Chapter 1

Introduction

1.1 Spectrum Scarcity

The entire electromagnetic spectrum is a naturally available resource that ranges from 3 Hz (extremely low frequency) to 300 EHz (gamma rays) as shown in Fig. 1.1. Such range has been divided into different frequency sub-bands, out of which, the frequency band from 3 Hz - 300 GHz is referred to as Radio Spectrum and it is illustrated in Fig. 1.1. Here, such radio spectrum has been further sub-divided into different frequency ranges and it is used for various wireless communication technologies such as: Amplitude Modulation (AM) transmission, TeleVision (TV) broadcasting, Global System for Mobiles (GSM), Near-Field-Communication (NFC), Frequency Modulation (FM) radio broadcasting, Long-Term Evolution (LTE) mobile transmission, Global Positioning System (GPS), Wi-Fi, bluetooth etc.

Presently, there is a surge in the demand of higher data rate or bandwidth by millions of wireless devices (primarily smart phones) around the world that access ≈2.5 quintillion bytes of data every day [1]. Additionally, there is a rapid growth in the usage of smart phones, that consume 24× more data than the traditional cell phones. Statistics of such aforementioned growth in global wireless data has been presented by Resonant based on Cisco annual internet report [2] as shown in Fig. 1.2(a). Here, the mobile data growth accelerates from 12 to 175 exabyte/month. Furthermore, the spectrum deficit statistics has been presented by Resonant which is based on the model developed by Federal Communications Commission

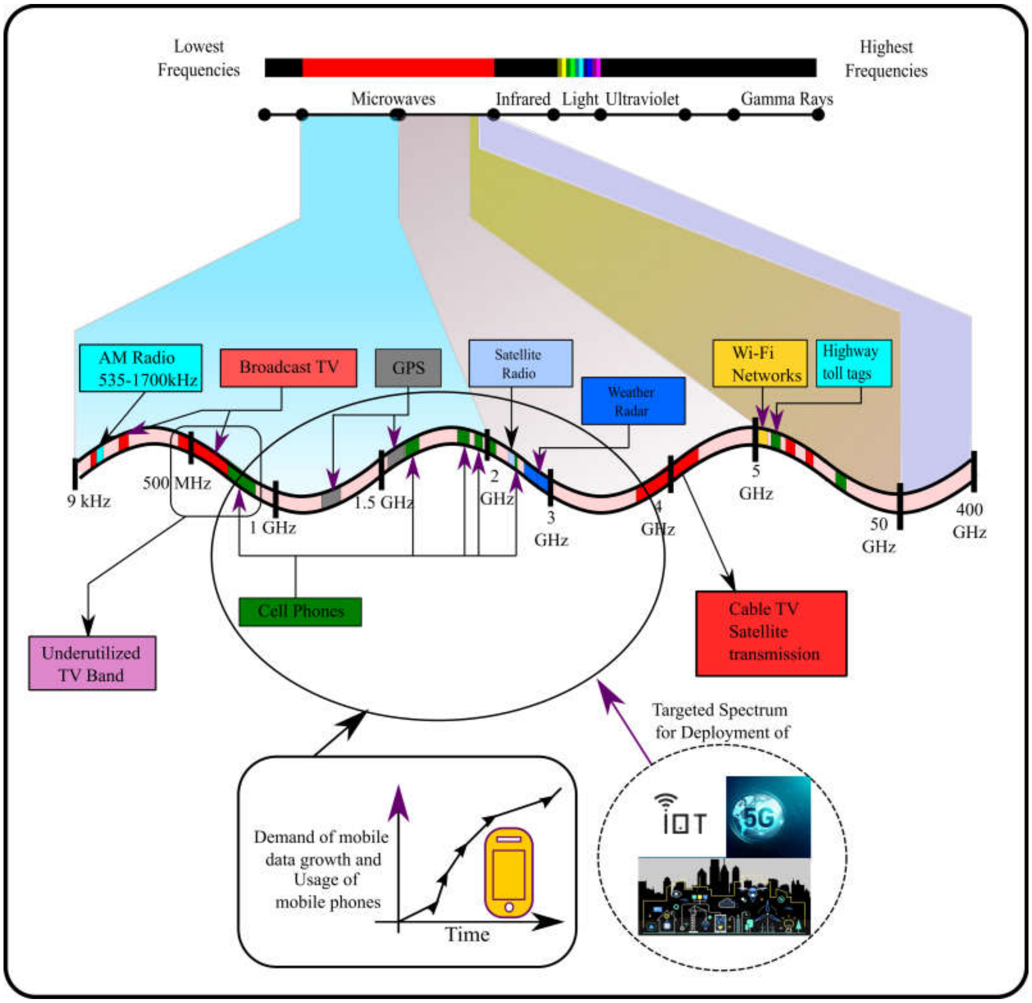

Fig. 1.1: Radio Spectrum.

(FCC), as shown in Fig. 1.2(b). It indicates that the demand for services will transcend the available spectrum from the year 2021 and the situation will exacerbate by 2025. Thus, leading to a problem of massive spectrum deficiency.

Furthermore, to envision a fully digitized world of disrupting technologies like smart cities, self-driving cars, smart grids, e-healthcare systems, and smart surveillance, it requires massive deployments of emerging wireless technologies such as Internet-of-Thing (IoT), holographic telepresence, Internet-of-Everything (IoE), 5th-Generation New Radio (5G-NR) and 6G technologies [3]. According to the data available at hand-sight for IoT, it is foreseen that, there will be 73 billion of connected IoT devices by the year 2025 [4].

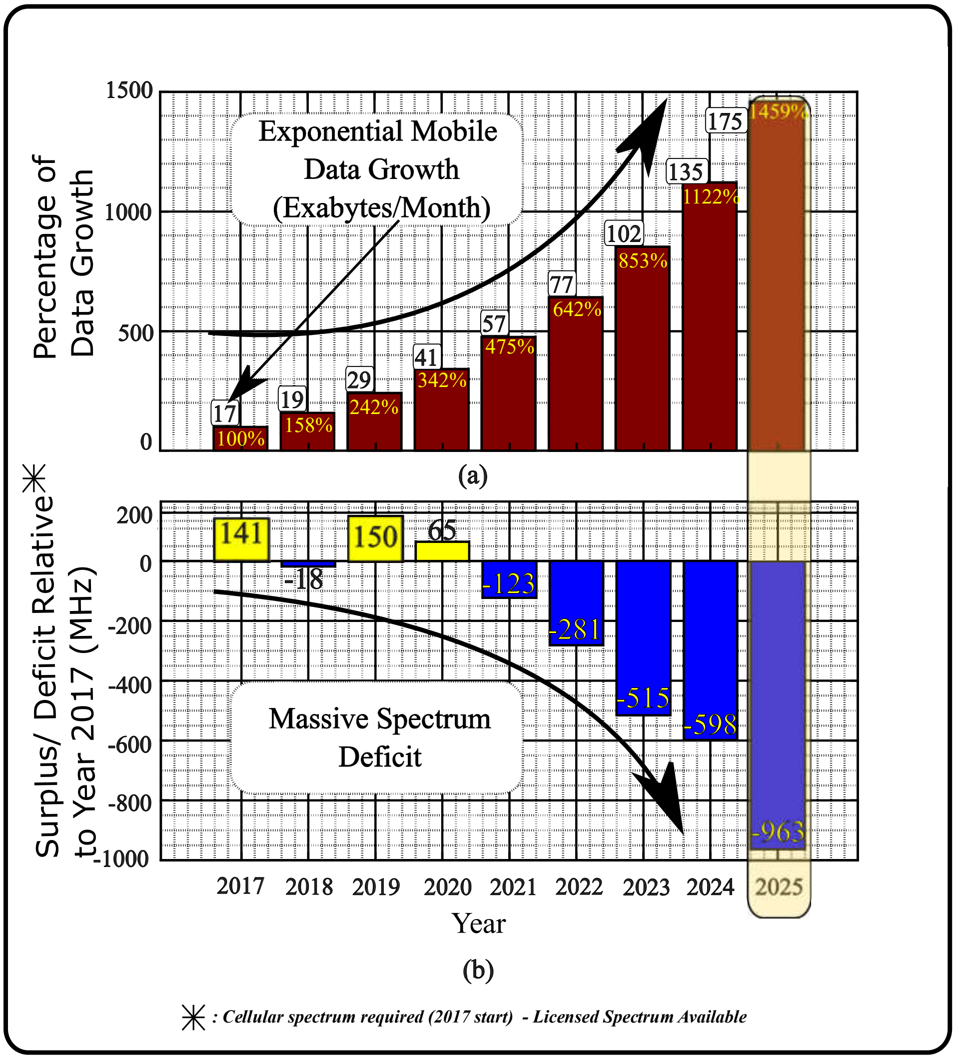

Fig. 1.2: Mobile data growth and spectrum deficit situation through 2025 based on the Resonant spectrum usage model.

On the other side, 5G-NR technology demands high-end specifications of peak data rate up to 20 Gbps, user experience data rate of 100 Mbps, peak spectral efficiency of 30 bit/s/Hz, latency of 1 ms, and connection density of 106 devices/km^2, based on International Mobile Telecommunication (IMT)-2020 [5]. To support these 5G-NR features, 5G-NR technology accesses the frequencies across low (sub 1 GHz), mid (3.3−3.8 GHz) and high (≥26 GHz) bandwidth ranges. Additionally, it has been predicted that 6G will move towards era of terahertz frequencies. However, the available spectrum is limited and it cannot be expanded beyond a certain limit. Such limited spectrum is made available to different service providers based on fixed-spectrum allocation policy. In fixed-spectrum allocation policy, the government agencies make a certain frequency band of RF spectrum available to wireless service providers for certain amount and issues the respective spectrum licensed to them. Such licensed wireless service providers are referred as primary users (PUs) and the drawback of such fixed spectrum allocation policy is that the allocated spectrum cannot be used for new wireless technologies. Thus, due to limited availability of spectrum and fixed spectrum allocation policy, the available spectrum is sparse to accommodate aforementioned surge in IoT devices, cater the increasing demand of exponential growth in mobile data-rate (as shown in Fig. 1.2) and to meet the high-end specifications of 5G-NR technology. Thus, spectrum scarcity is becoming a major snag for the deployment of emerging wireless technologies.

On the other side, it has been observed that huge range of radio spectrum is underutilized ; specifically, in the Ultra High Frequency (UHF) region that ranges from 470-806 MHz, as shown in Fig. 1.3. These underutilized spectrum is referred as TV white space, as it falls under TV Band. The basic reason for this under-utilization is widespread usage of satellite TV via C (4-8 GHz) and Ku (12-18 GHz) bands. It has been reported that only 1% of UHF TV band is utilized in India [6], 4.54% in Singapore [7], 6.2% in Auckland [8] and 17.4% in Chicago [9]. Specifically, in India, teressterial Doordarshan TV is a sole service provider that operates in TV UHF band and it consists of 15 channels of 8 MHz each. A recent assesment in TV UHF band of 470-585 MHz has shown that at least 12 out of 15 channels are available as TV white space at any location in India [10] [6]. Such under utilization of RF band can aid in alleviating spectrum scarcity problem through opportunistic communication. Therefore, to efficiently use the underutilized spectrum and increase the spectrum usage, the FCC has standardize IEEE 802.22 standard for Wireless Regional Area Network (WRAN) that uses cognitive-radio technology to access unutilized TV band (i.e. TV white space) for broadband communication [11]. Here, with CR technology, the unlicensed users referred as secondary users (SUs) are allowed to access the underutilized licensed spectrum provided they do not interfere with the licensed PUs.

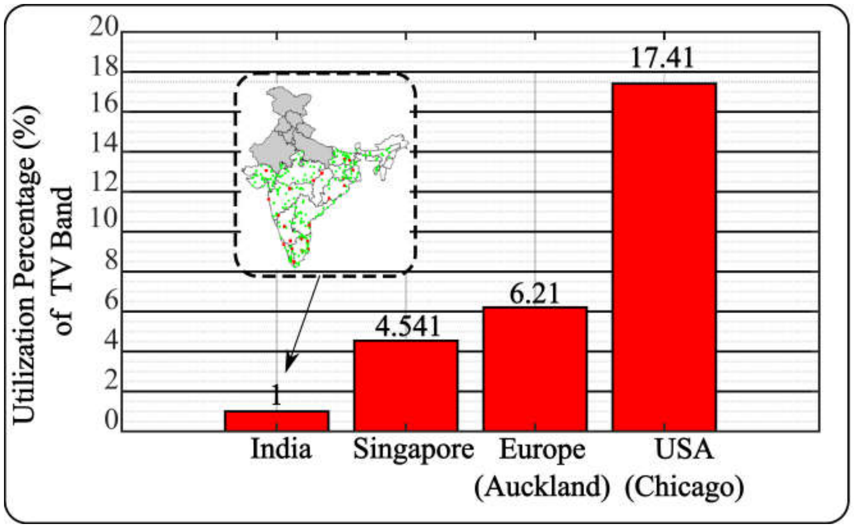

Fig. 1.3: Utilization statistics of TV band in different countries [6] [7] [8] [9].

1.2 Cognitive Radio

Cognitive radio coined by Mitola and Maguire [12] in 1999 has analogous vision of inculcating intelligence in radio that perceives communication environment and tunes its transmission/reception parameters. This technology addresses fundamental problem of spectrum scarcity that has been elobrated in the aforementioned section. The definition of Cognitive Radio (CR) as stated by Simon Haykin [13] is “cognitive radio is an intelligent wireless communication system that is aware of its surrounding environment, and uses the methodology of understanding-by-building to learn from the environment and adapt its internal states to statistical variations in the incoming RF stimuli by making corresponding changes in certain operating parameters (like, transmit-power, carrier-frequency, and modulation strategy) in real-time, with the aim of providing a reliable communication whenever and wherever needed along with the efficient utilization of the spectrum”. To enable such efficient spectrum utilization, the CR technology requires a dynamic spectrum management framework (DSMF) [14]. The DSMF consists of various stages such as spectrum sensing and monitoring, spectrum analysis, spectrum decision and spectrum mobility as shown in Fig.. Here, the aim of the spectrum sensing stage is to continuously monitor the spectrum band and detect the presence/ absence of PU. Spectrum sensing stage also maintains a proper observation about the spectrum holes and helps the spectrum analysis stage for spectrum characterization. In spectrum analysis stage, the informtion obtained from spectrum sensing stage is used to get knowledge about the spectrum hole such as channel error rate, interference estimation, link layer delay etc.. At spectrum decision stage, the best available spectrum is selected to satisfy user's quality of service (QoS) requirement. Further, the spectrum mobility stage refers to the ability of SU's to vacate the currently used licensed spectrum due to arrival of licensed user and carry out its ongoing communication through some other unoccupied licensed channel. From this discussion it is clear that the main function of CR is to carry out the process of spectrum sensing at spectrum sensing stage. Therefore, the main focus of our thesis is on spectrum sensing.

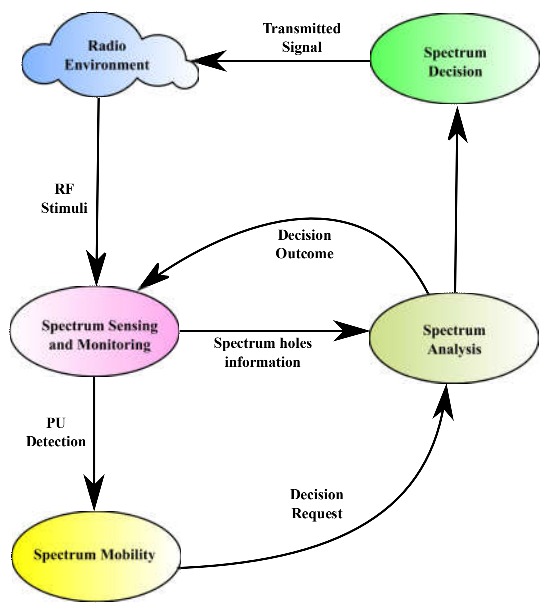

Fig. 1.4: Dynamic Spectrum Management Framework [14].

To better understand the operation of CR technology, consider the scenario shown in Fig.1.5. Here, a part of the radio spectrum has been divided into different frequency bands and each of them is dedicated to different wireless technologies such as GSM, TV, WLAN, military communication and LTE. The heavily utilized GSM-band and the underutilized TV band are clearly shown in Fig. 1.5(a). This imbalanced proportion of usage in frequency band is termed as spectral inefficiency.

Due to such spectral inefficiency, it is difficult to accomodate the increasing number

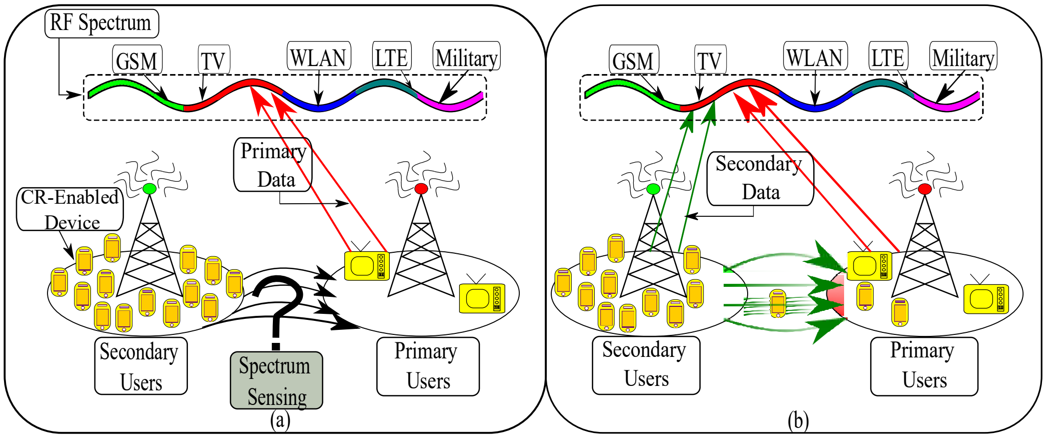

Fig. 1.5: (a) CR-enabled mobile device carrying out the process of spectrum sensing in a heavily utilized band. (b) CR-enabled mobile device carrying out its data-communication via underutilized band.

of mobile devices (subscribers) in the GSM band. Such problem of spectral inefficiency is solved by CR technology. Here, a CR enabled mobile device from GSM band (heavily utilized band) tries to sense the usage of licensed band (under utilized band) as in Fig. 1.5(a) and if it finds out that the licensed spectrum (TV band) is unoccupied, then the CR enabled mobile device changes its communication parameter and tries to communicate via TV band, as shown in Fig. 1.5b. Thus utilizing the unused spectrum more efficiently. In the CR Network (CRN), if a single SU attempts to detect the presence/ absence of PU, it is termed as stand-alone spectrum sensing scenario. On the other hand, when multiple SUs cooperate among each other to detect the PU, it is termed as cooperative spectrum sensing scenario that has been comprehensively discussed in the sections below.

1.3 Stand-Alone Spectrum-Sensing Scenario

In the Fig.1.5, a CR-enabled device/ SU performs independent spectrum sensing to detect the PU by the virtue of stand alone spectrum sensing algorithms (SSSAs). Here, to perform such task, each SU employs a sensing node. The internal sensing node architecture that consists of flexible front-end part and baseband processing part are shown in Fig. 1.6.

Here, the baseband processing part incorporates a standalone spectrum sensor (SSSR). Such SSSR is built using digital circuits that is based on SSSAs. Thus, it is the nucleus

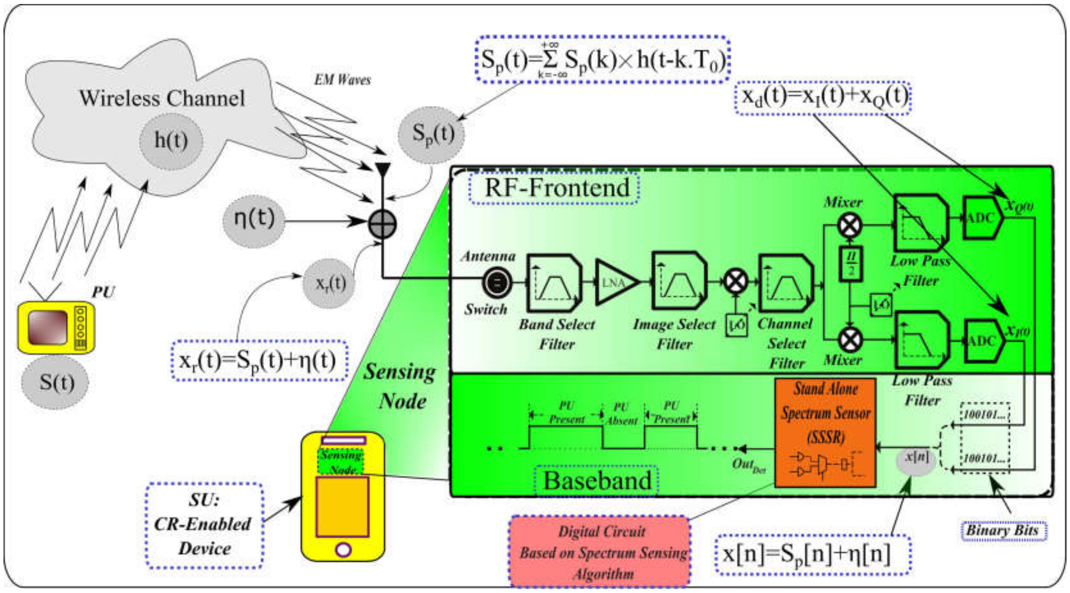

Fig. 1.6: An overall illustration of communication signal flow from PU to CR-enabled device in a CRN and internal hardware organization of sensing node at CR-enabled device.

of spectrum sensing task in a CR technology that detects the presence/ absence of PU. The SSAs are further classified as non-blind, semi-blind and blind SSAs as shown in Fig. 1.7. Here, the non-blind SSAs require prior knowledge of PU such as modulation technique, packet format, pulse shaping, bandwidth etc. to detect the PU. On the other hand, the semi-blind SSAs require feature knowledge of PU such as cyclic prefix or prior estimation of noise variance. In contrast, for the blind SSAs, no knowledge of PU is required to perform the spectrum sensing task. Fig. 1.7 shows different algorithms that fall under such categories. Further, these SSAs carry out the detection process based on Neyman-Pearson hypothesis test [15]. One of these hypotheses H_0 indicates the absence of PU signal and another hypothesis H_1 represents its presence as follows:

$$\begin{aligned} H_0 &: x[n] = \eta[n], \\ H_1 &: x[n] = h[n]\cdot s[n] + \eta[n], \end{aligned} \tag{1.1}$$

$\forall\ n = \{1, 2, 3, \ldots\ldots\ N_s\}$ where N_s is the total number of signal samples used for detection and $h[n]$ is frequency flat channel. Subsequently, $x[n]$ are the signal samples received at the SU, $s[n]$ are the samples of transmitted signal by PU and $\eta[n]$ represents Additive White

Gaussian Noise (AWGN) which is independent and identically distributed (i.i.d) with zero-mean and variance σ_n^2. A brief description of each SSSA from Fig. 1.7 has been discussed in following section.

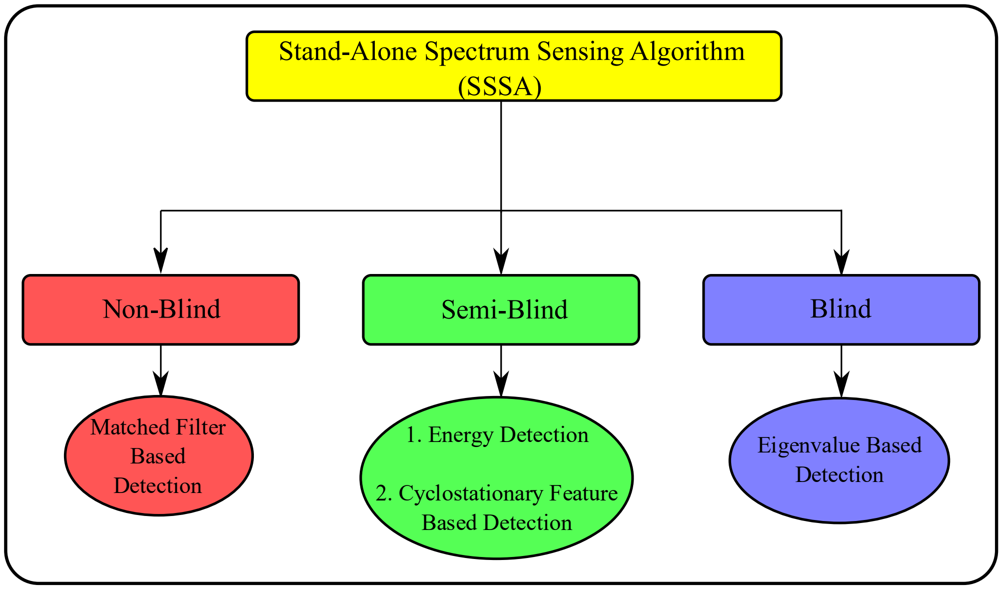

Fig. 1.7: Classification of Stand-Alone Spectrum-Sensing Algorithms.

1.3.1 Energy Detection (ED)

In the energy detection based SSSA, the energy of the received signal sample is computed. Thereafter, it is compared with the pre-defined threshold value to decide on the presence/ absence of PU. Here, the pre-defined threshold is set based on a-priori estimated noise variance. However, this estimated noise variance may differ from the true noise variance and thus ED suffers from the problem of noise uncertainty that eventually leads to signal-to-noise ratio (SNR) wall problem [21]. The SSSR based on energy detection algorithm is termed as energy detectors. Such energy detectors have a low hardware complexity and lower implementation complexity..

1.3.2 Cyclostationary Feature Detection (CFD)

Many signals used in wireless communication system posses some unique pattern/ periodicity such as presence of repetitive frequency in sinusoidal carrier, preambles, pilots, beacon frames, hopping sequence, cyclic frequency etc. In CFD based SSA, such periodicity present in Orthogonal-Frequency-Division Multiplexing (OFDM) based PU signal is used to detect the presence/ absence of PU. Here, in OFDM based PU signal, the cyclic prefix (CP) is attached to the periodicity of PU signal and it is extracted at the SU to detect the presence of PU. The CFD based SSA performs well under the presence of noise uncertainty because, noise signal rarely posses any cyclostationary feature. Therefore, the CFD technique delievers better detection performance even under low SNR regime. However, as discussed, the CFD based SSA requires prior knowledge of CP present in PU signal. Further, it has higher implementation complexity and slow sensing time as compared to energy detection [21]. Furthermore, Higher detection accuracy requires longer length of known sequence and thus it results in lower utilization efficiency of the spectrum.

1.3.3 Matched Filter based Detection (MFD)

The MFD is commonly referred as optimal detector because it maximizes the output SNR under the presence of AWGN. Further, it is also referred as coherent detector as it requires prior information of PU signal such as pilot symbols, modulation type, carrier frequency, frame structure, guard interval etc. present in PU waveform. To detect such pilot symbols, the MFD performs cross-correlation between known sequence and the received signal and if a true correlation peak appears, the MFD indicates that PU is present otherwise it delivers a decision that PU is absent. Therefore, it has robust performance under low SNR regime. However, the main disadvantage of MFD is that it has high hardware complexity and it requires full knowledge of PU to accurately detect the PU. Therefore, the detection performance of MFD degrades if the knowledge of frequency offset, fading channel and proper timing are not available in-prior.

1.3.4 Eigenvalue Based Detection (EBD)

In eigenvalue based SSA, a sample covariance matrix (SCM) is formed from the received signal samples of PU. Thereafter, extreme eigenvalues of such SCM is computed and their values are used with specific mathematical combination for the computation of test statistic to detect the presence or absence of PU. Based on such combination of extreme eigenvalues, there are different EBD SSAs [26]. For example, in maximum-minimum eigenvalue (MME) based SSA, ratio of maximum to minimum eigenvalue of SCM is obtained and it is compared with pre-computed threshold value to decide on the occupancy of PU. On the other hand, in Maximum Eigenvalue based Detection (MED) SSA, maximum eigenvalue of SCM is used to detect the PU. The major advantage of EBD algorithm is that it doesn't require any prior information of PU, therefore it is the most reliable method for detection of PU as it overcomes the noise uncertainty problem of aforementioned detectors. Further, due to no prior information requirement of PU signal, the EBD SSAs are referred as blind SSA. The major challenge in EBD algorithm is the higher computational complexity to form the SCM and obtain its eigenvalues [28] that esclates the consumption of hardware resources, and thus degrading the hardware efficiency. Fig. 1.8 illustrates the reliability, hardware complexity and blindness of aforementioned SSA algorithms.

1.4 VLSI Design of Spectrum Sensor

Referring to discussion regarding spectrum scarcity and CR technology from aforementioned sections 1.1 and 1.2, it can be envisioned that CR enabled-devices will become necessary requirements in the near future. These CR enabled-devices can be a hand-handled and battery operated devices. Therefore, it becomes necessary to efficiently implement the key enabling block of CR technology that is the sensing node of CR-enabled devices, as shown in Fig. 1.6). The efficient VLSI-implementation of such sensing node relies on the detection performance of SSSR, power consumption, area-efficiency and sensing time of SSSR. Here, the performance of SSSR refers to reliable detection of PU in a negative SNR regime and it is decided by choice of SSA for the sensing node. Such performance for SSA is measured by simulation parameter termed as (*probability of detection* P_d) for varying SNR of recieved

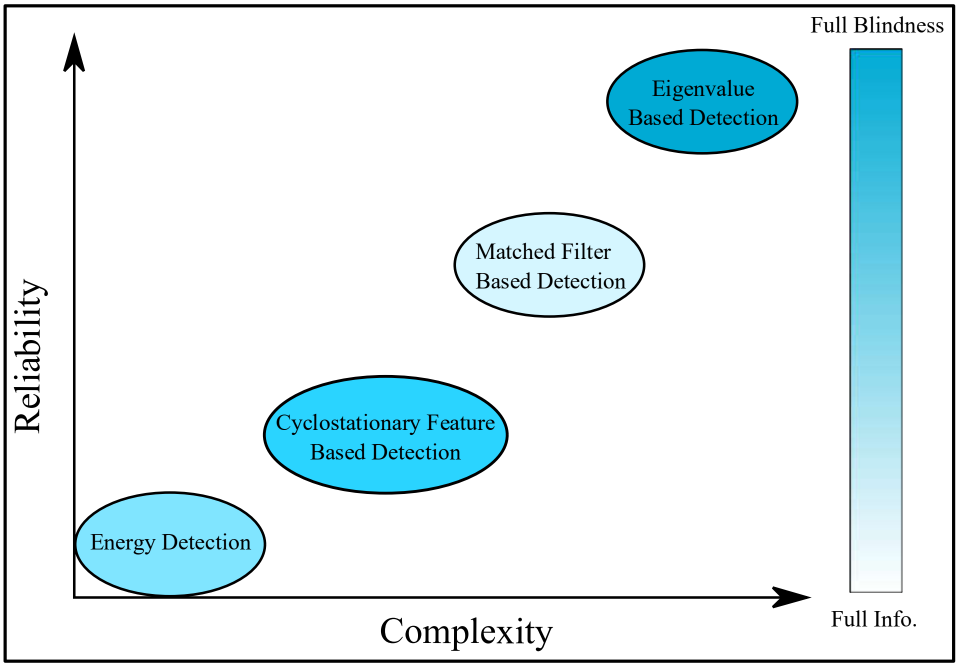

Fig. 1.8: Illustration of reliability, complexity and blindness of different stand-alone spectrum sensing algorithms [29].

PU signal at CR-enabled device. Ideally, the SSA under consideration should deliver a high P_d in negative SNR regime without any prior information of PU signal. Hence, the SSA in sensing node of mobile device should be preferably a blind SSA. Furthermore, the silicon area of SSSR dictates the overall cost of SSSR and power consumption of SSSR contributes towards battery-life of CR-enabled device. Therefore, the SSSR should ideally occupy low silicon area to make the CR-enabled device cost-effective and consume minimal power to enhance the battery-life of CR enabled-device. Furthermore, low sensing time is the prime requirement to handle contemporary issue of increasing data rate demand. To clearly understand this, we refer to the IEEE 802.22 standard. Here, the IEEE 802.22 standard enlists two stages sensing mechanism: inter-frame sensing and intra frame sensing. Here, the intra-frame sensing cycle length is shown in Fig. 1.9 [30] [31].

The intra-frame sensing cycle length consists of superframes that includes total 16 subframes. Here, each subframe includes a single sensing/quiet period and data transmission period. During the quiet period, the CR-enabled device (or customer premise equipment (CPE) as per IEEE 802.22 standardization [30]) [31] carries out in-band sensing and it in-

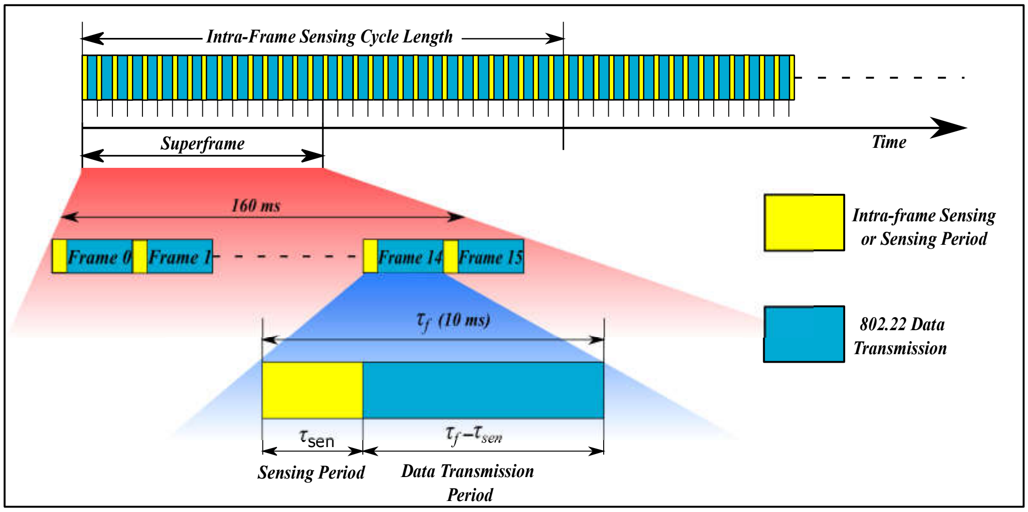

Fig. 1.9: Intra-Frame sensing cycle length of IEEE 802.22 standard.

dicates the presence of PU. Such sensing is carried out based on SSAs that requires quiet period of less than one frame size. As shown in Fig. 1.9, we refer the total duration of frame as τ_{fr}, the sensing slot with the duration of τ_{sen} and data transimission slot with duration of $\tau_{fr} - \tau_{sen}$. Here, the τ_{sen} for CR enabled-device with digital SSSR situated in baseband part of CR enabled-device (as shown in Fig.1.6) is equivalent to sum of the time required by RF-frontend to process the received signal of PU (τ_{RF}) plus the sensing time of digital SSSR (τ_{SSSR}). Here, the sensing time of digital SSSR (τ_{SSSR}) refers to the time required by SSSR to process the baseband PU signal available at the output of Analog to Digital Convertor (ADC) and deliver the decision regarding presence or absence of PU. This τ_{SSSR} of digital SSSR is defined as the total number of clock cycles (i.e latency) required to detect the presence/ absence of PU divided by maximum operating frequency of SSSR. Therefore, if Ω_{max} and Λ_{lat} represent maximum clock frequency and total latency (expressed in no. of clock cycles), respectively, then sensing time (τ_{sen}) can be generally expressed as:

$$\tau_{sen} = \tau_{RF} + \tau_{SSSR}, \tag{1.2}$$

$$\tau_{SSSR} = \Lambda_{lat}/\Omega_{max}. \tag{1.3}$$

Therefore, from Fig. 1.9 and eq.(1.2 and 1.3) it is clear that to have a longer data-period transmission time, a lower value of (τ_{sen}) is required. Since, τ_{sen} is directly proportional to τ_{SSSR}, a short sensing time (τ_{SSSR}) of digital SSSR will eventually lead to increase in data transmission period thereby increasing the data-throughput of CR Network (CRN).

Further, various implementations have been reported in literature for spectrum sensors implemented in RF front-end section and digital baseband section of sensing node which are based on different spectrum sensing algorithms. In the year 2012, Tsung-Han Yu et. al [16] reported a 1.64 mm^2, 7.4 mW wideband spectrum sensing digital baseband processor that is based on adaptive channel specific threshold and sensing time to achieve $P_d \geq 0.9$ and $P_{fa} \leq 0.1$. Kim and Rabaey [17] reported analog circuit based ED spectrum sensor for ultra-wideband (3.1-10.6 GHz) cognitive-radio applications with short sensing time. Analog CMOS-RF based ED spectrum sensor has been implemented by Khatri and Banerjee [18] for wideband sensing. Similarly, successive approximation register (SAR) based ED spectrum sensor for low power application has been reported by Banivić and Carusone [19]. Further, multi-resolution spectrum sensing functionality has been implemented in [20]. Unlike these contributions, there are digital implementations of ED based spectrum sensors in literature [21] [22]. Such ED spectrum-sensing algorithm senses presence of PU by comparing energy or power-spectral-density (PSD) of the received signal with noise variance and thereby, its true estimation is key factor for reliable detection. ED algorithm performs adequately under ideal scenario without noise uncertainty; albeit in real-world scenario, noise uncertainty is always present. Thus, the performance of such algorithm degrades drastically in negative SNR regime and eventually results in SNR wall problem [23]. The Cyclostationary Feature Detection (CFD) algorithm senses spectrum without the true estimation of noise variance (under noise uncertainty) [21]. However, it is mainly suitable for OFDM signals that requires prior knowledge of cyclic prefix as well as OFDM-symbol lengths and has longer sensing time as well as complex hardware architecture [21]. Recent implementation of memory efficient and reconfigurable CFD based spectrum sensor has been reported by Murty and Shrestha [24] [32]. Unlike CFD and MFD based spectrum sensing, eigenvalue based SSA are highly preferable for heterogeneous wireless-sensor network as this EBD algorithms are blind. However, such EBD SSA has higher mathematical complexity and results in inefficient implementation [27] [28]. Such EBD based digital spectrum sensor has been implemented by Safavi et. al [25], where it occupies a larger silicon area of 3.4 mm^2 in 180 nm CMOS technology and consumes huge power of 78 mW while operating at 150 MHz of clock frequency. However, such implementation may not be suitable for battery operated hand-handled CR-enabled devices. Fig. 1.10 summarizes the aforementioned implementations of various analog and digital SSRs along with the advantages and disadvantages of respective SSA.

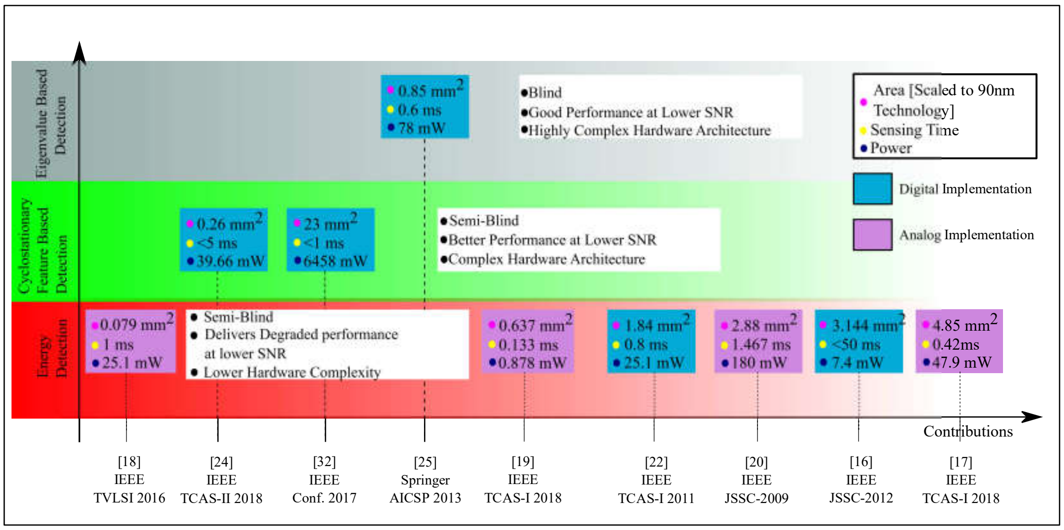

Fig. 1.10: Illustration of various analog and digital implementations for different SSAs along with their advantages and disadvantages.

Fig. 1.10 clearly depicts that the ED based SSA has lower hardware complexity. However, the detection performance of such SSA decreases under the negative SNR regime due to noise uncertainity problem. Therefore, the challenge in ED based SSA is to perform a reliable detection of PU without having any dependency on noise variance while maintaining the lower hardware complexity. Furthermore, CFD based SSA has complex hardware architecture and it requires prior knowledge of cyclic prefix to deliver reliable detection performance. Hence, the challenge for CFD based SSA is to reduce the hardware complexity of spectrum sensor and make the SSA independent of PU information (i.e. to transform it into a blind SSA) without causing any performance degradation in detection of PU. On the other hand, the EBD SSA delivers reliable detection performance without any prior information of PU signal. However, it has a highly complex hardware architecture , primarily due to the computation of eigenvalues of a SCM. Therefore, the challenge for such EBD based SSA is to reduce the implementation hardware complexity without affecting the detection performance while maintaining its blind feature.

Therefore, aforementioned discussion about different SSAs and their implementations clearly reflect the key challenge of balancing detection performance and VLSI-implementation of SSA for CR enabled-devices. Hence, this thesis proposes efficient digital SSSR that uses blind SSA to support hetrogeneous network and it delievers adequate performance under negative SNR regime. Furthermore, we concieve an hardware-efficient and low sensing time digital SSSR to make it suitable for portable devices that support higher data-rate..

1.5 Cooperative Spectrum-Sensing Scenario

To solve the problem of spectrum scarcity, it is important to efficiently utilize the unused spectrum by reliably detecting the PU under real-time practical scenarios, where the effect of multipath fading and shadowing are dominant [33]. The SSAs discussed in aforementioned section has a degraded performance under such practical scenarios. Such ramification has been addressed by cooperative spectrum sensing (CSS) algorithms that takes advantage of spatial diversity wherein multiple SUs cooperate with fusion center in CR network to generate global decision on the spectrum occupancy by PU(s) [33]. It has been demonstrated that CSS (with 10 SUs) in CR network outperforms conventional SSA by 11 dB and the former delivers robust detection under negative SNR regime [34]. Centralized CSS is one of the various reported topologies that can be classified into decision-fusion or data-fusion based CSS [35], [36], as shown in Fig. 1.11a. In decision fusion based CSS, each of the SUs perform spectrum-sensing individually and only transmit their decisions (in single/multi bit format) via reporting channel to the fusion center which further processes these received decisions from SUs to generate a global decision that indicates the presence/absence of PU(s). In contrast, SUs of data fusion based CSS retransmit the entire received signal sample (from PU(s) of the sensed spectrum band) to fusion center where the sophisticated CSS algorithm processes these samples to deliver global decision on PU detection [36].

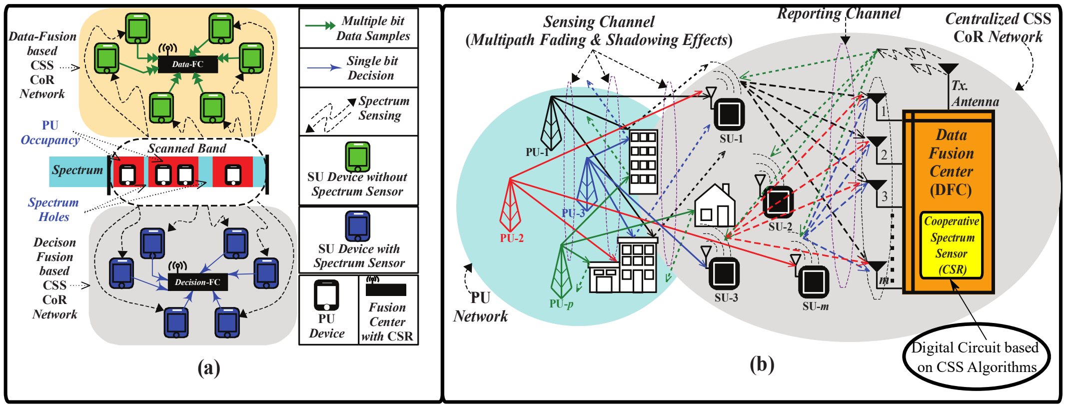

Fig. 1.11: (a) Schematic illustration of data-fusion- and decision-fusion-based CSS in the cooperative CR network. (b) System-level overview of the centralized cooperative-spectrumsensing CR network.

Due to lack of information at the fusion center of decision fusion based CSS process, it delivers degraded performance compared to its counterpart data fusion based CSS process [37]. Hence, the data-fusion based CSS is better suited for real-world applications; however, demanding higher bandwidth for reporting channel [38], [39]. A system-level view of data-fusion based CSS network is shown in Fig.1.11 (b). It comprises of "p" PUs whose spectrum occupancies have been detected (via sensing channel) by a data-fusion center (DFC). Here, the cooperative spectrum sensor (CSR) at DFC processes the signal samples received from m SUs (via reporting channel) using a sophisticated CSS algorithm that provides the global decision to SUs, regarding the occupancy of the sensed spectrum by PU(s), as shown in Fig.1.11 (b). Here, the CSR consists of digital circuits that are implemented based on CSS algorithms. Different blind CSS algorithms like maximum-minimum eigenvalue (MME) [25], arithmetic-to-geometric mean (AGM) [40], and eigenvalue based generalized likelihood-ratio-test (GLRT) [41] are reported algorithms for data-fusion based CSS that deliver excellent performance at higher computational cost. Unlike, energy detection and Maximum Eigenvalue-Detection (MED) based semi-blind CSS algorithms incur lower complexity with degraded performance in real-world scenario due to the dependency on noise uncertainty [42]. Among the blind CSS algorithms, eigenvalue based GLRT algorithm delivers the best performance [43], [44], [45]. However, determining all eigenvalues in this algorithm is a highly complex task and standard methods for such computations are QR decomposition, Jacobi and iterative Jacobi methods [46]. The hardware implementation of conventional method such as iterative Jacobi to compute all the eigenvalues of a matrix incurs higher implementation cost [25]. Therefore, to solve such challenge of algorithmic complexity for blind CSS algorithms, this thesis proposes to use hardware-friendly algorithm that has lower computational complexity. Further, the CSR at DFC (as shown in Fig. 1.11 (b)) for aforementioned CSS algorithms has higher hardware complexity in comparison to SSSR , discussed in earlier sections, because, the CSS algorithm processes signal received from multiple SUs at multiple antennas of DFC. Therefore, the CSR has degraded hardware efficiency as compared to SSSR. Furthermore, the hardware resources for CSR exaggerates when the number of supported SUs scales up. Subsequently, referring to Fig.1.9, the frame structure for SSSR consists of sensing time and data transmission period; unlike, the sensing time and data-transmission period for CSR may incur additional overhead, as shown in Fig. 1.12 [47]. Here, τ_{CSR} denotes the sensing time required by CSR at DFC to detect the presence or absence of PU.

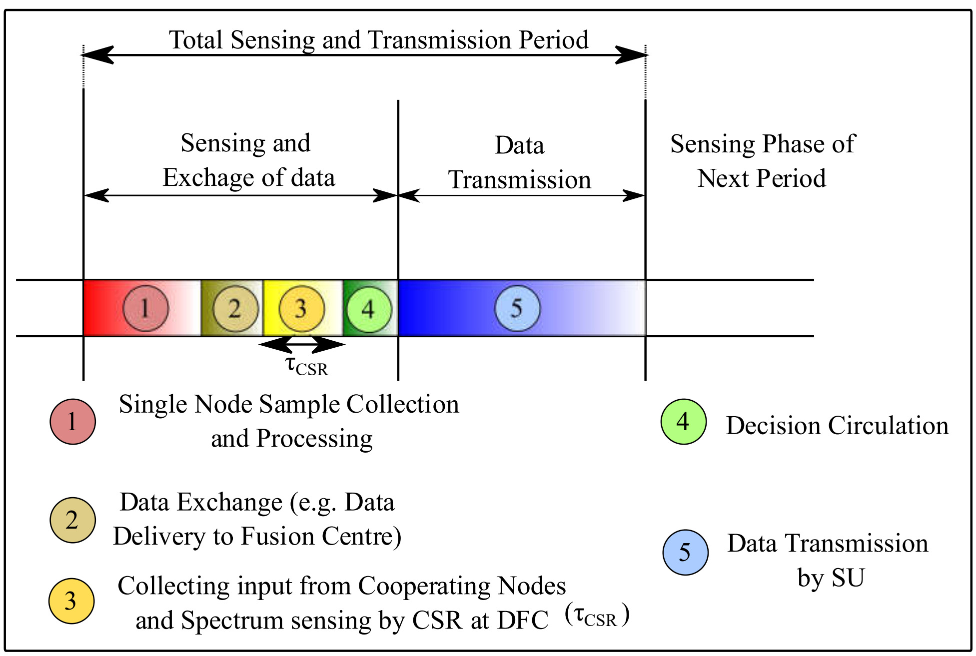

Fig. 1.12: Illustration of Sensing and Data Transmission Period for CSS Scenario.

As shown in Fig.1.12, the overhead in sensing period of frame structure for CSS scenario imposes a tight constarint on data-throughput of CR network. Hence, it becomes necessary to have a CSR that is able to deliever a reliable detection result as fast as possible. To the best of our knowledge, the data-fusion based CSR architecture has not been reported till date. Therefore, we propose hardware-efficient VLSI-implementation of CSR at DFC with low sensing time to support higher data-rate in CSS cognitive radio network.

1.6 Contributions

This thesis extensively delves into several computationally complex eigenvalue-based stand-alone spectrum sensing algorithms (SSSAs) and suggests hardware-friendly VLSI algorithms for them. Based on these proposed algorithms, hardware-efficient and fast-sensing time digital hardware-architectures for eigenvalue-based stand-alone spectrum sensors (SSSRs) are presented in this thesis. However, these SSSRs deliver degraded performance in practical scenarios. In order, to address such limitation of SSSRs, hardware-efficient and fast-sensing time cooperative spectrum sensors (CSRs) based on the proposed hardware-friendly cooperative spectrum sensing (CSS) algorithms are conceived here. Among all our CSR architectures, four CSRs have been ASIC-chip fabricated on a single silicon die in 130 nm-CMOS technology node. Eventually, our thesis presents detailed chip characterization process for the fabricated CSRs using the real-world test setup of cooperative cognitive radio network. A comprehensive list of contributions from this thesis are enumerated as follows.

- Hardware-friendly VLSI SSSAs have been suggested for maximum-eigenvalue based detection (MED), maximum-minimum eigenvalue based detection (MME), energy-to-minimum eigenvalue based detection (EME) and mean-to-square extreme eigenvalue (MSEE) based detection algorithms. These algorithms use iterative power method (IPM) and IPM with shift technique for computing maximum and minimum eigenvalues, respectively, of the sample covariance matrix (SCM). Performance analysis for the proposed SSSAs has been carried out in additive white Gaussian noise (AWGN) channel-environment and it indicates that the proposed SSSAs deliver minimal degradation in detection performance, compared to the conventional SSSAs. Further, MED based SSA delivers reliable detection performance for highly correlated signal and it is adequate for detecting licensed user under high signal-to-noise ratio (SNR) regime.