Performance of WIBA Energy Detector in Rural and Remote Area Channel

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***Abstract*—Connectivity in low-density rural and remote areas where distances are long is a big challenge because of high deployment costs and challenging radio channels with long delay profiles. Spectrum sharing can make spectrum available for 5G local network deployments to serve rural and remote areas. Spectrum sensing can be used to complement the traditional database approach in order to enable efficient and dynamic use of the radio spectrum. In rural and remote areas, long range coverage is required in order to enable flexible and cost-effective solutions. This calls for efficient and low-complex sensing methods who are able to operate in those challenging environments. In this paper we study spectrum sensing method called the window-based (WIBA) energy detector in a challenging rural area channel model for 5G networks. The results are compared to that of the localization algorithm based on double-thresholding (LAD) energy detector. Simulations using a rural area channel model with long delay profile indicated that the WIBA method is able to operate in a rural area channel, and it clearly outperforms the LAD method in terms of detection distance. The detection difference was even 15-fold for the WIBA method, depending on the transmit power and the signal bandwidth.**

***Index Terms*—spectrum sensing, signal detection, rural area, channel model.**

I. INTRODUCTION

The exploitation of TVWSs (Television White Spaces) [1], using dynamic and fragmented spectrum allocation (DSA) [2] controlled by a cognitive engine [3], is a key feature for remote and rural area wireless 5G networks. This innovative and flexible use of spectrum is not allowed to harm the incumbent spectrum users, which have priority over the spectrum. Initial propositions for TVWS exploitation have relied on a geolocation database [4] that store all technical and geographic information about the TV stations and use a propagation prediction algorithm to define which channels can be used in a given geographic position.

Relying only on the geolocation database is not enough to provide the necessary protection for the primary users or to fully exploit the vacant spectrum for two main reasons. The first one is related to the fact that the coverage prediction algorithms do not consider all propagation mechanisms, which means that areas considered to be uncovered can indeed be reached by the primary transmitter signal, resulting in performance degradation for the secondary usage. The second reason is related to potential unauthorized transmissions which cannot be prevented in all cases. For example, pirate TV stations which are as a problem in some countries do not have their data inserted in the geolocation database. Although these broadcasting signals do not need to be protected, they can hinder the operation of the secondary networks running in the same channel, which would be considered available by the geolocation database. Therefore, spectrum sensing performed by the secondary networks is essential for providing the appropriate protection of the secondary user for the incumbents. In this case, each a secondary node measures the spectrum at its geographic position and performs a spectrum sensing algorithm to determine if the channel is available or occupied. This decision can be combined with the geolocation database to improve the protection of the primary users and increase the exploitation of all spectrum opportunities.

In this paper, a wide-band window-based spectrum sensing technique called the WIBA [5] energy detector (ED) is proposed to be used for the detection of signals in remote area scenario. Unlike conventional energy detectors, the WIBA ED can detect signals also below the noise level. This increases the detection distance between the transmitter and the receiver, that is very important in rural and remote areas. The performance of the WIBA ED is evaluated in terms of determining the achievable detection distance. This is the first case when the recently proposed WIBA ED is studied in other

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than AWGN channel. The results are compared to that of the localization algorithm based on double-thresholding (LAD) ED, which is among the most efficient ED methods [6].

This paper is organized as follows. First, a rural area channel model is introduced in Section II. Section III introduces the WIBA energy detector. Simulation results are provided in Section IV and conclusions are drawn in Section V.

II. Rural Area Channel Model

To evaluate the performance of the proposed spectrum sensing algorithm in a remote rural area, a rural channel model proposed in the Remote Area Access Network for the 5th Generation (5G-RANGE) project [7] was used. The model is based on measurements of Root Mean Square (RMS) delay spread and path loss performed in four different rural areas with varying terrains by the companies Ericsson and Telstra for frequency of 850 MHz and distance range up to 200 km [8]. From the measured data it was proposed a simple path loss and shadow fading (SF) models, as follows:

$$\mathrm{PL}(d, f) = \mathrm{FSPL}(d, f) + K, \tag{1}$$

$$\mathrm{SF} \sim \mathcal{N}(0, 4.47^2), \tag{2}$$

respectively, where d is the distance distance in km, f is the central frequency in MHz, $\mathrm{FSPL}(\cdot)$ is the Free Space path loss model, $K = 29.38$ dB is an additional loss coefficient due to varying terrains shapes in the rural area propagation path that contribute with additional loss effects, such as diffraction, reflections and scattering. Since the measurements were obtained in varying terrains, the introduced channel model is here expected to be generally applicable for different rural and remote area scenarios.

Fig. 1 depicts cumulative distribution function (CDF) of the overall large scale fading, i.e., path loss combined with the SF, experienced by a user equipment (UE) deployed within the radius 1 km $\leq d \leq$ 50 km. In this figure it is noted that the minimum and maximum losses are 110 dB and 165 dB, respectively, showing that even when a UE is close (not less than 1 km) to the base station (BS) a large attenuation is expected, characterizing a very challenging scenario for a successful sensing technique.

The small scale fading of the channel model is characterized by the combination of measurements from [8] and the 3rd Generation Partnership Project (3GPP) Clustered Delay Line (CDL)-A model. The main parameters used to adjust the CDL-A model and generate the small scale fading are summarized in Table I. From the parameters in Table I, the root mean square (RMS) delay spread (DS) plays an important role in the system designing since it is used to characterize the coherence bandwidth, as follows:

$$B_{\mathrm{c}} \approx \frac{1}{5\mathrm{DS}} = 2 \text{ MHz}, \tag{3}$$

i.e., any signal which occupies a bandwidth larger than 2 MHz will experience frequency selective channel conditions. This restricted bandwidth will bring additional challenges for sensing based on energy detection due to the increasing

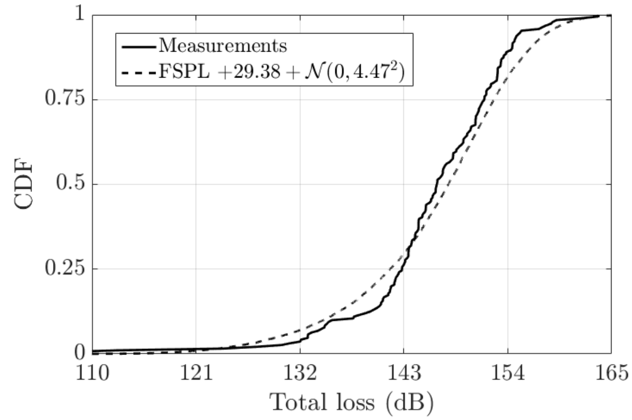

Fig. 1. CDF of the measured data from [8] and CDF of the path loss model in (1) combined with the SF in (2), respectively, assuming a distance d ranging from 1 km to 50 km.

TABLE I
Root mean square delay and angular spreads adopted in the rural channel model.

DS (ns)	ASD (deg)	ASA (deg)	ZSD (deg)	ZSA (deg)
100	1	30	0.1	1

DS is root mean square delay spread
ASD and ASA are the root mean square azimuth spread of the departure and arrival angles, respectively
ZSD and ZSA are root mean square zenith spread of the departure and arrival angles, respectively

occurrences of deep fadings in the received signal which will reduce the received energy below the noise floor.

III. The WIBA method

The WIBA method [5] uses detection windows and a detection threshold when defining is there a signal (=occupied channel) or only a noise (=unoccupied channel) present. Assume that there are N received frequency domain samples x_i that are are zero mean, independent and identically distributed Gaussian complex random variables. Then a sample energy $y_i = |x_i|^2$ follows a chi-squared distribution with $2M$ degrees of freedom. In the WIBA algorithm, the received frequency domain samples are divided into L blocks (detection windows) whose length is M (see Fig. 2). Window length M can be selected beforehand based on the expected signal bandwidths (BW). It has been shown that an optimal window length equals to the signal BW, and too long detection window degrades the detection performance [5]. The WIBA algorithm is using 50% overlapping of detection windows, i.e., first block $L_1 = 1, \cdots, M$, second block $L_2 = \frac{M}{2}+1, \cdots, \frac{M}{2}+M$, third block $L_3 = M+1, \cdots, 2M$, and so on. Energy samples y_i in each block are summed up to get the total energy in each block: $Z_i = \sum_{l=1}^{M} Y_i(l)$, $i = 1, \cdots, L$.

The signal detection threshold is [5]

$$T_h = T \frac{1}{L} \sum_{i=1}^{L} Z_i, \tag{4}$$

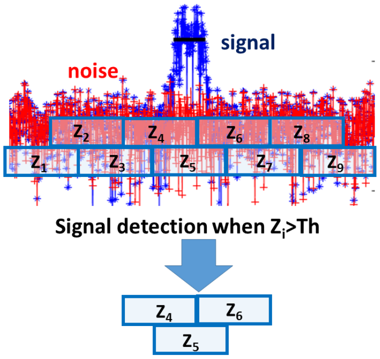

Fig. 2. The WIBA method operation principle.

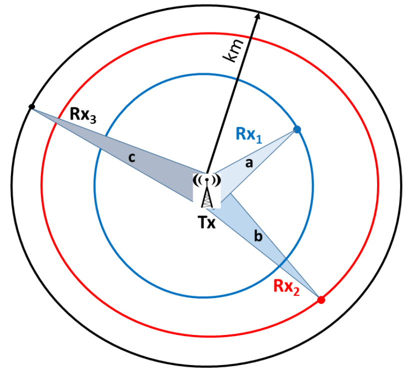

Fig. 3. Detection distance (Tx-Rx) depends on the transmit signal power, signal BW and the channel.

where threshold parameter T comes from [9], [10]

$$P_{\text{FA}} = e^{-TM} \sum_{k=0}^{M-1} \frac{1}{k!}(TM)^k, \tag{5}$$

where P_{FA} is the desired false alarm rate. The P_{FA} defines how many samples are above the threshold if there is only a noise present. For example, if $N = 1024$ and $P_{\text{FA}} = 0.01$ (=1%), 10 samples from total of 1024 samples are above the threshold in the noise-only case. The threshold parameter T is constant for specific M and P_{FA}, and is calculated before beforehand and given as an input to WIBA algorithm.

In the performance evaluation, a well-known signal detection method called the LAD method [11] [12] is used as a point of comparison. The LAD method utilizes iterative forward consecutive mean excision (FCME) threshold setting [13]. The threshold setting process corresponds to the WIBA threshold setting when $M = 1$ (and $L = N$). In that case, the threshold parameter can be derived from (5) as

$$T_{\text{CME}} = -\ln(P_{\text{FA}}). \tag{6}$$

The FCME algorithm rearranges frequency domain samples in an ascending order according to sample energy. The detection threshold is $T_h = T_{\text{CME}}\overline{y}$, where T_{CME} is from (6) and $\overline{y}$ denotes the mean of energy samples. In the first iteration, the mean is calculated from the initial set that contains 10% of the samples with smallest energy. The samples below the threshold are added to the initial set, and this iteration continues until there are no samples below the threshold. The LAD method uses two FCME thresholds (upper and lower), by using two different threshold parameters. The LAD method clusters adjacent samples above the lower threshold. The cluster is from a signal if at least one of the samples in the cluster is also above the upper threshold. ACC parameter that allows p (usually $p = 3$) samples [12] to be below the lower threshold between two accepted clusters, is used to increase the detection performance [12].

IV. Simulations

The detection performance of the WIBA method was studied by Matlab simulations, and the results were compared to the LAD method performance. The LAD method is known as a simple and effective ED method. Typical performance requirement for spectrum sensing algorithms is that probability of detection $P_d > 0.9$ (i.e. 90%) [14], therefore it is also assumed here. Detection distance in kilometers (km) was of interest in our performance evaluation. In practice, the detection distance corresponds a radius of a circular detection zone as illustrated in Fig. 3. Therein, transmitter Tx transmits three signals a, b and c with different transmit powers and BWs. Figure illustrates the detection distance for three receivers, Rx_1-Rx_3, that are able to detect the signals on different distances, depending on the signal power, BW and the propagation channel.

Rural area channel model presented in Section II was used in the simulations and the signal to be detected was a band-limited raised-cosine binary shift keying (RC-BPSK) modulated signal. This signal was chosen to represent a general telecommunication signal. Note that both the studied methods are robust to signal and modulation types, and also to the frequency areas [5], [12]. Assumed total sensing BW was 23.4 MHz and carrier frequency was 700 MHz. There were $N = 1024$ frequency domain samples. Transmit power, signal BW and detection window length M varied. Transmitted signal powers were $17 - 83$ dBm and used signal BW values were $0.9 - 6$ MHz corresponding to $4 - 25.6\%$ of the total BW, respectively. Corresponding window lengths M were $44 - 768$ samples, so that the lengths equal to the signal BW. The number of Monte Carlo iterations was 3000. The WIBA method used $P_{FA} = 0.01$, 50% overlapping, and $L \approx 2\frac{N}{M}$. The LAD threshold parameters were 13.81 ($P_{FA} = 10^{-6}$) and 2.66 ($P_{FA} = 0.07$), and ACC parameter $p = 3$.

In the simulations, detection probability P_d vs. detection distance between Tx and Rx was studied. In Table II, it is shown what is the maximum distance between Tx and Rx for different transmit power and signal BW values so that the detection probability requirement $P_d \geq 0.9$ will be met in the WIBA and the LAD methods case. For example, when transmit power is 53 dBm and signal BW is 2 MHz, signal can be detected (detection probability $P_d \geq 0.9$) when Tx-

TABLE II
FOR DIFFERENT TRANSMIT POWER [DBM] AND SIGNAL BW VALUES [MHZ], THE MAXIMUM TX-RX DISTANCE WITH A REQUIREMENT THAT DETECTION PROBABILITY $P_d \geq 0.9$.

Transmit power $[dBm]$	Signal BW $[MHz]/\%$	Tx-Rx distance WIBA method	Tx-Rx distance LAD method
83	5.85/25	$>$ 200 km	40 km
53	2/8.6	$<$ 34 km	$<$ 7 km
53	4/17.1	$<$ 20 km	$<$ 3 km
53	6/25.6	$<$ 15 km	$<$ 1 km
46	2/8.6	$<$ 15 km	$<$ 6 km
46	4/17.1	$<$ 9 km	$<$ 3 km
46	6/25.6	$<$ 6 km	$<$ 1 km
43	5.85/25	$<$ 4 km	-
36	5.85/25	$<$ 2 km	-
30	2/8.6	$<$ 3 km	-
30	4/17.1	$<$ 2 km	-
30	6/25.6	$<$ 1 km	-
17	0.9/4	$<$ 900 m	$<$ 200 m

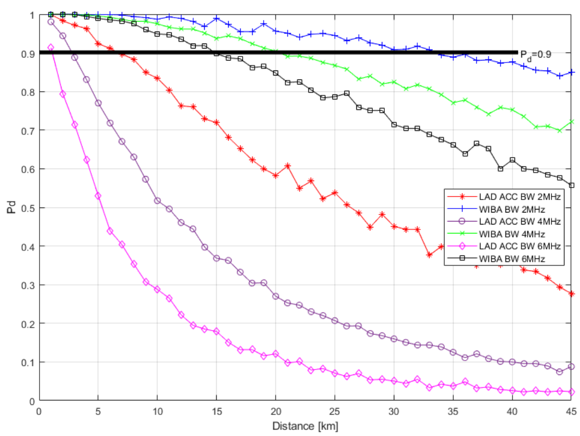

Fig. 4. P_d vs. detection distance results when transmit power of the signal is 53 dBm. $M = 102$ for 3 MHz signal, 180 for 4 MHz signal and 264 for 6 MHz signal.

Rx distance is 34 (WIBA) and 7 (LAD) km (second line in Table II). The performance difference is remarkable, being almost five-fold. It can be seen that the narrower the signal is, and the higher the transmit power is, the longer is the Tx - Rx distance that the signal can be detected. When transmit power is 83 dBm and signal BW is 5.85 MHz ($= 25\%$), the WIBA method is able to detect signal when Tx-Rx distance is even 200 km. Instead, the LAD method is able to detect the signal when Tx-Rx distance is at most 40 km. The WIBA method outperforms the LAD method in all studied cases: it gives $3 - 15$ times larger detection distances than the LAD method. The wider the signal the bigger the detection distance difference.

In Figs. 4 - 7, transmitted signal power values were $53, 46, 30$ and 20 dBm. While used BW values of the detected signal were $2, 4$ or 6 MHz corresponding to $8.6\%, 17.1\%$ and 25.6% of the sensing BW, respectively. Corresponding window lengths were 102, 180 and 264 samples, being optimal so that

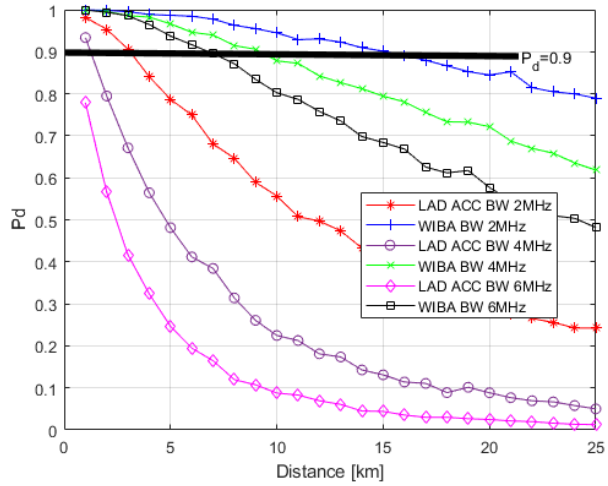

Fig. 5. P_d vs. detection distance results when transmit power of the signal is 46 dBm. $M = 102$ for 3 MHz signal, 180 for 4 MHz signal and 264 for 6 MHz signal.

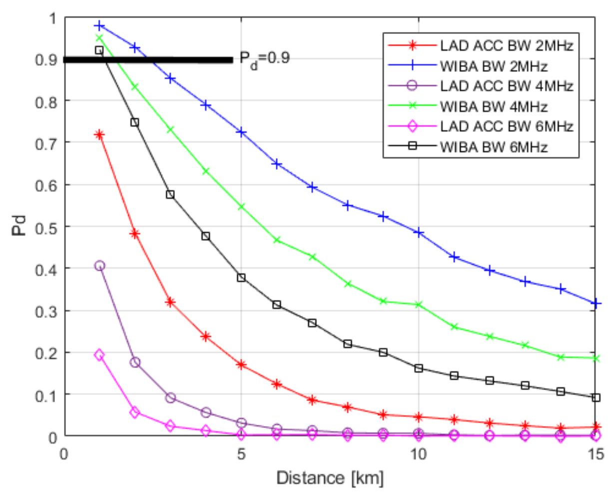

Fig. 6. P_d vs. detection distance results when transmit power of the signal is 30 dBm. $M = 102$ for 3 MHz signal, 180 for 4 MHz signal and 264 for 6 MHz signal.

the lengths equal to the signal BW. The performance target of signal detection was $P_d \geq 0.9$, which is marked with the horizontal lines in the pictures. When the WIBA method is used and transmit power is high (≥ 46 dBm), the curves fall evenly whereas in the LAD method case the curves first fall steeply. From Fig. 4 can be seen that both the methods are able to find all the signals from some distance. However, there is a big difference between the detection distances. For example, when signal BW is 2 MHz and the WIBA method is used, the detection distance is 34 km. When the LAD method is used, the detection distance is 27 km less, that is, only 7 km. In Fig. 5 case, the WIBA method can detect all the signals, as the LAD method detects only the two narrowest ones (2 and 4 MHz). When transmit power is 30 dBm, the WIBA method is

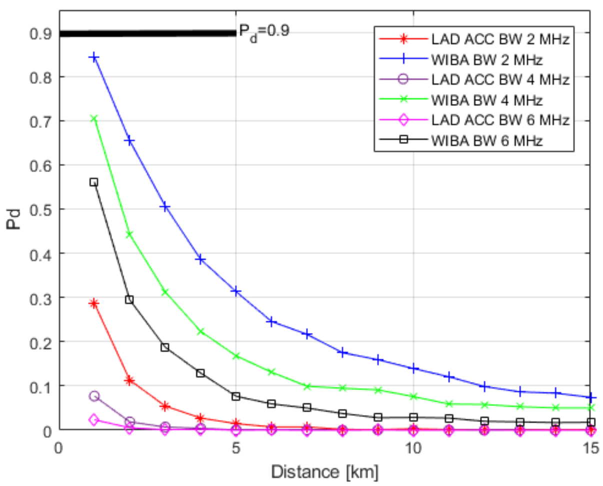

Fig. 7. P_d vs. detection distance results when transmit power of the signal is 20 dBm.

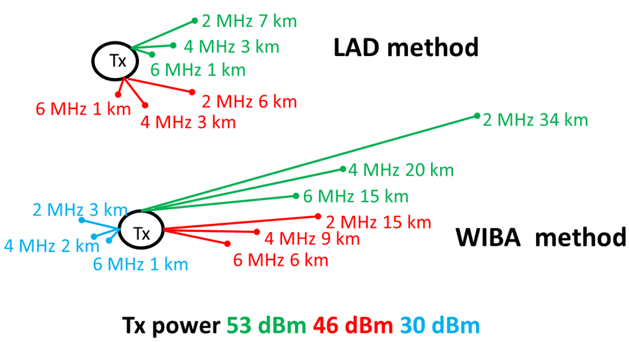

Fig. 8. Distance [km] where the LAD and WIBA methods can detect the signal at $P_d \geq 0.9$. Transmit power is $53, 46$ and 30 dBm and signal BW is $2, 4$ and 6 MHz.

able to detect the signals (Fig. 6). However, the LAD method gets at its best $P_d = 0.7$, so the signals can not be detected using the LAD method. When transmit power is 20 dBm, for both the methods, the signal can not be detected at all (Fig. 7). Results for $53, 46$ and 30 dBm signals are illustrated in Fig. 8. It can clearly be seen that the WIBA method outperforms the LAD method. The wider the signal and the higher the transmit power, the bigger is the performance difference.

V. CONCLUSION

This paper has studied the performance of the window-based WIBA energy detector spectrum sensing method to complement the traditional database based spectrum sharing approaches for providing rural and remote area connectivity with 5G networks. Spectrum sensing can help in detecting unauthorized transmissions as well as facilitating the deployment of several secondary networks. Focus in this paper has been on assessing the achievable detection distance in kilometers which is critical for the establishment of remote area networks. The simulation results show that the WIBA method has excellent performance in a challenging rural area channel, and it clearly outperforms conventional energy detectors.

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