A PYTHON-BASED FRAMEWORK FOR ADVANCED RESEARCH AND DEVELOPMENT ON SPECTRUM SENSING FOR COGNITIVE RADIO

George GROSU, Romulus TEREBEȘ
Technical University of Cluj-Napoca, Communications Department, Cluj-Napoca, Romania
George.Grosu@com.utcluj.ro; Romulus.Terebes@com.utcluj.ro

Abstract: The work of this paper is addressing the issue of narrowband spectrum sensing (SS) applications for cognitive radio networks assuming the OFDM signal over noisy and various fading channels with focus on the development of an open-source simulation and development software. The paper also proposes a residual and recurrent convolutional Neural Network (NN)-based method for spectrum sensing. This method is compared with a baseline energy detection (ED) approach. Detection performance of the models is analysed given various Signal-to-Noise Ratio (SNR) values using three-base scenarios. First two scenarios correspond to an additive white gaussian noise (AWGN) channel respectively Rayleigh flat fading channel and the third one corresponds to the frequency-selective Rayleigh fading channel since the SNR value and fading can affect drastically the detection performance in terms of false positives/false negatives leading to erroneous estimators. The experimental results are analysed through the receiver operating characteristics (ROC) plot containing the curves for both ED models enhanced by the denoising methods. On average, the classic ED algorithm with dynamic threshold outperforms the NN-based model, especially in low SNR domains. The NN-based model trained on constrained, tailored dataset characteristics outperforms the classic ED model in scenarios described by the corresponding characteristics.

Keywords: *Cognitive Radio, Energy Detection, Neural Network, Time Series, Spectrum Sensing, Wavelet.*

I. INTRODUCTION

The technology of the wireless communication systems relies on the exploitation of the radio frequency spectrum, which is a physical, naturally limited resource. The entire frequency spectrum is delimited in distinct bands and sub-bands, each presenting technological difficulties to a different degree to develop an efficient communication system in accordance with applications requirements due to channel properties of the resulted fragmented radio resources, making domains of the spectrum more appealing and recommended for different communication applications. Given these aspects the radio spectrum is highly regulated by static allocation policies on long-term and relatively wide geographical areas. Technological advances from last decades, increasing number of communication and wireless devices and increasing demands for high data rates rapidly increase the requirements for greater spectrum availability leading to the issue of *spectrum scarcity.*

To these days the problem of efficient and intelligent spectral resource management presents difficulties when it comes to spectrum allocation in such a manner to avoid interference, reduce allocation time by identifying the available resources and detecting primary signals in a reasonable time thereafter performing the computation tasks in as fast and as accurate manner as possible. Spectrum sensing along with other coupled subjects are the topics intended to solve such aspects leading to the concept of cognitive radio. To emphasize on the limitations given by the current methods and the migration to higher frequencies, there are difficulties for the available hardware to efficiently work with limited power in the superior frequency spectrum as the digital signal processing applications must operate with higher sampling rate to satisfy reasonable processing time and so for the applications to be practical and beneficial. This last drawback is one of greatest among them, as even the spectrum sensing solutions must find a way to overcome it. Reliable spectrum sensing aims to enhance radio resource management through which users, primary or secondary, can safely occupy or evacuate the spectrum bands. The main scope of spectrum sensing in cognitive radio networks is to "intelligently" increase usage efficiency of radio resources in such way that higher number of users can access the medium at any given moment with minimized chances of interfering with each other. A brief illustration of the concept of spectrum scarcity and narrowband/wideband sensing is shown in Figure 1.

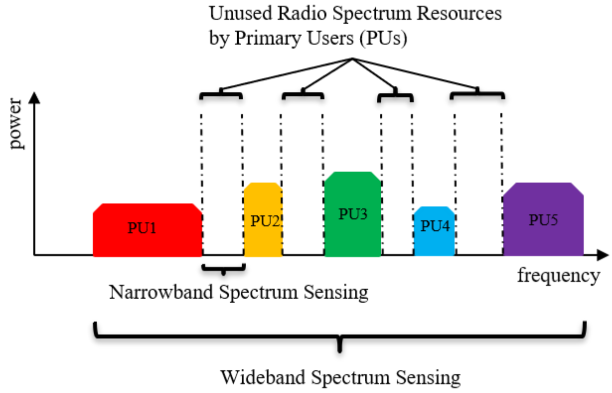

Figure 1. Illustration of spectrum scarcity given by the gaps representing available, yet not accessible radio resources, and the two paradigms of spectrum sensing.

The scope of this paper is to develop, analyse and

Manuscript received July 23, 2021; revised November 29, 2021

compare the performance of two spectrum sensing models in terms of simulation of time series data under noisy and fading channel conditions with wavelet denoising technique resulted by employing a dedicated Python-based framework. The first model is based on a classical energy detection algorithm with adaptive threshold and the second model is a proposed solution based on a Deep Learning (DL) algorithm composed of a residual recurrent and convolutional NN. The channel models considered for this paper are as follows: firstly, the AWGN channel, secondly the Rayleigh Flat fading channel, and lastly the Rayleigh Frequency Selective fading channel. The structure of this paper is as follows: in Section II are briefly described the latest advances made on the topic of cognitive radio and spectrum sensing, Section III presents the proposed methods, in Section IV the simulation results are presented and interpreted along with the performances of the models, finally in Section V the conclusions of the work are resumed.

II. RELATED WORK

Multiple spectrum occupancy measurement campaigns for licenced radio spectrum bands led to the identification of inefficiencies in the radio resources usage patterns of the Primary Users (PUs) in the bands allocated to communication service providers. This affirmation is based on the statistics of the measurements which show that on average a significant part of the radio bands is available (in some scenarios even greater that 50% of total bandwidth), this varying based on geographical area, daytime, and application type [1]. Spectrum sensing functionalities are essential for efficient cognitive radio networks solutions, if not the core idea behind the entire concept. They aim to solve the scarcity regarding the available radio resources which increases permanently and directly proportional to the increase of network users and active devices accessing the medium, which follow and exponential curve, but also the usage inefficiency of the licensed bands. Newer technologies and standards are already designed in such a manner that the required radio spectrum is extended to the usage of higher frequencies as the simplest and most natural solution for spectrum scarcity strictly. Although this simple solution is highly limited since free air medium behaves intrinsically as a Low Pass Filter (LPF) for electromagnetic waves in many spectral regions, especially for millimetre-wave and terahertz spectrum, which suffer drastic attenuations at high, respectively moderate distances from interactions with air particles and water vapours [2].

The first proposal of Cognitive Radio arises with the work of Mitola III Joseph and Gerald Q. in a paper [3] presented at the Royal Institute of Technology - Stockholm. The idea emerged together with the entire field of Software Radios, and it was firstly envisioned as a multiband multimode personal communication system described through Radio Frequency (RF) bands etiquettes, over-the-air interfaces, dedicated protocols together with radio spectrum moderation techniques based on spatial and temporal patterns. In this paper the authors describe cognitive radio as an extension of software radio focusing on the problem of reasoning regarding the RF etiquettes following a radio-domain model, offering the advantages of enhancing flexibility of the devices by the *Radio Knowledge Representation Language*. The radio knowledge representation language is briefly described as a software mapping and evidence which takes in account the RF etiquettes, existing devices, available software modules, channel information and propagation characteristics, networks and corresponding topologies, devices applications requirements in such a way that automated reasoning is possible to compute with the aim to optimize the global network efficiency and user experience. The authors also describe the concept of cognitive radio through an analogy with a chess game based on the idea that every user is in a competition for accessing the resources where the game board is the radio spectrum.

Since the first proposal of cognitive radio and spectrum sensing great efforts were devoted into research and solutions development of spectrum sensing techniques. A brief review of the recent research advances on this topic is presented in paper [4] where the issue is separated and defined in two paradigms: the *narrowband* spectrum sensing and *wideband* spectrum sensing. For each paradigm existing approaches are reviewed in-depth and classified according to their key component. The reviewed approaches for the narrowband spectrum sensing are *Energy Detection*, *Cyclostationary Detection*, *Matched Filter Detection*, *Covariance-based Detection* and *Machine Learning-based (ML) Detection*. On the other hand, for the paradigm of wideband spectrum sensing the corresponding reviewed approaches are *Wavelet Detection*, *Multiband Joint Detection*, *Filter Bank Sensing*, *Non-Blind* and *Blind Compressive Wideband Spectrum Sensing*. The authors also classify further the *Non-Blind* and *Blind Compressive Sensing to Compressive Wideband Sensing* and the rest of the wideband approaches into *Nyquist-based Wideband Sensing*. In paper [5] Arjoune and Kaabouch offer a comprehensive survey regarding spectrum sensing solutions for Cognitive Radio Networks with a focus on comparison of the existing and most recent solutions along with corresponding performance and limitations and finally highlighting future challenges.

Atapattu et al. are addressing the issue of spectrum sensing in detail from the perspective of energy detection technique in paper [6] which prescribes the use of the central limit theorem (CLT) for enhanced performance. The impediments given by the fading process of the channels are mitigated by exploiting the spatial diversity gains given by the employment of antenna arrays, leading to a two low-complexity diversity technique for energy detector. The method is evaluated in a Rayleigh fading scenario with high SNR regime where the spatial correlation can be performed. The other alternatives of the narrowband spectrum sensing are discussed briefly. The use of CLT is suggested in the scenario of a sufficiently large number of samples where better approximations of the false alarm and detection probabilities are computed. Evaluation is performed based on the ROC curves for the proposed detection techniques.

In paper [7] the author is proposing a classic approach for energy detection as a brief overview of the theoretical aspects focusing on the main parameters that affect the final decision. Similarly, in [8] the authors are addressing the problem by an enhanced cooperative spectrum sensing using the wavelet denoising techniques and a softened hard decision method with results that show an improvement of performance up to nearly 15% in probability of missed detection (or False Negative) at a probability of false alarm (False Positive) of 0.1 with a Signal-to-Noise Ratio (SNR) of -10 dB. The approach in paper [9] implements filter bank based multicarrier techniques, together with a subcarrier loading based of water filling algorithm which is shown to be effective for spectrum holes detection. A more complex work is presented in [10] for which spectrum sensing is addressed for signals from a lower range of SNR values, employing a cyclostationary spectrum sensing method based on Fast Fourier Transforms (FFT) accumulation.

An ensemble classifier approach is described through the work of Hassaan described in paper [11] in low SNR values and computational cost constraints. The approach is employed in an OFDM modulation-based signal generation over AWGN channel where the SNR of the primary user is varied. The problem of detection is addressed by exploring the cyclostationarity structure of the signal as it is more robust to lower SNR range. The technique of cyclostationary feature detection is firstly proposed by Gardner in [12] and [13]. Features are extracted from the accumulations of the FFT and included in training of an AdaBoost model based on Decision Tree algorithm. The performance of the ensemble classifier is compared to the performance of a Support Vector Machine (SVM). Results indicate that the classification model outperforms the SVM classifier. Other comparisons which indicate performance improvements are with the classic cyclostationary detector and energy detector which are both outperformed. Main contributions of the work of Gardner are reflected in the dataset synthetization algorithm for OFDM signals in various SNR conditions given by the AWGN channel and adjusting FFT Accumulations Method (FAM) for proper estimation of the generated signal cyclic spectrum features.

III. PROPOSED METHODS

A. Primary signal simulation based on Tapped Delay Line method & Sum of Sinusoids

Given the context of a narrowband spectrum sensing application, a cognitive radio must be able to precisely decide if a PU signal exists for a defined relatively small segment $[f_L, f_H]$ (up to the order of tens or hundreds of MHz at most) of spectrum during the probing process. If the probed bandwidth is decided to be free, a cognitive radio is said to be able to safely access the communication medium by that bandwidth. If the probed bandwidth is decided that is occupied by a PU, then the cognitive radio must abort any ongoing medium access processes and leave the respective resources available for the PU. In the simplest form the decision logic can be described as a binary hypothesis test for a set of observations at any given moment modelled by equation (1):

$$y(t) = \begin{cases} n(t): & H_0 \\ h(t) * x(t) + n(t): & H_1 \end{cases} \tag{1}$$

where $y(t)$ is the observation of the received signal at moment t, $n(t)$ is the noise in a form of AWGN process, $h(t)$ is the channel transfer function at given moment t, $x(t)$ is the signal at time t; H_0 marks an absent PU signal; H_1 marks the presence of PU signal. If the sensing narrowband is affected by flat fading phenomena the channel transfer function $h(t)$ is described by approximately the same attenuation across the entire bandwidth as the variations appear at the same scale, hence the received signal is said to suffer on average the same attenuation over the channel. This type of fading is commonly modelled by the Rayleigh flat fading channel which is implemented in the simulation framework. The AWGN channel can be considered as a special case of the flat fading channel in which the fading process of the channel does not apply any attenuation nor amplification (extremely unlikely in real scenarios) on the received communication signal, hence the channel transfer function is said to have the unity value across every frequency of the sensing bandwidth and only the noise accounts in the resulted signal. These two cases are the most common researched and simulated scenarios in literature for the context of narrowband applications. Although in practice this is not always the encountered situation. The higher one advances in the frequency spectrum, the higher the attenuation of the signals and the channel transfer function can drastically change stochastically from the effects of scattering and Doppler effect. Given enough attenuation, the fading process fluctuations domain order impacts much more the signal's power spectral density, therefore these fluctuations become more prominent. For this type of scenario, the frequency-selective fading channel model can describe the effect of frequency-dependent fluctuating attenuations across the sensing bandwidth. Furthermore, the same model of frequency-selective fading channel can describe and simulate the signal propagation behaviour in a wideband (the wideband spectrum segment is defined by f_L, f_H and is up the order of GHz) application. Hence this channel type is mor e suitable to extend the cognitive radio functionalities to the wideband spectrum sensing where effects of scattering, multipath propagations and Doppler spread have a greater impact on the cognitive radio capabilities. The channel transfer function for the Rayleigh flat fading scenarios can be modelled by the complex coefficients of an equivalent Tapped Delay Line (TDL) which are given by equation (2):

$$h(t) = \frac{1}{\sqrt{2}}(Re_M + j \cdot Im_M) \tag{2}$$

where $Re_M, Im_M \in X_1 \sim N(\mu, \sigma), X_2 \sim N(\mu, \sigma)$ are the values arrays of length M, sampled from two independent and identically distributed random variables with a normal distribution having mean μ and standard deviation σ. To simulate the AWGN channel alone, no fading phenomena is required to be performed, hence the generated AWGN signals is simply added to the PU signal rescaled to respect the SNR value.

An efficient mathematical model of the frequency-selective fading channel involves two or multiple complex coefficients (or channel taps) in order to describe the multipath propagation phenomena with the corresponding path delays, but also the Doppler spread effect. There are two popular models which are generally accepted: the *filtered Gaussian noise* technique and the *Jakes Sum-of-Sinusoids* technique with a multitude of modifications and optimizations described in existing literature. The second technique is part of simulation implementation, specifically the Generalized Method for Exact Doppler Spread (GMEDS) [14]. For computation optimization this model employs the band-limited discrete multipath channel based on the assumption that the power delay profile and the Doppler spectrum are separable. This is equivalent of a truncated finite impulse response filter (truncated convolution of the signal with the channel transfer function) having the set of tap weights defined by equation (3):

$$h_l = \sum_{k=1}^{K} a_k \cdot sinc(\frac{\tau_k}{T_s} - l) ; \ -N_1 \le l \le N_2 \tag{3}$$

where a_k is the set of complex path gains describing the multipath channel, τ_k contains the discrete path delays for each existing path, T_s is the sampling period of the channel, K is the number of paths and the values N_1, N_2 are selected so that the magnitude of h_l is smaller than a defined threshold when l is outside their range. Presented aspects were implemented in Python. Additional details are given in section C.

B. Bayes and Visu shrinkage denoising technique

Noise is part of all-natural processes, hence most of real information carrier signals, especially the ones from the wireless communications systems, suffer from distortions induced by the superposition with the channel noise. Many times, the additive noise is uniformly distributed in frequency spectrum making it specifically a form of white noise. Therefore, various filtering techniques can be applied to eliminate the noise in the frequency domain of interest so that a denoised signal can result which is less affected by distortions.

Many investigations of the discrete wavelet transform coefficients indicate that the coefficients with a relatively small absolute value are more affected by noise, whereas the coefficients with a relatively high absolute value are support for more information in comparison. This aspect is also demonstrated by the calculation of the resultant vector from the information carrier signal and the noise signal vector. If the difference between the magnitudes of the coefficients is high enough, the noisy coefficients (i.e. the ones with small magnitude) can be distinguished by the coefficients less affected by noise based on a thresholding technique. Given the wavelet coefficients by employing a proper thresholding method (hard or soft) with the corresponding value and rescaling factor one can perform efficient denoising by the *shrinkage of wavelet coefficients.* For the Visu Shrinkage technique the denoising algorithm is based on the usage of the *universal threshold* value defined by equation (4) which depends on N signal samples and the noise standard deviation as follows:

$$\gamma_{DWT} = \sigma\sqrt{2\ln N} \tag{4}$$

On the other hand, the Bayes Shrinkage denoising algorithm takes advantage of the Bayes uniform thresholding formula which is additionally data adaptive driven, sub-band and level dependent on the near optimal threshold. The Bayes algorithm is designed to minimize the Bayesian risk value, which is the estimated value of the cost function, usually calculated as the mean squared error or the minimum mean squared error The threshold value is computed for every sub-band section, resulting in an adaptive multi-threshold technique. The main advantage of Bayes Shrinkage technique is that can heavily shrink small arguments and apply just a slight shrinkage for the remaining large arguments, being specialized for denoising signals affected by AWGN noise. The uniform Bayes threshold value is described by the formula in equation (5):

$$\gamma_{Bayes\_uniform} = \frac{\gamma\sigma_n^2}{\sigma} \tag{5}$$

where σ_n^2 is the variance of the noise, σ is the standard deviation of the wavelet coefficients of the signal and $1 \leq \gamma \leq \sqrt{2}$.

Various thresholds are proposed in literature taking in account a fine range of variables like the variance of the noisy signal, maximum-minimum eigenvalues or the type of distribution, from which a wide diversity of DWT denoising methods emerge as the Bayes and Visu denoising algorithms employed for the work of this paper. The main concept of the denoising technique can be visualized in Figure 2.

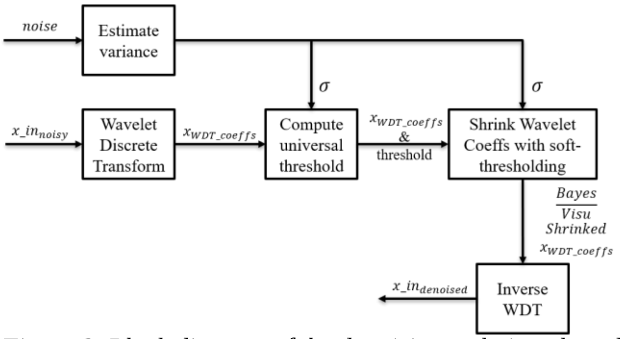

Figure 2. Block diagram of the denoising technique based on Bayes and Visu wavelets shrinkage according to the Python implementation.

C. Simulation framework

The design of the framework is inspired by the more general design of any end-to-end wireless communication system block. The implemented modules mainly focus on providing the functionalities from the transmission side (expect the FEC coding as it is not relevant in the context of energy detection methods), from the channel side (considering only the AWGN channel, the Rayleigh flat and frequency-selective fading channels), but discarding everything from the receiving side as the energy detection method aims to perform the detection immediately, avoiding all the computations commonly performed in a standard communication scenario until the cognitive radio decides it can access the sensing radio resources. In Figure 3 the framework is illustrated as the block diagram.

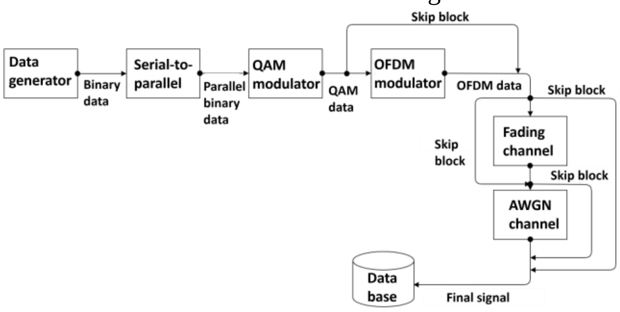

Figure 3. Block diagram of the simulation framework.

The first block, *Data Generator*, sequential binary data is generated continuously or discontinuously according to a binomial distribution with its tuneable parameter of success rate. The resulted binary data is parallelized simply through a tensorial transformation in the data structure, resulting parallelized binary data with word length according to the specified QAM constellation. The data is modulated by a QAM modulating block and finally by the OFDM modulating block with respect to modulation parameters, resulting the PU signal. Channel distortions are further applied on the PU signal through the *Fading channel* and *AWGN channel* blocks in accordance with the specified channel characteristics. An important advantage of the proposed framework is given by its ability not only to simulate, but to synthesize and store signals resulted after every block in the diagram and generate error proof ground truth of the existence of the PU signal at every timestamp.

D. Energy detection with adaptive threshold method

Energy detection is the most popular algorithm to this point in spectrum sensing applications due to its simplicity and low computation complexity which allows the development for embedded solutions. According to the detection strategy a detecting model computes a proxy regarding the energy of the signal received on the target spectrum band, leading to a specific formulation of the hypothesis test. To refer to the energy detection algorithm, an ED model computes a proxy regarding the energy of the signal received on the target spectrum band, leading to a specific formulation of the hypothesis test. The decision statistic is therefore formulated as the energy of the signal y given the window of N samples of a sampling moment as in (6).

$$E(y) = \sum_{k=1}^{K} |a_k|^2 \tag{6}$$

Given a chi-square distribution, for N=1 the distribution becomes a Rayleigh distribution given the degree of freedom equal to 2. The decision adaptive threshold value can be formulated as follows in (7) using the variance (σ^2) of the noise process and a fixed (or dynamic) value of expected false alarm or false positive rate P_f:

$$\gamma_{ED} = \sigma^2 (Q^{-1}(P_f) \cdot \sqrt{2N} + N) \tag{7}$$

The algorithm is illustrated by the block diagram in Figure 4.

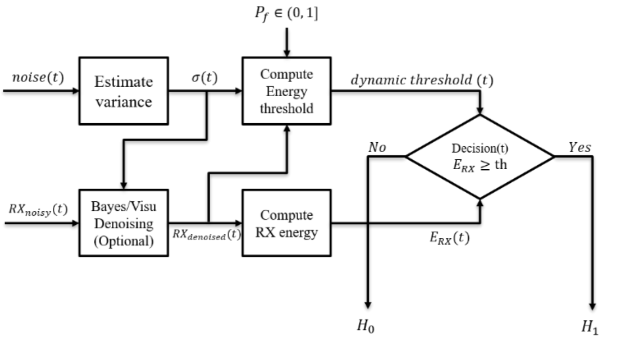

Figure 4. Illustration of the Energy Detection algorithm framework implementation.

Given any specific set of estimated false alarm rate and true detections rate one can compute the required values to ensure the estimating performance based on the trade-off relation given by the threshold formula. To this point is well known that the classic energy detection algorithm can offer bad performance at low SNR values, being much more favourable for moderate and high SNR from a computational point of view. Various methods are available to enhance the detection performance as the two dynamic thresholds technique. For a low SNR domain, a large value of samples N is required to achieve modest performance with the cost of processing time which in many applications is critical. The main difficulty in all advanced algorithms is to ensure a time computation bellow the critical time. In these terms, sensing algorithms must operate with as few as possible parameters and number of samples, motivating literature to dedicate an entire subject on the optimal number of sensing samples with various analysis techniques like CLT, threshold optimization based on a memory of previous observations and performance [15][16][17][18]. Further enhancement of the ED algorithm is possible by a *double threshold* approach on the observation that despite the benefits of low complexity and capacity to generalize over the wide range of PU signals and channel characteristics, the dynamic threshold is prone to estimation costs (like the noise estimation errors, parameters computation values precision depending on number of samples, interdependencies between groups of parameters).

E. Neural network energy detection method

The NN model is a custom-made, non-pre-trained model based on a classic combination of batch normalization layers, convolutional layers, pooling layers, dropout layers, long short-term memory (LSTM) layers and dense layers, shaping essentially a hybrid convolutional-1D LSTM architecture specialized in processing of one-dimensional signals. The hybrid form is given by the residual combination of the layers in two parallel blocks which extract features for a final classifying layer that outputs the sigmoid logits corresponding to the decision of detection in form of probabilities. The first block is constructed firstly of a batch normalization after which the first convolution with maximum pooling layers is applied, resulting in a feature map which is again convolved with a lower number of filters and with a dropout rate over the second feature map, finally applying an LSTM layer on top to extract possible time-space information. The second block or the residual branch is constructed with only a batch normalization layer and another LSTM layer on top to extract possible relevant temporal information from the signal. The outputs of the two blocks are summed up and given as input to a final dense layer to perform the classification of the decision. A detailed view of the network architecture and optimization parameters is presented in Figure 5.

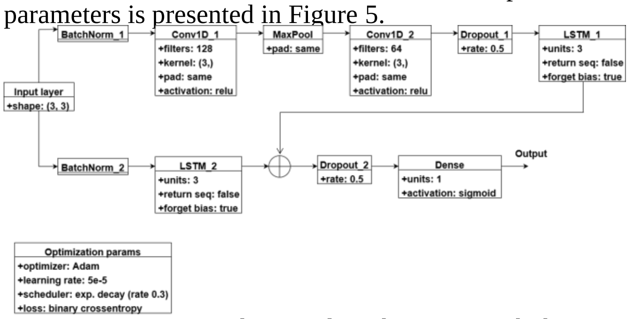

Figure 5. Neural network architecture with the corresponding optimization parameters configuration.

The input features of the NN are considered to be the same as the input variables of the classic ED, specifically the Bayes-based denoised OFDM received signal, the variance of the noise over the channel and additionally the power of the signal computed for a window of 50 signal samples. In this setup is ensured that the model can be compared easy in terms of performance if the two algorithms are exposed approximately to the same signal and channel information, hence the model approximates another ED function which is agnostic of signal characteristics and requires no prior knowledge regarding the PU configuration of communication medium access. Although other feature engineering techniques are shown to greatly increase NNs performance.

IV. SIMULATION RESULTS

To evaluate the discussed SS methods three popular scenarios are simulated and presented below. Each simulation resulted in the synthetization of the corresponding PU signal together with the afferent features extracted from the PU signal and channels characteristics such as the power of the PU signal, the PU signal denoised according to the Bayes, respectively Visu algorithms based on the wavelet discrete transform, the magnitudes and frequencies coefficients resulted from the wavelet transform, the channel noise and its variance, and the ground truth of the PU signal. In an attempt to identify other possible features by experimentally employing non-linear functions the history of the logistic map is also stored as a time series. Despite being reasonably sufficient correlated with the ground truth this feature proved to be trivial and thus redundant according to a correlation analysis with the rest of the features, as it shows high correlation with the power of the PU signal, although the later one is more correlated with the ground truth. In Figure 6 is briefly illustrated how the data is generated for the first two scenarios and the NN model employed. Similarly, the third scenario is generated by additionally accounting for the multipath propagation and Doppler effect parameters.

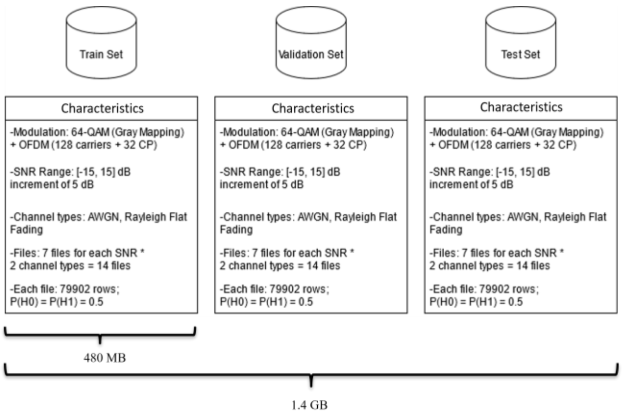

Figure 6. Training, validation, and test set data synthetization characteristics (signal modulation, channel type, ground truth distribution, length of data) for the AWGN and Rayleigh flat fading channel performance simulations. Note: Train Set & Validation Set are dedicated for the NN model training.

A. *Additive White Gaussian Noise Channel*

The AWGN channel is the very first type of channel simulation model available in the proposed framework and the simplest one. The implementation of the block is class-based of which attributes are the input signal and the expected SNR value at the receiving endpoint. In this scenario, if equation (2) or (3) is considered, the channel transfer function has no impact on the gain or spectrum of the transmitted signal. Thus, for computation efficiency and simplicity only the noise signal is modelled accordingly for the channel parameters and simply summed up with the primary signal if existing or added alone to simulate the noisy channel with no existing or active primary signal. For the work of this paper the PU signal is selected to be generated in a discontinuous manner to generate diverse and realistic events. Although a vigorous implementation takes in consideration the process of modelling the channel according to either equation (2) or (3) under the constraint that the transfer function must present a single complex coefficient and the modulus or absolute value of the transfer function must have the unity value, which is virtually equivalent to a neutral element for the convolution operation (despite the fact that mathematically the convolution has no identity element). The data for this scenario is generated with a 0.5 probability of having an active PU over the channel, meaning that the rest of 0.5 is non-active, so the channel is free. By these means the testing set is designed to be balanced. Performance analysis from Figure 7 indicates that the NN model is drastically outperformed at low SNR if compared to both ED methods, although the Bayes and Visu methods have similar performance regardless of the SNR value. At higher SNR, the NN model is still outperformed but comparable to ED model.

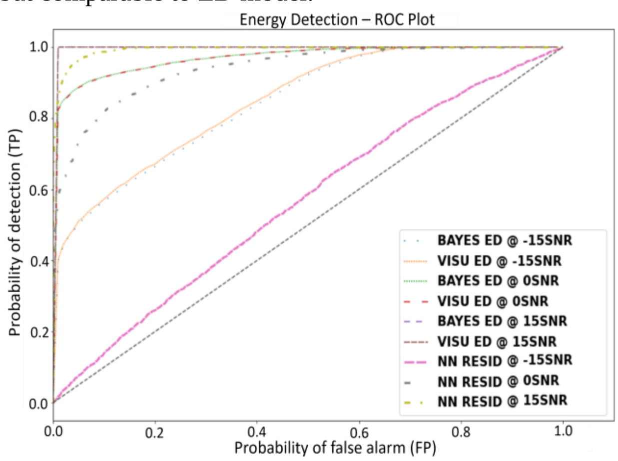

Figure 7. SNR related ROC curves of NN model and ED algorithm with corresponding denoising methods for AWGN Channel

B. *Rayleigh Flat Fading Channel*

Considering again equation (1), for this scenario the channel transfer function is modelled as a finite impulse response filter with a single complex coefficient. This type of channel can be simulated either by employing the TDL addon specifying to sample a single complex coefficient from the Rayleigh distribution, or by the GMEDS method in which the discrete path delays have a single delay with the corresponding path gain and Doppler shift, making it equivalent with a Rayleigh Flat fading channel. For the simulation diversity the TDL model is selected in this scenario and the GMEDS is dedicated for the last one. The ED and NN performance can be analysed in Figure 8. The observations made from Figure 6 are still valid for the Flat Fading scenario with a slight change in the detection proportion as the signal is also affected by the fading process and not just noise. To be noted that the curve of the NN model in the case of -15 dB SNR converges to the diagonal, suggesting a performance comparable to a random classifier.

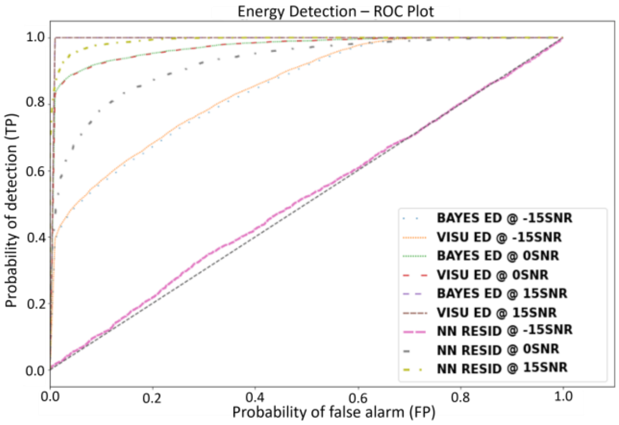

Figure 8. SNR related ROC curves of NN model and ED algorithm with corresponding denoising methods for Rayleigh Flat Fading Channel

C. *Rayleigh frequency-selective fading channel*

The purpose of this channel scenario is to analyse how the frequency-selective fading process generate by multipath propagation together with the Doppler spread effect emerged from mobility of the terminals impact the ED and NN detection ability. This type of scenario is much closer to real-life scenario, especially in the urban areas where the signal is likely to reflect and scatter due to existing moving or static objects. For this type of scenario additional parameters come into play like stated in previous paragraphs, as the discrete path delays which describe the time delay for each reflected and the discrete path gains which usually assign an attenuation for the reflected, delayed paths. Additionally, the Doppler frequency shift which is directly related to the relative movement between transmitter and receiver where the relative velocity and the incident angle is taken in account. This parameter is filled with a floating-point value so that the model can make abstraction of the actual values of the carrier frequency, relative velocity, and the incident angle. For this scenario is precisely 0.01.

For the multipath configuration six paths contribute to the frequency-selective fading process with an increasing fading attenuation proportional to the increase of delay time. The rest of the data characteristics are preserved to be same with the ones from previous scenarios. The same NN-based model employed for inference in the first two channel types is considered here for performance comparison with the ED algorithm. The results are presented in Figure 9.

When compared with the two previous simulations, in this scenario for the case of -15 dB SNR the NN-based model and the ED algorithm perform slightly better than in the scenario of the flat fading channel. This can be explained by the fact that the randomly generated flat fading complex coefficient implied a deeper fade in contrast with the fade introduced by the frequency-selective channel. For the case of 15 dB SNR the ROC curve of the NN-based model suggests a decrease in detection performance compared to AWGN channel. The cause of this can be due to still relevant fading effect of the frequency-selective channel even in the case of higher SNR values, especially if the fade phenomena affect the lower spectra of the signal. The curve of the NN-based model almost matches both Bayes and Visu denoising resulted curves of the ED algorithm at 0 dB starting with the false alarm rate of approximately 0.2. Otherwise, the classic ED algorithm with dynamic threshold outperforms the NN-based model still for the region bellow 0.2 false alarm rate, ensuring a clear increased performance with difference of 0.88-0.7 detection rate for a false alarm rate of 0.01.

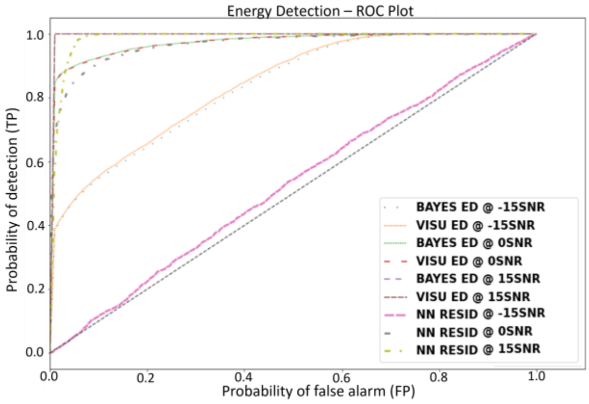

Figure 9. SNR related ROC curves of NN model and ED algorithm with corresponding denoising methods for Rayleigh frequency-selective fading channel

A technique for tailored models, if performed correctly, can lead to a significant detection improvement with a decrease of the false alarm rate, specifically in a narrow range of SNR values. This technique implies generation of training data with a higher density of samples for the desired SNR range. Furthermore, another solution implies the training of ensemble of ED models to perform the classification voting. Each model from the ensemble technique is expected to be trained on a constrained set of data parameters, hence the variance within the data is distributed across the models, resulting in predicting specialization relative to the channel. Also increasing diversity within training data can have a positive impact on the overall detection ability of the model. Taking into account the presented aspects, we generated a new training and testing set in the same manner as before with two differences: the resulted training set contains the files for AWGN, Rayleigh flat fading and frequency-selective fading channels, with an increase of samples density in the range of -5 dB, 0 dB and -5 dB SNR values, and the new testing set is composed only of files corresponding to the Rayleigh frequency-selective fading channel. The ROC curves of the previous, respectively resulted model can be visualized in Figure 10 and Figure 11 again compared to the ED algorithm.

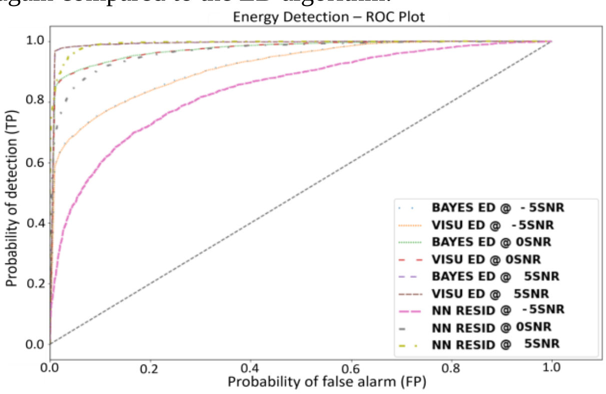

Figure 10. SNR (-5 dB, 0 dB and 5 dB) related ROC curves of ED algorithm and previous NN model on Rayleigh frequency-selective fading channel

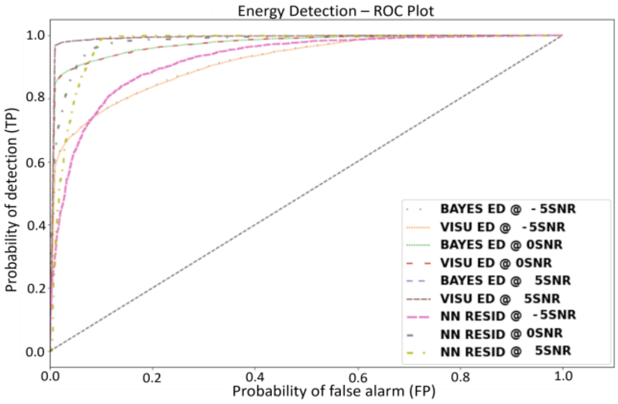

Figure 11. SNR (-5 dB, 0 dB and 5 dB) related ROC curve of ED algorithm and newly resulted NN model on Rayleigh frequency-selective fading Channel

By comparing the detection performance of the NN-based model to the classic ED algorithm with dynamic threshold. Although from the 5 dB value the detection ability starts to decrease in comparison with the previous model. For a fixed value of TP ≈ 0.8, the NN model achieves this detection rate with a cost of FP ≈ 0.12 in the case of -5 dB SNR, while the ED algorithm achieves the same detection rate with a cost of FP ≈ 0.2. In the case of 0 dB SNR, if the detection rate is fixed to 0.95, the NN model ensures this value by introducing the rate of FP ≈ 0.1. Same detection rate is achieved by the ED model with an acceptance rate of FP ≈ 0.23.

V. CONCLUSIONS

In this paper the performances of both classical ED algorithm with a single dynamic threshold and NN-based ED techniques are compared for a narrowband spectrum sensing application in the AWGN, respectively Rayleigh flat and frequency-selective fading channel given a range of ±15 dB SNR. Realistic, rich, and diverse data is generated by employing the dedicated Python framework for each scenario in a stochastic manner. The framework is comparable in terms of utilization and quality of results with other common closed-source tools for wireless communication channels simulation. Both detection models indicate promising performance for moderate and high SNR values, although the NN model becomes unreliable in scenarios with low SNR. From first results the threshold-based approach outperforms the baseline NN model on all treated scenarios if the training data is scarce, making the ED algorithm a fit solution for real applications due to its performance and low complexity. The detection performance of the NN model can be improved in the same approach and paradigm by designing training datasets most representative for a specific narrow range of SNR values with a detriment of decreased detection outside the selected range. The NN model trained with this approach of more diverse and dense data in a narrow SNR range outperforms the ED algorithm in that range.

Future work will focus on the extension of the Python framework to generate datasets of spectrograms/scalograms resulted from *short-time Fourier transforms* and *superlet transforms*. Focus is also set to deploy the researched solutions on real-case scenario applications by integration in a transmit-receive simulation system which operates on SDR-based equipment.

REFERENCES

[1] S. Subramaniam, H. Reyes and N. Kaabouch, "Spectrum occupancy measurement: An autocorrelation based scanning technique using USRP," *2015 IEEE 16th Annual Wireless and Microwave Technology Conference (WAMICON)*, 2015, pp. 1-5, doi: 10.1109/WAMICON.2015.7120376.
[2] Y. Zeng, Y.-C. Liang, A. T. Hoang, and R. Zhang, "A Review on Spectrum Sensing for Cognitive Radio: Challenges and Solutions," EURASIP J. Adv. Signal Process., vol. 2010, pp. 1–16, 2010.
[3] J. Mitola and G. Q. Maguire, "Cognitive radio: making software radios more personal," in IEEE Personal Communications, vol. 6, no. 4, pp. 13-18, Aug. 1999, doi: 10.1109/98.788210.
[4] Tellambura, Chintha. (2017). Spectrum sensing methods and their 6 performance. 10.1007/978-981-10-1394-2_6.
[5] Arjoune, Y.; Kaabouch, N. A Comprehensive Survey on Spectrum Sensing in Cognitive Radio Networks: Recent Advances, New Challenges, and Future Research Directions. *Sensors* **2019**, *19*, 126. https://doi.org/10.3390/s19010126.
[6] Atapattu S., Tellambura C., Jiang H. (2014) Alternative Forms of Energy Detectors. In: Energy Detection for Spectrum Sensing in Cognitive Radio. SpringerBriefs in Computer Science. Springer, New York, NY. https://doi.org/10.1007/978-1-4939-0494-5_3
[7] Ranjan, A.; Singh, B. Design and analysis of spectrum sensing in cognitive radio based on energy detection. In Proceedings of the International Conference on Signal and Information Processing, Vishnupuri, India, 6–8October 2016; pp. 1–5.
[8] G, Padmavathi. (2014). An Enhanced Cooperative Spectrum Sensing with Wavelet Denoising and Softened Hard Decision for Cognitive Radio Networks. International Journal of Future Generation Communication and Networking. Vol. 7. pp. 81 -90. 10.14257/ijfgcn.2014.7.6.09.
[9] Dikmese, Sener & Srinivasan, Sudharsan & Renfors, Markku, FFT and filter bank-based spectrum sensing and spectrum utilization for cognitive radios. 10.1109/ISCCSP.2012.6217788.
[10] Oualid, Khatbi & Hachkar, Zakaria & Mouhsen, Ahmed. (2018). Cyclostationary Spectrum Sensing Based on FFT Accumulation Method in Cognitive Radio Technology. 10.1007/978-3-319-77712-2_51.
[11] Hassaan Bin Ahmad, "Ensemble Classifier Based Spectrum Sensing in Cognitive Radio Networks", *Wireless Communications and Mobile Computing*, vol. 2019, Article ID 9250562, 16 pages, 2019. https://doi.org/10.1155/2019/9250562.
[12] W. Gardner, "Cyclostationaryprocesses," in Introduction to Random Process with Applications to Signals and Systems, pp.323–402, McGraw-Hill, New York, NY, USA, 2nd edition, 1990.
[13] W. Gardner, "An introduction to cyclostationary signals," in Cyclostationarity in Communications and Signal Processing, Chapter1, pp.1–81, IEEEPRESS, NewYork, NY, USA, 1993.
[14] Iskander, C. "A MATLAB R ©-based Object-Oriented Approach to Multipath Fading Channel Simulation.".
[15] N. Swetha, P. N. Sastry and Y. R. Rao, "Analysis of Spectrum Sensing Based on Energy Detection Method in Cognitive Radio Networks," *2014 International Conference on IT Convergence and Security (ICITCS)*, 2014, pp. 1-4, doi: 10.1109/ICITCS.2014.7021738.
[16] Namburu, Swetha. (2014). Analysis of Spectrum Sensing based on Energy detection method in Cognitive Radio Networks. 10.1109/ICITCS.2014.7021738.
[17] Pandit, Shweta & Singh, Ghanshyam. (2017). Spectrum Sensing in Cognitive Radio Networks: Potential Challenges and Future Perspective. 10.1007/978-3-319-53147-2_2.
[18] Xu, Xiguang et al. "Diffusion Maximum Correntropy Criterion Based Robust Spectrum Sensing in Non-Gaussian Noise Environments." *Entropy (Basel, Switzerland)* vol. 20,4 246. 3 Apr. 2018, doi:10.3390/e20040246.