Chapter 2

Literature Survey

2.1 Introduction

The key enabling technology that emerges for dynamic spectrum access (DSA) techniques for radio communication is the cognitive radio (CR), which is supported by the Software Defined Radio (SDR) technology. The Cognitive Radio Network (CRN) has emerged as a strong candidate for next generation wireless communication networks due to its properties like - capacity to autonomically utilize unused spectrum portions opportunistically, and seamless communication. This dissertation contributes algorithms and schemes in the area of cognitive radio networks. In this context, this chapter provides the background about functionalities and a comprehensive survey on various works done in the field of spectrum sensing, power and channel allocation and primary user channel usage pattern modeling for medium access control (MAC) level sensing decision. This survey will provide a strong foundation to appreciate the different schemes developed throughout this dissertation. The rest of this chapter is organized as follows. Section 2.2 discusses about different spectrum sensing techniques and their working principles. Section 2.4 discusses about the technique of cooperative spectrum sensing. In this section the issues of cooperative spectrum techniques are also discussed. Section 2.5 presents the power and channel allocation techniques used for CR communication. This section also focuses on the capacity rate optimization issues related to CR communication. Section 2.6 discusses medium access control (MAC) layer level spectrum sensing techniques and their implications for protocol level decision making. This section also presents the channel access mechanisms used for medium access control by the application level protocols. Finally, section 2.7 concludes this chapter.

2.2 Spectrum Sensing

The advent of cognitive radio (CR) is to design the radio frequency (RF) unit of a terminal to be sensitive and aware of the possible changes in its surrounding radio environment. The spectrum sensing is the key function of CR which enables the CR to dynamically adapt to environmental changes by detecting the unoccupied spectrum portion called spectrum holes or white spaces [2]. The important and fundamental task of each user in CRN called secondary user (SU) is to detect the presence or absence of licensed users also called primary users (PUs) of a licensed spectrum band using the spectrum sensing functionalities. This results in detection of the PU signals if they are present in the spectrum band, otherwise identify the availability of the spectrum portion if PUs are absent. The other goal of spectrum sensing in the context of CRN is that depending on detection performance the SU transmissions should not cause interference to PUs through either limiting its interference level within tolerable level of PUs or switching to an another available spectrum band.

The detection performance of spectrum sensing function plays a crucial role in terms of accuracy for success of CR transmission while protecting primary transmission. In spectrum sensing, three important matrices are used to measure the detection performance. They are - *probability of detection, probability of miss detection* and *probability of false alarm* and are stated as follows:

- *probability of detection* - it is the probability that an SU declares the presence of a PU when the PU indeed occupies the spectrum band.
- *probability of false alarm* - it is the probability that a SU declares that the PU is present in a spectrum band when the spectrum is actually free (i.e. not occupied by PU).
- *probability of miss detection* - it is the probability that a SU declares that PU is absent when the PU indeed occupies the spectrum band. It can be defined as the opposite of *probability of detection*.

Based on the above measures for achieving an optimal probability of detection, a spectrum sensing function requires to generate miss detection and false alarm as minimum as possible. Since every miss detection causes the interference to the PU and a false alarm reduces the resultant spectral efficiency, therefore, improving spectral efficiency while maintaining a given level of detection accuracy or vice-versa is important.

Most of the spectrum sensing techniques in the literature [2] focuses on primary transmitter detection based on local/individual (i.e. non-cooperative sensing) observations by the SUs. The recent development is in the area of cooperative sensing, where CR nodes can collaborate or cooperate for improving spectrum sensing performance. But local/individual sensing schemes are the basis for all of those techniques.

Signal Processing for Spectrum Sensing

The spectrum sensing is the procedure that can be seen as a kind of receiving signal processing at SUs, because spectrum sensing detects spectrum holes by local measurement of input signal (PU signal) spectrum, which is referred to as local spectrum sensing. In CRN the SUs will independently detect the channel through continuously sensing the spectrum. In this process, the local/individual sensing for primary signal detection is formulated as a binary hypothesis testing model as follows [17]:

$$x(t) = \begin{cases} n(t), & H_0 \\ h(t).s(t) + n(t), & H_1 \end{cases} \tag{2.1}$$

where $x(t)$, $s(t)$, $h(t)$ and $n(t)$ denote the received signal at SU, the transmitted PU signal, the amplitude gain of the sensed channel, and the additive white Gaussian noise (AWGN) with mean zero respectively. H_0 and H_1 represent the hypothesis of absence and presence of the PU signal in the specified frequency band. With H_0 and H_1 the definitions of the probabilities of detection P_d, false alarm P_f and missed detection P_m as stated by Digham *et al.* [38] can be given by:

$$P_d = P\{decision = H_1|H_1\} = P\{Y > \lambda|H_1\} \tag{2.2}$$

$$P_f = P\{decision = H_1|H_0\} = P\{Y > \lambda|H_0\} \tag{2.3}$$

$$P_m = 1 - P_d = P\{decision = H_0|H_1\} \tag{2.4}$$

where Y and λ represent the decision statistic and the decision threshold respectively. The value of λ is chosen depending on a given detection performance requirement. Based on the measured values of P_d and P_f, the performance evaluation metric of spectrum sensing techniques are expressed and the plot of P_d versus P_f is called the receiver operating characteristic (ROC) curve.

In the literature various spectrum sensing techniques are proposed depending on amount of information about the primary signal available to the secondary users, as discussed in the following.

2.2.1 Matched Filter Detection

When the information about PU transmitter signal is known to SU, matched filter based technique is optimal for stationary Gaussian noise scenarios since it maximizes the received signal-to-noise ratio (SNR) [15, 16]. The advantage of the matched filter based technique is that it can achieve optimal performance requiring less time for processing due to coherency. But to achieve the optimal performance, it requires the perfect knowledge of structure of PU signal waveform (i.e. modulation type and order, the pulse shape and the frame format information) [1, 15, 16, 39] a priory. The matched filter based technique suffers severely if the accuracy of this information is not correct. In case of CRN such a priory knowledge is not suitably available to the SUs and the complexity and the implementation cost of this technique is very high especially when the number of licensed bands increases. Therefore, from the requirement of adaptive nature of CR technology, this technique is not practical and suitably applicable for CR.

2.2.2 Cyclostationary Feature Detection

Another detection technique used for spectrum sensing is the cyclostationary feature detection [2]. This technique can differentiate between noise signals and the modulated signals that is used for communication [1, 15, 16, 39–41]. The modulated signals are generated coupling with sine wave carriers, pulse trains, repeating spreadings, hopping sequences, and cyclic prefixes, which result in built-in redundancy of signal periodicity. These kind of modulated signals are called as cyclostationarity since their mean and autocorrelation exhibit the periodicity property. This technique of detection exploits the fact that the primary user signals are modulated signals exhibiting the cyclostationary property with spectral correlation while the noise present is a wide-sense stationary signal with no correlation [40, 41]. The detection is performed based on the features of the signal by analyzing a spectral correlation function during the sensing. Due to the capacity of this detection technique to discriminate the noise from transmitted signal it is robust to the uncertainty of noise power [1,15,16,39–41]. The disadvantage of this detection technique is that it requires higher computational complexity and long observation times to produce the result. Also, it needs the perfect knowledge of the cyclic frequencies of the primary user signal, which might not be available to the SUs.

2.2.3 Likelihood Ratio Test (LRT)

The spectrum sensing can be modeled as a binary hypothesis testing problem as discussed in section 2.2, with H_0 (the null hypotheses) and H_1 (the alternative hypotheses) [17]. For a given probability of false alarm, using the Neyman-Pearson (NP) theorem [17] the test statistic which maximizes the probability of detection is the likelihood ratio test (LRT) defined as:

$$L(X) = \frac{p(X|H_1)}{p(X|H_0)} \tag{2.5}$$

where X and $p(\cdot)$ denote the received signal vector and the probability density function (PDF) respectively. Although LRT is proven to be NP optimal [2, 17], it requires the exact distribution of PU signal, noise estimation and the channel gains, which makes it intractable in practical implementation.

2.2.4 Energy Detection

The energy detector (ED) based spectrum sensing is also known as radiometry or periodogram [2, 15]. Due to its low computational and implementation complexities, it is most commonly used to perform spectrum sensing. It is also called as blind detection technique since the SUs do not need any a priory information about the primary users signal and the channel gains. For a Gaussian noise model, the primary signal is detected depending on only the knowledge of the noise power (or noise floor) [42] present in the spectrum band. This technique works accumulating the energy of the received signal during the sensing interval and declares that the band is occupied if the energy level exceeds a specified threshold value. The threshold is chosen depending on a given desired probability of false alarm [15] to be achieved. In order to measure the energy level of primary signal, the output signal of a bandpass filter with certain bandwidth, say B is squared and integrated over the observation interval, say T. Then, the output of the integrator, say Y is compared with the given threshold to decide the absence or presence of the PU signal. Since the implementation of the ED technique is simple and less expensive it is adopted in most of the spectrum sensing techniques in the literature [1, 15–18, 39]. The performance of the ED technique is susceptible to noise uncertainty while it is very robust to unknown fading channel. Again since it is unable to differentiate signal types, it can only determine the presence or absence of the signal. Because of which it is prone to produce false alarm by unintended signals in a spectrum band.

2.3 Limitations of Local Spectrum Sensing

Since CR transmission is considered to be lower priority in a licensed spectrum, a fundamental requirement is to avoid harmful interference to potential PUs in their vicinity. On the other hand, PUs are supposed to be operating without any change in their infrastructure for spectrum sharing with cognitive networks. Therefore, SUs should be able to independently detect presence of PUs through spectrum sensing. Although it is raveled that theoretically the interference can only happens at primary receivers, it is difficult for SU to have direct measurement of the communication link between PU transmitter and receivers. Consequently due to the complex wireless environment and uncertainty of the locations of PU receivers, the SU must ensure high sensitivity such that it outperforms PU receivers by a large margin in order to prevent hidden terminal problem. The hidden terminal problem occurs when the SU is shadowed, in destructive multhi-path fading environment, or inside the buildings with high penetration loss, while in a close neighborhood a PU exists with the marginal reception capacity because of the channel conditions. In such a situation, the SU would inflict interference to the PU. Therefore, the performance of spectrum sensing under low signal-to-noise (SNR) is crucial in such an environment. This results in a difficulty in detection of PU activity in the spectrum band, which can be related by the trade off between false alarm probability and miss detection probability. That is, high false alarm probability leads to low spectrum utilization and high missing detection probability increases interference to PU. From such a scenario it can be stated that that local spectrum sensing always suffers from limitations on detecting weak signal. Hence, the cooperative Spectrum Sensing(CSS) is the solution to improve spectrum utilization and the detection ability of SUs especially under low SNR situations.

2.4 Cooperative Spectrum Sensing (CSS)

The techniques discussed in section 2.2 adopt spectrum sensing to be performed by SUs individually, which face the challenges in terms of sensing efficiency due to inherent spectral diversity problems [3, 15–22, 43] like multipath fading, shadowing, hidden terminal problem and receiver uncertainty problem. Again for CRN, the reliability of spectrum sensing is crucial in terms of accuracy to spot the white space in the spectrum. It is revealed that the problem of inherent spectral diversity issues can be overcome using cooperative spectrum sensing [3,32,33] performed by the SUs. The aim of cooperative sensing is to improve the spectrum sensing performance by exploiting the spatial diversity during the observations of SUs, which are located spatially in distant locations apart. By cooperation, SUs can share their individual sensing information to make a combined decision more accurate than the individual decisions. Using the cooperation among SUs, the enhanced sensing performance that can be achieved due to the spatial diversity is called cooperative gain.

2.4.1 Classification of Cooperative Sensing

Depending on techniques to share the sensing information in the network by the cooperating SUs, cooperative spectrum sensing (CSS) can be classified into three categories [3]: centralized, distributed, and relay-assisted as shown in Figure 2-1.

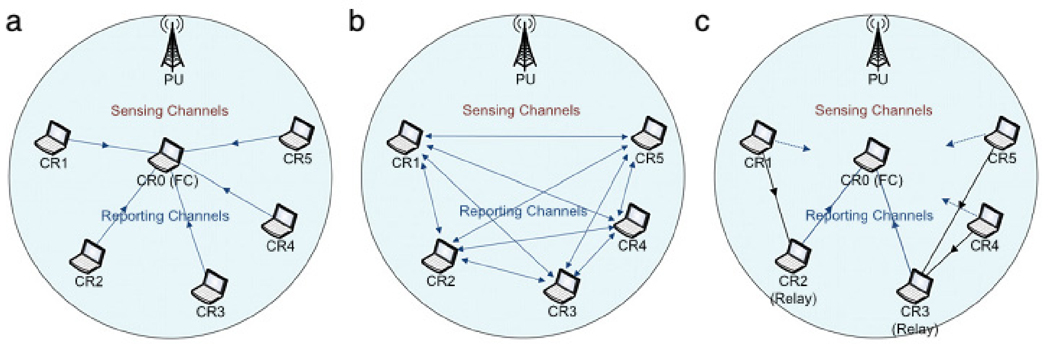

Figure 2-1: Classification of CSS: (a) centralized, (b) distributed (c) relay-assisted [3].

- **Centralized CSS** - In this category the process of cooperative sensing is controlled by a central authority called fusion center (FC). The FC is responsible to initiate the sensing process by selecting a channel or a frequency band of interest and sends control information to the cooperating SUs to perform local sensing by them. Using the control channel the SUs report their sensing results back to the FC, which then performs the fusion operation on the received individual sensing information from the SUs and takes a decision about the presence or absence of PUs in the band. Finally the FC informs the decision back to SUs. The method of centralized CSS is shown in Figure 2-1(a).

- **Distributed CSS** - In this case, the SUs share their individual sensing information through communicating among themselves in a distributed manner and eventually converge to a unified decision about the presence or absence of PUs by iterations. As shown in Figure 2-1(b), based on distributed procedure, every SU sends their own sensing information to every other SUs followed by combining their own result with the received sensing information from others, and then takes a decision about PU's presence or absence by using a local criterion. Until the the given criterion is not satisfied, the SUs send their combined results to every other SUs again and repeat the process until the algorithm converges. At the convergence a consensus among the SUs is reached about a decision.

- **Relay-assisted CSS** - As shown in Figure 2-1(c), depending on the strength of sensing channel/spectrum and reporting channel some of the SUs might be in under duck situation if the strength of reporting channel from them are weak. In such a situation, a SU with a strong reporting channel, can serve as relays to assist others in forwarding the sensing results from the under duck SUs to the FC in case of centralized implementation or to the other SUs in case of distributed implementation.

2.4.2 Components of Cooperative Spectrum Sensing

The conventional process for cooperative sensing involves three steps as: local sensing, reporting information to fusion center and data fusion. As given by Akyildiz *et al.* [3], these steps are supported by other components as follows, which are important for implementation of cooperative sensing framework:

- *Cooperation Model* - refers to the model of cooperation used by the SUs to implement the cooperation framework for sensing. Two approaches are used namely: parallel fusion (PF) model and game theoretic model.

- *Sensing Technique* - refers to the spectrum sensing techniques used by SUs for their individual sensing to observe the RF environment and to collect the information about PU signals or to indicate the availability of the spectrum band.

- *Hypothesis Testing* - refers to the statistical test used by the SUs individually to take a decision about presence or absence of a PU in a spectrum of interest.

- *Control Channel and Reporting* - refers to the common control channel to be used by the cooperating SUs to report to the fusion center or to the leader/head node, who is responsible for taking decision in collaborative way.

- *Data Fusion* - refers to the mechanism used by fusion center or the leader/head to fuse the sensing data received from all the cooperating SUs for a decision to make out. Techniques like AND rule, OR rule, voting rule are used to take a decision.
- *User Selection* - refers to how to optimally select the cooperating SUs to frame the cooperation footprint, which will maximize the cooperative gain and minimize the cooperation overhead.
- *Knowledge Base* - refers to the information in the knowledge base either having with a priori information or the knowledge accumulated through the experience, which may facilitates the CSS process to improve the overall detection performance. The knowledge may include PU and/or SU location information, PU activity models and received signal strength (RSS) profiles.

2.4.3 Cooperation Framework

Different approaches are used to design the cooperation framework for spectrum sensing, which uses the cooperation model based on PF or game theoretic modeling. Depending on the modeling it can be stated that the parallel cooperation model focuses on the "sensing" part, while the game theoretic model emphasizes on the cooperation part in cooperative sensing.

2.4.3.1 Parallel Fusion (PF) Model

It is the most popular and widely used approach to model the cooperation framework for distributed detection and data fusion [3]. As shown in Figure 2-2, to perform distributed detection and data fusion, a group of spatially distributed SUs observe a frequency band using hypothesis H_1 or H_0 through the observations called y_i. The SUs then report their results u_i to a central authority called fusion center (FC). The FC combines all the reported information using a data fusion technique and makes a global sensing decision u by using the binary hypothesis testing. Finally the decision is broadcast to all cooperating SUs. The advantage is that the PF model targets to achieve the detection performance utilizing the distributed signal processing approach.

2.4.3.2 Game Theoretic Model

The game theory [23, 24] is a mathematical tool which can analyze the strategic interactions among multiple decision makers dynamically and can address the optimization issues on run. It is revealed in the literature [44] that the game theory can be used to model and analyze a collaborative framework efficiently. Between

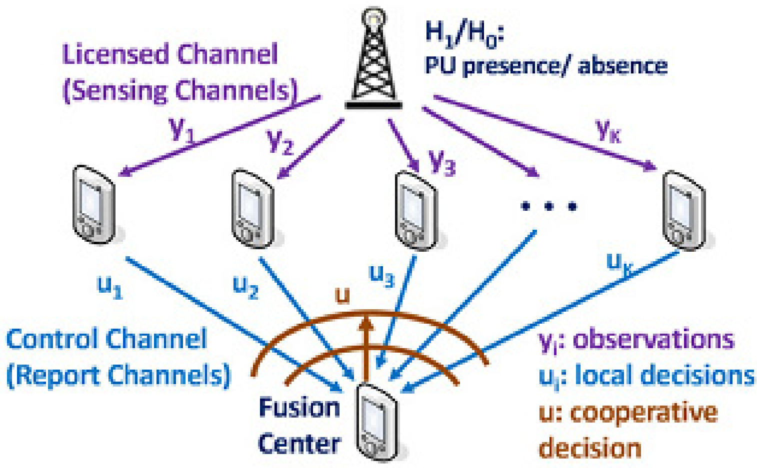

Figure 2-2: The Parallel Fusion Cooperation Model [3].

the two categories of game theoretic approaches (i.e. non-cooperative and cooperative game theory) [23, 24], the cooperative game theory considers the behavior of rational players with improvement of their mutual benefit via cooperation. As shown in Figure 2-3, using the coalitional game theory [23], the cooperative sensing framework is modeled as a cooperative game having the SUs as set of players. The SUs in the game behave in collaborative and cooperative manner to achieve a common goal in terms of improving detection performance, which is derived as the utility function. Depending on the nature of the game to be played using different strategies, the behaviors (cooperative and/or selfish behavior) of the cooperating SUs are modeled differently.

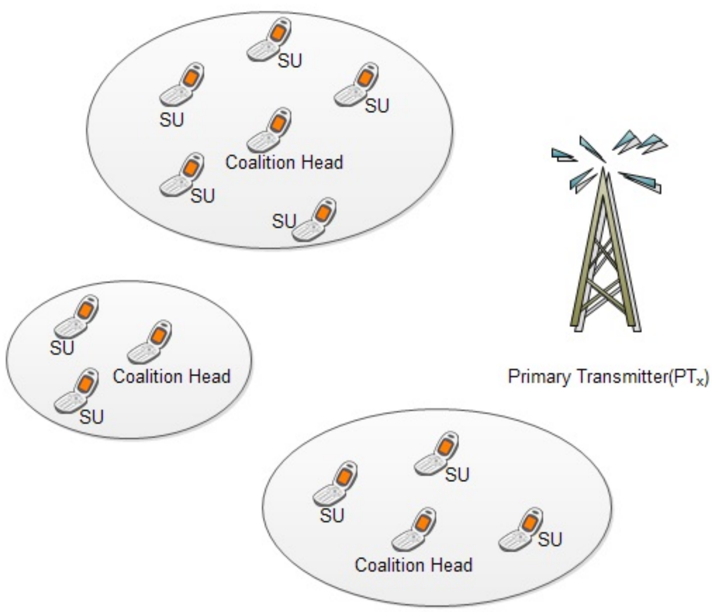

Figure 2-3: The Coalitional Game based Cooperation Model.

In the literature, the works in [34, 45] address the modeling of CSS framework by means of game theoretic approach. In [34], the problem of cooperative spectrum sensing is modeled as a non-transferable coalitional game. The game is represented by $(\mathcal{N}, \nu)$, where $\mathcal{N}$ be a finite set of cooperating players (SUs) and ν is the utility or payoff associated with each of the players within a coalition. Since each of the SUs have their own utility, the game said to have non-transferable utility. The utility of a coalition S is defined as

$$\nu(S) = Q_{d,S} - C(Q_{f,S}) \tag{2.6}$$

where $Q_{d,S}$ and $Q_{f,S}$ of coalition S are the detection and false alarm probabilities respectively. $C(Q_{f,S})$ is the cost function in terms of $Q_{f,S}$. Playing the game the SUs collaborate and self-organize into disjoint coalitions dynamically, while taking into account the trade off between maximization of probability of detection to the cost incurred in terms of reducing the probability of false alarm. Depending on the improvement of the utility of the SUs coalitions merge and split autonomously. In [45], an evolutionary game is used to model a distributed cooperative sensing framework, which study the cooperation and non-cooperation behaviors of selfish SUs to maximize their individual throughput. In this model SUs can select an action from a set of actions composing with rules like "interested to participate" or "denies to participate" in cooperation. The throughput of the SUs depends on their willingness to join cooperation or not. SUs interacting with other SUs in the game using the replicator dynamics learn the best strategy to decide to cooperate or not during cooperative sensing. The CSS technique given in [46] addresses a throughput-efficient sensing as selfish or altruistic coalition formation game depending on their individual gain, which considers the sensing duration and reporting delay of SUs as cooperation overhead. But the cooperation overhead because of constraints like reporting time, reporting energy, possible error on reporting channel due to the spectral diversity of the SUs and delay required for computing for a decision by the fusion center play important roles in CSS performance, which are challenging.

2.4.4 Cooperative System Issues

The cooperative gain that can be achievable through cooperation can be affected by many factors.

- The spatially correlated shadowing impacts the sensing detection performance. Because of some obstacle SUs face the situation of spatially correlated shadowing leading to impact their observations to be correlated in nature. This gives rise the problem of selection of SUs for cooperation.
- The cooperative system incurs cooperation overhead in terms of extra sensing time, delay, reporting delay, reporting energy, and operations to perform cooperative sensing compared to the individual spectrum sensing.
- The cooperation overhead due to the possible vulnerability to security attacks in terms of impacting the parameters of cooperative sensing.

2.5 Power Allocation in CRN

Power allocation is the key technique for success of CRN, yet to maintain the quality of service (QoS) of PUs. Utilizing the detected spectrum opportunities by means of maximization of capacity rate requires optimal power allocation into the channels by a SUs. The power allocation for secondary transmission is needed to be performed provided the allowed aggregated interference to PU-receivers are maintained. Depending on different objectives like utility maximization and power minimization, the optimal power allocation strategies in CRN have been studied for different network structure/system models including: 1) single antenna based CRNs as in [47, 48] 2) orthogonal frequency division multiplexing (OFDM) based CRNs as in [49, 50] 3) cognitive relay networks [51] and 4) multi-antenna based CRNs [51]. The power allocation problem in CRN can be addressed using tools like game theory [23, 24, 51], graph coloring theory [51], evolutionary algorithms like genetic algorithm [51], particle swarm optimization [51], ant colony algorithm, [51], and convex optimization theory [51].

2.5.1 Classification of Power Allocation Infrastructure

Depending on the availability of dedicated base stations to control transmit power levels of SUs the power allocation insfrastructure can be classified into two categories [13]: centralized and distributed.

- **Centralized Power Allocation** - In this category as in conventional wireless communications, dedicated base stations control the transmit-power levels of SUs so as to provide the required coverage area and thereby achieving the receiver performance. The base station is responsible to regulate the power allocation for SUs provided the PU protection from harmful interference.

- **Distributed Power Allocation** - In this category, SUs operate in decentralized manner and the power allocation is based on adopting distributed recourse allocation techniques like water-filling [25] rooted in information theory [13].

2.5.2 Water Filling Concept

Water-filling (WF) [25] is a technique used in communication systems design and in practice for equalisation strategies on communications channels, which is rooted in information theory. Like water finds its level even when filled in one part of a vessel with multiple openings, as a consequence of Pascal's law [52, 53], the amplifier circuitry in communications network repeaters, or receivers amplify each channel up to the required power level compensating for the channel impairments. The required power level is regulated based on total power feasibility of an user

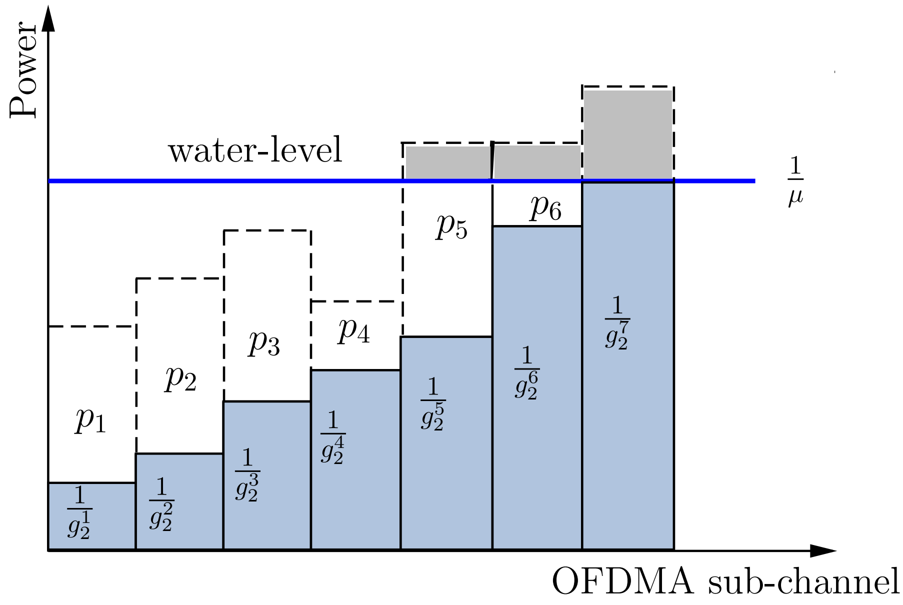

Figure 2-4: The graphical representation of constraint water-filing [4]

terminal, while adjusting against the channel impairments or noise floor in terms of the inverse of the channel gain. Therefore, the principle of WF method [25, 28, 54] is to allocate power in channels/sub-channels provided the water level is settled so as to satisfy the total power feasibility constraint of an user terminal. The water level is measured capturing the difference between a user terminal's maximum feasible total power level to be allocated in a channel/sub-channel and the channel impairment or noise floor present in the channel/sub-channel. The water level is denoted by the inverse of Lagrange multiplier for the total power constraint. From the Figure 2-4 [4], the concept of the WF procedure can be understood, which shows the graphical interpretation of the constrained water-filling. It is shown that the maximum allowable transmit power on each sub-channel is represented as a dotted rectangular box, while $\frac{1}{\mu}$, p_i and $\frac{1}{g_2^i}$ being the water level, allocated power in a channel/sub-channel and the channel/sub-channel impairment for a channel/sub-channel index i. For simplicity of presentation, the inverse of channel gain is sorted in ascending order in the Figure 2-4.

2.5.3 Power Allocation for Underlay Mode CRN

For a CR communication, the maximization of SUs capacity rate requires optimum power allocation, which is regulated by the interference power constraint of PUs. Coexisting with PUs in underlay mode communication, SUs implement the strict PU protection, while power allocation is performed. Considering the channel to be used in orthogonal frequency division multiplexing (OFDM) manner, the classic traditional water-filling (WF) [25] based power allocation techniques are used for OFDM sub-channels. Because of the capability of OFDM framework to use the spectrum bandwidth of a given wireless channel through number of orthogonal sub-channels in parallel manner, the WF based technique adaptively pours power into the sub-channels. This can offer the improved capacity rate for SUs. For underlay mode CR transmission, the PU protection depends on the interference tolerance behavior of the PU receiver. Using the OFDM framework, interference tolerance of PU can be done in two ways [29].

- The peak interference power (PIP) constraint of each of the sub-channels and

- The average interference power (AIP) constraint over all the sub-channels

Compared to PIP, AIP imposes lose constraint on SUs and offers larger instantaneous interference in a sub-channel providing larger throughput as long as the interference averaged over all the sub-channels is within the threshold limit.

In the literature, various power allocation techniques [4, 13, 26–28, 54–60] have been proposed. An optimization problem of capacity rate maximization is addressed in [26, 27] using water-filling (WF) [35] framework of power allocation, which uses a binary search method to iteratively invoke the classic WF algorithm. Most of these approaches in the literature assume that the SU transmitter has the knowledge of the channel state information (CSI) [4, 13, 26] to the PU receiver and performs the power allocation considering the total transmit power constraint initially and then followed by the interference constraint accordingly. It is also found that the classic WF based power allocation approaches face challenges [13, 26–28] in terms of ensuring strict PU protection and the computation overhead to find the water level for optimal solution, which indirectly affects the capacity rate of a SU. Optimizing the power allocation on the channels without resorting to expensive search to find water level is challenging. The schemes based on iterative water-filling (IWF) for multiuser power allocation to maximize the capacity rates suffer from the issue of convergence. To address these problems a number of approaches have been proposed by the researchers. Further, in presence of average interference power (AIP) [29] constraint of primary user this problem of power allocation is more interesting. Accordingly, the power allocation problem needs to be addressed as optimization problem to achieve the capacity rate improvement.

2.6 MAC Layer Sensing

The protocol level decision about the availability of opportunities in the licensed spectrum is taken at medium access control (MAC) level sensing [30]. The task of the MAC level sensing is to improve the opportunity detection efficiency with protocol level policy making and decide about the availability of a licensed channel for secondary communication. The MAC layer sensing determines when a SU has to sense and which channels. A SU takes decision for MAC layer level sensing depending on application level requirement.

2.6.1 Difference between Physical Layer Sensing and MAC Layer Sensing

The term spectrum sensing in cognitive radio communication refers to the traditional physical layer sensing techniques discussed in section 2.2 and cooperative spectrum sensing techniques discussed in section 2.4, which is used to detect spectrum holes or absence of primary user signal at physical layer level. The spectrum sensing at medium access control (MAC) layer refers to the MAC layer policy which is used to decide how often and in which order to sense those physical channels depending on application requirement.

2.6.2 MAC Layer Sensing Techniques

The MAC layer level sensing can be done in ways: *proactive* or *reactive* sensing. The proactive sensing indicates the policy of periodic sensing, whereas the reactive category is performed following the on demand policy. The aim of both the techniques are to optimize the sensing period that maximizes the discovery of opportunity and to determine the order of sensing the channels that minimizes the delay in finding an idle channel.

- **Proactive Sensing** - In this sensing mode SUs periodically monitor the licensed channels with certain sensing periods. The periodically collected channel information is used to estimate channel usage patterns of PUs so that SUs can determine the sensing order of channels depending on their need to locate an idle channel. The periodic sensing operation is derived as a common sampling procedure. The sampling period and the sampling interval are decided in terms of sensing period and listening interval of the SUs. Since different channels have their own usage pattern, the sampling parameters are determined channel by channel basis. The proactive sensing suffers from high sensing overhead since even when there is no data to be transmitted it periodically senses multiple channels. But it can reduce the searching time to find an idle channel so that an end-to-end packet delay can be minimized.

- **Reactive Sensing** - In this sensing mode while a SU has packet to transmit or receive, it sequentially monitors all the licensed channels to find an idle channel. Without the knowledge of channels dynamics, SUs cannot determine their optimal sensing order, which minimizes the time required to locate an idle channel. So, in this sensing mode, an SU senses the channels in random order. This technique does not incur unnecessary sensing overheads, but requires a larger channel searching delay than the optimally ordered sensing based on the estimation of channels dynamics.

With the strict requirement to primary protection for underlay mode channel access, the policies for MAC layer sensing of SUs require the information about the availability of licensed channels and the estimation of interference level to PUs.

In such a scenario, the SUs require to learn about the channels usage pattern of its PUs. Depending on learning SUs can predict future availability of a channel, which helps to alleviate the sensing overhead problem of proactive sensing. The channel usage pattern of PUs in terms of ON and OFF state of a PU follows the Markovian process.

2.7 Conclusion

In this chapter, we have presented a comprehensive survey on the background of CRN and the existing works related to the problems addressed in this dissertation. With a detailed understanding of the state-of-the-art, the research contributions are presented in the subsequent chapters.