Novel Filter Bank Based Cooperative Spectrum Sensing under RF Impairments and Channel Fading Beyond 5G Cognitive Radios

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Abstract. Cognitive radio (CR) technology with dynamic spectrum management capabilities is widely advocated for utilizing effectively the unused spectrum resources. The main idea behind CR technology is to trigger secondary communications to utilize the unused spectral resources. However, CR technology heavily relies on spectrum sensing techniques which are applied to estimate the presence of primary user (PU) signals. This paper mostly focuses on novel analysis filter bank (AFB) based cooperative spectrum sensing (CSS) algorithms to detect the spectral holes in the interesting part of the radio spectrum. To counteract the practical wireless channel effects, collaborative subband based approaches of PU signal sensing are studied. CSS has the capability to eliminate the problems of both hidden nodes and fading multipath channels. FFT and AFB based receiver side sensing methods are applied for OFDM waveform and filter bank based multicarrier (FBMC) waveform, respectively. Subband energies are then applied for enhanced energy detection (ED) based CSS methods. Our special focus is on sensing potential spectral gaps close to relatively strong primary users, considering also the effects of spectral regrowth due to power amplifier nonlinearities. The study shows that AFB based CSS with FBMC waveform improves the performance significantly.

Keywords: Cognitive radio, FFT/AFB based cooperative spectrum sensing, energy detector, frequency selective channel, OFDM and FBMC, PA non-linearity, frequency selectivity.

1 Introduction

With the growing attention on wireless communications, radio spectrum scarcity is becoming modern days' challenge. Higher demand of spectral bandwidth is pushing spectrum usage to utmost limits. However, the limitations of traditional wireless technology lead to spectrum wastage, inviting opportunistic usages of those valuable unused resources [1]. These studies have mainly focused on technologies that solve the problem of spectral scarcity by using opportunistically the frequency band to establish secondary communication. Such technology is

commonly known as cognitive radio (CR) technology, which defines new dimension to the modern communication systems advocating environment-adaptive radio transmission [2]. CR keeps track of the radio transmission environment continuously while it dynamically varies its transmission parameters so as to adjust its operation to the surroundings.

Spectrum sensing based CR technology is considered as highly interesting topic in wireless communications. Spectrum sensing, in other words, involves tracking of the PU activity so as to estimate the spectral holes. Different sensing algorithms find the availability of spectral holes as an opportunity to enable the secondary communication [3, 4]. Recent studies have suggested a wide variety of spectrum sensing techniques, but none of them is fully satisfying in terms of all relevant metrics like implementation complexity, reliability, and loss in secondary system throughput . Especially, spectrum sensing under low signal-to-noise ratio (SNR) is widely covered in the literature, under conditions where the noise dominates the weak PU signal [3–5]. Under these conditions, the spectrum sensing becomes critically sensitive to imperfect knowledge of the power and characteristics of noise and interferences [6–8].

Spectrum that is originally assigned to the PU can be used by a secondary user (SU) if and only if PU becomes idle. Since SUs can only use spectrum as an opportunity in terms of the spectrum sharing, spectrum sensing has a great role to play in CR technology [3, 4, 9]. Regarding the importance of the radio scene analysis function, basic spectrum sensing methods show numerous limitations. Shadowing, hidden node problems, etc., always make spectrum sensing challenging. A PU transmission may be unobservable for a CR sensing station while its signal is fully usable by a nearby PU receiver. In order to make the spectrum sensing function reliable, efficient, and to counteract both multipath and hidden node problems, cooperative spectrum sensing (CSS) is considered as a vital solution. CSS involves two or more cooperative radio receivers in decision making during spectrum sensing. Recent research [10] suggests possibility of collaboration among number of CR users to enhance the detection performance. Our studies further exploit the collaborative approach of spectrum sensing commonly termed as CSS. The studies of this paper mainly focus on subband based spectrum sensing methods that add the collaboration among a number of CR receivers to enhance the sensing performance and to counteract practical wireless channel effects. CSS exploits the diversity among a number of CR receivers having different multipath channel profiles and experience different large-scale fading (shadowing) characteristics towards the PU transmissions [11].

More specifically, the contributions of this paper are listed below:

- Conceptually and computationally simplified CSS methods based on subband energies are developed. Subband energies are evaluated either using fast Fourier transform (FFT) or analysis filter bank (AFB).
- Subband ED based CSS methods are applied on the traditional OFDM and on filterbank multicarrier (FBMC) waveforms, the latter one as a candidate beyond-OFDM/beyond-5G scheme.
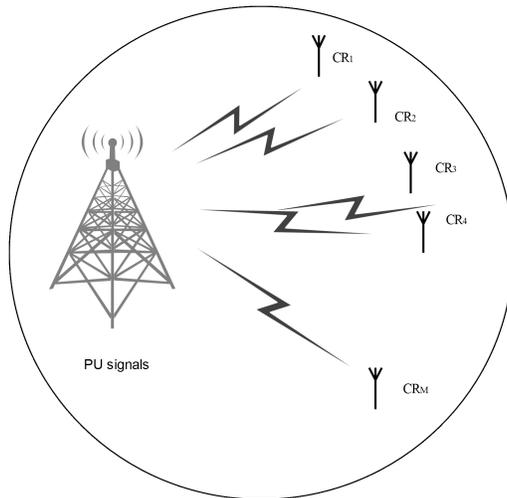
Fig. 1. CR topology including a PU transmitter and M CR stations.

- The effects of both power amplifier (PA) non-linearities and practical wireless channels on subband ED based CSS are investigated, comparing the performance of FFT and AFB based CSS schemes.

The remainder of the paper is organized as follows: Section 2 gives a general idea about traditional CSS methods. Novel FFT and AFB based CSS methods are presented in Section 3. Signal models including PA non-linearities, frequency-selective fading, and shadowing are described in Section 4. Numerical results for sensing performance are shown in Section 5. Finally, closing remarks are given in Section 6.

2 Traditional Cooperative Spectrum Sensing

Practical wireless channels show characteristics like noise uncertainty, multipath fading, and shadowing. In order to mitigate the effects of practical wireless channels, cooperation among many CR users, i.e., CSS is considered. CSS is regarded as a potential solution to mitigate effects of both multipath and shadowing which causes the hidden node problem. It also enhances the detection performance and reliability [5].

As suggested in the literature [10], the cooperative scheme can help to mitigate effects of the hidden node problem. Spatial diversity among multiple receivers is achieved, as illustrated in Fig. 1. The concept of exploiting SUs' spatial diversity to counteract the hidden node effects and enabling cooperation among SUs is coined as CSS and has reached growing attention in recent years. Our studies consider the ED based CSS approach with hard decision combining. Hard

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decision combining refers to the combination of binary decisions from spatially separated CR receivers at the fusion center (FC) [12], [13].

CSS uses two or more CRs to combine their sensing results so as to increase the reliability of the sensing decision. Combining the results from different CR receivers is performed at the FC. Different rules may be considered for combining the individual sensing results in order to achieve the highest accuracy at the FC, depending on the radio environment. With an increase in the number of CR users, the CSS procedure becomes more complicated. On the other hand, sufficient number of sensing CR stations is needed to reach sufficient sensing performance. So there is a trade-off between sensing performance and complexity of the CSS system. With increased number of CR receivers, the sensing performance enhances significantly, considering performance parameters like sensing time and reliability.

Cooperative schemes can be classified as hard and soft fusion schemes. When CRs provide binary information about the presence of PUs, the FC applies hard fusion rules. If the CRs may provide reliability information about their sensing results in the form of non-binary soft decisions, the FC applies a soft fusion scheme [13].

2.1 Hard Decision Fusion with Linear Fusion Rules

Hard fusion can be implemented using linear rules such as *AND rule*, *OR rule*, or *Majority rule*. Hard decision fusion does not need to exchange data among secondary nodes. Soft schemes generally improve the sensing result by sending richer information to the FC. Soft fusion techniques increase the complexity compared to hard fusion techniques. Linear fusion rules are commonly applied by the FC to exploit the cooperation among CR receivers. Binary decision from independent CR receivers is forwarded to the FC. FC processes the decisions from all CRs to make the collective decision. Linear fusion rules are based on the general k-out-of-M *rule* [13], [14].

OR Rule is one of the fusion rules which is applied at FC. When at least one SU detects the PU signal, *OR rule* declares the presence of PU. With M SUs, the cooperative detection probability $P_{D,t}$ and false alarm probability $P_{FA,t}$ after the decision at the FC are computed as follows:

$$\text{OR-Rule}: \begin{cases} P_{D,t} = 1 - (1 - P_D)^M \\ P_{FA,t} = 1 - (1 - P_{FA})^M \end{cases}. \tag{1}$$

Here P_D and P_{FA} are the detection and false alarm probabilities of individual SUs reported to the FC, which are assumed to be equal for all CR stations.

AND Rule declares the presence of a PU signal if and only if all SUs detect the PU signal individually. With M SUs, the cooperative detection probability $P_{D,t}$ and false alarm probability $P_{FA,t}$ at a FC are computed as follows:

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$$\text{AND Rule}: \begin{cases} P_{D,t} = {P_D}^M, \\ P_{FA,t} = (P_{FA})^M. \end{cases} \tag{2}$$

Majority Rule: According to various studies, both *AND rule* and *OR rule* are limited in terms of detection and false alarm probabilities. *Majority rule* is another case of the generalized k-out-of-M rule. If at least half of the SUs report the presence of PU, FC declares the presence of PU, otherwise it declares that the spectrum is free to use for CR transmission [11] [12]. Considering an even number M of sensing stations in the CSS, the cooperative detection and false alarm probabilities of the *Majority rule* can be written as follows:

$$M/2+1 \text{ -out-of- } M: \begin{cases} P_{D,t} = \sum_{j=M/2+1}^{M} \binom{M}{j} P_D^j \cdot (1-P_D)^{M-j} \\ P_{FA,t} = \sum_{j=M/2+1}^{M} \binom{M}{j} (1-P_{FA})^{M-j} \cdot P_{FA}^j. \end{cases} \tag{3}$$

Generalized k-out-of-M rule: The generalized form of the linear rule can be defined by requiring k SUs out of M to report the presence of a PU signal. Here the number k can take any value between 1 to M, based on the requirements. As discussed earlier, the special cases $k = 1$, $k = M/2+1$, and $k = M$ are equivalent to *OR rule*, *Majority rule*, and *AND rule*, respectively. Nevertheless, the number k can be optimized according to the targeted detection and false alarm performance [12] [14]. The cooperative detection and false alarm probabilities of this rule are as follows:

$$K_{of}N: \begin{cases} P_{D,t} = \sum_{j=k}^{M} \binom{M}{j} P_D^j \cdot (1-P_D)^{M-j} \\ P_{FA,t} = \sum_{j=k}^{M} \binom{M}{j} (1-P_{FA})^{M-j} \cdot P_{FA}^j. \end{cases} \tag{4}$$

3 Novel FFT and AFB based Cooperative Spectrum Sensing

FFT and AFB based techniques are applied to a wideband signal to generate equally spaced subband signals. Subband energies are then calculated and the subband energy detector (SED) decides on the presence of PU signal(s) within the processed frequency band based on the subband energies [4,6,8]. The entire procedure is represented in Fig. 2. The receiver front-end collects the PU signals which is followed by a channel filter and analog-to-digital converter (ADC). The subband signals can be obtained either via FFT or AFB and then processed accordingly [6].
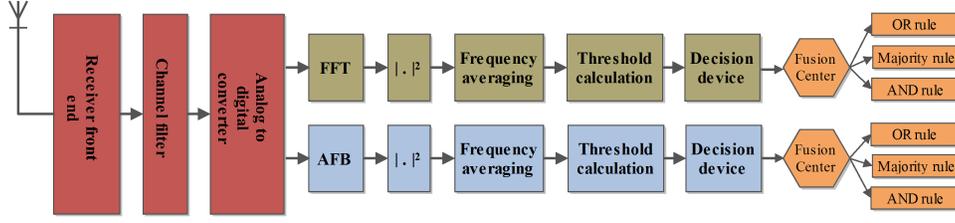
Fig. 2. Block diagram of alternative filter bank (AFB) and fast Fourier transform (FFT) based spectrum analysis methods for subband energy based cooperative sensing schemes.

A subband signal can be represented as follows,

$$Y_k[m] = \begin{cases} \mathcal{W}_k[m] & \mathcal{H}_0, \\ S_k[m]H_k + \mathcal{W}_k[m] & \mathcal{H}_1. \end{cases} \tag{5}$$

Here $S_k[m]$ is the transmitted signal by PU as it appears at the mth FFT or AFB output sample in subband k and $\mathcal{W}_k[m]$ is the corresponding channel noise sample. $\mathcal{H}_1$ denotes the *present hypothesis* of a PU signal whereas $\mathcal{H}_0$ denotes the *absent hypothesis* of a PU signal. When the AWGN only is present, the white noise is modeled as a zero-mean Gaussian random variable with variance σ_w^2, i.e., $\mathcal{W}_k[m] = \mathcal{N}\left(0, \sigma_w^2\right)$. The OFDM and FBMC signals can also be modeled in terms of zero-mean Gaussian variables, $S_k[m] = \mathcal{N}(0, \sigma_k^2)$, where σ_k^2 is the variance (power) at subband k. The subband energy is calculated from the subband signals of Eq. (5). The integrated test statistics to be used in the SED process is calculated as

$$T(y_{m0}, k_0) = \frac{1}{N_t N_f} \sum_{k=k_0-[N_f/2]}^{k_0+[N_f/2]-1} \sum_{m=m_0+N_t+1}^{m_0} |y_k[m]|^2. \tag{6}$$

Here N_f and N_t are the averaging window lengths in frequency- and time-domains, respectively. Assuming flat PU spectrum over the sensing band, the probability distribution of the test statistics can be expressed as

$$T(y_{m0}, k_0)|\mathcal{H}_0 \sim \mathcal{N}\left(\sigma_{w,k}^2, \frac{\sigma_{w,k}^4}{N_t N_f}\right) \tag{7}$$

and

$$T(y_{m0}, k_0)|\mathcal{H}_1 \sim \mathcal{N}\left(\sigma_{x,k}^2 + \sigma_{w,k}^2, \frac{\left(\sigma_{x,k}^2 + \sigma_{w,k}^2\right)^2}{N_t N_f}\right). \tag{8}$$

This yields

$$P_{FA} = P_r(T(y) > \lambda|\mathcal{H}_0) = Q\left(\frac{\lambda - \sigma_{w,k}^2}{\sigma_{w,k}^2/\sqrt{N_f N_t}}\right) \tag{9}$$

and

$$P_D = P_r(T(y) > \lambda | \mathcal{H}_1) = Q\left(\frac{\lambda - \sigma_{w,k}^2(1 + \gamma_k)}{\sigma_{w,k}^2(1 + \gamma_k)/\sqrt{N_f N_t}}\right). \tag{10}$$

Here, $\gamma_k = \sigma_{x,k}^2/\sigma_{w,k}^2$ is the SNR of subband k and $\sigma_{w,k}^2 = \sigma_w^2/N_{FFT}$ and $\sigma_{x,k}^2$ denote noise variance and the PU signal variance in subband k, respectively. With FFT/AFB based processing, it is possible to tune the sensing frequency band to the expected bandwidth of the PU signal and sense multiple PU channels simultaneously. For given P_{FA}, the threshold λ can be calculated as

$$\lambda = \sigma_{w,k}^2\left(1 + \frac{Q^{-1}(P_{FA})}{\sqrt{N_f N_t}}\right). \tag{11}$$

As described earlier in this paper, three linear fusion rules have been proposed for combining the binary decisions received by the FC. Here, three different fusion rules, *OR rule*, *Majority rule* and *AND rule* are considered. The false alarm and detection probabilities with three different linear fusion rules are calculated as follows;

$$P_{FA,t}: \begin{cases} = 1 - (1 - P_{FA})^M & OR \\ = P_{FA}^M & AND \\ = \sum_{j=M/2+1}^{M} \binom{M}{j} P_{FA}^j \cdot (1 - P_{FA})^{M-j} & MAJ. \end{cases} \tag{12}$$

and

$$P_{D,t}: \begin{cases} = 1 - (1 - P_D)^M & OR \\ = P_D^M & AND \\ = \sum_{j=M/2+1}^{M} \binom{M}{j} P_D^j \cdot (1 - P_D)^{M-j} & MAJ.. \end{cases} \tag{13}$$

Here $P_{FA,t}$ is cooperative false alarm probability and P_{FA} is non-cooperative false alarm probability. Similarly, $P_{D,t}$ and P_D are cooperative and non-cooperative detection probabilities, respectively.

4 System Model

4.1 Waveforms and Spectrum Sensing Schemes

OFDM with cyclic prefix, i.e., CP-OFDM is the dominating multicarrier technology in the field of wireless communications. Additionally, discrete wavelet multitone (DWMT), cosine modulated multitone (CMT), filtered multitone (FMT), and OFDM with offset-QAM (OFDM/OQAM, also known as FBMC/OQAM) are commonly considered alternative forms of multicarrier techniques [15]. FBMC waveforms, especially FBMC/OQAM have been widely considered as candidates for beyond-OFDM multicarrier systems. It is particularly suitable for dynamic

opportunistic spectrum use and CR [16], [17]. FBMC/OQAM shows better spectral efficiency compared to CP-OFDM. Such FBMC/OQAM systems utilize a signal model with real valued symbol sequence at twice the QAM symbol rate, instead of complex QAM symbols. Polyphase filter banks in transmultiplexer configuration constitute the core elements of the transmission link. Specifically, synthesis filter bank (SFB) and AFB are used at the transmitter and receiver sides, respectively [17].

On the receiver side, the FFT of an OFDM receiver or AFB of an FBMC receiver can be used also for spectrum sensing purposes, providing SED capability without additional processing elements. Subband based ED can be used in wideband spectrum sensing which covers multiple PU frequency channels or even the whole service band. For FBMC, the PHYDYAS prototype filter with overlap factor $K = 4$ is used [17]. Such filter bank reaches about 50 dB stopband attenuation, providing efficient detection of narrow spectral gaps between PU channels [15], [16].

In the following, we consider two scenarios: (i) Sensing CP-OFDM signal using FFT-based SED and (ii) Sensing FBMC/OQAM signal using AFB-based SED. The two waveforms have the same number of active subcarriers with common subcarrier spacing.

4.2 Power Amplifier Model for PUs

Various interference leakage effects due to RF imperfections affect critically the spectrum sensing performance in practice. The most significant issue in this context is the spectral regrowth due to the nonlinear PA of the PU transmitter. For a practical PA model, we consider the linear time-invariant (LTI) portion of the Wiener PA model, which has a pole/zero form of the system function given by [4]

$$H(z) = \frac{1 + 0.3z^{-2}}{1 - 0.2z^{-1}}. \tag{14}$$

This is extracted from an actual Class AB PA with fifth order nonlinearity. In this study, 5 dB backoff is assumed with this PA model.

The potential spectral hole between two relatively strong PUs is shown in 3 for both scenarios, as determined by the corresponding sensing process, i.e., FFT for CP-OFDM and AFB for FBMC. While FBMC/OQAM has superior spectral containment, AFB on the receiver side enhances the resolution of spectrum sensing, making it possible to detect potential narrowband PUs within the sensing band.

4.3 Channel model

This study applies frequency selective multipath channel models together with log-normal shadowing model. All PU and CR channels use *Indoor* and *SUI-1* frequency selective channel models having 90 *ns* RMS delay spread with 16 taps, and 0.9 μs delay spread with 3 Ricean fading taps, respectively [17], [18].

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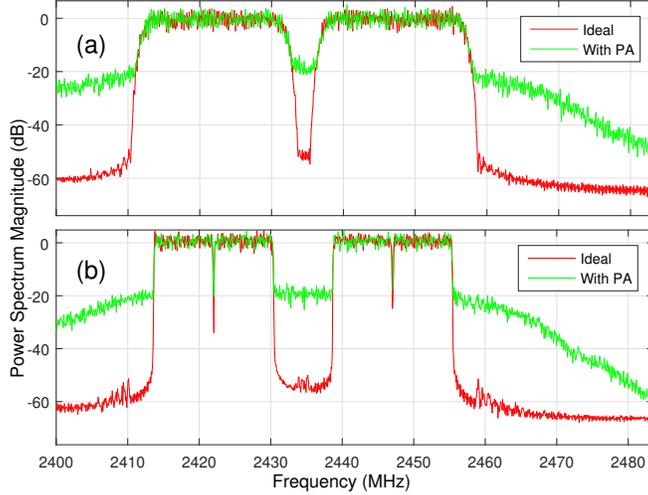
Fig. 3. Effects of the PA model on (a) OFDM and (b) FBMC based PU spectra. A Wiener behavioral model with fifth order nonlinearity and 5 dB backoff is used for the PA.

The log-normal path loss can model is as follows:

$$PL = PL_0 * \left(\frac{d_j}{d_0}\right)^a * \varphi, \tag{15}$$

or in dB scale as,

$$PL_{dB} = PL_{0dB} + 10 * a * log(d_j/d_0) + \varphi_{dB}. \tag{16}$$

Here, PL_0 is the path-loss at the reference distance d_0, a represents the path-loss exponent, d_j represents the distance of jth CR receiver, and φ represents the shadow fading with Gaussian distribution, zero mean, and standard deviation σ.

We consider the two scenarios mentioned above, while the CR waveform is always FBMC. For log-normal fading $\sigma = 9$ dB and the path-loss exponent $a = 2$.

5   Numerical Results

In this study, the potential spectral hole between two relatively strong OFDM or FBMC channels is illustrated in Fig. 3. We focus on two cases, one with a gap between two OFDM channels and another one between two FBMC channels. The results can be generalized to cases where the gap is between an OFDM channel and an FBMC channel. The spectrum leakage due to transmitter nonidealities can lead to eventually filling up this spectral gap and raising the false alarm rate of the spectrum sensing module.

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In this paper, we specifically focus on a spectrum use scenario with two active PU channels, which operate in the 2.4 GHz ISM band. This is an unlicensed frequency band which is utilized by various applications, including WLAN signals, cordless phones, Bluetooth wireless devices, and even microwave ovens. OFDM based 802.11g-type WLANs, or 802.11g-like FBMC spectra are considered at 3rd and 8th WLAN channels. The PU spectra do not overlap each other, and a 5 MHz or 8 MHz spectral hole is available between the two channels in the OFDM and FBMC cases, respectively. The difference is due to wider guardbands needed around the active subcarriers in the OFDM case. Both active signals are assumed to have the same power level, normalized to 0 dB in our scenario.

Additionally, it is assumed that in the test situtaion, there is no additional signal in the spectral hole. However, the spectrum sensing may give false alarms due to interference leakage from the PUs due to their non-linearity. Such an effect is found to be dependent on the SNR values of the PUs, as observed at the sensing stations. A smaller subband spacing of 81.5 kHz is used for spectrum sensing and CR transmissions, instead of the 312.5 kHz sub-carrier spacing of WLAN. This improves the spectral resolution of spectrum sensing and CR operation. The frequency window is chosen as $N_f = 5$ to increase the detection performance. Then the effective sensing subband width is 407.5 kHz. With FBMC/OQAM, the 8 MHz spectral gap contains 19 sensing subbands and with CP-OFDM, the 5 MHz gap contains 12 sensing subbands. A SU reports the presence of a PU if the sensing threshold is exceeded in any of the subbands.

The required sample complexity for $P_D = 0.99$ and $P_{FA} = 0.1$ at the target SNR= -3 dB is determined with the aid of Eq. (8) in [6] as $N_t = 91$ for non-cooperative spectrum sensing as a reference case. The same sample complexity is considered in our CSS study and desired cooperative $P_{FA,t} = 0.1$ is assumed with all fusion rules. The PA non-linearity introduces interference leakage to the spectrum gap between the PUs, as illustrated in Fig. 3, and the width of the spectral hole is reduced.

Results from ideal and practical PA cases using the *Indoor* frequency selective channel with log normal path loss model are shown in Fig. 4 and 5, respectively. FBMC based WLAN-like signal model shows much-improved spectral containment compared to OFDM based WLAN under both the ideal and practical PA cases. Furthermore, AFB-based SED shows significant enhancement over the FFT-based one. Looking at the cooperative false alarm probability close to the target level of 0.1, the *OR rule* makes the CSS process least sensitive to interference leakage from the adjacent relatively strong PUs, while the *Majority rule* shows highest sensitivity. This is true for both scenarios and both PA models. FBMC/OQAM with AFB based SED is quite robust towards the interference leakage with linear (or well linerised) PA. Also with the used practical PA model, the benefit over CP-OFDM with FFT-based SED is quite significant, allowing about 20 dB stronger PUs at the adjacent frequencies.

Corresponding results for the *SUI-I* channel are shown in Figs. 6 and 7. The results and conclusions are quite similar with the *Indoor* channel case.
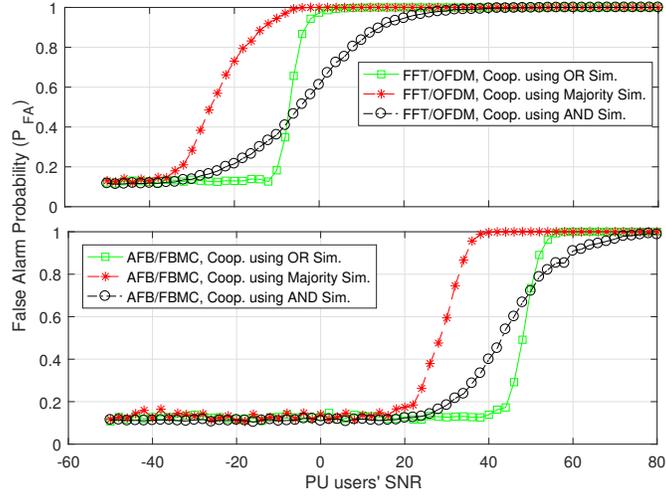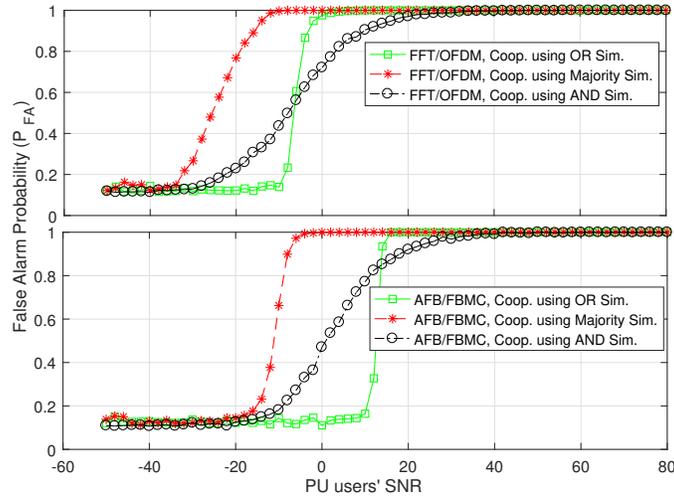
Fig. 4. Comparison of cooperative false alarm probabilities between FFT-based SED for CP-OFDM PU (upper) and AFB-based SED for FBMC/OQAM PU (lower). Three different linear fusion rules are applied under *Indoor* channel & log-normal fading, linear PU transmitter, time record length of $N_t = 91$, and $M = 8$ sensing stations.
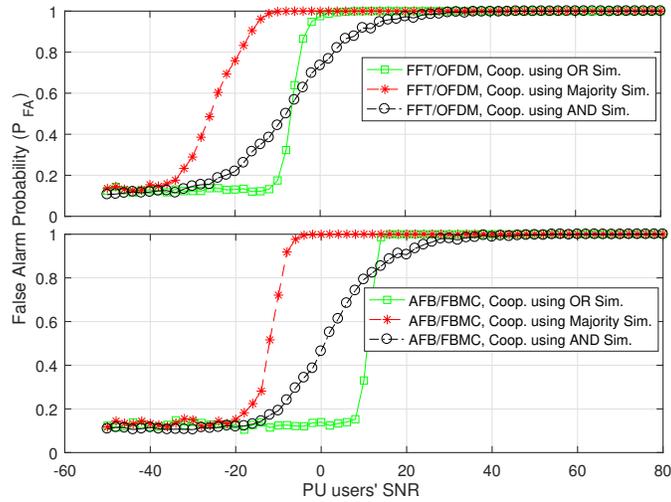
Fig. 5. Comparison of cooperative false alarm probabilities between FFT-based SED for CP-OFDM PU (upper) and AFB-based SED for FBMC/OQAM PU (lower). Three different linear fusion rules are applied under *Indoor* channel & log-normal fading, PU non-linearity effects, time record length of $N_t = 91$, and $M = 8$ sensing stations.

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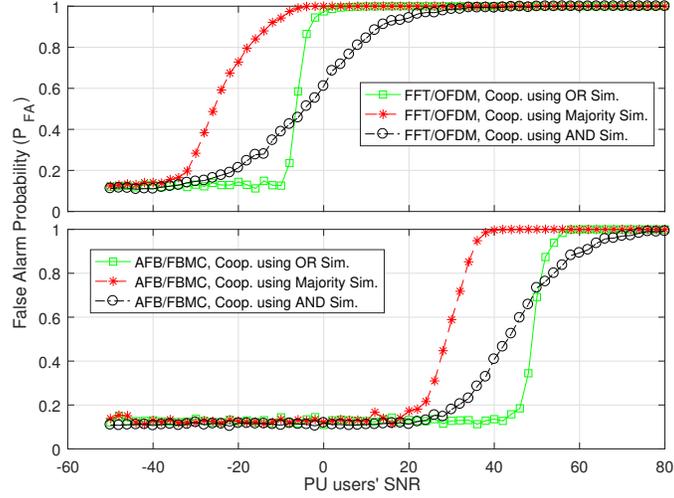
Fig. 6. Comparison of cooperative false alarm probabilities between FFT-based SED for CP-OFDM PU (upper) and AFB-based SED for FBMC/OQAM PU (lower). Three different linear fusion rules are applied under *SUI-1* channel & log-normal fading, linear PU transmitter, time record length of $N_t = 91$, and $M = 8$ sensing stations.

Fig. 7. Comparison of cooperative false alarm probabilities between FFT-based SED for CP-OFDM PU (upper) and AFB-based SED for FBMC/OQAM PU (lower). Three different linear fusion rules are applied under *SUI-1* channel & log-normal fading, PU non-linearity effects, time record length of $N_t = 91$, and $M = 8$ sensing stations.

6   Conclusion

In this paper, enhanced energy detection based cooperative spectrum sensing was studied. The proposed subband-based scheme allows to effectively detect potential PU signals with widely varying bandwidths in possible spectral gaps close to strong PU channels. In such scenarios, the sensing task becomes difficult due to interference leakage from the relatively strong adjacent channels. The results demonstrated highly reduced sensitivity for filter bank based waveforms and sensing schemes towards such interference leakage, compared to basic CP-OFDM and FFT-based sensing. As for the CSS schemes, it was found that the *OR rule* is clearly least sensitive to the interference leakage, compared to the *AND rule* and *Majority rule*.

In addition to FBMC, these result are generally applicable to all advanced PU waveforms with improved spectrum containment, including filtered OFDM schemes which have received wide interest in the 5G-NR context.

This study does not cover soft decision based CSS, which remains as an important topic for future work. Moreover, analytical derivations for different subband based CSS schemes, including the interfernce leakage effects, is a rather complicated issue, and is left as a topic for future studies.

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