

SDR-Based Deep Learning Spectrum Sensing for TV White Space Applications

João Victor Fernandes Borges, Rausley Adriano Amaral de Souza, Luciano Leonel Mendes, Arismar Cerqueira Sodré Junior, and André Antônio dos Anjos

Abstract—This paper presents a real-time spectrum sensing system for TV white spaces (TVWS) applications based on offline-trained deep learning (DL) models for online inference. The system employs an Ettus USRP B210 software-defined radio (SDR) and MATLAB to evaluate, over ultra high frequency (UHF) ISDB-T_B signals, three DL-based sensing approaches: a dense fully connected network (DenseNet), a lightweight fully connected network (SimpleNet), and a convolutional neural network (CNN), with traditional energy detection (ED) as a baseline. Experimental evaluations were conducted under line-of-sight (LoS), non-line-of-sight (nLoS), and mobile propagation scenarios. The results show that DL-based sensing improves detection performance over ED in all evaluated cases, although the gain is significantly reduced under mobility. In addition, the execution-time analysis indicates that the trained models are suitable for real-time operation. These results demonstrate the practical feasibility of intelligent SDR-based spectrum sensing for future cognitive radio and 5G/6G networks.

Keywords—TV white spaces, spectrum sensing, energy detection, ISDB-T_B, wireless communication, deep learning.

I. INTRODUCTION

The emergence of next-generation applications such as Internet of Things (IoT), Industry 5.0, and intelligent wireless systems is accelerating the transition from 5G to future 6G networks while significantly increasing the demand for radio spectrum resources [1]. Consequently, spectrum scarcity has become one of the major challenges for modern wireless communications [2]. However, several studies have shown that large portions of the licensed spectrum remain underutilized due to static allocation policies [3].

This underutilization is particularly evident in the very high frequency (VHF) and ultra high frequency (UHF) bands allocated for television broadcasting. Due to their favorable propagation characteristics, these frequencies are highly attractive for long-range wireless communications and obstacle penetration. In this context, the opportunistic use of TV white spaces (TVWS) has emerged as a promising strategy to improve spectral efficiency without causing harmful interference to licensed users [4]. Following global trends, the Brazilian National Telecommunications Agency (ANATEL) recently established regulatory frameworks for the dynamic use of TVWS in the 470–608 MHz and 614–698 MHz bands [5]. Nevertheless, practical deployment of these cognitive radio

(CR) systems requires robust sensing techniques to identify spectrum occupancy and protect primary users (PUs).

Several spectrum sensing approaches have been investigated in the literature, including matched filtering, cyclostationary detection, and energy detection (ED) [6]. More recently, several studies have investigated innovative spectrum sensing strategies, including phase-based approaches and deep learning (DL)-assisted techniques, to improve detection performance under challenging wireless conditions [7]–[10]. However, practical experimental validations using real wireless channels and broadcasting signals remain relatively limited.

Among recent practical implementations, [11] evaluated spectrum sensing using eigenvalue techniques with the USRP N310 software-defined radio (SDR) under line-of-sight (LoS) conditions, while [12] investigated DL-based sensing using the USRP B210. However, these studies remain restricted to simplified propagation conditions, controlled environments, or generic communication signals, without considering realistic mobility and obstruction effects typically encountered in practical TVWS scenarios.

To address this gap, this paper presents an experimental SDR-based spectrum sensing system for TVWS applications using offline-trained DL models for online inference. The sensing system was implemented in MATLAB using the Ettus USRP B210 SDR, while GNU Radio was used to generate the ISDB-T_B signals. The proposed system evaluates a dense fully connected neural network, referred to as DenseNet, a lightweight fully connected baseline referred to as SimpleNet, and a convolutional neural network (CNN), comparing their performance with conventional ED. The experimental analyses are conducted under LoS, non-line-of-sight (nLoS), and mobile propagation scenarios, considering different observation window lengths (N) and signal-to-noise ratio (SNR) conditions. In addition, an execution-time analysis is performed to evaluate the practical feasibility of real-time spectrum sensing using DL in future cognitive radio networks.

II. SPECTRUM SENSING FRAMEWORK

A. System Model

The fundamental objective of the spectrum sensing process is to distinguish between two competing hypotheses: $\mathcal{H}_0$, representing the absence of a PU signal, and $\mathcal{H}_1$, indicating its presence. The received signal $y(t)$ at the CR receiver can be expressed as

$$y(t) = \begin{cases} n(t), & \text{if } \mathcal{H}_0 \\ h(t)x(t) + n(t), & \text{if } \mathcal{H}_1 \end{cases} \quad (1)$$

João V. F. Borges and André A. dos Anjos are with Universidade Federal de Uberlândia (UFU), Patos de Minas, MG, Brazil (e-mails: joao.borges04@ufu.br, andre.anjos@ufu.br). Rausley, A. A. Souza, Luciano L. Mendes, and Arismar C. Sodre, Jr. are with Instituto Nacional de Telecomunicações (INATEL), Santa Rita do Sapucaí, MG, Brazil (e-mails: rausley@inatel.br, luciano1@inatel.br, arismar@inatel.br).

where $x(t)$ is the signal transmitted by the PU, $h(t)$ represents the channel gain, and $n(t)$ denotes the thermal additive white Gaussian noise (AWGN) at the receiver front-end. A test statistic T is then computed from $y(t)$ and compared with a threshold λ . If $T > \lambda$, the channel is declared occupied; otherwise, it is considered idle. In practice, λ is typically chosen to satisfy a target constant false alarm rate (CFAR).

B. Energy Detection

ED is adopted as a conventional benchmark for comparison with the evaluated DL-based sensing approaches, as it is widely used in practical CR systems due to its low computational complexity and independence from PU signal priors [13]. Its decision statistic is given by

$$T = \sum_{i=1}^N |y(i)|^2, \quad (2)$$

where N is the number of collected samples and $y(i)$ is the i -th digitized received sample. For large N , T can be approximated as Gaussian under both hypotheses, i.e., $T \sim \mathcal{N}(N\sigma_w^2, N\sigma_w^4)$ under $\mathcal{H}_0$ and $T \sim \mathcal{N}(N(\sigma_s^2 + \sigma_w^2), N(\sigma_s^2 + \sigma_w^2)^2)$ under $\mathcal{H}_1$. Thus, the false alarm and detection probabilities are

$$P_{fa} = Q\left(\frac{\lambda - N\sigma_w^2}{\sqrt{N\sigma_w^4}}\right), \quad (3)$$

$$P_d = Q\left(\frac{\lambda - N(\sigma_s^2 + \sigma_w^2)}{\sqrt{N(\sigma_s^2 + \sigma_w^2)^2}}\right), \quad (4)$$

where σ_w^2 and σ_s^2 are the noise and PU signal variances, respectively.

C. Deep Learning Architectures

Motivated by the potential of DL to enhance spectrum sensing under noise uncertainty and challenging propagation conditions, this study evaluates three neural-network-based sensing approaches: DenseNet, SimpleNet, and CNN. Unlike conventional machine learning (ML) methods based on handcrafted features, DL models can learn discriminative representations from preprocessed signal data [14].

During preprocessing, the acquired time-domain samples are converted into frequency-domain representations using the Fast Fourier Transform (FFT). The log-magnitude spectrum is then normalized using z-score normalization based only on the training set, avoiding information leakage between training and testing data. This procedure produces an N -dimensional feature vector, where N denotes the number of frequency bins. For implementation in the MATLAB deep-learning framework, this vector is reshaped into an $N \times 1 \times 1$ input array.

For each evaluated combination of propagation scenario, SNR, and observation window length N , a dedicated dataset was acquired and randomly split at the trial level into training and testing subsets using a 70/30 ratio. The models were independently trained from scratch for each condition for 40 epochs with a mini-batch size of 128, using cross-entropy loss and the Adam optimizer with both learning rate and

L2 regularization factor set to 10^{-4} . The final layer of each architecture consists of two neurons followed by a Softmax activation for binary classification between $\mathcal{H}_0$ and $\mathcal{H}_1$.

The considered architectures are summarized as follows:

- **DenseNet:** A dense multilayer perceptron composed of three fully connected hidden layers with 100, 50, and 20 neurons, respectively. Rectified Linear Unit (ReLU) activations and a 20% dropout rate are used after each hidden layer to reduce overfitting.
- **SimpleNet:** A lightweight baseline neural network composed of a single fully connected hidden layer with 20 neurons and ReLU activation.
- **CNN:** A one-dimensional convolutional neural network implemented using convolutional filters along the frequency dimension. It comprises two convolutional blocks with 16 filters of size 5×1 and 32 filters of size 3×1 , respectively, followed by batch normalization, ReLU activation, and max pooling. A fully connected layer with 50 neurons and 20% dropout precedes the final classification layer.

III. SDR SYSTEM IMPLEMENTATION AND CONFIGURATION

A. TVWS Primary User

The PU transmission was modeled according to the ABNT 15601 specification, which defines the ISDB-T/T_B digital television standard adopted in Brazil, Japan, and several regions of Latin America and Africa. Since ISDB-T_B employs an OFDM-based waveform, the obtained results may also provide useful insights for other digital television systems based on multicarrier transmission, such as DVB and ATSC 3.0.

The signal generation was implemented in GNU Radio, enabling flexible transmission of digital television signals over the UHF spectrum. The main technical parameters of the implemented ISDB-T_B PU signal are summarized in Table I.

TABLE I

OFDM ISDB-T_B SYSTEM TRANSMISSION PARAMETERS.

Parameter	Value
Total number of carriers	8192 (Mode 3)
Number of active carriers	5617
Guard Interval	1/32
Number of segments Layer A	13
Data carriers modulation Layer A	64-QAM
Encoding rate of layer A	7/8
Pilot carriers and TMCC modulation	BPSK/DBPSK
OFDM symbol duration	1.26 ms
Subcarrier spacing	0.992 kHz
Pilot spacing	11.9 kHz
IFFT clock	512/63 MHz
BW	5.572 MHz

B. Experimental Setup and Data Acquisition

The experiments were conducted at the Wireless Lab of the *Universidade Federal de Uberlândia* (UFU), Patos de Minas campus. The indoor environment, with workstations, computers, printers, and metallic cabinets, creates rich multipath conditions with signal reflections, supporting realistic validation of the proposed sensing system.

The experimental setup employed two Ettus USRP B210 SDRs¹, acting as the primary transmitter (TX) and cognitive receiver (RX). The TX was configured in GNU Radio to transmit the PU ISDB-T_B signal over UHF Channel 40 (629.143 MHz), while the RX operated in MATLAB with a 30.72 MHz Master Clock, a 6.144 MHz sample rate, and a fixed gain of 5 dB. The TX gain was adjusted through GNU Radio to obtain the desired SNR at the receiver. Both SDRs employed VERT400 omnidirectional antennas positioned approximately 0.5 m above the floor.

To evaluate the proposed sensing platform under realistic propagation conditions, practical measurements were conducted in three scenarios, as illustrated in Fig. 1. In **Scenario a (LoS, Fig. 1(a))**, the TX and RX antennas were fixed 0.6 m apart with a clear LoS. In **Scenario b (nLoS, Fig. 1(b))**, the devices were separated by approximately 5 m, with a physical wall obstructing the propagation path and introducing indoor attenuation and shadowing effects. In **Scenario c (Mobile, Fig. 1(c))**, the TX and RX were initially placed 0.6 m apart to establish a baseline target SNR; then, the TX was laterally displaced along the red trajectory indicated in Fig. 1 (approximately 4 m long) at an approximate speed of 1 m/s, producing dynamic envelope fluctuations, Doppler effects, and a reduction in the final average SNR.

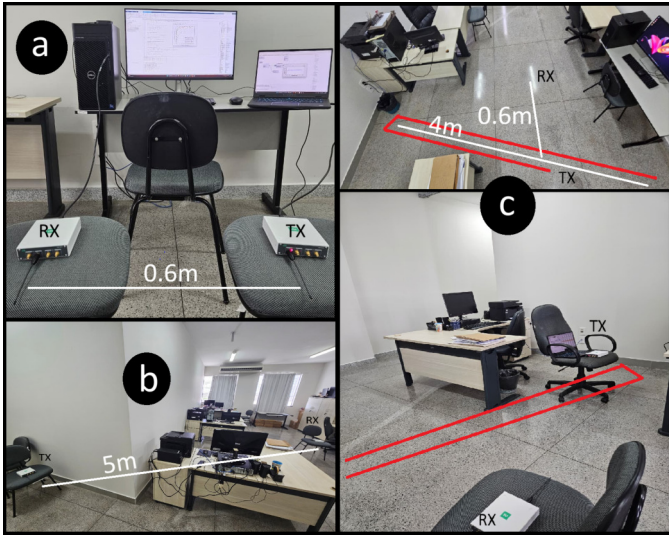


Fig. 1. Experimental measurement scenarios: (a) LoS, (b) nLoS with physical obstructions, and (c) Mobile trajectory.

C. Offline Training, Performance Evaluation, and Real-Time Operation

The proposed sensing system comprises offline and online stages. In the offline stage, labeled SDR measurements under $\mathcal{H}_0$ and $\mathcal{H}_1$ are used to extract features, train the DL models, and evaluate their performance using receiver operating characteristic (ROC) curves and area under curve (AUC) values. Experimental ROC curves are obtained by sweeping the decision threshold over the ED statistic T or the $\mathcal{H}_1$ Softmax score for the DL-based methods. This enables comparison with

conventional ED under different propagation conditions, SNR levels, and observation N . After training and validation, the model previously trained for the corresponding experimental condition is deployed in the online sensing routine. Automatic scenario identification or model selection was not considered in this work. During real-time operation, the SDR acquires new signal frames from the monitored channel. For the DL-based methods, each frame is converted into FFT-based log-magnitude features, normalized using the training-set statistics, and classified as idle or occupied by the trained network. For ED, the decision is obtained by computing the received signal energy over the same observation window and comparing it with a threshold. Therefore, real-time operation in this work refers to the online acquisition, preprocessing, and inference stages performed after offline training and validation.

IV. PERFORMANCE EVALUATION

This section presents the obtained experimental results. For each evaluated condition, 30,000 experimental SDR acquisition trials were collected, equally divided into 15,000 trials under $\mathcal{H}_0$ (TX off) and 15,000 under $\mathcal{H}_1$ (TX on). Each trial corresponds to a new SDR frame acquisition, from which the first N complex samples form the observation window; no sliding-window segmentation or overlapping windows were employed. The measurements were conducted on UHF Channel 40. The noise power was first estimated with the TX off. Subsequently, the TX gain was adjusted through GNU Radio to achieve the target average SNR, calculated as $\text{SNR}_{\text{dB}} = 10 \log_{10} \left(\frac{\sigma_s^2 + \sigma_w^2}{\sigma_w^2} - 1 \right)$.

For all scenarios, performance is evaluated in terms of the average SNR. In the static cases (Scenarios a and b in Fig. 1), the instantaneous SNR was kept as close as possible to the target value. In Scenario c (Mobility), where the SNR fluctuates due to TX movement, the results are reported using the average SNR over the complete trajectory. The theoretical benchmarks were obtained from the ED expressions for P_{fa} and P_d in (3) and (4), respectively.

A. Performance Under Static Conditions

Fig. 2 presents the ROC curves obtained under static propagation conditions. Fig. 2(a) evaluates the impact of SNR under LoS conditions, Fig. 2(b) analyzes the effect of N at low SNR, and Fig. 2(c) compares the performance under LoS and nLoS environments.

In Fig. 2(a), the results are obtained under LoS conditions with $N = 100$. As expected, reducing the SNR degrades the detection performance of all methods. At -5 dB, the CNN achieves the highest experimental AUC of 0.9576, followed by DenseNet (0.9248), SimpleNet (0.9154), and empirical ED (0.9072). The CNN approaches the theoretical ED benchmark (0.9719), while remaining below this reference. At -10 dB, the same performance ordering is observed, but the gap between the DL-based methods and empirical ED becomes smaller. In this case, the CNN, DenseNet, SimpleNet, and empirical ED achieve AUC values of 0.7152, 0.7011, 0.6844, and 0.6832, respectively.

¹The Ettus USRP B210 SDR operates from 70 MHz to 6 GHz and supports up to 56 MHz of real-time bandwidth [15].

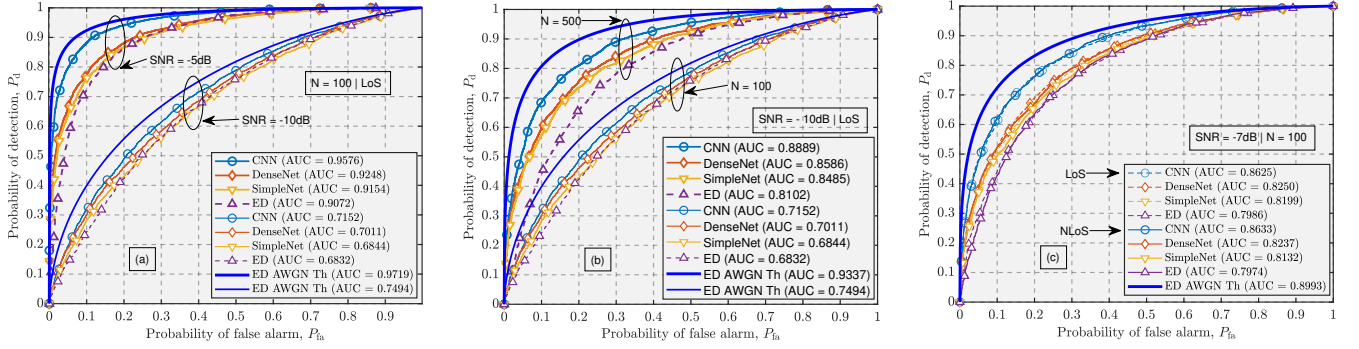


Fig. 2. ROC curves: (a) LoS condition with varying SNR, (b) LoS condition with varying N , and (c) LoS and nLoS conditions.

In Fig. 2(b), the effect of the observation window length is evaluated at a fixed SNR of -10 dB under LoS conditions. Increasing N from 100 to 500 improves the ROC curves of all techniques, confirming that longer observation windows provide a more reliable sensing statistic under low-SNR conditions. For $N = 500$, the CNN achieves the highest experimental AUC of 0.8889, followed by DenseNet (0.8586), SimpleNet (0.8485), and empirical ED (0.8102). Compared with the $N = 100$ case, the gain is particularly noticeable for the DL-based methods, which move closer to the theoretical ED benchmark of 0.9337. This result indicates that increasing the number of received samples improves the separability between $\mathcal{H}_0$ and $\mathcal{H}_1$, especially for feature-based classifiers operating under severe SNR degradation.

In Fig. 2(c), the performance is evaluated under LoS and nLoS conditions for a fixed SNR of -7 dB and $N = 100$. Under LoS, the CNN achieves the highest experimental AUC of 0.8625, followed by DenseNet (0.8250), SimpleNet (0.8199), and empirical ED (0.7986). Interestingly, when transitioning to the nLoS environment, only minor performance variations are observed for all evaluated techniques. In particular, the CNN maintains nearly identical performance, with an AUC of 0.8633, while DenseNet, SimpleNet, and empirical ED achieve AUC values of 0.8237, 0.8132, and 0.7974, respectively. These results indicate that, under the evaluated stationary indoor nLoS conditions, multipath propagation preserves sufficient signal information for reliable sensing, preventing severe performance degradation. Moreover, the DL-based methods remain consistently superior to empirical ED under both propagation conditions, demonstrating robustness against the absence of a direct propagation path. The theoretical ED benchmark achieves an AUC of 0.8993.

B. Performance Under Mobility

Fig. 3 compares static and mobile LoS scenarios for $N = 100$ and an average SNR of -5 dB. Under static conditions, the CNN achieves the highest experimental performance with an AUC of 0.9576, outperforming DenseNet (0.9248), SimpleNet (0.9154), and empirical ED (0.9072). Moreover, the CNN approaches the theoretical AWGN ED benchmark (AUC = 0.9719), indicating an improved ability to extract relevant spectral features under controlled propagation conditions.

When mobility is introduced, the detection performance degrades for all evaluated methods due to instantaneous SNR

fluctuations and time-varying channel effects caused by TX movement. Consequently, all experimental curves move farther from the theoretical AWGN ED benchmark. Under mobility, the CNN remains the best-performing method, achieving an AUC of 0.8736, followed by DenseNet (0.8680), SimpleNet (0.8616), and empirical ED (0.8545).

Compared with the static case, the performance gap between the DL-based methods and empirical ED becomes substantially smaller. In particular, the AUC gain of the CNN over empirical ED decreases from 0.0504 under static conditions to only 0.0191 under mobility. This result suggests that rapid channel variations reduce the ability of the neural models to exploit discriminative spectral features, bringing their performance closer to the conventional energy-based approach.

Although the neural networks still provide the highest detection performance, the reduced gains under mobility reveal an important trade-off between sensing accuracy and computational complexity. In this scenario, empirical ED remains highly competitive due to its lower processing cost and latency, as well as its independence from an offline training stage.

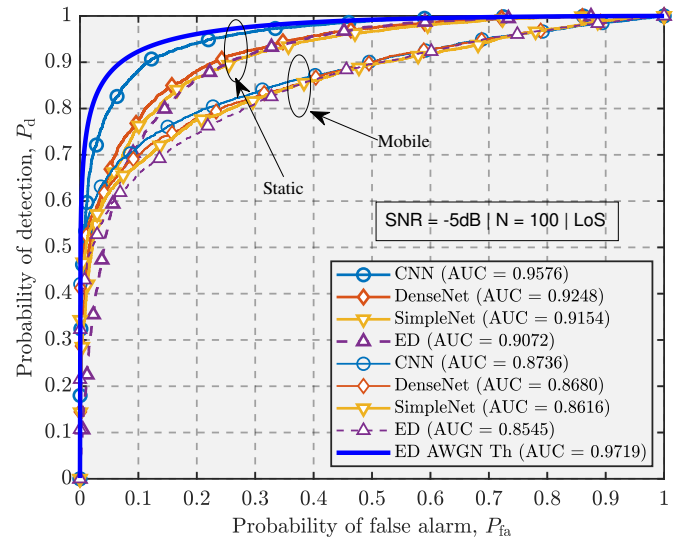


Fig. 3. ROC curves comparing static and mobile scenarios.

C. Execution Time Analysis

Table II reports the average online execution time for different N . The total pipeline time includes SDR frame

TABLE II

AVERAGE ONLINE EXECUTION TIME IN MILLISECONDS FOR DIFFERENT N .

Operation / Technique	$N = 100$	$N = 500$	$N = 1000$
<i>Hardware Acquisition</i>			
SDR Capture	0.0960	0.1447	0.1875
<i>Total Online Pipeline Time</i>			
ED	0.0988	0.1527	0.1996
SimpleNet	1.0275	1.0734	1.1331
DenseNet	1.3039	1.3338	1.3948
CNN	1.3259	1.3361	1.3961

acquisition and energy computation for ED, and additionally FFT-based preprocessing and neural-network inference for the DL-based methods. Offline training is not included, since it is performed before deployment.

As expected, ED achieves the lowest latency, remaining below 0.20 ms even for $N = 1000$. Its total time closely follows the SDR acquisition time, indicating negligible computational overhead and making it attractive for ultra-low-latency, low-complexity operation without training.

The DL-based methods require higher processing times, from approximately 1.02 ms to 1.40 ms, but remain compatible with online sensing. Increasing N from 100 to 1000 only slightly increases latency; for example, the CNN rises from 1.3259 ms to 1.3961 ms. Thus, the processing time is mainly dominated by inference overhead rather than the observation window length.

Among the neural models, SimpleNet provides the lowest latency for all N values, achieving the best latency-performance trade-off. Therefore, ED is preferable when latency, simplicity, and independence from training are critical, whereas offline-trained DL models are viable alternatives when improved detection performance justifies millisecond-level processing latency.

V. CONCLUSION

This work presented a real-time SDR-based spectrum sensing system for TVWS applications using offline-trained DL models for online inference. The system was experimentally evaluated with ISDB-T_B signals under LoS, nLoS, and mobile scenarios, comparing DenseNet, SimpleNet, and a CNN with conventional ED.

The results showed that the DL-based methods outperformed empirical ED in all evaluated scenarios. Under static LoS conditions, the CNN achieved the best performance and approached the theoretical AWGN ED benchmark. Increasing N improved the separability between $\mathcal{H}_0$ and $\mathcal{H}_1$, particularly under low-SNR conditions, while only minor performance variations were observed in the stationary nLoS scenario.

Under mobility, all techniques degraded due to SNR fluctuations and time-varying channel effects. Although the CNN still achieved the highest AUC, its advantage over empirical ED decreased, highlighting a trade-off between accuracy and complexity. The execution-time analysis showed that ED provides the lowest latency, while the trained DL models remain suitable for online operation, with SimpleNet offering the best latency-performance trade-off. Thus, DL-based sensing is viable when higher detection performance is required, whereas

ED remains attractive for low-latency and resource-constrained implementations.

ACKNOWLEDGMENTS

This work was partially funded by CNPq (302085/2025-4, 306199/2025-4), by FAPEMIG (RED-00194-23, PPE-00124-23, APQ-04523-23, APQ-05305-23, APQ-03162-24), by the Brasil 6G project (01245.020548/2021-07), supported by RNP and MCTI, and by the project XGM-AFCCT-2024-9-1-1 supported by xGMobile – EMBRAPII-Inatel Competence Center on 5G and 6G Networks, with financial resources from the PPI IoT/Manufatura 4.0 from MCTI grant number 052/2023, signed with EMBRAPII, and by FINEP (n° 1060/2 contract 01.25.0883.00).

REFERENCES

- [1] C. D. Alwis, A. Kalla, Q.-V. Pham, P. Kumar, K. Dev, W.-J. Hwang, and M. Liyanage, "Survey on 6G frontiers: Trends, applications, requirements, technologies and future research," *IEEE Open J. Commun. Soc.*, vol. 2, pp. 836–886, 2021.
- [2] Y.-C. Liang, J. Tan, H. Jia, J. Zhang, and L. Zhao, "Realizing intelligent spectrum management for integrated satellite and terrestrial networks," *J. Commun. Inf. Networks.*, vol. 6, no. 1, pp. 32–43, 2021.
- [3] H. B. Sandya, K. Nagamani, and L. Shavanthi, "A review of cognitive radio spectrum sensing methods in communication networks," in *2018 International Conference on Communication and Signal Processing (ICCCSP)*, 2018, pp. 0457–0461.
- [4] A. Ivanov, K. Tonchev, V. Poulkov, and A. Manolova, "Probabilistic spectrum sensing based on feature detection for 6G cognitive radio: A survey," *IEEE Access*, vol. 9, pp. 116 994–117 026, 2021.
- [5] "ANATEL Resolution No. 747," ANATEL Board of Directors, 10/2021, Accessed: April 2024. [Online]. Available: {<https://informacoes.anatel.gov.br/legislacao/resolucoes/2021/1593-resolucao-747>}
- [6] V. Amrutha and K. V. Karthikeyan, "Spectrum sensing methodologies in cognitive radio networks: A survey," in *2017 International Conference on Innovations in Electrical, Electronics, Instrumentation and Media Technology (ICEEIMT)*, 2017, pp. 306–310.
- [7] A. A. dos Anjos, C. R. N. da Silva, and R. A. A. de Souza, "Fading evaluation in a robust spectrum sensing system based on phase difference distribution," *IEEE Trans. Veh. Technol.*, vol. 74, no. 6, pp. 9404–9418, 2025.
- [8] P. M. R. Pereira, A. A. Dos Anjos, F. A. P. d. Figueiredo, and R. A. A. d. Souza, "Interpretable and feature-aware spectrum sensing in generalized mobile environments," *IEEE Open J. Commun. Soc.*, vol. 7, pp. 5118–5134, 2026.
- [9] W. R. d. Silva, A. A. dos Anjos, and R. A. A. de Souza, "Análise comparativa de técnicas de sensoriamento espectral baseadas em redes neurais, matriz de covariância e densidade espectral de potência," in *XLI Simpósio Brasileiro de Telecomunicações e Processamento de Sinais (SBrT 2023)*, São José dos Campos, SP, Oct. 2023.
- [10] L. Zhang, M. Zhao, C. Tan, G. Li, and C. Lv, "Research on spectrum sensing system based on composite neural network," in *2020 2nd International Conference on Advances in Computer Technology, Information Science and Communications (CTISC)*, 2020, pp. 22–26.
- [11] A. Sabra and M. Berbineau, "Experimental assessment of eigenvalue-based spectrum sensing using USRP-based MIMO testbed for cognitive radio applications," *IEEE Sens. Lett.*, vol. 6, no. 10, pp. 1–4, 2022.
- [12] Z. Sabrina, T. Djamel, T. Camel, M. Ammar, S. Said, and N. Okba, "SDR implementation of spectrum sensing using deep learning," *Int. J. Sens. Wirel. Commun. Control.*, vol. 13, no. 4, pp. 226–236, 2023.
- [13] D. M. M. Plata and Á. G. A. Reátiga, "Evaluation of energy detection for spectrum sensing based on the dynamic selection of detection-threshold," *Procedia Engineering*, vol. 35, pp. 135–143, 2012.
- [14] S. N. Syed, P. I. Lazaridis, F. A. Khan, Q. Z. Ahmed, M. Hafeez, A. Ivanov, V. Poulkov, and Z. D. Zaharis, "Deep neural networks for spectrum sensing: A review," *IEEE Access*, vol. 11, pp. 89 591–89 615, 2023.
- [15] Ettus Research, "USRP B200/B210/B200mini/B205mini/B206mini getting started guides," 2026, [Online]. Available: https://kb.ettus.com/B200/B210/B200mini/B205mini/B206mini_Getting_Started_Guides. Accessed: May 14, 2026.