing time optimization is required to obtain a proper balance between sensing time and transmission duration to achieve an efficient CRN. The detection threshold is another important criterion to be considered for coherent spectrum sensing. A high value of detection threshold results in low false alarm probability (preferred), but it also reduces the detection probability (non-preferred). Similarly, transmission power and sensing power are also required to be optimized for an energy-efficient spectrum sensing. Moreover, to have an opt decision on the presence and the absence of the PU, it is necessary to optimize the fusion weights in case of cooperative spectrum sensing [148]. Existing spectrum sensing methodologies lags in obtaining the proper trade off between spectrum sensing parameters.

Conventional spectrum sensing techniques perform the basic operation of sensing but to have the optimized values of different sensing parameters; it is necessary to incorporate soft computing techniques for spectrum sensing. An optimal value of sensing time, detection threshold, and other sensing parameters can result in effective spectrum sensing, thus enhancing the performance of a Cognitive Radio Network. The soft computing techniques employed for spectrum sensing is discussed as under:

5A. Meta-heuristic Approaches: Deterministic nature of traditional classical algorithm calls for the need of stochastic algorithm for solving real-time non-linear problems.Classical algorithms like Newton Raphson which uses gradient descent method are well suited for smooth unimodal problems, if there is any discontinuity then these methods will not work well. That is the reason why stochastic algorithm are so preferred as they are gradient free which are gradient free and based on function values only [92]. Stochastic algorithms are classified as *heuristic* and *Metaheuristic*, having subtle difference. The word heuristic means to learn or discover via trial and error process. A good preferable solution can achieved via heuristic algorithm in a less number of iteration but its not necessary to get best solution all the time. Metaheuristic is an advanced form of heuristic, as its performance is better than simple heuristics. Metaheuristic algorithm use tradeoff between randomization and local search. Since randomization gives better solution in global search and local search in local area exploitation. Therefore, a better tradeoff between randomization and local search can result in global optimization, which can be achieved through Metaheuristic algorithm. In the case of spectrum sensing, there should be proper tradeoff between various spectrum sensing parameters like sensing time and throughput so, optimization plays a key role in spectrum sensing. Figure 18 shows the frame structure of spectrum sensing which shows various aspects to be considered for spectrum sensing optimization. There are various Metaheuristic algorithms which have been used for spectrum sensing optimization in the proceeding section each metaheuristic algorithms that have been used to improve the spectrum sensing methodologies have been discussed:

a. **Genetic Algorithm(GA)**: Authors in [77] emphasized on optimization of collaborative spectrum sensing and finding optimum decision fusion for hard and soft combining in a cooperative spectrum sensing scheme. For soft combining authors proposed GA-based weighted optimization strategy. The proposed scheme comprised of SUs and fusion center, detection results from SUs combined with weights were transmitted to fusion center. GA so employed was used to optimize the weighted spectrum sensing results from SUs, to improve the overall cooperative spectrum sensing scheme with respect to receiver operating characteristics. Based on simulation results, it can be inferred that GA-based technique for spectrum sensing weight optimization has improved the overall sensing performance in terms of low value for probability of missed detection. In [127], authors proposed Genetic Algorithm(GA) based optimization scheme for frequency hoping CRN performing joint out of band spectrum sensing and channel allocation. Proposed GA-based technique comprises an algorithm dealing with sensing and data transmission utility. In GA, the solution of an objective function is represented by the chromosomes comprising of genes which in turn represents a set of parameters for optimization. In this paper for the proposed objective function, the chromosome's structure was made up of sensing gene and data gene each with different size and characteristics. The proposed GA model consists of K elements each representing different hopping channel. N bit binary string is associated with each element and the position of each bit represents a particular member node. K number of elements comprises data gene, each having q bits indicating power level. Simulation results showed the efficacy of the proposed method. Another GA approach for cooperative spectrum sensing scheme was proposed in [128]. In the proposed approach for the minimization of error probabilities and for the identification of available spectrum holes, GA-based spectrum sensing is employed. The proposed method is then compared with Bacterial Foraging Optimization Algorithm(BFOA). From the simulation results, it was inferred that proposed method is better option for spectrum sensing as compared to conventional BFOA. For the spectrum sensing scenario probability of correct detection $P_{j\det}$ and probability of false alarm $P_{f\text{alarm}}$ plays the major role. With the help of these two functions probability of total error can be evaluated as in Eq. 10 [121].

$$P_{j\text{error}} = P(H_0)P_{f\text{alarm}} + P(H_1)(1 - P_{j\det}) \tag{10}$$

$P(H_0)$ and $P(H_1)$ indicates used and vacant channel respectively. GA evaluates the values of the fitness

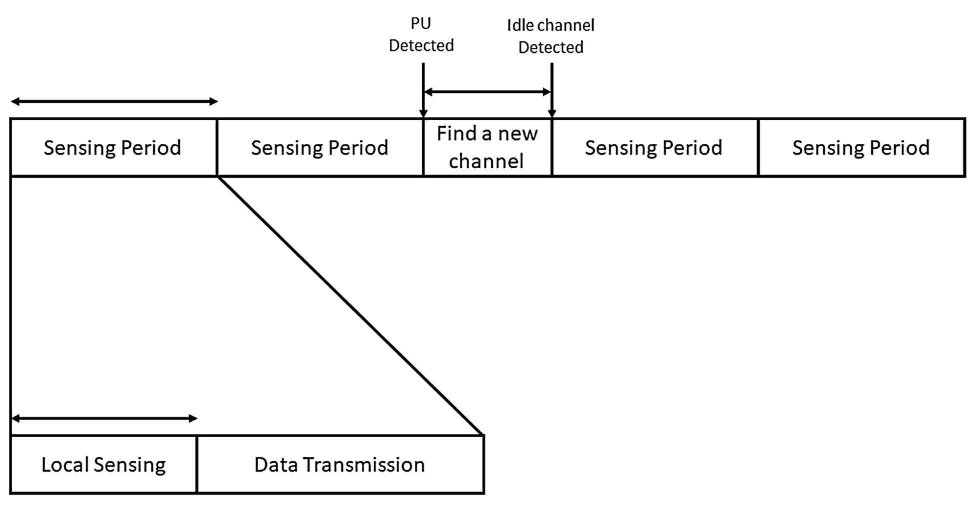


Fig. 18 Spectrum sensing frame [125]

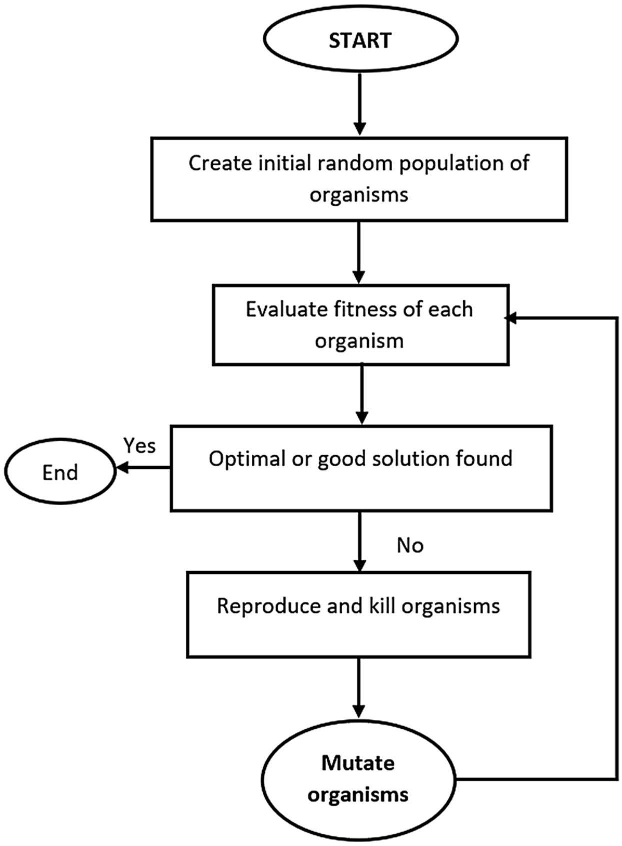


Fig. 19 Flowchart genetic algorithm

function to each chromosome, where fitness function is the P_{jerror}. Flowchart in Fig. 19 depicts the basic work flow of GA.

GA is easy to implement and requires minimum human involvement, and supports multiobjective optimization. It is inherently parallel and easily distributed. There are many ways to speed up and improve a GA based application as knowledge about problem domain is gained. In GA optimized solution gets better with time. With these noted advantages, there are also few drawbacks associates with GA, there is no guarantee of finding global maxima, and likely of getting stuck with local maxima at the early stage is bit high. Need a decent sized population and a lot of generations to get good results [68].

b. **Swarm Intelligence Algorithm**: Swarm Intelligence is the computational study of cooperative intelligence acting in a group of homogeneous agents in the environment, like school of fish, flocks of birds, colonies of ants, which they use for searching food, evading prey or re-allocating colony [93]. This type of intelligence is not centralized, rather distributed through out the environment but are self organizing. Using such swarm intelligence, various optimization algorithms have been developed, Table 4 lists out some of the swarm intelligence-based optimization algorithms.

Table 4 List of swarm intelligence algorithms

Algorithm	Author	Year
Stochastic diffusion search	Bishop	1989 [3]
Particle swarm optimization	Kennedy and Eberhart	1995 [8]
Ant colony optimization	Dorigo and Decaro	1999 [11]
Self propelled particle	Vicsek	2000 [12]
Bacterial Foraging	Passino	2002 [15]
Fish swarm algorithm	X Li	2003 [19]
Shuffled frog leap algorithm	Muzzaffar and Kevin	2003 [18]
Multi swarm optimization	Blackwell and Branke	2004 [20]
Glowwarm swarm optimization	Krishanand and Ghose	2005 [24]
Artificial Bee colony algorithm	Karaboga and Basturk	2007 [39]
River formation dynamics	Rubio	2007 [42]
Magnetic optimization algorithm	Tayarani	2008 [44]
Gravitational search algorithm	Saryazadi	2009 [53]
Firefly algorithm	Xin She Yang	2009 [66]
Cuckoo search	Xin She Yang	2009 [67]
Bat algorithm	Xin She Yang	2010 [74]

Swarm intelligence algorithms which is used for spectrum sensing optimization is discussed as under:

- *Ant Colony Optimization(ACO)*: It is an optimization technique which follows the behavior of ants to find the shortest path between their food and nest.This technique was proposed by Marco Dorigo in 1999 [11]. Ants initially randomly search and on finding food they return to their colony while laying down pheromone trails. A successful pheromone trail (trail to food) is continuously fortified, pheromone trail is more efficient if the path taken by ants towards the food source is shorter so, the time taken will be less and eventually lesser time for pheromone to evaporate. In this manner, ants successfully find the path which is shortest to the food source. ACO is an optimization technique which mimics this behavior of ants. ACO comprises virtual ants which traces the search space representing the solutions of the objective function to solve and find the locally productive areas [72]. ACO performs parallel search over numerous constructive computational models constructed from problem data and dynamic memory structure. The dynamic memory structure stores information about the quality of the previously obtained results. The probability of ants moving from a node x to another node y depends on two factors [23].

1. Particular path's attractiveness: It is the prior desire of the move and is calculated by heuristics approach. Basically, it is the reciprocal of distance between x and y.
2. Pheromone edge's density: It is the concentration of pheromone on the edge trailing from x to y.

When ACO is applied to some problem, then the objective function of the problem will be treated as food source of ants and all feasible solutions are the paths to the objective function (food) and the optimal solution is the shortest path to the objective function. Authors in [103] proposed ant colony system for efficient spectrum assignment to SUs. The proposed ant colony algorithm is based on graph coloring problem used for allocating spectrum to SUs in CRN. The performance of the algorithm is compared with particle Swarm Optimization (PSO). Simulation results showed that though the performance of ACO is better than PSO but it has twice the running time as compared to PSO.

Key benefits associated with ACO is that, it can easily adapt to the changes in real time and have positive feedback that leads to speedy discovery of optimal solutions. Few disadvantages associated with ACO are: Difficulty in analyzing ACO theoretically, sequences of dependent random sequence, uncertainty in the convergence time but guaranteed convergence even if the optimization technique takes long time [64].

- *Particle Swarm Optimization*: PSO-based spectrum sensing was proposed by Zheng et al. [70], the PSO algorithm is proposed for cooperative spectrum sensing where constraints were optimized using PSO. Furthermore, the performance comparison was made between the PSO and MDC (Modified deflection coefficient)-based method. The proposed method turned out to be superior because of higher detection probability than MDC. Xia et al. [71] proposed binary particle swarm optimization (BPSO) for cooperative spectrum sensing to find the optimal solution for the cooperation nodes which in turn improves the sensing performance which is proved by the simulation results obtained from this paper. Cai et al. [101] proposed a method to obtain nonlinear threshold using particle swarm optimized support vector machine(PSO-SVM) and is compared with linear threshold used in traditional energy detection. In this approach, spectrum sensing is considered as binary classification problem and energy detection as linear classifier.For low signal to noise ratio of received signal and small number of received signal samples for sensing, the binary classification problem becomes linearly inseparable. In such scenario, PSO-SVM proposed in [101] is proven to be much better than that of traditional energy detection. Proposed method has two distinct modules i.e offline and online. In offline decision is made based on false alarm probabilities and in online mode decision function obtained in the offline mode is used for the detection of primary user. Benefits of this approach is that it does not require any prior knowledge of signals and channels. Better than traditional energy detection in hostile environment and it works well even in low SNR. Mohammed et al. [113] proposed PSO-OR algorithm using two threshold energy detector for spectrum sensing. The term double threshold is used by the authors because here fusion center collects local decision and also the energy values from the SUs, PSO optimizes the decisions made by SUs and final inference is made based on local decision and the optimized value. Simulation results showed that proposed PSO-OR method performed better than equal gain combining-OR(EGC-OR) method. Rashid et al. in [124] proposed PSO-based scheme for the optimization of sensing time and throughput for in band local spectrum sensing to achieve better trade off between them. Author also proposed a fast convergence PSO(FC-PSO) by applying distribution-based stopping criteria for detection performance, optimization time and secondary user gain and made a comparison of the proposed FC-PSO with that of conventional PSO, Artificial Immune system (AIS) algorithm and Golden section Search (GSS) algorithm. Proposed FC-PSO performed better than AIS and GSS algorithm in terms of lower computational complexity, better trade off between secondary user sensing time and overall system throughput. It gave the maximum value of throughput with minimum interference to the primary user and better convergence time. PSO is basically based on population and stochastic optimization approach which mimics the school of fish or flock of birds' social behavior [16, 86]. Fundamental equations that governs the PSO algorithm is the equation indicating the position and velocity of the particles at any specific instant. And this velocity and position component of the particle gets updated at the end of each iteration until the algorithm reaches to the optimum condition. Mathematically, velocity and position of each particle at $t+1$ are represented as in Eqs. 12 and 13, respectively [16, 86]:

$$v_{i,d}(t+1) = w(t)v_{i,d}(t) + \phi_p r_p(t)(pBest_{i,d} - x_i d(t)) + \phi_g r_g(t)(gBest_d - x_{i,d}(t)) \tag{11}$$

$$x_{i,d}(t+1) = x_{i,d}(t) + v_{i,d}(t) \tag{12}$$

here $v_{i,d}(t+1)$ = Velocity of particle of i for dimension d at iteration $t+1$ $x_{i,d}(t+1)$ = Position of particle i for d dimension at iteration $t+1$ $w(t)$ = Inertia weight (Maintains tracking of the preceding velocity of each particle and impacts it on their current velocity) ϕ_p and ϕ_g = Cognito and social learning factors. Inertia weight helps in balancing the tradeoff between exploration and exploitation process of the swarm. Particle velocity tracks the particle whether its on right flight direction and it prevents sudden change in the direction of the particle [124]. Position of the particle corresponds to optimal solutions. $\phi_g r_g(t)$ = Global best constant weight with random factor(measure performance of the particle). In PSO, mostly when a particle reaches the global optimum solution then the rest of the evaluation does not have much impact on cumulative new knowledge, so by applying a rule to stop evaluation after global optimum is reached, the performance of PSO can be improved thus resulting in FC-PSO [124]. Accurate algorithm is required for in band spectrum sensing for CRN, so that it can adapt to dynamic environment. For that purpose, distribution-based stopping criterion proposed in [124] along with adaptability stops objective function evaluation. The stopping rule differentiates FC-PSO with absolute PSO. Authors in [135] introduced hybrid particle swarm optimization-golden section search (PSO-GSS) for optimizing weights, decision threshold and sensing time for improving the throughput in multiband cooperative spectrum sensing scheme under constrained environment of aggregate interference, subband interference and subband utilization. With hybridization, authors were successful in improving the performance of PSO in terms searching ability. With simulation results, the proposed method was validated against ABC, GA and PSO. With PSO-GSS, the substantial improvement in overall throughput was noticed.

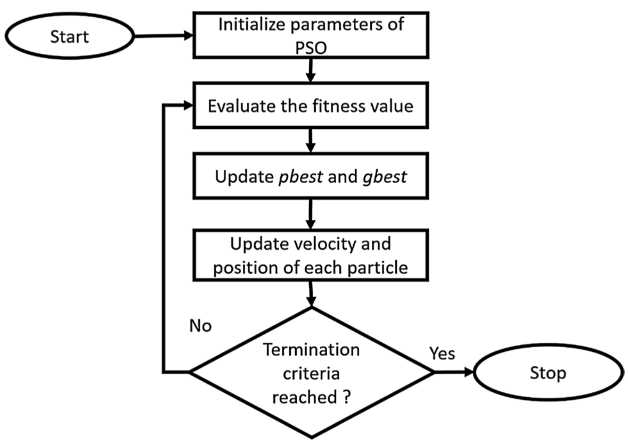
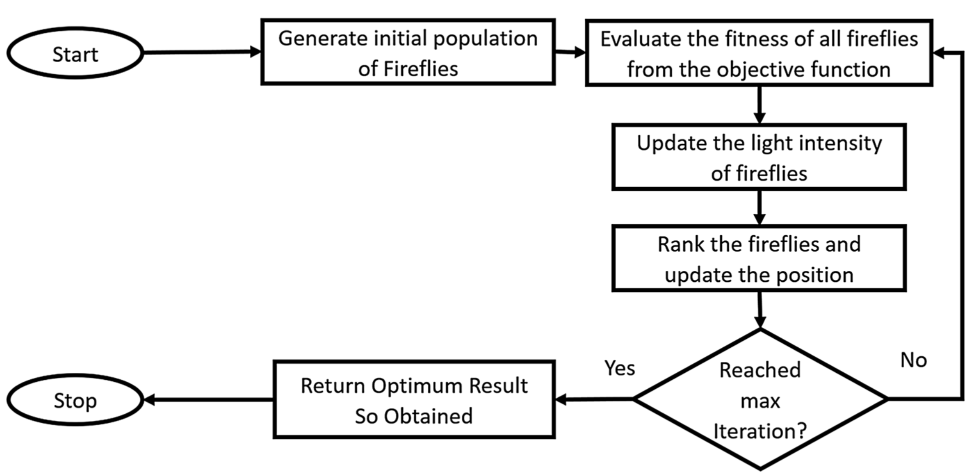


Fig. 20 Particle swarm optimization working

Figure 21 shows the basic working of PSO.

- *Firefly algorithm(FFA) and Fish School search(FSS))*: Azmat et al. [123] proposed bio inspired technique for collaborative spectrum sensing. Proposed method basically has a center point where the energy measurement data of all collaborative cognitive radios are combined together to make a final detection decision. Collaborative spectrum sensing scheme is better than standalone energy detector as its having less overheads [104]. The proposed model in [123] used Particle swarm Optimization(PSO), FSS, FFA for collaborative spectrum sensing and allocation. Figure 20 shows the basic flowchart of Firefly Algorithm. For solving non-linear optimization problems with noise, FFA has emerged as more powerful tool compared to other optimization technique. FFA performs self-improving process in the current space and thus improves its own space with respect to its previous stages [123]. Under noisy conditions with various local optima FFA performs better as compared to PSO while evaluating benchmark functions [111]. Before applying bio-inspired techniques to CRN, it is important to correlate CRN terms with respect to the parameters of the bio inspired technique. Such as, the number of samples sensed by CRN is represented by number of particles, number of cognitive radios are referred as the dimensions with respect to the position of the m^{th} particle. The objective function or the fitness function for CRN, is rep-

Fig. 21 Work flow firefly algorithm



resented as the food concentration in bio inspired techniques. The best position of the particle with maximum fitness values is the representation of optimal weight vector in CRN. PSO and FFA are powerful optimization tool but they lag a bit in exploration and exploitation trade-off, in such cases FSS is to be considered which has auto regulating capability [87]. FSS-based spectrum sensing starts with the initializing the position of each particles as $w^k_m \epsilon a$, where a is uniform random variable between [0 1]. Then, the fitness of each particle $P_D(w^k_m)$ is evaluated using the objective function. w^k_m is updated as in Eq. 11 [51]:

$$w^k_m = \frac{P_D(w^k_m) - P_D(w^{k-1}_m)}{\max \left|P_D(w^k_m) - P_D(w^{k-1}_m\right|} \quad (13)$$

All the particles move individually and the fitness of the solution of all the particles are calculated based on the weighted average of their movements and the optimal results gets summed up to the current particle position. Those particles having successful individual movements cause more effect on search direction than the other ones.

- *Artificial Bee Colony Algorithm-ABC*: The authors in [125] presented an efficient adaptive artificial bee colony (EA-ABC) algorithm for cooperative spectrum sensing in a CRN. This EA-ABC comprises an adaptive mutation mechanism, guaranteed convergence mechanism and optimal tracking. Author compared EA-ABC with that of ABC, PSO and modified PSO algorithm and proved that EA-ABC can achieve better detection probability as compared to other under the same false alarm probability. The drawback associated with conventional ABC is its searching efficiency and computational time [134]. So, the authors in [134], authors implemented modified ABC algorithm for joint optimization of weight coefficients and detection thresholds in a cooperative spectrum sensing scheme. The proposed modification in ABC is applied by introducing the crossover and mutation so as to enhance the diversity and searching potential of conventional ABC. The validation of the proposed scheme was carried out by comparing it against the algorithms like PSO, GA, ABC and EA-ABC for multi-band cooperative spectrum sensing. The proposed algorithm effectively improved the searching efficiency of conventional ABC, but the computational time ws compromised. Working of basic ABC algorithm is shown in Fig. 22.
- *Cuckoo Search*: In [129], authors discussed about spectrum sensing for satellite cognitive system, where cuckoo search algorithm was used to enhance the performance of spectrum sensing. Cuckoo search algorithm is based on the behavior of cuckoo,where each cuckoo lays egg on a random host nest [79]. Eggs represent the solution, best eggs or solutions goes for the next iteration. Solutions are replaced by performing Levy flights. Levy flights and random walk uses the equation $x_{(t+1)} = x_t + m * F_t$, where F_t belongs to Levy distribution for Levy flights, s is the step size whose value determines how far a random solution go for a fixed number of iterations. If value of s is too large then the new solution will be waived far from the older one and too small value of step size will not be having significant impact on search space resulting in inefficient searching mechanism. So its important to maintain proper value of s. Based on the quality and fitness, these solutions are ranked and current best solution is so obtained. Simulation results obtained from the algorithm proposed by author in [129] shows that cuckoo search is more efficient than sequential search scheme with better probability of detection for fixed step size. Table 5 shows the comparative analysis of metaheuristic methodologies used for spectrum sensing

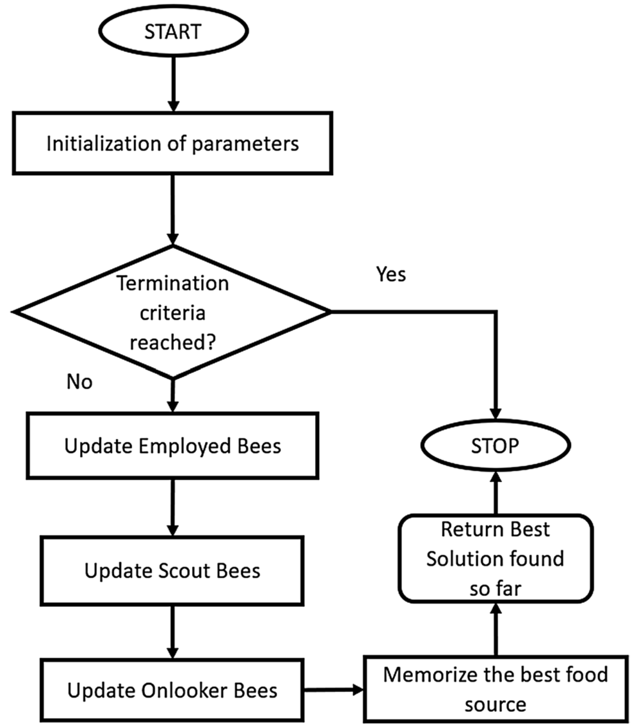


Fig. 22 Flowchart artificial bee colony algorithm

5B. Multi-objective optimization for spectrum sensing: From the literature review, it can be inferred that the various optimization problems associated with the spectrum sensing in CRN have been dealt with by separately considering it as the single objective optimization problem. But for a real-time scenario, it is required for an efficient spectrum sensing to consider multiple factors simultaneously. Variables governing these factors have

Table 5 Comparative study of metaheuristic methodologies used for spectrum sensing

S.No	Parameters	Genetic algorithm	Particle swarm optimization	Firefly algorithm	ACO	ABC	Cuckoo search
1	Control parameters	Generation rate, crossover rate, mutation rate	Cognitive and social factor, inertia weight	Attractiveness coefficient, randomization coefficient	Pheromone density of the edge, attractiveness of the edge and Pheromone evaporation	Maximum cycle number, colony size	Host nest, random cuckoo, Levy flight
2	Convergence rate	Less	More than GA,ABC and ACO	More than PSO	Slow due to Pheromone evaporation rate	Better than GA, less than PSO	Comparable to FFA
3	Complexity	More	Less complex	Comparable to ABC	More	Less than GA and PSO	Less complex
4	Convergence speed	Less in large space	Better than GA	Better than PSO	Better than GA but less than PSO	Less than PSO, Better than ACO	Comparable to FFA
5	Flexibility	Flexible	More than GA	Similar to PSO	Better than GA	Less than PSO	Flexible compared to ACO, ABC but less than PSO
6	No. of function evaluation	More	Less than ABC, ACO	Comparable to PSO	More, but less than GA	Better than ABC	Similar to FFA
7	Standard deviation	Larger deviation from the best solution	Less deviation from the best solution	Better than PSO	Better than GA but less than PSO	Approaches optimum better than PSO	Better than PSO less than ABC

Performance evaluation based on literature survey

multiple trade-offs for which single objective optimization technique cannot be efficient and the problem calls for multi-objective optimization algorithms. In [114] and [122] multi-objective optimization problems for spectrum sensing have been considered with respect to throughput and interference, probability of detection and false alarm respectively, authors in [114] employed MOCSO for solving multi-objective optimization problem. Authors in [119] employed multi-objective Genetic Algorithm for spectrum sensing with primary aim of enhancing the spectrum opportunities while maintaining the sensing overheads within the permissible limits. The multi-objective optimization has resulted in better approach towards the real-time implementation of CRN as compared to single objective optimization techniques [114].

5C. Artificial Intelligence-based approach for Spectrum Sensing: After surveying through metaheuristic approaches used for spectrum sensing, in this section, other prominent soft computing techniques based on artificial intelligence used for spectrum sensing are dealt. Artificial Neural Network(ANN) is one of the powerful soft computing method. A comparative study between ANN and metaheuristic approach is discussed in Table 6. *Artificial Intelligence-based Soft Computing techniques used in CRN for spectrum sensing are:*

a. Artificial Neural Network: Artificial intelligence plays a important part in CRN specially in sensing the the surrounding environment.It adapts and learn according to input and provide the desired output, CRN is one such system. Incorporation ANN in CRN maximizes the performance with maximum utilization of wireless communication. ANN works similar to human brain and has adapting property. It thus can provide solution for non-linear and probabilistic problems with the application of learning techniques of ANN to CR it enables it to learn and to work more intelligently.

Like biological cells of human brain ANN also consist of numerous interconnected processors called as neurons. An ANN is defined by its neuron model, architecture, and learning algorithm. Neurons and interconnected links in different layer is referred as architecture. The links connecting the neurons are known as weights and they are adjusted while training the network. An ANN develops a specific relationship between input and output data(training sets). Neuron model receives input processes the information and produces the output. Processing the input is done via training ANN by some learning algorithm which forms the essential and fundamental part of ANN. Weights are adjusted automatically using the gradient of mean square error. If an error

Table 6 Comparison between ANN and Metaheuristic approaches

Algorithm	Strengths	Limitations	Options
ANN	Can identify new patterns, capable of evaluating multiple functions, excellent for classification, conceptually it is easy/scalable to implement	Direct impact of network size on training period, more complex the network greater will be the training period thus training may be slow down, lacks theoretical references for linking objective function with required network	Can implement training phase with the help of different learning techniques
Metaheuristic technique	High quality performance for parameter optimization, outstanding ability of generating relationship between parameter values	Formulating rule space is tedious when learning and optimization are not constrained to boundary values	Hybridization of metaheuristic approach for better result

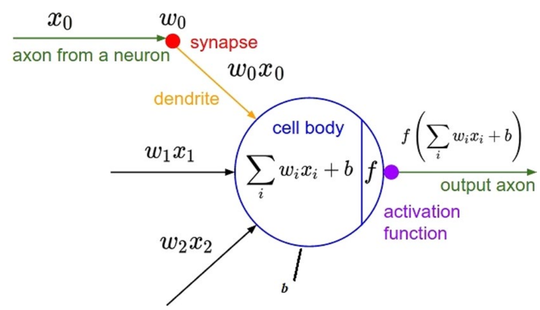


Fig. 23 Mathematical model of neuron [149]

is found then that error signal is feed again into the lower layer of ANN. ANN structure basically consist of three layers-incoming neuron layer in which incoming signals are received, hidden neuron layer and output neuron layer. Neuron is the basic unit of computation in a neural network. It receives input from other nodes or from external source and computes the output. Each input has associated weight(w), which is assigned on the basis of its relative importance to other inputs and a bias(b). The node applies the function to the weighted sum of inputs as shown in Fig. 23.

ANN-based Spectrum Sensing: Tang et al. [73] proposed a spectrum sensing method using ANN under low SNR condition. SU performs ANN-based sensing of primary user and collects information about the occupancy of channel by primary user. For the proposed model, neurons have 4 input,one is energy of the signal and remaining 3 are the cyclic spectrum values. During the training weights and threshold of each neurons are updated at each iteration. For low values of SNR, additive white gaussian noise is added to primary user's signal. Proposed approach resulted in better detection performance even for low values of SNR and its anti-interference ability was boosted by incorporating the beneficial points of energy detection and cyclostationary method.

In Zhang et al. [100] ANN for cooperative spectrum sensing is proposed. Author considered a fusion center to find the probability of weights. Secondary user sense for primary user and accumulates the information which is then sent to fusion center(FC). FC finds the probability of weights, which acts as the input for ANN. A spectrum sensing model is proposed consisting of 3 suppositions which are:

- Spectrum sensing of individual SU
- Communication between FC and SU
- Third one is the fusion scheme

While undergoing training phase FC transmits the reference which is sensed by SUs and they make local decision, based on the difference between reference signal and local decision, Back propagation-based ANN is trained. These local signals sensed by SUs are weighted and then transmitted to FC, where based on weighting function FC makes final decision and broadcast the signal and also transmits to SUs for further ANN training. Because of the FC, this method is termed as centralized cooperative spectrum sensing scheme. Proposed model in [100] resulted that it can forecast the precise detection probability at the end of training and FC can obtain outstanding performance on judgment (satisfactory detection and false alarm probability) as compared to the conventional spectrum sensing techniques.

Papoola and Van Olst in [107] proposed ANN-based modulation classifier for spectrum sensing. The Authors implemented proposed algorithm on GNU Radio and Universal Software Radio Peripheral 2 (USRP 2) for developing CRE. The proposed algorithm has better performance than Energy Detector techniques.

b. Fuzzy Inference System(FIS): Pradhan et al. [114] proposed multi-objective cat swarm optimization for solving two clashing objective functions i.e probability of detection and probability of false alarm. Authors then employed the strategy of Fuzzy Logic, to determine the feasible solution among the set of nondominated solutions. For a multi-objective optimization problem, a multi-objective algorithm is used to obtain a set of optimal solutions termed as pareto optimal. Finding out the most appropriate solution among the pareto optimal set is a tedious work. With FIS authors in [114] were successful in finding out the compromise solution among the optimal solution set. The FIS works by assigning the fuzzy variable to the solutions based on their contribution towards each objective function. The values of these membership functions of FIS is calculated as discussed in [114]. The solutions with the maximum value for the membership function can be termed as the most appropriate optimal solution.
c. Genetic Fuzzy Inference System(GFIS): GFIS is a combinatorial algorithm of GA and Fuzzy Inference System(FIS). FIS controls the system parameters and thus controls the operation,where as GA is used for improving the performance of FIS. In fuzzy logic theory, variables are not constrained to only two values(True or False) [1, 6], rather it assume any value between the two extremities of variables defining a problem statemnet [2]. FIS considers these fuzzy variables as an input and with the application of IF-THEN rules, it generates an inference [7]. Genetic Algorithm is an evolutionary-based optimization technique capable of solving problems having large solution space. **GFIS for spectrum sensing**:Mohamedou et al. [97] proposed a scheduling-based spectrum sensing which uses FIS to optimize the sensing parameter. But because of the static nature of FIS scheduler, Genetic Algorithm is used to make FIS scheduler able to evolve and adapt the new environment. In addition to that, heuristic-based scheduling algorithm is proposed by the author to provide supporting mechanism for GFIS-based scheduler. Here, author considered access point-based coordination in wireless LAN, Access point synchronizes the timing with respect to the other stations and dispense information regardless of activities of primary user. Proposed system model in [97] assumes that the participating stations of the network hears the access point transmissions and that is important for synchronizing the operation within the stations. Based on the presence or the absence of PU, Channel in the spectrum can have two states busy or idle, respectively. In the proposed model, author has made an assumptions that the period length of idle state and busy state has been exponentially distributed so that proposed model can be considered as a realistic assumption for high dynamic systems like mobile telecommunication. Scheduling algorithm so proposed has two levels; higher level (Genetic architecture) and lower level genetic fuzzy scheduler producing scheduling decision. In general, architecture channels are mapped as elements of eligibility test. Scheduler picks the channel the largest eligibility value. Eligibility values are updated by scheduler after every sensing. The lower level genetic fuzzy scheduler calculates the eligibility values. Apart from GFIS a supporting algorithm is also used to generate scheduling in faster and simplex manner. Proposed model in [97] with GFIS is slower than FIS, but FIS being static and considering a dynamic environment then GFIS technique along with supporting technique (based on heuristic approach) gave a better scheduler.

Brief Summary on Spectrum Sensing Methods

In this subsection, under the section Spectrum Sensing Methodologies, brief survey on methodologies used for spectrum sensing in CRN is done and represented via Table 7 and continued in Table 8.

Performance Analysis of Spectrum Sensing Optimization Methodology

Based on the system criteria for efficient spectrum sensing like Probability of Detection, Probability of False Alarm, Probability of missed detection, Optimized sensing time for proper trade off, Optimization method's convergence time, Complexity and their convergence rate, performance of spectrum sensing optimization methodologies is evaluated in terms of Throughput, Delay, BER, Energy Consumption, Energy Efficiency. Performance ratings have been given on the basis of literature survey so done and it is illustrated in Table 9. The performance rating is done based

Table 7 Brief note on spectrum sensing methods

S. No	Reference	Spectrum sensing methodology	Advantages	Disadvantages
1	[22]	Matched filter	Matched Filter—maximizes received SNR, so its a better way of detecting signals. With its Coherency property matched filter method is capable of achieving high processing gain in a small time period since it need only O(1/SNR) samples to obtain desired detection probability constraint	Matched Filter—Dedicated receiver is required by cognitive radio for each primary user
		Energy Detection (ED)	Energy Detector- Non Coherent, Less complex, easy to implement	Energy detector-Setting a threshold value, and it does not have any special technique to recognize difference in between modulated signals, noise and interference
2	[69]	Energy Detection	Energy Detector-Least Complex	Energy Detector-Least Accurate
		Cyclostationary Detection	Cyclostationary-Complexity less than Matched Filter,Accuracy greater than ED	Cyclostationary-More complex than ED, Accuracy less than Matched filter
		Matched filter	Matched filter-Highly Accurate	Matched filter-Highest level of complexity
3	[30]	ED-based Network Cooperation	If large number of samples are used in for sensing then an energy detector is capable of obtaining proper value of Probability of detection and false alarm probability.	Poor performance in low SNR, Increased Sensing Time, Difficult to set the threshold
			Applicable to all signal type	Large effect on estimation error because of limited sensing time, number of samples is a function of SNR

on the performance remarks in [22, 33, 62, 69, 73, 97, 114, 123–125, 148] for obtaining the probability of detection (Pd) and probability of false alarm (Pfa) in different SNR conditions resulting different performance values of opportunistic throughput, delay, BER and energy efficiency. Each performance metrics have been discussed below:

♦ Throughput: Measurement of definite amount of user data/information transmitted per unit of time. Throughput can also be defined as number of bits per second successfully delivered over the medium. Average throughput can be calculated as total number of bits received at the destination divided by total simulation time, it is basically measured in kilo bits per second(Kbps). There should always be a better tradeoff between sensing time and throughput. An efficient optimization technique with better system criteria would eventually result in increased throughput.

The opportunistic throughput involved in the CRN can be written as [148]:

$$\begin{aligned} C_T &= \sum_{r=1}^{4} c_r \\ C_T &= T_p p^{off}(1-q_f)(B-B_s)\times \log_2(1+|h|^2\frac{G_t(B-Bs)}{G_o(B-Bs)}) \end{aligned} \tag{14}$$

here,

$s(n)$ – PU Signal
$w(n)$ – Noise Signal
h – Channel Gain
σ_s^2 – Signal Variance
σ_w^2 – Noise Variance
p^{on} – Probability of busy channel
p^{off} – Probability of idle channel
q_d – Probability of detection by Energy Detector
q_f – Probability of detection by Energy Detector
T_p – Frame Period
B_s – SU Spectrum Sensing Bandwidth
$(B-B_s)$ – SU Transmission Bandwidth
G_t – Power Spectral Density of the SU signal
G_o – Power Spectral Density of the Noise
$Q_{t,\max}$ – Maximum Transmission Power

♦ Delay: It is the average transit time for packets to travel from source to destination. End-to-end delay depends on propagation rate of data in a particular communication medium (satellite or terrestrial), distance, the number and type of network elements (design, processing, switching, and buffering capabilities), routing schemes (dynamic, static, queuing, and forwarding mechanisms), bit error rate in transmission (hence the number of lost or re-transmitted packets).

Considering R_n as the time instant at which *nth* packet arrives at a network, and G_n be the time instant at which *nth* packet departs from the network. Then, the end-to-end delay can be mathematically modeled as [156]:

Table 8 Brief note on spectrum sensing methods

4	[81]	Energy Detection Cooperative Spectrum Sensing	Low Implementation complexity,Low computational complexity,Advantageous for unknown signal form so its more generic	Poor performance in low SNR,Estimation error due to noise degrade detection performance,Performance is largely affected when user experiences fading effect(its compensated by using cooperative SS)
5	[116]	**ED,** $\kappa - \mu$ extreme fading model	Through $\kappa - \mu$ extreme fading model its possible to obtain appropriate characteristics of the fading effect even at low SNR regime and thus improving the energy detector's performance.	Performance of ED is largely affected when user experiences fading effect(its compensated by $\kappa - \mu$ fading model),In ED sensing time influence performance in terms of Pfa and Pmissed detection
			Improved energy detector can lead to more energy efficient cognitive radio-based communication systems.	Because of the periodic sensing intervals the detector is unable to utilize the spectrum opportunities at its best
6	[125]	EA-ABC Cooperative Sensing	Detection probability is high keeping the false alarm probability unchanged	Higher convergence time as compared to PSO and APSO with only slight increase in Pd as compared to PSO & APSO
7	[123]	Fire Fly Algorithm	Fire Fly Algorithm-Powerful in solving noisy non linear optimization problem,Self Improving process with current space and its own space	Fire Fly Algorithm-Interference highly degrade the performance of FFA,More execution time
		Fish school Search	Fish school Search-Capable of auto regulating exploitation & Exploration Trade off	Fish school Search-In Noisy and interference condition it has lower performance index as compared to FFA
		Particle Swarm Optimization	Particle Swarm Optimization-Powerful optimization tool,Execution time is less as compared to all model	Particle Swarm Optimization-FFA performs better than PSO under noisy situation and in problems having numerous local minima, Some times it can't tackle Dynamic optimization problems
8	[110]	ANN model for detection of spectrum holes	The designed ANN model can effectively identify spectrum holes even at low SNR of around − 20 dB	Complex system
			No need of further training of Neural Network once it is optimized and trained and the weights and bias obtained after optimization can be used to design the CAD model	

Table 9 Performance metric evaluation of spectrum sensing methodologies

S.No	Spectrum sensing methodology	System Performance (Rating 1–10)*	Performance metrics evaluation (Ratings 1–10)*				
			ThroughPut	**Delay	BER	**Energy consumption	Energy efficiency
1	Energy Detector	4	5	4	4	5	4
	Cyclostationary Detector	6	6	3	6	5	5
	Matched Filter	7	7	6	8	6	5
	Filter Bank Detector	6	7	7	7	5	6
	Multi-tapper	6	6	5	5	5	6
	Co-Variance Detector	5	5	4	4	5	4
2	Genetic Algorithm	5	6	5	5	6	5
	Particle Swarm Optimization	7	8	8	8	7	7
	Fire Fly Algorithm	8	8	8	7	7	7
	Ant Colony Optimization	6	6	7	7	6	6
	Artificial Bee Colony Algorithm	7	7	6	7	8	8
	Cuckoo Search Algorithm	7	7	6	7	8	7
	Simulated Annealing	6	6	6	7	6	7
3	FIS	7	8	8	7	7	7
	GFIS	7	7	7	7	6	6
	ANN	8	8	6	8	6	7

*(Based on the performance of optimization methodology performance metric is rated between 1 to 10)

(Higher rating value indicates better performance in the particular metric)

**Higher the rating in Energy consumption and Delay,Lower the performance

$$D(n) = G_n - R_n \tag{15}$$

⧫ Bit Error Rate(BER): The bit error rate or bit error ratio is the number of bit errors divided by the total number of transferred bits during a studied time interval.

BER = Bit with Errors/Total Number of Bits

The bit error probability ρ_e is the expectation value of the BER as shown in Eq. 16

$$\rho_e = \frac{1}{2}(1 - erf)\sqrt{E_b/N_o} \tag{16}$$

where erf is the error function.

E_b is the energy per bit.

N_o is the noise power spectral density (noise power in a 1 Hz bandwidth)

E_b (energy per bit) can be determined by dividing the carrier power by the bit rate.Its unit is joule. N_o is in power (joules per second) per Hz. E_b/N_o is a dimensionless numerical ratio.

⧫ Energy Consumption: Cumulative energy used by CR user for sensing channels and transmitting data, its unit is Joules.

⧫ Energy Efficiency: With most of the research work focused on increasing the spectrum sensing efficiency so as to increase the overall throughput. As compared to other communication devices, Cognitive Radio devices requires additional energy because it performs periodic sensing. The accuracy of sensing result also effect the energy consumption. To increase the accuracy of sensing transmission time decreases and it eventually decreases overall throughput. Therefore, probable solution is cooperative spectrum sensing which increases the accuracy without decreasing overall throughput, but it will cause an additional energy consumption due to extra sensing time and delay. And also extra energy consumption by Cooperative spectrum sensing for reporting the result to the fusion center [120]. Therefore, dedicated research work is required with focus on increasing the energy efficiency of CR devices, which are mostly battery powered [146]. Energy efficiency for Cognitive Radio system in general can be represented as the ratio of Throughput and the total power consumed which includes transmission power, sensing power consumed and the circuitry power [146, 155].

Research Challenges Associated with Cooperative Spectrum Sensing

Challenges associated with cooperative spectrum sensing is discussed as under:-

- ⧫ Cooperation overhead modeling: Cooperative gain is the main aim of most of the cooperative sensing models.

But considering cooperative overhead and its proper modeling is also an important aspect of cooperative spectrum sensing. Because proper modeling of cooperative overhead can help in knowing the achievable cooperative gain for realistic scenario.

- Compressed Sensing: Traditional sensing techniques like energy detection and cyclostationary detection senses one sample at a time and is sampled at nyquist rate by ADC (Analog to Digital Converter). Such techniques senses one band at a time and for sensing multiple frequency bands CRUs based on theses techniques require multiple RF front ends. Therefore, for wideband sensing such approaches can lead to long sensing time, higher computational complexity which inturn leads to higher cost. Compressed sensing proposed in [38] can perform sampling of wideband signal at subnyquist rate preferred by ADC. But compressed sensing has few research challenges such as *Near Far Problem* in which weak PU signal with less number of samples and with strong near by signal can lead to improper detection of PU signal in a wideband spectrum. Another issue associated with compressed sensing is its implementation. Since compressed sensing is based on random sampling for which it requires new ADC structure with non uniform timing and pseudo random clock generator as discussed in [38]. Implementing complex clocking system for random sampling in compressed sensing is an issue.
- Reliability and dynamic allocation of control channel: Common control channel is an integral part of cooperative spectrum sensing, common control channel is basically used by CRUs for sending local sensing information to the Fusion Center and sharing information among CRUs. Important aspects required for establishing a reliable control channel are Bandwidth, Reliability, and Security. Issue associated with control channel is in designing control channel which is able to withstand the impairments of channel, sturdy to PU activity, bandwidth efficient. Control channel should be able to perform dynamic allocation in accordance to PU activity,channel availability and network topology which is a tedious task for common control channel.
- Knowledge base modeling: Knowledge base plays an important role for efficient spectrum sensing, it keeps the track of PUs and carries information like PU's location, transmitting power and traffic pattern. For cooperative spectrum sensing, knowledge base has two key roles.

(a) With the help of available information and knowledge about PU, increase the probability of detection.

(b) With its learning experience obtain the spectrum information. Since the knowledge base carries information about PUs so security of this information is a big concern. A knowledge base should maintain a parallel knowledge stream that is able to differentiate between CRUs and malicious user.

- Energy efficiency: As compared to other communication devices, Cognitive Radio devices requires additional energy, because it performs periodic sensing [153]. The accuracy of sensing result also effect the energy consumption. To increase the accuracy of sensing transmission time decreases and it eventually decreases overall throughput. Therefore, probable solution is cooperative spectrum sensing which increases the accuracy without decreasing overall throughput, but it will cause an additional energy consumption due to extra sensing time and delay. And also extra energy consumption by Cooperative spectrum sensing for reporting the result to the fusion center. Therefore, dedicated research work is required with focus on increasing the energy efficiency of CR devices, which are all battery powered. Energy efficiency plays a crucial when using CR network as a sensor network as discussed by authors in [95] where energy efficiency scheme is devised for spectrum sensing in distributed mode for CR based sensor networks. In application front like patient monitoring system CR-based sensor networks plays an important role [96], therefore, energy efficiency optimization is extremely crucial for CR-based sensor networks.
- Sensing efficiency: Sensing scheduling and convergence rate is important aspects which contribute to sensing efficiency. Time is a constraint here so sensing should be properly scheduled to sense the channel in a given time. It should also consider how the CRUs should cooperate to access the multiple channel without degrading sensing efficiency. Fast and fine sensing and scheduling narrow band and wideband sensing are also to be considered for efficient sensing. Converging to a common decision is an important criteria for cooperative spectrum sensing.Proper scheme should be devised such that CRUs' decision should be well analyzed and also fast converging.
- Sensing and Throughput tradeoff: Major parameters that define spectrum sensing are probability of detection,probability of false alarm, probability of missed detection and throughput. It is desirable to have high values of probability of detection and throughput, low values of probability of false alarm,probability of missed detection. As the sensing time increases, high value of probability of detection and low values of probability of false alarm, probability of missed detection is

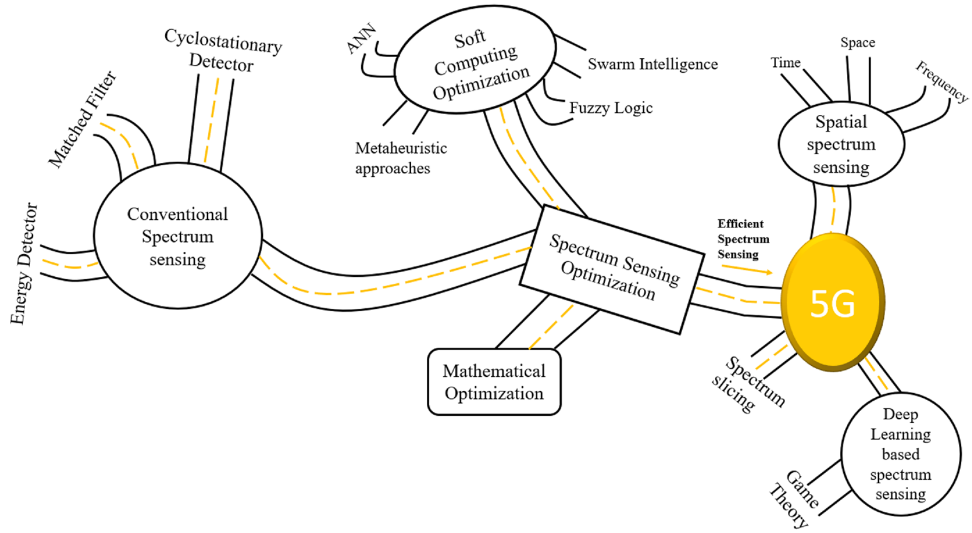


Fig. 24 Road map for spectrum sensing towards 5G

achievable but throughput also reduces and vice-versa takes place as the sensing time decreases. So a proper optimization of sensing time is required to have an efficient tradeoff between these parameters of spectrum sensing.

Road Map of Spectrum Sensing Towards 5G

Spectrum sensing is going to play an important role towards the implementation of 5G technology. Figure 24 depicts the road map of spectrum sensing towards 5G technology. The conventional spectrum sensing methodologies have been improved using optimization techniques, different soft computing techniques have been surveyed via this paper. Efficient spectrum sensing will be an important asset for 5G technology. Spectrum slicing which going to be the part of network slicing in 5G technology, is basically allocating dedicated resources, infrastructure and services to a specific applications such as mobile broadband slice, health care slice, internet of Things slice [136, 137]. Advanced spectrum sensing would be enabling the aspects of 5G technology. Spatial spectrum sensing considering space, time and frequency helps in better detection of spectrum holes [109]. And further deep learning and game theory implementation of spectrum sensing will enhance the efficiency of spectrum sensing, making it more intelligent CRN [141]. The road map shows that how spectrum sensing optimization and soft computing techniques plays a crucial role in forming the building blocks for efficient spectrum sensing based CRN for 5G. The importance of soft computation for 5G technology is further supported by the proceeding discussion in "Challenges and Future Directions Towards 6G Technology".

Challenges and Future Directions Towards 6G Technology

As the wireless telecommunication technology advance towards 6G, it is necessary that a CRN should not only adapt to environment but also should have ability to adapt its hardware [157]. The existing CRN's spectrum sharing is opportunistic and 6G calls for artificial intelligence and soft computing enabled features for CRN [157]. The 6G-based CRN requires deep neural network trained physical layer transmission and reception.

Recent Spectrum Sensing Methods

In this section, the development in the spectrum sensing with respect to the current scenario is discussed.

In [147], authors developed spectrum sensing method for OFDM (Orthogonal Frequency Division Multiplexing) signal via employing Mean Ambiguity Function. For detecting the continuous time baseband OFDM signal transmitted by PU (denoted as $x(t)$), discrete Mean Ambiguity Function is developed as:

$$\overline{A} \triangleq \sum_{m=0}^{M-1} C[m, m-p] e^{-j\frac{2\pi}{M}lm}, \tag{17}$$

where p, l are discrete time delay and frequency delay, respectively. C is the auto correlation function of the PU signal samples.

Authors in [158] developed log-likelihood-ratio-test based energy detector for the PU signal detection in multiuser MIMO system. The log-likelihood-ratio-test for the nth SU at dth observation to detect the PU signal is given as:

$$T(y(k)) = \frac{p(y(k), H_1)}{p(y(k), H_0)} \tag{18}$$

here, $p(y(k))$ is probability density function at the nth SU for the received PU signal under the hypothesis H_1, H_0.

The game theory-based multi-channel cooperative spectrum sensing is developed in [159] which focused on spectrum allotment via game theory approach. In [160], compressive spectrum sensing via complementary matrices is employed for PU detection. The Golay-paired Hadamard matrices is the complimentary sensing matrices used for the spectrum sensing. The $\mathbf{P}$ is a $N \times N$ Golay-paired Hadamard matrice, then for the lth SU of the ith set the compressed measurements is denoted by:

$$y_{il} = \mathbf{P}x_{il} \tag{19}$$

here, x_{il} is the received signal. The proposed method is tested for AWGN, Rayleigh, multi-path fading.

Complexity Analysis of the Spectrum Sensing Methods

The big O notation for the different spectrum sensing technique has been analyzed as shown below [148]:

a. Conventional Energy Detector: $O((N_s))$, where N_s is the number of energy samples sensed.
b. Cooperative Spectrum Sensing: The complexity of cooperative spectrum sensing depends on the number of SUs within a Fusion Center, Spectrum sensing technique employed by the each SUs and the complexity associated with the evaluation at the fusion center. Therefore, the complexity associated with the cooperative spectrum sensing is higher than the conventional energy detector.
c. PSO-GSA-based Spectrum Sensing: Complexity of PSO-GSA+Complexity of Energy Detector, $O((N_s)) + (O(m \times n/2) + O(m^2))(O(mutation) + O(crossover))$
d. PSO-based Spectrum Sensing: Complexity of PSO+Complexity of Energy Detector, $O((N_s)) + O(m \times n)$
e. ABC-based Spectrum Sensing: Complexity of ABC+Complexity of Energy Detector, $O((N_s)) + O(n^5)$
f. Fire Fly Algorithm-based Spectrum Sensing: $O((N_s)) + O(N * maxit * log(N))$ where $maxit$ is maximum number of iterations.
g. Ant Colony Optimization-based Spectrum Sensing: $O((N_s)) + O(g(n))$, $g(n)$ is the polynomial function of size n.
h. ANN : $O((N_s)) + O(z^6$, where z is the number of hidden layer neurons.

Future Scope for the Soft-Computing-Based Spectrum Sensing

From the previous section, it is observed that for an efficient spectrum sensing, it is required to have optimized value of energy efficiency, sensing efficiency, power efficiency. With the optimized value of sensing time, detection threshold, and power, the proper tradeoff between sensing, and throughput, and power and throughput can be achieved. Therefore, an efficient optimization technique plays a pivotal role in having an efficient spectrum sensing technique, which in turn is very crucial in modeling an effective CRN. In this section, different training and optimization techniques are dealt which have been used for various modeling and optimization-based problems. These techniques could be further modified and possibly be proposed for CRN to improve overall spectrum sensing efficiency. Two major promising techniques have been reviewed as under:

Hybridized Artificial Neural Network

Traditional ANN techniques are trained using back propagation algorithm based on gradient descent which is a popular technique because of its simplicity and ease of implementation. But few drawbacks are associated with gradient descent method like getting stucked to local optimum values [9] and it takes long time to converge to an optimum value [4]. Because of which there was need to focus on training mechanism of ANN. Researchers felt that swarm intelligence technique is the one good option. Training ANN with the help of evolutionary algorithm and swarm intelligence technique is termed as Hybridized ANN.

Evolutionary algorithms have been used for training ANN, its a meta-heuristic optimization technique. Evolutionary algorithm is based on biological evolution, Genetic Algorithm is one popular example of evolutionary algorithm. ANN-GA (Artificial Neural Network-Genetic Algorithm) was proposed by Ganatra et al. [84] and author inferred from the simulation results so obtained that the ANN-GA technique has significantly improved the result as compared to ANN-BP (Back propagation) in terms of convergence speed and local optima. ANN can also be trained using swarm intelligence technique [41]. PSO which is one of the popular swarm intelligence technique have been used to train ANN for some of the optimization problems such as load classification [58], crop identification [83], Results obtained in [58, 76, 82, 83] shows that PSO trained ANN has an upper edge as compared to conventional ANN. Farshidpour and Keynia in [105] proposed ABC trained ANN and proved from the simulation results the superiority of ANN-ABC over back propagation trained ANN. Firefly trained ANN was discussed by Nandy et al. [106], results showed that the proposed method has better convergence speed than ANN-BP.

Hybrid Metaheuristic Approach

Metaheuristic-based approaches such as PSO, ABC, FFA, etc are powerful optimization technique as discussed in (section IV-(N)), still it has drawbacks in terms convergence speed, local optimum, etc. One metaheuristic approach may be good in one thing and another approach may be good in another. Combining meta-heuristic technique based on test function, so that their pros can get add-on results in hybrid metaheuristic which in most of the cases have proved to be performing better than their conventional counterparts. Csebfalvi et al. [52] proposed a hybrid metaheuristic method, combination of ACO, GA and local search(LS) strategy named as ANGEL. In the proposed method, ACO and GA combinely perform the initial search of optimum solution, once the solution is obtained then the LS method is used to obtain a better solution. Results of test examples used for simulation showed that ANGEL method is more efficient than the gradient-based and traditional population-based method for solving constrained and unconstrained optimization problem. Shankar et al. [130] proposed hybrid Harmonic Search Algorithm and PSO(HSA-PSO) for energy-efficient selection of cluster heads. Results so obtained showed the superiority of proposed method over conventional metaheuristic approaches. Kaur and Mahajan [143] proposed hybrid ACOPSO based energy-efficient clustering protocol. Authors proposed an ACOPSO-GSTEB-based routing technique to enroute shortest path between cluster heads and sink. Proposed technique was compared with existing GSTEB (General Self-Organized Tree-based Energy Balance) routing protocol. Performance metrics in terms of stability period, network lifetime, residual energy and throughput were evaluated for 100 sensor nodes. Simulation results showed that the proposed method outperformed the conventional GSTEB for different performance metrics. Apart from that, proposed method was energy efficient too.

Hybrid metaheuristic approach have also been implemented for weight optimization in CRN. Das et al. [117] proposed multi-objective hybrid technique comprising invasive weed optimization and PSO termed as IWA/PSO for obtaining the optimal value of global decision and CRUs' weight coefficient vector. Simulation results showed the efficacy of the proposed method as compared to nondominated sorting genetic algorithm (NSGA-II), multiobjective particle swarm optimization (MOPSO) and nondominated sorting invasive weed optimization (NSIWO) with respect to nondominated solution and detection accuracy.

Future Research Challenges and Open Issues

In this section, different issues and research challenges associated with developing efficient soft computing techniques in CRN are addressed.

To the best of our knowledge, no neural network-based prediction scheme is implied for spectrum sharing. The major reason is the challenges associated with the efficient prediction of SU activities in time, frequency, and space domain [144]. In a heterogeneous network, it is a challenging task to predict the uncertainty associated with the SU services request and communication.

It can be observed from this survey paper, that most of the soft computing approach for spectrum sensing is predicting or optimizing the channel state for the immediate next time slot. It would be challenging for a soft-computing technique to be able to optimize or predict channel state for a long-term basis, as there would be more chances of erroneous prediction.

One of the major issues associated with soft-computing techniques is to find the optimal algorithm for optimization. Based on the concept of "No Free Lunch" [79], different algorithms have varying performances based on the objective function. Therefore, it would be a challenge for the soft-computing technical engineers to find the optimal algorithm for a specific problem in spectrum sensing.

For a spectrum sensing technique, it is crucial to have high detection probability with low interference and low false alarm probability. With soft computing techniques, the performance of the conventional spectrum sensing increases, but the time complexity also increases. The increased computation complexity has a negative impact on the energy efficiency of the CRN [33, 82]. The CRN is a battery powered device, and energy efficiency becomes an essential aspect of being considered while incorporating soft-computing techniques for spectrum sensing [148, 154].

Conclusion

Radio spectrum is an extremely important asset in the field of wireless communication, and it has been a point of convergence for innovative research work throughout the most recent years. The cognitive radio, which is one of the endeavors to use the accessible spectrum more efficiently through opportunistic spectrum use, has turned into an energizing and promising idea. One of the vital components of cognitive radio is to detect the accessible vacant spectrum and it is performed by spectrum sensing process. In this paper, the spectrum availability and detecting ideas are rethought by considering diverse spectrum sensing techniques. Various aspects of the soft computing scheme for spectrum sensing are explained in detail. Apart from that, different critical issues associated with spectrum sensing and the design of cognitive radio networks are highlighted. The new understanding of spectrum sensing gives rise to new openings and also the challenges associated with it. To tackle these contemporary issues, hybridized meta heuristic and artificial intelligence-based schemes that could be implemented for spectrum sensing have been proposed which can give an upper edge for spectrum detection and thus enhancing the performance of the cognitive radio network.

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Compliance with Ethical Standards

Conflict of interest First author, Mr.Geoffrey Eappen declares that he has no conflict of interest. Second author, Dr. Shankar T declares that he has no conflict of interest.

Ethical approval This article does not contain any studies with animals performed by any of the authors.

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