Misdetection Probability Analyses of OFDM Signals in Energy Detection Cognitive Radio Systems

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***Abstract*— Cognitive radio (CR) networks are an intelligent wireless communication technology that is aware of its surrounding environment. The main process of the cognitive radio is spectrum sensing. Energy detection (ED) method was found to be a promising candidate for spectrum sensing in the CR networks. However, the detection performance of the ED method is susceptible to noise fluctuations at the receiver side, known as noise uncertainty. To obtain better performance when noise uncertainty impacts ED process, it is necessary to incorporate a dynamic signal detection based on sensing threshold adaptation. In this paper, the influence of noise uncertainty and dynamic threshold adaptation for the ED of signals transmitted using orthogonal frequency division modulation (OFDM) is investigated. The major contribution of this work is the analyses of the influence of different parameters including: modulation constellations, noise uncertainty level, dynamic threshold and signal to noise ratio values on a probability of received signal misdetection. Simulation results show that a combination of some of the analysed parameters can significantly improve ED process for OFDM signals.**

Keywords—*cognitive networks, OFDM, energy detection, QPSK, 16 QAM, 64 QAM, noise uncertainty, dynamic threshold*

I. INTRODUCTION

Due to the booming growth and popularity of wireless devices and technologies, radio frequency (RF) spectrum has become crowded. Therefore, it is necessary to use the devices that are aware of their RF environment and can facilitate flexible, efficient and reliable operation and utilization of available spectral resources. Many licensed wireless spectrum parts are not effectively used and are idle in some periods of the time and in the certain geographical areas [1-3].

Cognitive radio networks (CRN) has the ability to identify and share underutilized spectrum. Spectrum sensing as one of the most challenging and crucial activities in CRN enables a cognitive radio (CR) to measure, learn and be aware of its environment [4]. Various methods have been proposed in the literature for spectrum sensing.

Although Cyclostationarity and Matched-filter spectrum sensing methods have shown better performance than Energy Detection (ED) method [5], ED method is selected for analyses in this paper due to its low computational complexity. However, a major challenge of this method is that any variations in the noise power, also known as noise uncertainties (NUs), leads to a significant reduction in the detection performance. For that reason, to have better signal detection, it is necessary to consider the dynamic adaptation of the sensing threshold. Setting an appropriate detection threshold according to which decision about the presence or absence of a primary user (PU) signal will be made is a challenging task. The conventional energy detector uses a fixed threshold that is set directly above the noise floor level to judge occupation of the spectrum. Unlike the fixed threshold approach, adaptive threshold approach enables the secondary user (SU) to dynamically adjust its energy detection threshold according to the signal-to-noise ratio (SNR), sensing time or transmit power [6]. Dynamic threshold (DT) techniques are more robust to noise uncertainty as compared to fixed threshold techniques [7, 8]. However, DT techniques are more complex for practical implementation.

Several authors have investigated the impact of DT adaptation and NU variation in CRNs. In [9-11], spectrum sensing performance of ED for non-OFDM signals impacted by NU in the channel and for sensing with fixed DT adaptation has been presented. Additionally, in [12] the impact of NU and DT on ED performance was analysed separately and jointly without OFDM signal. For discrete wavelet packet transform and other than ED signal sensing method such as Welch's methods in [13], an adaptive algorithm for detecting orthogonal frequency division multiplexing (OFDM) signals with varying influence ratio is presented.

OFDM method is seen as a promising candidate for the usage in CRNs because it has the capability of transmitting many data streams orthogonal to each other. OFDM multi-carrier modulation method was chosen for implementation in this work because it is currently deployed in some of the major communication technologies [14-16].

Although OFDM is vastly implemented, the impact of different OFDM modulation schemes such as quadrature phase shift keying (QPSK), 16-QAM (quadrature amplitude modulation) and 64-QAM on ED performance was not analysed in the literature. Since one of ED disadvantages is the requirement of high SNR at the position of SU, in this paper impact of different SNRs levels on the probability of misdetection will be analyzed for different OFDM modulations. Additionally, this work tackles the impact of DT adaptation and noise variations on the performance of ED for signals transmitted using OFDM technique. Expressions for ED probabilities impacted by NU variations, DT adaptations and both were derived and simulated using MATLAB software.

The paper is structured as follows: mathematical expression for ED model which takes into account impact of: NU variations, DT adaptations and both on the probability of OFDM signals misdetection is given in Section 2. In Section 3, simulation results obtained for energy detection of OFDM signals are presented and discussed. Finally, some concluding remarks are given in Section 4.

II. Energy Detection Model

OFDM is a multiplexing scheme which divides a single wideband data stream into parallel narrowband data streams for transmission. OFDM is used in many telecommunication systems with QPSK, 16 QAM and 64 QAM as the most frequently used modulation constellations [17-22].

The main process of the CR is spectrum sensing which enables a CR to assess spectrum availability and interference status. Energy detection model for cognitive radio can be represented as a following binary hypothesis [13, 23-27]:

$$H_0: y_i(n) = w_i(n), \quad i = 1, \ldots, M, \; n = 1, \ldots, N \quad \text{if PU is absent}$$
$$H_1: y_i(n) = h(n) \times x_i(n) + w_i(n), \quad i = 1, \ldots, M, \; n = 1, \ldots, N \quad \text{if PU is present} \tag{1}$$

where y_i(n) is the average received signal by *i-th* SU during the *n-th* sensing sample, $w_i(n)$ is the additive white Gaussian noise (AWGN) received by *i-th* SU with variance $\sigma_{n_i}^2$, $x_i(n)$ is a signal from *i-th* PU during the *n-th* sample, N is a total number of samples during sensing time and M is a total number of SU users. Since most of the OFDM based communication systems prefer existence of the line of site link between receiver and transmitter, AWGN model is selected in this paper for channel modelling of such systems.

A decision on whether the spectrum is being occupied by PU is made by comparing DT signal level (λ_i) with a generated energy test statistic signal level (τ_i). The detection rule is defined by:

$$\tau_i > \lambda_i, \; PU\ present$$
$$\tau_i < \lambda_i, \; PU\ absent \tag{2}$$

where the test statistic signal level (τ_i) is obtained calculating the received signal's energy. Test statistic signal level is then compared to a predetermined DT (λ_i) for *i-th* SU to determine whether the licensed user (PU) is present or not. The DT (λ_i) can be fixed or adaptively determined based on variations in noise (NU) impacting received signal. Setting adaptively the proper DT is a challenging task, and it is out of the scope of this work.

Test statistic in an ED process can be defined as average energy of received signal for N samples. The energy of the received signal, which represents the test statistic, is given by [10, 12, 28]:

$$\tau_i(n) = \frac{1}{N} \sum_{n=1}^{N} |y_i(n)|^2 \tag{3}$$

Table 1. lists all parameters used in the analyses. As shown in (2), the decision rule is applied to the test statistic. The performance of the detector is characterized by: the probability of detection (P_{d_i}) and the probability of false alarm (P_{fa_i}). The probability of detection and probability of false alarm can be expressed as [10, 12, 28]:

$$P_{d_i} = Q\left(\frac{\lambda_{di} - (P + \sigma_{n_i}^2)}{\sqrt{\frac{2}{N}}(P + \sigma_{n_i}^2)}\right) \tag{4}$$

$$P_{fa_i} = Q\left(\frac{\lambda_{fai} - \sigma_{n_i}^2}{\sqrt{\frac{2}{N}}\sigma_{n_i}^2}\right) \tag{5}$$

where Q (.) is the standard Gaussian complementary cumulative distribution function (CCDF) [2] and *P* is SU received signal power. The probability of detection (P_{d_i}) is defined as the probability that the SU correctly declares that a PU is present, when PU is really present. The probability of false alarm (P_{fa_i}) is the probability that SU will incorrectly declare the presence

Table 1: Parameters With Corresponding Descriptions

Index	Description
H_0	Hypothesis which determine the absence of the PU signal
H_1	Hypothesis which determine the presence of the PU signal
$y_i(n)$	Averaged received signal for *i*-th SU and for n-th sample
$w_i(n)$	AWGN noise signal for *i*-th SU
$\sigma_{n_i}^2$	Variance of AWGN signal for *i-th* SU without NU variations and DT adaptation
$\sigma_{NUDT_i}^2$	AWGN variance for ED with NU variations and DT adaptation
$\sigma_{NU_i}^2$	AWGN variance for ED with NU variations
$x_i(n)$	Signal from PU for *i*-th SU
τ_i	Energy test statistic signal
P_{m_i}	The probability of misdetection
λ_i	The decision threshold signal level
λ_{di}	Probability detection threshold in case of no NU variations and no DT adaptation
λ_{fai}	False alarm threshold in case no NU variations and no DT adaptation
$\lambda_i'^{DT}$	Dynamic threshold in case of DT adaptation (without NU variation)
$\lambda_i'^{NUDT}$	Dynamic threshold in case of DT adaptation and NU variation
P_{d_i}	The probability of detection in case of no noise uncertainty and no dynamic threshold
P_{fa_i}	The probability of false alarm in case of no noise uncertainty and no dynamic threshold
$P_{m_i}^{NU}$	The probability of misdetection for noise uncertainty
$P_{fa_i}^{NU}$	Probability of false alarm for noise uncertainty
$P_{fa_i}^{DT}$	Probability of false alarm for dynamic threshold
$P_{m_i}^{DT}$	The probability of misdetection for dynamic threshold
$P_{m_i}^{NUDT}$	The probability of misdetection for noise uncertainty and dynamic threshold
$P_{fa_i}^{NUDT}$	The probability of false alarm for NU variation and DT
ρ	NU factor
ρ'	DT factor
Q	Standard Gaussian complementary cumulative distribution function (CCDF)
P	Average received signal power of PU
N	Total number of samples during sensing time in case of no noise uncertainty and no dynamic threshold
N^{NU}	Total number of samples during sensing time for noise uncertainty
N^{DT}	Total number of samples during sensing time for DT adaptation
N^{NUDT}	Total number of samples during sensing time for noise uncertainty and dynamic threshold

of a PU, when PU is actually not present. In addition to this probabilities, the probability of misdetection (P_{m_i}) is also used in the analyses of ED performance. It represents the probability that PU is actually present while SU declares that PU is absent. Misdetection probability (P_{m_i}) for *i –th* SU can be written as:

$$P_{m_i} = 1 - P_{d_i} \qquad (6)$$

A. Energy detection with noise uncertainty variation

Relations developed in previous section does not include impact of NU on energy detection probability. In practice, noise power is randomly changing in time and space and SU often experiences fluctuation in noise power known as the NU. This fluctuation causes the drop in quality of sensing sensitivity. For that reason, energy detection performance is highly susceptible to uncertainty in noise power.

To have realistic detection conditions, the impact of NU on ED performance can be incorporated in the simulated ED system through the introduction of NU factor ρ [28, 29]. Limits of AWGN variance ($\sigma^2_{NU_i}$) are modelled with NU factor ρ in order to be in the interval $\sigma^2_{NU_i} \epsilon [\sigma^2_{n_i}/\rho, \rho\sigma^2_{n_i}]$. For that reason, the $\sigma^2_{n_i}$ in relation (4) and (5) would be replaced by these limiting values and expressions for P_{m_i} and P_{fa_i} for a scenario which includes ED impacted with NU are modified as [12, 19]:

$$P^{NU}_{m_i} = 1 - \min_{\sigma^2_{NU_i} \epsilon [\sigma^2_{n_i}/\rho,\ \rho\sigma^2_{n_i}]} Q\left(\frac{\lambda_i - (P+\sigma^2_{NU_i})}{\sqrt{\frac{2}{N^{NU}}}(P+\sigma^2_{NU_i})}\right) = 1 - Q\left(\frac{\lambda_i - (P+\frac{\sigma^2_{n_i}}{\rho})}{\sqrt{\frac{2}{N^{NU}}}(P+\frac{\sigma^2_{n_i}}{\rho})}\right) \qquad (7)$$

$$P^{NU}_{fa_i} = \max_{\sigma^2_{NU_i} \epsilon [\sigma^2_{n_i}/\rho,\ \rho\sigma^2_{n_i}]} Q\left(\frac{\lambda_i - \sigma^2_{NU_i}}{\sqrt{\frac{2}{N^{NU}}}\sigma^2_{NU_i}}\right) = Q\left(\frac{\lambda_i - \rho\,\sigma^2_{n_i}}{\sqrt{\frac{2}{N^{NU}}}\rho\,\sigma^2_{n_i}}\right) \qquad (8)$$

Relations between probabilities of misdetection P_{m_i} and $P^{NU}_{m_i}$ and for different values of ρ are expressed in (9) and (10):

$$P_{m_i} = P^{NU}_{m_i}, \qquad \forall N = N^{NU}, \rho = 1.00 \qquad (9)$$

$$P^{NU}_{m_i} > P_{m_i} \qquad \forall N = N^{NU}, \rho > 1.00 \qquad (10)$$

The case when NU is $\rho=1$ means that ED process is free from the simulation of NU impact, and relations (7) and (8) converge to relations (5) and (6), respectively. For factor $\rho>1$, NU is included in the simulation of the ED process and higher values of ρ imply higher variations of the noise component in the received signal. In the case of an equal number of samples N, for $\rho=1$ probabilities of misdetection when NU is and it is not included in the simulation are the same. However, when $\rho>1$, the probability of misdetection $P^{NU}_{m_i}$ will be higher than P_{m_i} due to the impact of NU on ED process.

B. Energy detection with dynamic threshold adaptation

Energy detection performance can be improved when a well- chosen DT will be selected. In this case, DT is selected form the range of DTs and it is not constantly fixed to some predefined value. To model a range of DTs, the DT factor ρ′

TABLE 2: BER OVER AWG CHANNEL FOR DIFFERENT OFDM MODULATIONS

OFDM modulat.	Bit-Error-Rate (BER) expressions
QPSK	$P_{b,QPSK} = \frac{1}{2} erfc\left(\sqrt{\frac{SNR\ B}{R_b}}\right)$
M-QAM (*M*≥ 4)	$P_{b,M-QAM} = \frac{2}{log_2 M}\left(1-\frac{1}{\sqrt{M}}\right) erfc\left(\sqrt{\frac{3\,(log_2 M)}{2(M-1)}\frac{SNR\ B}{R_b}}\right)$

will be introduced in order to set DTs laying in the interval $\lambda'^{DT}_i \epsilon [\lambda_i/\rho',\ \rho'\lambda_i]$. In the case when factor ρ'=1, there is no DT, while ρ′>1 implies the existence of a selection of DT from the predefined range in the simulation of the ED performance. Relations (4-6) can be extended to express $P^{DT}_{m_i}$ and $P^{DT}_{fa_i}$ as:

$$P^{DT}_{m_i} = 1 - \min_{\lambda'^{DT}_i \epsilon [\lambda_i/\rho',\ \rho'\lambda_i]} Q\left(\frac{\lambda'^{DT}_i - (P+\sigma^2_{n_i})}{\sqrt{\frac{2}{N^{DT}}}(P+\sigma^2_{n_i})}\right) = 1 - Q\left(\frac{\frac{\lambda_i}{\rho'} - (P+\sigma^2_{n_i})}{\sqrt{\frac{2}{N^{DT}}}(P+\sigma^2_{n_i})}\right) \qquad (11)$$

$$P^{DT}_{fa_i} = \max_{\lambda'^{DT}_i \epsilon [\lambda_i/\rho',\ \rho'\lambda_i]} Q\left(\frac{\lambda'^{DT}_i - \sigma^2_{n_i}}{\sqrt{\frac{2}{N^{DT}}}\sigma^2_{n_i}}\right) = Q\left(\frac{\rho'\lambda_i - \sigma^2_{n_i}}{\sqrt{\frac{2}{N^{DT}}}\sigma^2_{n_i}}\right) \qquad (12)$$

The relationship between P_{m_i} and $P^{DT}_{m_i}$ for different values of ρ′ are expressed in (13) and (14):

$$P_{m_i} = P^{DT}_{m_i}, \ \forall N = N^{DT}, \rho' = 1.00 \qquad (13)$$

$$P^{DT}_{m_i} < P_{m_i}, \quad \forall N = N^{DT}, \rho' > 1.00 \qquad (14)$$

For the case when ρ′= 1.00, the probability of misdetection for $N = N^{DT}$ is the same. When ρ′> 1.00, the probability of misdetection (P_{m_i}) is higher than the probability of misdetection ($P^{DT}_{m_i}$) with DT adaptation. Although in Section IIIB the NU is not taken into account, higher probability of P_{m_i} compared to $P^{DT}_{m_i}$ is the direct consequence of dynamic adaptation of sensing threshold which adjusts its level from the range of threshold levels $\lambda'^{DT}_i \epsilon [\lambda_i/\rho',\ \rho'\lambda_i]$ according to a current channel state environment of the SU.

C. Energy detection with nose uncertainty and dynamic threshold

In the previous Sections 3A and 3B, the DT factor and NU factor are introduced to model the impact of noise variations and DT adaptation in the ED process. However, the impact of both factors is modelled separately. To have the most realistic simulation of ED process, it is necessary to take into account the NU variations and DT adaptations jointly.

In further analyses, P_{m_i} and P_{fa_i} will be expressed as a function of NU and DT. For that reason, in (4-5) the $\sigma^2_{n_i}$ is replaced by the predefined rage of NU variations $[\sigma^2_{n_i}/\rho,\ \rho\sigma^2_{n_i}]$, while sensing threshold level λ_i can be set within the range $[\lambda_i/\rho',\ \rho'\lambda_i]$. Expressions for P_{m_i} and P_{fa_i} in the case of the scenario which includes NU and DT are modified in order to be [12, 28]:

TABLE 3: SIMULATION PARAMETERS

Parameter	Value/Type
PU signal transmission technique	OFDM
Modulation type	QPSK, 16 QAM and 64 QAM
Channel noise type	AWGN
Number of samples/FFT size (samples)	128
SNR ratio (dB)	-25 to 0
The probability of detection/false alarm	0 to 1
Number of Monte-Carlo iterations	10,000
Noise uncertainty factor ρ	1.02, 1.05
Dynamic threshold factor ρ'	1.01, 1.03, 1.05

$$P_{m_i}^{NUDT} = 1 - \min_{\lambda_i'^{NUDT} \epsilon \left[\lambda_i/\rho',\ \rho'\lambda_i\right]} \ \min_{\sigma_{NUDT_i}^2 \epsilon \left[\sigma_{n_i}^2/\rho,\ \rho\sigma_{n_i}^2\right]} Q\left(\frac{\lambda_i'^{NUDT} - \left(P + \sigma_{NUDT_i}^2\right)}{\sqrt{\frac{2}{N^{NUDT}}}\left(P + \sigma_{NUDT_i}^2\right)}\right) = 1 - Q\left(\frac{\frac{\lambda_i}{\rho'} - \left(P + \frac{\sigma_{n_i}^2}{\rho}\right)}{\sqrt{\frac{2}{N^{NUDT}}}\left(P + \frac{\sigma_{n_i}^2}{\rho}\right)}\right) \quad (15)$$

$$P_{fa_i}^{NUDT} = \max_{\lambda_i'^{NUDT} \epsilon \left[\lambda_i/\rho',\ \rho'\lambda_i\right]} \ \max_{\sigma_{NUDT_i}^2 \epsilon \left[\sigma_{n_i}^2/\rho,\ \rho\sigma_{n_i}^2\right]} Q\left(\frac{\lambda_i'^{NUDT} - \sigma_{NUDT_i}^2}{\sqrt{\frac{2}{N^{NUDT}}}\sigma_{NUDT_i}^2}\right) = Q\left(\frac{\rho'\lambda_i - \rho\sigma_{n_i}^2}{\sqrt{\frac{2}{N^{NUDT}}}\rho\sigma_{n_i}^2}\right) \quad (16)$$

Relations between P_{m_i}, $P_{m_i}^{NU}$, $P_{m_i}^{DT}$ and $P_{m_i}^{NUDT}$ for the same number of samples ($N = N^{NU} = N^{DT} = N^{NUDT}$) and for different values of factors ρ and ρ' are expressed in (17) and (18) as

$$P_{d_i} = P_{d_i}^{NU} = P_{d_i}^{DT} = P_{d_i}^{NUDT}, \forall\, N = N^{NU} = N^{DT} = N^{NUDT}, \quad \rho = \rho' = 1 \quad (17)$$

$$P_{m_i}^{DT} < P_{m_i} < P_{m_i}^{NUDT} < P_{m_i}^{NU}, \forall\, N = N^{NU} = N^{DT} = N^{NUDT}, \quad \rho > 1,\ \rho' > 1 \quad (18)$$

For the case when $\rho = \rho' = 1$, there is no influence of NU and DT adaptation on ED process, and consequently probability of misdetection for all four cases is the same.

For the case when $\rho > 1$, $\rho' > 1$ and the same radio conditions at the location of SU, the $P_{m_i}^{DT}$ will have the highest expected values. This is the consequence of dynamic adaptation of sensing threshold to the received signal variations which are not impacted by the NU. However, this is the least realistic situation in practice. According to relation (18), a somewhat higher probability of misdetection P_{m_i} will be in the case when there is no NU and threshold is set to some predefined fixed value. This is the consequence of the fact according to which better sensing results in the ED process can be accomplished if the threshold is dynamically adjusted.

If the impact of NU will be taken into account, than expected values of probability of misdetection $P_{m_i}^{NUDT}$ will be even higher than those of $P_{m_i}^{DT}$ and P_{m_i}. This is the consequence of noise variations influence which will further diminish sensing sensitivity what results with an increase in misdetection probability. Finally, the highest expected misdetection probability will be for $P_{m_i}^{NU}$. This is the consequence of the impact of NU on a signal received based on the fixed threshold approach. All these cases are confirmed practically through simulation which results are presented in Section 3.

D. *BER performance of different OFDM modulation techniques in AWGN channel*

Theoretical expressions for bit-error-rate (BER) of OFDM modulated signals transmitted over AWGN channel are presented in Table 2. The expressions in Table 2 presents the probabilities of bit error rate for coherent detection of the signal with even number of bits per symbol. The *erfc* in Table 2. represent the complementary error-function according to which BER probability for different OFDM modulation types depend on the signal-to-noise ratio (SNR) at the location of SU, OFDM modulation order (constellation) *M*, overall channel bandwidth *B* and the channel bit rate R_b. Based on expressions presented in Table 2, for higher SNR, BER probability decreases what improve communication reliability. In addition, transmission with the higher constellation number *M* increases BER, and for OFDM modulations with the higher constellation, the probability of erroneous detection increase.

III. SIMULATION RESULTS AND DISCUSSION

The performance of the spectrum sensing for the ED method is evaluated by the Matlab simulation toolbox (version R2016a). Parameters used for simulation of the ED process in the CRN are shown in Table 3. Values of parameters used for simulation correspond to those of the real OFDM systems. Simulations are performed for different false alarm probabilities which pass through the values in the range [0, 1]. Appropriate sensing thresholds are simultaneously computed using Monte Carlo simulations.

All scenarios for which mathematical expressions of probability of misdetection are derived in previous sections are simulated and analysed. The results of analyses are presented in the form of receiver operating characteristic (ROC) curves. The ROC curves present interdependence between the probability of misdetection and probability of false alarm or SNR, for different modulations and NU/DT related parameters.

A. *Effects of noise uncertainty and dynamic threshold on energy detection*

In Fig. 1, the ROC curves for different values of NUs and DTs are presented for the signal transmitted by means of QPSK modulation. The results are obtained for a fixed number of samples (N=128) and relatively low SNR values (SNR= -15 dB) of the received signal. Simulated results show that the

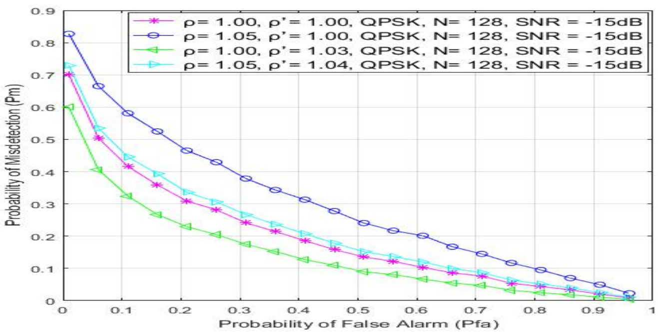

Figure 1. Interdependence between probability of false alarm and probability of misdetection for analysed scenarios

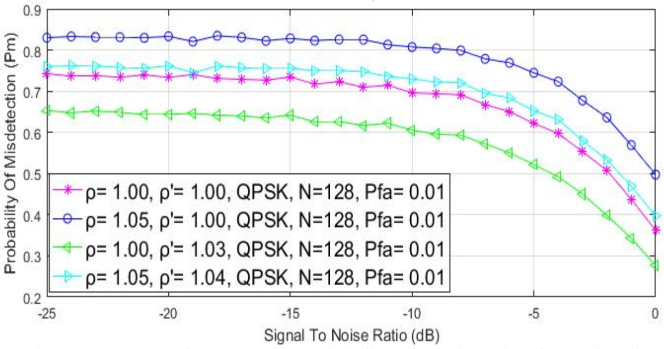

Figure 2. Impact of SNR on the probability of misdetection for analysed scenarios

probability of misdetection decreases when the probability of false alarm increase and vice versa. This is consequence of the fact according to which for low values of probity of false alarm, the probability that SU will declare that PU is absent when it is actually present is very low.

Results in Fig. 1 further show that the probability of misdetection is very sensitive to noise uncertainty. As the NU factor ρ increases, to get lower values of the probability of misdetection, it is necessary to incorporate DT adaptation. Interdependence among different probabilities of misdetection, which are expressed with relations (17) and (18) and explained in Section 3C, are confirmed through simulation results presented in Fig. 1.

B. Effects of signal- to- noise ratio on energy detection

Fig. 2. presents the impact of different values of NUs, DTs and SNRs on the probability of misdetection of OFDM signal modulated with QPSK modulation. The results are obtained for fixed and relatively low values of probability of false alarm ($P_{fa_i}^{NUDT} = 0.01$). For lower values of SNR, the probability of PU energy misdetection (P_{m_i}) is high. This is expected since low values of SNR simply mean low levels of the received PU signal power at the location of SU cognitive radio. With the increase of SNR, the probability of misdetection decreases. This is a direct consequence of higher SNR ratio which enables better detection of PU signal at the position of SU. Consequently, to get lower probabilities of OFDM signal misdetection, it is necessary to have higher values of SNR at the location of SU.

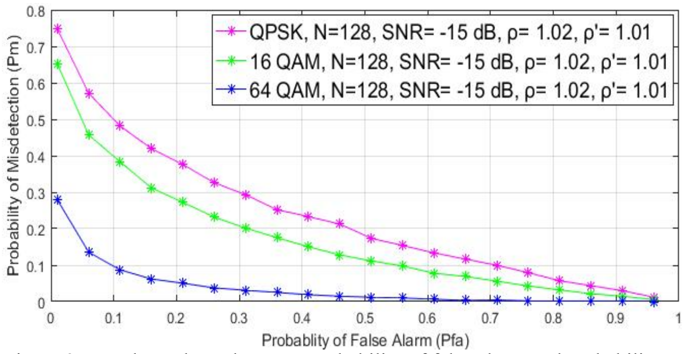

Figure 3. Interdependence between probability of false alarm and probability of misdetection for different OFDM modulations

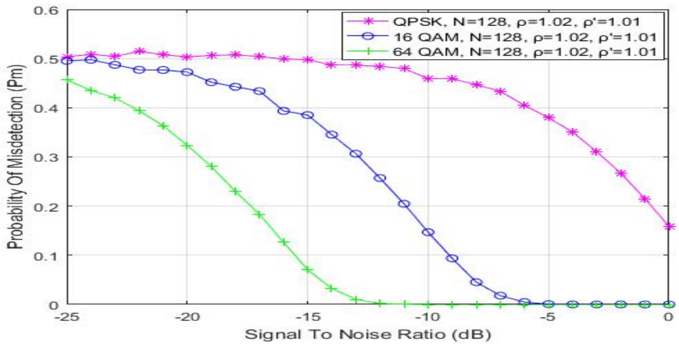

Figure 4. Impact of SNR on probability of misdetection for different OFDM modulation types

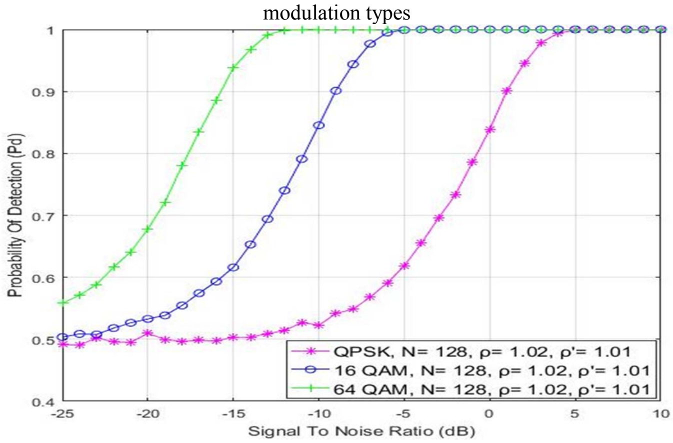

Figure 5. Impact of SNR on probability of detection for different OFDM modulation types

C. Effects of noise uncertainty and dynamic threshold on different OFDM modulations

The ROC curves for different modulation techniques are presented in Figure 3. According to the obtained results, for different OFDM modulations (QPSK, 16 QAM, 64 QAM), the probability of misdetection will be different for the same probability of false alarm. Hence, selection of modulation constellation impact on the probability of misdetection. Lower probabilities of misdetection are noticed for modulations with higher constellation factor. This is because the modulations with a higher number of constellations transmit a higher number of separate signal levels, what results with a lower probability of PU signal misdirection.

In Figure 4, the impact of the SNR on misdetection probability for different OFDM modulations is presented. According to Fig. 4, the existence of SNR threshold for each of OFDM modulation constellations is confirmed. SNR threshold represents a level of SNR for which probability of misdetection reaches negligible values. Modulations with higher constellation number will have the SNR threshold at lower SNR levels, and vice versa. This is the consequence of the fact that OFDM signals with higher constellations have a higher probability of detection. Hence, the higher constellation factor of OFDM modulation schemes has a positive impact on misdetection probability.

Fig. 5 presents the impact of SNR on the probability of detection for different OFDM modulation techniques. Fig. 5 actually shows that that the probability of detection is reverse proportional to the probability of misdetection what is theoretically confirmed in relation (6). According to Fig. 5, for the same SNR and NU/DT factors, transmission with higher constellation order of OFDM signal offer the higher probability of detection.

IV. Conclusion

In this work, the impact of NU variations and DT adaptations on the performance of ED of OFDM signals in CRNs was analysed. Analyses indicate that fluctuations in noise power have a significant impact on ED of OFDM signals. For better signal detection, it is necessary to involve DT adaptation in the ED process. The results of analyses show that for higher SNR ratio of the received signal, the probability of PU signal misdetection will be lower. Also, different OFDM modulations have an impact on the probability of signal misdetection. It is shown that the probability of PU signal misdetection is lower for OFDM signals modulated with modulations having a higher constellation factor. The overall results of analyses show that the probability of PU signal misdetection will be lower for reception of OFDM signals with lower NU if adaptive adjusting of DTs is implemented. Further research will be dedicated to the improvement of detection probability of OFDM signals modulated with different modulation schemes.

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