Energy detectors performance evaluation for interweave cognitive radio network scenario in 5G

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Abstract. With the recent advances in resource allocation methods for 5G heterogeneous networks and dynamic spectrum access, the convergence between them becomes a more prevalent topic in scientific research. By implementing cognitive functionalities in the 5G network’s nodes, its efficiency can be improved and, in addition, the integration with existing wireless standards will be smoother. To enable this, the intelligent sensors are required to achieve rigid detection accuracy. Thus, the purpose of this paper is to examine the ability of popular energy detection spectrum sensing techniques to identify the primary user’s signal in an interweave (autonomous operation of the secondary users) 5G deployment scenario. This evaluation is performed through comprehensive simulations for differing number of primary and secondary users, and for different data stream types transmitted by the primary base station.

1. Introduction
The usefulness of Cognitive Radio (CR) enabled dynamic spectrum access (DSA) has been very well established over the course of the recent years. Its aspects of accurate spectrum characterization (either from the point of view of a single user equipment, UE or of the whole CR network) and available spectrum distribution among the cognitive nodes (secondary users), are still objects of intense scientific examination. This field is further expanded through the application scenarios of heterogeneous, ultra-dense and Internet of Things (IoT) networks within the scope of 5G [1], [2], [3]. Additionally, implementing device-to-device (D2D) communications in mobile networks can increase the utilization of the same through adaptive resource distribution [4]. The mobile network’s performance indicators should also be carefully examined in order to suggest further improvement through general frameworks and within operator-specific scenarios [5], [6]. Furthermore, CR-aided non-orthogonal multiple access (NOMA) is envisioned as a promising technology for spectral efficiency improvement in 5G systems [7], [8]. All of these technologies can greatly benefit from the DSA capabilities of CR. Central place in the integration of CR capabilities in modern and future networks is given to the vital function of spectrum sensing which is required to provide accurate assessment of spectrum occupancy by the incumbent (primary) users so as to avoid unwanted interference in their communications. Energy detection has been established as the most prominent sensing method due to its speed which allows for decision on spectrum vacancy to be made within a short time so that the available frequency channel can be used before the incumbent users resume its utilization [3], [9], [10].
This paper evaluates the detection accuracy of two popular types of energy detectors (ED) for spectrum sensing within a 5G heterogeneous network scenario through the use of the novel 5G-air-simulator [11]. The effect of different data stream types and number of primary and secondary users on detection performance is studied via the simulation results.

2. System model and simulation details

The examined system model is a modification of the “Single Cell with Femto-Cells” model of the 5G-air-simulator. It incorporates a micro-cell (mC) with radius of 350 m within the scope of which operate the primary (micro-cell UEs, mUEs) and the secondary users (SUs), all of which are stationary. The SUs are based on the femto-cell UEs implemented in the simulator, and are randomly distributed within two single-floor buildings with random locations inside the micro-cell’s coverage. The CR spectrum sensing function is implemented within the SUs to determine whether the frequency channel is free from mC and mUE transmissions or not. Within the simulator environment’s core, functionality for idle periods for the mC PU is implemented, in order to simulate the PU’s absence from the spectrum at random times during the simulation. The mC continuously transmits data streams throughout the simulation’s runtime (600 s).

Two common types of ED methods are implemented - Traditional ED (TED) and Rayleigh-fading ED (RFED) [9], [10]. For each of them, the signal-to-noise ratio $\gamma$ or SNR (estimated using the Mutual Information Effective SNR Mapping [12] method implemented by default in the 5G-air-simulator) is compared to the respective decision threshold $\lambda$. For the TED and RFED the threshold values are defined respectively in [9] and [10]. It is assumed that uplink (UL) transmissions with overhead information from both mUEs and SUs are present for communication establishment. Thus, the SNR is defined as:

$$SNR = \frac{P_{mC} + \sum_{i=1}^{M} P_{mUE_i}}{P_N + \sum_{j=1}^{K} P_{SU_j}}, \quad (1)$$

where the UL transmissions from SUs (i.e. the sum of their power at the receiver - $\sum_{j=1}^{K} P_{SU_j}$) are interfering because from the detector’s point of view, it is only required to detect the MC (represented as the received power $P_{mC}$) and mUEs ($\sum_{i=1}^{M} P_{mUE_i}$) signals. $P_N$ is the noise power. The detector’s performance is characterized using the probabilities of detection ($P_D$) and of false alarm ($P_{FA}$) which are calculated from the respective equations in [9], [10].

3. Simulation results

The simulation is performed for two cases for the number of SUs (6 and 10) and for each of them, the detectors’ performance is evaluated for 4 different types of data streams – Video (with quality of 440 kbps), Voice over Internet Protocol (VoIP), Constant Bit-Rate (CBR) data transfer and a combination of those three (“All types”), and for the cases of 5 and 10 mUEs. The relevant parameters for calculation are the following – $P_N$ and $N = \tau f_s$. The overall bandwidth is 1.4 MHz, with sub-channels 180 kHz wide. Therefore, the sampling frequency $f_s$ is assumed as 360 kSps, whereas $\tau$ is the reception time for each simulation instance. The transmission power of the mC is 43 dBm while that of all mUEs and SUs is 23 dBm.

The simulation results are shown on figure 1 to figure 4. For the case of 5 mUEs being present, it is obvious that for both detector types, the results’ curves follow similar patterns, with the general difference that the TED shows slightly higher overall performance. Lowest detection accuracy is exhibited for the CBR traffic ($P_D$ of 90% and $P_{FA}$ of 10% at -8 dB SNR for 5 mUEs) whereas the highest is noted for the VoIP type ($P_D$ of 90% and $P_{FA}$ of 10% at -10 dB SNR for 5 mUEs, i.e. a 2 dB gain). This can be attributed to the traffic pattern of CBR which due to its non-real-time requirements for communication, leads to more retransmissions in the examined low-SNR scenario. Video traffic just like the VoIP type has more stringent latency (and respectively, tolerating loss) requirements and thus less retransmissions and higher detection probability. It is also observed that there are some discrepancies in the results for the VoIP traffic which lead to sudden degradations in the $P_D$ and $P_{FA}$ (more specifically, at -17, -14 and -11 dB of SNR). They can be attributed to multiple retransmissions.
within shorter reception time and smaller number of samples and thus, lower performance for the same
SNR values. For the case of “All types”, the video stream being the most bandwidth intensive (440
kbps) takes precedence over the others and for this reason, its detection accuracy is nearly the same as
that of the Video stream type. Thus, the curves for these two cases (“All types” and Video) overlap
almost completely and they have about 1 dB difference in comparison to the results for VoIP and
CBR. As for the PFA of the TED, the results show similar patterns but in the opposite direction. In
regards to the RFED, the results are very similar though showing slightly lower performance for SNR
levels above -10 dB. There is a bigger gap between the results for 5 and 10 mUEs of about 3 – 4 dB.
Also, for more interfering mUEs, the difference between the result curves for the different traffic types
is bigger. Thus, the REFD improves the detection performance for the different traffic types slightly
more than the TED for the lower SNR ranges (below SNR of -10 dB) but the TED still has better PD at
higher SNR but it has variations in its PFA, whereas the same is always zero for the RFED which is
why it is not plotted in figure 2 and figure 4. This advantage is due to the RFED accounting for the
fading in its formulation.

Figure 1. Probabilities of detection and of false alarm for TED for 5 and 10 mUEs, different types of
traffic and 6 SUs.

Figure 2. Probabilities of detection for RFED for 5 and 10 mUEs, different types of traffic and 6 SUs.

The results’ patterns for the 10 SUs case follow very similar distributions to those of the
alternative. A significant change, however, is exhibited in the results for 5 mUEs in that they are very
close to those for 10 mUEs (the difference between them is less than 1 dB). The reason for this
development is the interference created by the additional SUs for their UL overhead communications.
It is also observed that nearly perfect performance (PD close to 100% and PFA near 0%, respectively) is
reached for lower SNR of -8 dB, whereas the same is achieved at SNR of -2 dB in the alternative case.
Thus, increasing the number of SUs leads to higher detection. However, the increased interference levels as a consequence will deteriorate the SUs’ communication exchange.

Figure 3. Probabilities of detection and of false alarm for TED for 5 and 10 mUEs, different types of traffic and 10 SUs.

Figure 4. Probabilities of detection for TED for 5 and 10 mUEs, different types of traffic and 10 SUs.

4. Conclusions
This paper presents a performance study for two popular types of ED for spectrum sensing of the within a 5G heterogeneous network scenario through the use of the 5G-air-simulator. The simulation results show the effect of different data stream types and number of primary and secondary users on detection performance. Consequently, it has been found that primary user detection is more potent when real-time data streams (such as VoIP or video) are prevalent in modern mobile communications. In addition, increasing the number of SUs in the interweave CR network, has much greater effect on detection accuracy degradation for low SNR levels than the differing number of mUEs. Thus, adaptive interference cancellation is necessary for communications in dense and IoT networks for 5G.

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