LSTM-Based Spectrum Sensing for Improved Detection in Low-SNR Cognitive Radio Networks

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***Abstract*—Spectrum sensing is the first step in cognitive radio systems; before transmitting, a secondary user must confirm that a licensed channel is truly free. The classical energy detector is used as a baseline in this work, and it is improved by reconsidering the way the decision threshold is selected. This makes the test less sensitive to environmental conditions, especially when the signal-to-noise ratio is low. To maintain full control over the evaluation process, binary phase-shift keying sequences are generated and transmitted through an additive white Gaussian noise channel over a wide range of signal-to-noise ratio values. Two versions of the energy detector are investigated: a conventional version based on a fixed threshold and an adaptive version in which the threshold is adjusted according to an estimate of the noise level. In parallel, a detector based on a long short-term memory network is also examined. Unlike the energy detector, this model does not reduce the observation to a single energy value, but instead processes the received samples directly and exploits their temporal structure. The performance is assessed in terms of probability of detection, probability of false alarm, and probability of miss. The results show that adaptive threshold selection improves the performance of the energy detector at intermediate signal-to-noise ratio levels, whereas the long short-term memory based approach remains more robust when noise is dominant and energy-based detection becomes less reliable.**

***Index Terms*—Cognitive Radio Networks, Spectrum Sensing, Energy Detection, LSTM, Dynamic Threshold, BPSK.**

I. Introduction

The wireless environment has undergone a lot of changes in the past decade: wireless networks have been supporting an ever-growing number of connected devices, mobile-broadband data traffic has continued to grow, and new use cases such as industrial IoT, autonomous vehicles, and ultra-high-definition video streaming are becoming increasingly reliant on high data rates [1], [2]. This further widens the gap between the radio resources available and the demand for spectrum, as radio spectrum remains a scarce resource [3].

However, scarcity is more than just a bandwidth problem. Numerous licensed bands are continuously found to be inactive for extended periods of time, as well as across particular locations and frequency segments, according to measurement campaigns and regulatory evaluations. The traditional allocation model, which reserves spectrum for specific services regardless of short-term activity, is primarily to blame for this underutilization. Static assignments make coordination and regulation easier, but they also limit flexibility and may result in missed opportunities, which is becoming more and more out of step with the demands of the next generation.

Using dynamic spectrum access, cognitive radio (CR) was proposed to take advantage of these underutilized resources by allowing secondary users (SUs) to transmit opportunistically in licensed bands during periods of inactivity [4]. To shield primary users (PUs) from detrimental interference, SUs in CR networks modify their transmission behavior according to the sensed radio context [5]. Because the sensing result shows whether a band is available or occupied, spectrum sensing (SS) becomes a fundamental function [6], [7]. SUs can detect gaps in the spectrum, enhance spectrum utilization, and maintain the quality of service of PUs by sensing before transmission [8], [9].

SS has been extensively researched due to its critical nature. Energy detection (ED) [10], [11], matched-filter detection [12], [13], and cyclostationary feature detection [14] are examples of local sensing techniques. Every strategy has trade-offs of its own. Since it doesn't require prior knowledge of the PU waveform, ED is attractive for low-complexity implementations. However, it is susceptible to noise uncertainty and frequently performs poorly at low SNR, which is typical in fading channels. By using periodic statistical structure, cyclostationary techniques can be more resilient to noise and interference, but usually at the cost of longer observation windows and higher computational costs. Although it relies on precise knowledge of the PU signal, which may be unobtainable or unreliable in real-world implementations, matched filtering is optimal under ideal circumstances [15].

Multipath fading, shadowing, interference, hardware impairments, and heterogeneous signal conditions all make sensing

more difficult in practice. Furthermore, the true occupancy state may be obscured by deep fades or hidden-terminal effects on a single sensing node. Sensing strategies that are still effective in imperfect and time-varying environments are motivated by these factors.

Recent research is looking more and more into deep learning (DL) and artificial intelligence (AI) as data-driven SS substitutes in an effort to address these issues. Such models can capture non-linear effects, adjust to changing conditions, and lessen sensitivity to noise uncertainty through learned representations by directly learning decision rules from observations. In order to improve PU detection accuracy, particularly in low-SNR regimes where CR systems must meet strict detection requirements, AI-enabled sensing frameworks are being actively investigated.

CR is a way to use the radio spectrum more efficiently. This is done by allowing devices to dynamically access the spectrum. CR devices can check what is happening on the spectrum see if anyone is using it and then change how they send signals based on what's going on around them. This is very different from the way of doing things, where a specific frequency band is given to a particular service and that is it. In the future when we need spectrum and it is still hard to get CR will be really helpful. CR will let devices adjust to the radio conditions around them which's a big improvement. CR is going to be very important, for networks, where CR devices will be able to use the spectrum in a more flexible way.

There are typically two kinds of users, in a CR network. PUs have the right to use a band because they are licensed to do so. SUs on the hand can use that band if it is not being used by PUs [16]. The protection of users is very important which means that SUs transmissions should not interfere with the communications of PUs. Detecting the activity of users accurately is crucial because it affects how efficiently the spectrum is used and how much interference is avoided. As a result SS becomes a part of how CR operates [17].

Three paradigms—interweave, underlay, and overlay—are frequently used to structure practical CR systems from an access-policy standpoint. SUs only transmit in spectrum holes, or time-frequency intervals devoid of PU activity, when using the interweave approach. Due to the possibility of interference at the PU receiver from missed detections, this paradigm is highly dependent on sensing reliability. As long as SUs' transmit power stays below a predetermined interference threshold—typically requiring power control and explicit interference constraints—they are permitted to transmit concurrently with the PU in the underlay paradigm. In contrast, more complex processing is used in overlay techniques, where SUs may support PU transmissions or use sophisticated coding techniques to preserve PU performance while still gaining access to the band.

Because of its close alignment with sensing-driven architectures and relatively low implementation complexity, interweave CR is still one of these paradigms that is widely used. Interweave operation, however, necessitates extremely reliable sensing choices, especially in fading and low-SNR scenarios where the PU signal may be significantly reduced. Thus, a key area of research in CR networks is the development of strong SS techniques that control false alarms while maintaining a high probability of detection.

CR is an intelligent wireless-communication framework that seeks to improve spectrum efficiency by enabling dynamic spectrum access. The ability to monitor the radio environment, use sensing results to determine spectrum availability, and adjust operating parameters appropriately are the typical characteristics of a CR terminal. A cognitive cycle comprising four fundamental functions—SS, spectrum decision, spectrum sharing, and spectrum mobility—is frequently used to explain CR operation.

1) Spectrum sensing: SS is a central component of CR systems, allowing SUs to determine whether PUs are active within a target band [15]. Whether or not SUs have access to transmission opportunities is directly indicated by the sensing result. To prevent detrimental interference to licensed links, particularly in the presence of low SNR, fading, shadowing, and noise-uncertainty effects, high sensing reliability is necessary.

2) Spectrum decision: Following the identification of potential spectrum resources, the CR chooses the best band for communication while taking quality-of-service (QoS) requirements and existing channel conditions into consideration [18]. Metrics like SNR, interference level, available bandwidth, and an estimation of how long the band is expected to be available may all be taken into account when making the decision. The goal of this step is to facilitate effective SU communication without sacrificing PU security.

3) Spectrum sharing: Spectrum sharing refers to the set of procedures that coordinate how multiple SUs access the available spectrum [19]. Channel allocation, transmit-power control, scheduling, and, when appropriate, cooperative sensing are examples of resource-management techniques that are commonly included. Good sharing techniques keep interference toward PUs within reasonable bounds while increasing SU fairness and lowering mutual interference.

4) Spectrum mobility: When PU activity returns or link quality deteriorates, spectrum mobility, also referred to as spectrum handoff, allows an SU to switch to a different operating band [20]. When you quickly switch SU transmissions to another channel this function helps keep the service going without any breaks. Spectrum mobility is really important in situations where the spectrum occupancy changes over time because it helps you keep using the service without any problems. Spectrum mobility is very useful, in these situations so you can keep using the SU transmissions.

These functions make CR networks work well and help use the spectrum better. To make them work properly we need to be able to sense things accurately and make good decisions. This is why we need to create ways of learning and detecting things that are strong and reliable, for CR networks. CR networks need these learning-based SS techniques and robust detection methods to perform well.

In this work, we investigate SS for CR networks and propose

a framework to improve detection performance under varying SNR conditions. The main contributions and the adopted methodology can be summarized as follows:

- We generate BPSK-modulated signals corrupted by additive white Gaussian noise (AWGN) in order to emulate realistic and controllable sensing scenarios.
- We perform SS using ED under two thresholding strategies:
  - a *static threshold* setting, representing the conventional ED approach,
  - a *dynamic threshold* setting, where the detection threshold is adaptively adjusted according to the SNR to improve robustness.
- We also investigate a DL-based sensing alternative by employing a Long Short-Term Memory (LSTM) network, enabling temporal feature learning from sensing observations.
- Finally, we compare the detection performance of the proposed ED strategies and the LSTM-based model across different SNR regimes, highlighting the strengths and limitations of each approach.

The remainder of this paper is organized as follows. Section II presents the related work. Section III describes the adopted methodology. Section IV reports and discusses the obtained results. Finally, Section V concludes the paper.

TABLE I
LIST OF ACRONYMS

Acronym	Definition
AI	Artificial Intelligence
ANN	Artificial Neural Network
AWGN	Additive White Gaussian Noise
CFO	Carrier Frequency Offset
CR	Cognitive Radio
DL	Deep Learning
ED	Energy Detection
IoT	Internet of Things
LSTM	Long Short-Term Memory
ML	Machine Learning
OFDM	Orthogonal Frequency Division Multiplexing
OSA	Opportunistic Spectrum Access
PU	Primary User
QoS	Quality of Service
RNN	Recurrent Neural Network
SNR	Signal-to-Noise Ratio
SS	Spectrum Sensing
SU	Secondary User

II. RELATED WORK

With the recent adoption of machine learning (ML) and DL, SS for CR networks has made significant progress, particularly in difficult scenarios where classical detectors struggle with fading, noise uncertainty, and non-stationary traffic patterns. In early ML-driven approaches, SS was typically formulated as a supervised classification problem. For instance, Shah and Koo [21] used KNN to detect PU activity and improved reliability at a fusion center by fusing cooperative sensing with majority-vote fusion. Tian *et al.* [22] introduced a learning-aided sensing method for OFDM for multicarrier signals that outperforms conventional energy detection (ED), particularly in low-SNR scenarios, by utilizing OFDM-specific features. Cooperative SS has also been enhanced through probabilistic fusion strategies. Lu *et al.* [23] employed probability vectors to support fusion decisions in the presence of channel fluctuations and sensing uncertainty. Similarly, Vyas *et al.* [24] and Tang *et al.* [25] studied ANN-based SS, including hybrid schemes that use conventional sensing statistics to improve robustness against fading and noise uncertainty.

Recent studies have used complex systems and better ways to understand things to make sensing more accurate. Nasser *et al.* [26] proposed a model that uses a type of neural network and combines many sensing features to work better when the signal is very weak. This new model is really good, at detecting things when the signal to noise ratio is very low. Beyond the sensing task itself, Ahmed *et al.* [27] employed DL for intelligent spectrum utilization by introducing a learning-driven opportunistic spectrum access framework for cognitive 5G and beyond-5G networks. Temporal correlation in PU activity has also been exploited using recurrent models. for instance, Soni *et al.* [28] applied LSTM networks to capture primary activity statistics and improve sensing reliability in dynamic traffic scenarios.

In addition, several works have explored DL-based SS using different feature spaces and network designs. Du *et al.* [29] combined information geometry with DL in a centralized cooperative SS framework (IG-DNN): covariance matrices computed from sensing observations are mapped to a Riemannian manifold, geodesic distances are extracted as features, and an MLP is trained to decide PU presence; with a fixed P_{FA}, they reported improved sensing performance as the number of cooperating SUs increases and as the SNR becomes higher. Gao *et al.* [30] addressed the SNR-wall limitation of ED under noise uncertainty by exploiting the structure of modulated signals using DL, without requiring prior knowledge of channel state information or background-noise statistics; their dataset considers eight modulation schemes {BPSK, QPSK, 8PSK, CPFSK, QAM16, QAM64, GFSK, PAM4} with CSCG noise as the negative class, and they further analyzed the impact of modulation type and sample length as well as extensions to cooperative sensing. Solanki *et al.* [31] proposed DLSenseNet, which operates on complex baseband I/Q samples and uses energy normalization to improve robustness under varying noise conditions; evaluated on RadioML2016.10b (SNR from -20 dB to $+18$ dB), their model was compared with several DL architectures (e.g., CNN, LSTM, CLDNN, ResNet, Inception, and DetectNet) using standard metrics such as P_D and P_{FA}. Xing *et al.* [32] designed a time-series DL model combining 1D-CNN feature extraction, BiLSTM temporal modeling, and a self-attention mechanism to emphasize informative samples, reporting reduced missed-detection and false-alarm probabilities—particularly at low SNR—while also studying the influence of modulation schemes and sample length. Finally, Cheng *et al.* [33] focused on OFDM signal sensing under practical impairments (noise uncertainty, timing delay, and carrier-frequency offset) and proposed stacked-

autoencoder (SAE) based schemes, namely SAE-SS and SAE-TF; by learning hidden representations directly from received samples (and from joint time–frequency representations in SAE-TF), they achieved higher sensing accuracy than state-of-the-art OFDM sensing techniques without relying on explicit OFDM-specific structures such as pilot tones or cyclic prefix.

The evaluation of our detector is based on three key metrics: The probability of detection, the probability of false alarm, and the probability of non-detection. The probability of detection corresponds to the probability that a SU will correctly identify the presence of the PU when the channel is actually occupied by a licensed user. On the other hand, the probability of false alarm represents the probability that the SU will wrongly detect the presence of the PU when the channel is actually free. Finally, the probability of non-detection means the detector is unable to identify that the PU is using the band. False alarms make the spectrum efficient and missing detections causes interference, with the PU. So it is very important to make the detector work well. The goal is to detect much as possible and reduce false alarms so the spectrum is used efficiently and interference is limited.

III. Methodology

This section details the proposed SS methodology in CR networks. The considered sensing task is formulated as a binary hypothesis testing problem, where the receiver decides whether the PU signal is absent or present in a given observation window. We generate BPSK signals impaired by additive white Gaussian noise (AWGN) to emulate controlled sensing conditions across a wide SNR range. SS is first performed using classical ED with both static and SNR-adaptive thresholds. In addition, an LSTM-based detector is trained on received sample sequences to provide a data-driven baseline for comparison. Performance is evaluated using the probability of detection P_D, the probability of false alarm P_{FA}, and the probability of miss P_M.

A. Binary Hypothesis Test Formulation

Let $r[k]$, $k = 1, \ldots, L$, denote the received discrete-time samples collected over a sensing window of length L. The SS decision is cast as:

$$\begin{aligned} &\mathcal{H}_0 : r[k] = w[k], \\ &\mathcal{H}_1 : r[k] = s[k] + w[k], \end{aligned} \quad k = 1, 2, \ldots, L, \tag{1}$$

where $s[k]$ is the PU signal (BPSK waveform in this work), and $w[k] \sim \mathcal{N}(0, \sigma^2)$ is AWGN with variance σ^2. The goal is to decide between $\mathcal{H}_0$ (idle band) and $\mathcal{H}_1$ (occupied band) while controlling false alarms and maximizing detection.

B. Signal Generation: BPSK Model

A binary sequence $\{b_i\}_{i=1}^{n}$, $b_i \in \{0, 1\}$, is randomly generated and mapped to BPSK symbols $x_i \in \{-1, +1\}$ as

$$x_i = 2b_i - 1, \quad i = 1, 2, \ldots, n. \tag{2}$$

Each symbol is repeated over T_{sym} samples, yielding the discrete-time transmitted sequence

$$s[k] = x_i, \quad k \in [(i-1)T_{\text{sym}} + 1,\ iT_{\text{sym}}], \tag{3}$$

with total samples $L = nT_{\text{sym}}$.

C. AWGN Addition and SNR Control

For a target SNR_{dB}, the linear SNR is

$$\text{SNR} = 10^{\text{SNR}_{\text{dB}}/10}. \tag{4}$$

Assuming average symbol energy E_{sym}, the noise variance is set to

$$\sigma^2 = \frac{E_{\text{sym}}}{\text{SNR}}. \tag{5}$$

The received signal is then generated according to (1). We sweep $\text{SNR}_{\text{dB}} \in [-20, 20]$ dB to evaluate detector robustness under very low to high SNR conditions.

D. Energy Detection (ED)

ED decides on PU presence by comparing the energy of the received samples to a threshold. The ED test statistic is

$$\Lambda(r) = \sum_{k=1}^{L} |r[k]|^2. \tag{6}$$

The decision rule is

$$\Lambda(r) \begin{cases} < \gamma, & \mathcal{H}_0, \\ \geq \gamma, & \mathcal{H}_1, \end{cases} \tag{7}$$

where γ is the decision threshold.

1) Distribution of the ED Statistic: Under $\mathcal{H}_0$, $r[k] = w[k]$, and the statistic Λ follows a scaled chi-square distribution. Under $\mathcal{H}_1$, it becomes non-central due to the signal component. In practice, for sufficiently large L, Λ can be approximated as Gaussian (by the central limit theorem), which yields tractable expressions for P_{FA} and P_D.

Let μ_0, σ_0^2 and μ_1, σ_1^2 denote the mean and variance of Λ under $\mathcal{H}_0$ and $\mathcal{H}_1$, respectively. Using standard ED approximations, we write:

$$P_{FA} = \Pr(\Lambda \geq \gamma \mid \mathcal{H}_0) \approx Q\left(\frac{\gamma - \mu_0}{\sigma_0}\right), \tag{8}$$

$$P_D = \Pr(\Lambda \geq \gamma \mid \mathcal{H}_1) \approx Q\left(\frac{\gamma - \mu_1}{\sigma_1}\right), \tag{9}$$

and

$$P_M = 1 - P_D. \tag{10}$$

The Q-function is

$$Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^{\infty} e^{-t^2/2}\, dt. \tag{11}$$

E. Thresholding Strategies

The choice of γ governs the trade-off between false alarms and missed detections. We consider two strategies.

1) Static Threshold (Fixed P_{FA}): In the static setting, the threshold is computed to satisfy a predefined constant false alarm probability P_{Fs}. From (8), the threshold can be written as

$$\gamma_{\text{static}} = \mu_0 + \sigma_0\, Q^{-1}(P_{\text{Fs}}), \tag{12}$$

where $Q^{-1}(\cdot)$ is the inverse Q-function. This yields a constant operating point across all experiments.

2) Dynamic Threshold (Adaptive P_{FA} or Adaptive Noise): In the dynamic setting, γ is updated to reflect changes in operating conditions (e.g., estimated noise level, SNR regime, or target false alarm constraint). A general form consistent with (8) is

$$\gamma_{\text{dynamic}} = \mu_0(\widehat{\sigma}^2, \text{SNR}) + \sigma_0(\widehat{\sigma}^2, \text{SNR})\, Q^{-1}(P_{FA}), \quad (13)$$

where $\widehat{\sigma}^2$ denotes a noise variance estimate and P_{FA} may be adjusted depending on the real-time sensing requirement. This strategy aims to preserve robustness when the noise floor or SNR varies.

F. LSTM-Based Spectrum Sensing

To compare model-driven ED with a data-driven approach, we train an LSTM network to classify the received observation window into $\mathcal{H}_0$ (PU absent) or $\mathcal{H}_1$ (PU present). The LSTM processes the received sample sequence $\{r[k]\}_{k=1}^{L}$ (or a framed version of it) and produces a binary output through a final dense layer with a sigmoid/softmax activation [34].

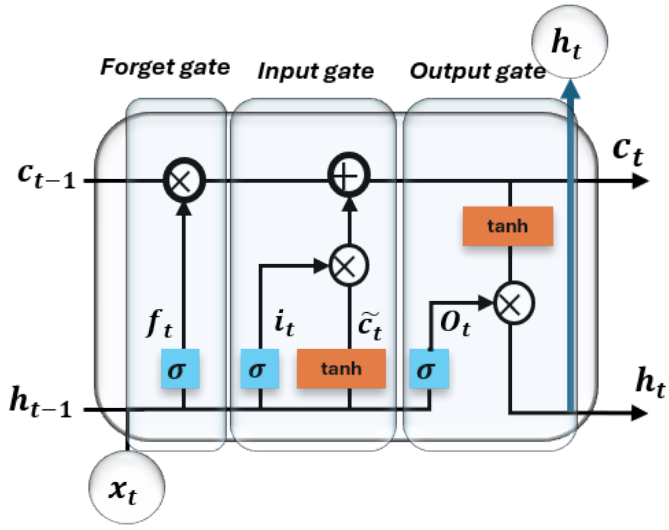

Fig. 1. LSTM Architecture for Robust Detection of BPSK Signals in Noisy Environments.

Let $\mathbf{x}_t \in \mathbb{R}^d$ denote the input vector at time step t, obtained from the received samples (e.g., $\mathbf{x}_t = r[t]$ for sample-wise input, or a short frame of samples). The LSTM updates its internal states using three gating mechanisms: the forget gate f_t, the input gate i_t, and the output gate o_t. These gates are defined as:

$$\mathbf{f}_t = \sigma\left(\mathbf{W}_f \mathbf{x}_t + \mathbf{U}_f \mathbf{h}_{t-1} + \mathbf{b}_f\right), \quad (14)$$

$$\mathbf{i}_t = \sigma\left(\mathbf{W}_i \mathbf{x}_t + \mathbf{U}_i \mathbf{h}_{t-1} + \mathbf{b}_i\right), \quad (15)$$

$$\mathbf{o}_t = \sigma\left(\mathbf{W}_o \mathbf{x}_t + \mathbf{U}_o \mathbf{h}_{t-1} + \mathbf{b}_o\right), \quad (16)$$

where $\sigma(\cdot)$ is the sigmoid activation function, $\mathbf{h}_{t-1}$ is the previous hidden state, and $\mathbf{W}.$, $\mathbf{U}.$, and $\mathbf{b}.$ denote the trainable weight matrices and bias vectors.

The candidate cell state $\tilde{\mathbf{c}}_t$ is computed as:

$$\tilde{\mathbf{c}}_t = \tanh\left(\mathbf{W}_c \mathbf{x}_t + \mathbf{U}_c \mathbf{h}_{t-1} + \mathbf{b}_c\right), \quad (17)$$

where $\tanh(\cdot)$ is the hyperbolic tangent activation function. The memory cell state $\mathbf{c}_t$ is then updated by combining the previous memory content and the new candidate information:

$$\mathbf{c}_t = \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \tilde{\mathbf{c}}_t, \quad (18)$$

where $\odot$ denotes element-wise multiplication.

Finally, the hidden state $\mathbf{h}_t$ is obtained as:

$$\mathbf{h}_t = \mathbf{o}_t \odot \tanh(\mathbf{c}_t). \quad (19)$$

As illustrated in Fig. 1, the forget gate $\mathbf{f}_t$ filters irrelevant temporal information, while the input gate $\mathbf{i}_t$ and candidate state $\tilde{\mathbf{c}}_t$ capture new signal-related patterns. The memory cell $\mathbf{c}_t$ accumulates relevant evidence over time, and the output gate $\mathbf{o}_t$ controls the hidden representation $\mathbf{h}_t$, which is used for final classification.

To obtain the sensing decision, the last hidden state (or a pooled representation over time) is fed to a fully connected layer:

$$\hat{y} = \sigma\left(\mathbf{w}^\top \mathbf{h}_T + b\right), \quad (20)$$

where T denotes the final time step, $\hat{y} \in [0, 1]$ represents the predicted probability of $\mathcal{H}_1$, and $\mathbf{w}$, b are trainable parameters. The final decision is given by:

$$\hat{y} \begin{cases} < \tau, & \mathcal{H}_0, \\ \geq \tau, & \mathcal{H}_1, \end{cases} \quad (21)$$

where τ is a decision threshold. The proposed LSTM-based detector is implemented as a sequence classifier. The network takes a univariate input sequence through a `sequenceInputLayer`(1), followed by a single `lstmLayer` with 50 hidden units and `OutputMode` set to `last`. The resulting representation is passed to a `fullyConnectedLayer`(2) and a `softmaxLayer`, and the final decision is produced by a `classificationLayer` (two classes: $\mathcal{H}_0$ and $\mathcal{H}_1$). The model is trained using the Adam optimizer for 10 epochs with a mini-batch size of 64. The dataset is split into 80% for training and 20% for testing using a hold-out partition. For clarity and reproducibility, the adopted hyperparameter configuration is reported in Table II.

TABLE II
LSTM MODEL AND TRAINING CONFIGURATION

Item	Setting
Input layer	`sequenceInputLayer`(1)
LSTM layer	50 units, `OutputMode=last`
Classifier head	FC(2) + Softmax
Loss / output	`classificationLayer`
Optimizer	Adam
Epochs	10
Mini-batch size	64
Train/Test split	80% / 20% (hold-out)

G. Performance Metrics

The performance of the SS algorithm is evaluated using the following metrics:

- **Probability of Detection** (P_D): The probability that the algorithm correctly detects the presence of a signal.

- **Probability of False Alarm** (P_{FA}): The probability that the algorithm incorrectly detects a signal when none is present.
- **Probability of Miss** (P_M): The probability that the algorithm fails to detect a signal when it is present.

The four possible detection outcomes are:

1) True Negative (H_0/H_0) – correctly detecting absence.
2) True Positive (H_1/H_1) – correctly detecting presence.
3) Missed Detection (H_0/H_1) – failing to detect a signal.
4) False Alarm (H_1/H_0) – detecting a signal when absent.

These metrics are calculated as:

$$P_D = \frac{\text{Number of correct detections}}{\text{Total number of trials}}, \tag{22}$$

$$P_{FA} = \frac{\text{Number of false alarms}}{\text{Total number of trials}}, \tag{23}$$

$$P_M = 1 - P_D. \tag{24}$$

The overall sensing procedure is summarized in Algorithm 1.

Algorithm 1 Proposed Spectrum Sensing Framework

Generate a BPSK signal $s[k]$ and noise $w[k] \sim \mathcal{N}(0, \sigma^2)$
Form received samples: $r[k] = s[k] + w[k]$
Compute the ED statistic: $\Lambda = \sum_{k=1}^{L} |r[k]|^2$
Compute the decision threshold γ:
if static threshold **then**
    $\gamma \leftarrow \gamma_{\text{static}}$
else
    $\gamma \leftarrow \gamma_{\text{dynamic}}$
end if
Decide PU activity using $\Lambda \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \gamma$
Train/test the LSTM on $\{r[k]\}$ sequences and output $\hat{y}$
Evaluate P_D, P_{FA}, and P_M across SNR values

IV. Results and Discussion

In this section, we benchmark two ED configurations (fixed versus adaptive thresholding) and then contrast them with the proposed LSTM-based detector over the considered SNR range. The comparison is shown through P_D, P_{FA} and P_M, which together describe how detection and false alarms balance each other. Of just showing curves the analysis looks at two main things: how choosing a different threshold changes the ED operating point when noise levels change and how much a sequence model that uses temporal structure can reduce the gap seen at low SNR.

A. Results

1) Threshold influence on metrics: To understand the performance of energy detection (ED) under different conditions, it is imperative to understand the role of decision thresholds. The performance of ED in terms of reliability is significantly affected by the decision thresholds, especially in low signal-to-noise ratio (SNR). Generally, improper selection of thresholds can cause more false alarms or missed detection. Keeping this in view, this study focuses on static and dynamic thresholding techniques. Although static thresholds are simple and easy to employ, this technique might not be efficient in dealing with situations where signal or noise conditions change. On the other hand, dynamic thresholds might be more efficient in terms of performance. The impact of static and dynamic thresholds on different performance parameters, such as probability of detection (P_D) and probability of miss detection (P_M), is discussed in this study. The advantages and limitations of each technique are discussed, which helps in choosing the most efficient techniques for SS.

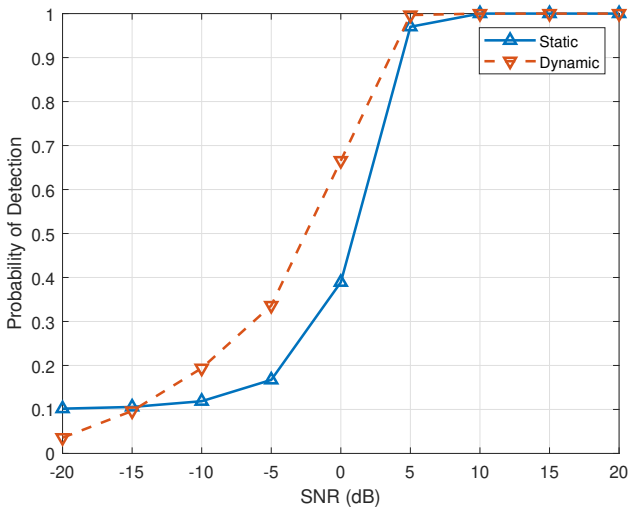

Fig. 2. Probability of detection vs. SNR

Figure 2 shows us how using a threshold makes a big difference in finding signals. It really helps when the signal is very weak. This figure clearly shows that dynamic thresholds are better than thresholds. We can see that dynamic thresholds work well and can find signals more accurately than static thresholds. The dynamic threshold is also very good, at adjusting to levels of noise. This means it can find PU signals when things are tough.

Figure 3 shows how dynamic thresholding is better at reducing the chances of alarms. The static threshold gives the performance across different signal to noise ratios but it is not that great. On the hand the dynamic threshold works really well especially when the signal to noise ratio is high resulting in fewer false alarms. This means dynamic thresholding is good at telling the difference, between noise and real signals.

Figure 4 explicitly compares dynamic and static thresholds in terms of the probability of non-detection, particularly emphasizing scenarios with challenging, low-SNR conditions. The results clearly indicate that the dynamic threshold approach significantly reduces the probability of non-

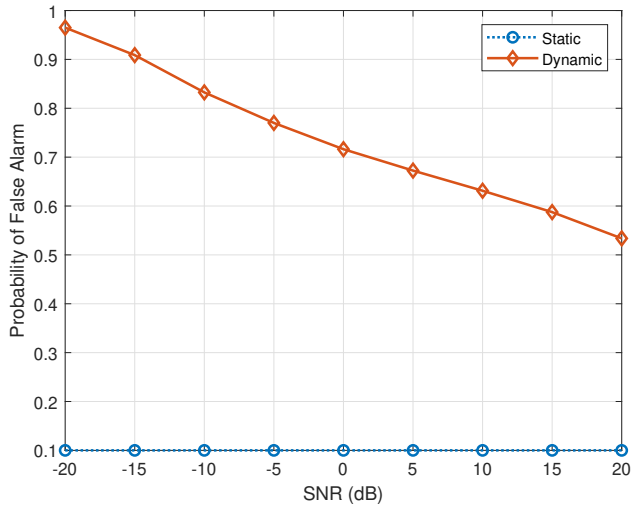

Fig. 3. Probability of False Alarm vs. SNR

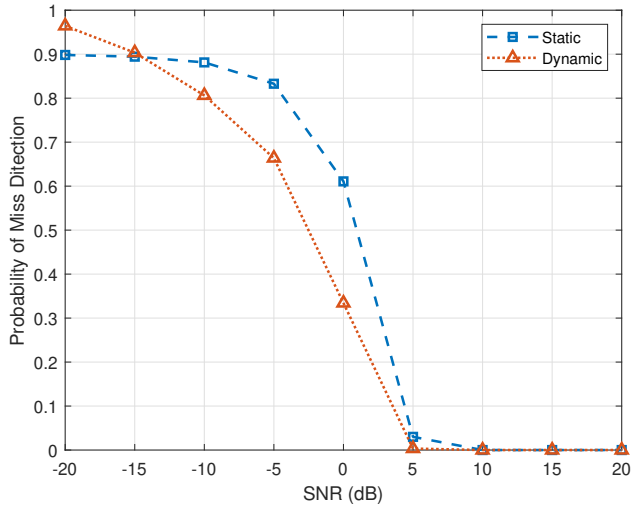

Fig. 4. Probability of non-detection vs. SNR

detection compared to the static threshold. This improvement underscores the ability of the dynamic threshold to adapt effectively to varying noise conditions, ensuring better reliability in SS and minimizing missed detections, thus safeguarding PU transmissions more efficiently.

2) Performance of Energy Detection and LSTM Model: This section presents a comparative analysis between the traditional ED technique and the LSTM model under varying signal-to-noise ratio (SNR) conditions. While ED demonstrates reasonable performance at moderate SNR levels, its effectiveness deteriorates significantly in low SNR environments due to its limited ability to distinguish weak signals from noise. In contrast, the LSTM model leverages temporal dependencies within the input sequences, enabling it to achieve higher detection accuracy and improved robustness, particularly under challenging noise conditions. This comparison highlights the potential of DL approaches for enhanced SS in dynamic wireless environments.

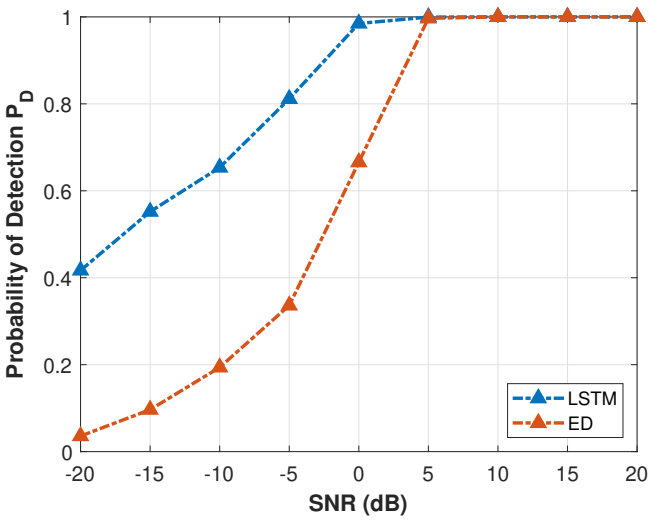

Fig. 5. Probability of detection (P_d) vs. SNR

As illustrated in Figures 5 and 6, the LSTM model demonstrates a significantly higher probability of detection (P_d) and a lower probability of miss (P_m) compared to the ED method. This highlights the LSTM's superior capability to detect signals and reduce missed detections, particularly in low SNR environments, where conventional methods like ED struggle.

The LSTM effectively learns temporal dependencies in the input signal, enabling it to distinguish weak signal patterns from background noise. Its recurrent structure allows it to maintain memory of past signal characteristics, which enhances its robustness in noisy and dynamic environments.

The conclusions of the study show the advantages using the proposed method of SS with LSTM compared to traditional ED methods. Even with dynamic thresholding, the ED technique is less effective because disable lower bound triggers and raises false alarms; still, the LSTM model yields the highest detection and lowest misses at every SNR level. This is due to temporal dependencies being captured and complex patterns learned through the data which enables accurate discrimination between identifying noise and signals even within low-SNR settings. Despite the computational simplicity and ease of ED, the shortcomings of noisy environments further validate the need for datadriven models like LSTM. In general, the change from static threshold template matching to learning-based recognition offers better versatility and precision for CR spectrum sensing.

To complement the previously reported results, we further evaluated the considered recurrent models under flat Rayleigh fading conditions in order to assess their robustness in a more realistic wireless propagation environment.

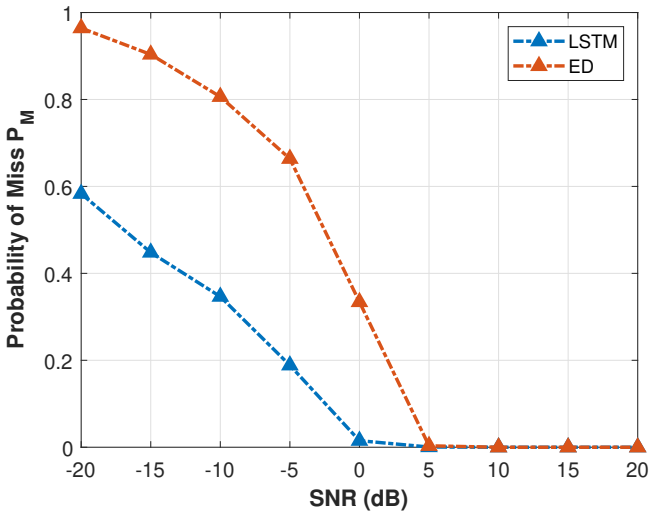

Fig. 6. Probability of non-detection (P_M) vs. SNR

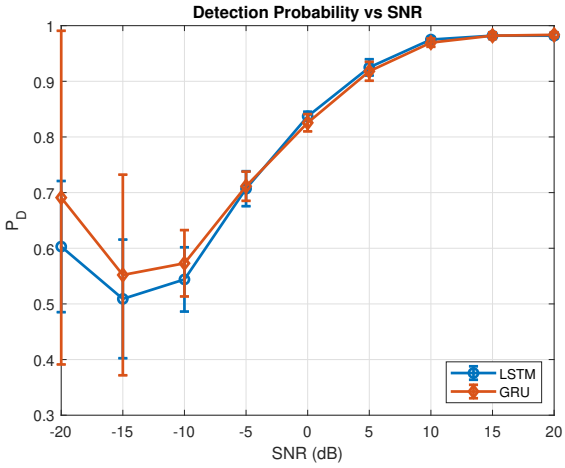

Fig. 7. Probability of detection versus SNR for the LSTM and GRU models under flat Rayleigh fading. The error bars represent the 95% confidence intervals over multiple runs.

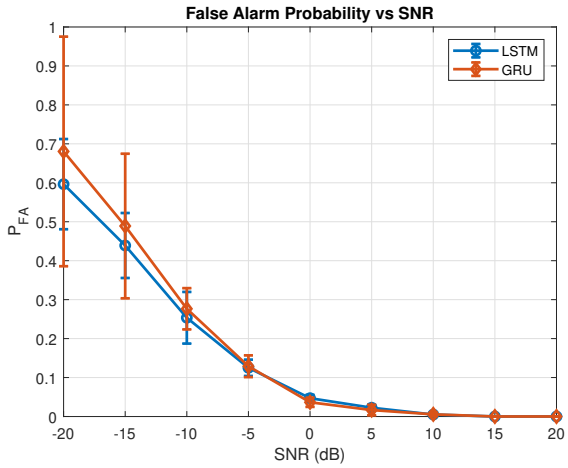

Fig. 8. Probability of false alarm versus SNR for the LSTM and GRU models under flat Rayleigh fading. The error bars correspond to the 95% confidence intervals over multiple runs.

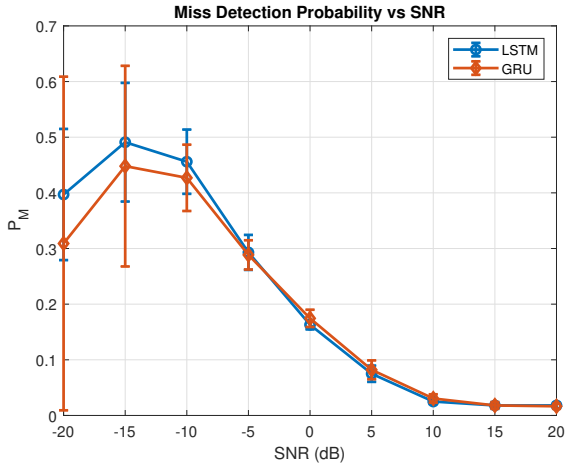

Fig. 9. Probability of miss detection versus SNR for the LSTM and GRU models under flat Rayleigh fading. The error bars indicate the 95% confidence intervals over multiple runs.

In this additional experiment, the transmitted BPSK signal was affected by both additive white Gaussian noise and flat Rayleigh fading. This complementary evaluation was introduced to examine the behavior of the LSTM and GRU models in the presence of random channel amplitude fluctuations, which better reflect practical wireless propagation conditions.

Fig. 7 shows the probability of detection as a function of SNR under Rayleigh fading. It can be observed that the detection probability increases steadily with SNR for both recurrent architectures. At very low SNR values, the detection performance remains limited due to the combined impact of severe noise and fading. In addition, the confidence intervals are wider in this region, indicating a larger variability across independent runs. As the SNR increases, both models become progressively more stable and achieve high detection probabilities.

The false alarm probability under Rayleigh fading is depicted in Fig. 8. At low SNR values, both models exhibit relatively high false alarm rates, reflecting the difficulty of distinguishing weak signal samples from noise under strongly degraded conditions. However, as the SNR increases, P_{FA} decreases significantly, which indicates an improved separation between the two hypotheses.

Fig. 9 reports the miss detection probability as a function of SNR. A clear decreasing trend is observed for both models, which is fully consistent with the corresponding increase in detection probability. At low SNR values, the miss detection probability remains relatively high, while it becomes very small at medium and high SNR values.

To further analyze the discrimination capability of the considered recurrent models, Fig. 10 presents the AUC values across the considered SNR range. At very low SNR

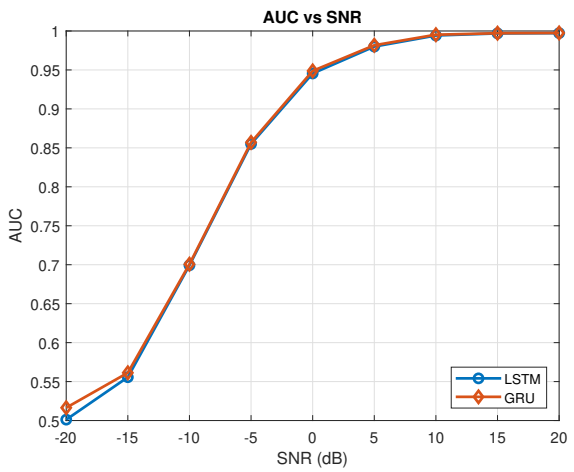

Fig. 10. AUC versus SNR for the LSTM and GRU models under flat Rayleigh fading.

values, the AUC remains close to 0.5, indicating limited separability between signal-present and noise-only samples in highly degraded conditions. As the SNR increases, the AUC rises progressively and approaches unity, confirming that both models become increasingly effective in distinguishing the two hypotheses.

Overall, these additional results confirm that both recurrent architectures preserve the expected performance trends under Rayleigh fading conditions. The probability of detection increases with SNR, whereas the false alarm and miss detection probabilities decrease accordingly. Moreover, the AUC results show that the separability between the two classes remains limited at very low SNR values but becomes excellent at moderate and high SNR levels. It is also observed that the LSTM and GRU models provide very similar performance over the entire SNR range. No substantial performance gap is noted in terms of P_D, P_{FA}, P_M, or AUC. Nevertheless, the GRU remains slightly more attractive from a computational perspective due to its lower training and inference complexity. These complementary results further support the suitability of recurrent neural-network-based spectrum sensing under more realistic fading channel conditions.

B. Limitations and Future Work

Although the experimental evaluation was extended under flat Rayleigh fading conditions, the present study still relies on synthetically generated data and a single modulation format, namely BPSK. This controlled setting is useful for analyzing the proposed framework, but it does not fully reflect the diversity of practical wireless environments. Future work will therefore focus on extending the evaluation to more diverse signal conditions, including additional modulation schemes, more complex channel models, and more realistic spectrum sensing scenarios.

V. Conclusion

To improve spectrum utilization efficiency, CR enables SUs to opportunistically access underutilized spectrum resources while avoiding harmful interference to PUs. Due to its simplicity and low computational complexity, ED was first investigated in this work. To better cope with fluctuating SNR conditions, its performance was enhanced through dynamic thresholding. Although this adaptation improves the detection capability, ED still shows clear limitations in very noisy environments, where the detection of weak signals remains difficult. To further address this issue, recurrent deep learning models were investigated for SS. The obtained results show that both LSTM- and GRU-based models provide robust and accurate detection performance, with clear improvements as the SNR increases. In addition, the extended evaluation under flat Rayleigh fading confirms that these recurrent architectures remain effective under more realistic channel conditions. Overall, the results highlight the potential of recurrent neural networks as promising tools for more intelligent and adaptive spectrum sensing in cognitive radio systems.

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