An Efficient Cooperative Spectrum Sensing Method Using Renyi Entropy Weighted Optimal Likelihood Ratio for CRN

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Abstract — The main concept behind employing cognitive radio is to enable secondary users (SUs) or unlicensed users to utilize the available spectrum. Spectrum sensing methods detect the existence of primary users (PUs) and have become the main topic of research in the CRN industry and in academia. This paper proposes a new framework based on the Adam gradient descent (Adam GD) algorithm to develop a spectrum sensing mechanism used in CRNs and detecting the availability of free channels. The signal's components are extracted from the received signal and the spectrum is searched for availability which is detected through a fusion center using the proposed algorithm. The proposed Adam GD algorithm attains the maximum detection probability rate and the minimum false alarm probability of 0.71 and 0.39, respectively, for a Rayleigh channel.

Keywords — cognitive radio, eigen statistics, optimal weight, signal energy, spectrum sensing

1. Introduction

The conventional static spectrum allocation mechanism allows certain primary users (PU) to access the spectrum, whereas secondary users (SU) are restricted [1], [2]. To increase spectrum efficiency, the cognitive radio technology is introduced to allow SU to utilize the licensed spectrum band during the period of PU inactivity [3]–[5]. CR is a solution that may potentially solve the issue of spectrum scarcity by accessing the spectrum in a dynamic manner and serves as a key 5G enabler [2]. CRNs adjust the radio framework based on their own knowledge. They also efficiently and opportunistically access the licensed spectrum thus increasing its usage rate [5]. The CR technology is considered to be the primary solution for spectrum underusage, as it provides access to spectrum bands that are not free from PUs, without any interference. Therefore, a reliable and accurate spectrum sensing method is required on the SU side before communication may be established.

A key issue in spectrum sensing is to model test statistics in order to achieve higher probability of detection (PD) [4], [8]–[10]. The following solutions are used for this purpose: cyclostationary based method [11], energy detection model [12], matched filter approach [13], eigenvalue-based approach [14], and likelihood-based scheme [15]. The cyclostationary based detection mechanism offers improved performance, but it is sensitive to synchronization and faces computational complexity issues [16]. It is capable of efficiently detecting spectrum holes, but it requires longer sensing times [6]. The spectrum sensing method based on the machine learning approach is designed to increase the performance of the process [17]. A spectrum sensing approach based on convolutional neural networks was developed in [4]. In [18], deep learning is utilized for spectrum sensing purposes. In recent decades, various deep learning-based detection models have been developed for spectrum sensing. In [19], a long short-term memory (LSTM) network model is designed for detecting PUs in a spectrum sensing scenario. A convolutional neural network (CNN)-based model is used to learn the energy correlation textures of PU signals in [20].

This paper proposes a spectrum sensing framework based on the Adam GD algorithm and relying on the extraction of signal components. At the receiver end, the signal is analyzed for energy by using test statistics relying on the generalized likelihood ratio test (GLRT), Renyi entropy and eigen statistics. The extracted signal components are then fused by weight parameters. The value of each weight parameter is determined using the Adam GD algorithm, i.e. a combination of Adam optimization with the gradient descent (GD) algorithm. Finally, spectrum availability is detected using the proposed algorithm in order to allocate the free channels to unlicensed users.

The remaining portion of the paper is organized as follows. Section 2 reviews different conventional schemes, while Section 3 portrays the model of a CRN. Section 4 describes the spectrum availability sensing approach developed by the authors. Section 5 discusses the results achieved, while Section 6 presents the conclusions.

2. Related Works

Kaur *et al.* [21] designed a decentralized multi-agent reinforcement learning approach relied upon in CRNs to efficiently utilize the spectrum. It reduces the operating cost and offers good flexibility. It increases performance in terms of outage probability, network capacity and convergence speed, but it fails to consider different application-specific requirements of CR in the context of cooperative networks. Eappen *et al.* [6] designed a multi-objective modified grey wolf optimization (MOMGWO) algorithm for solving the optimization issues in CRN. It obtained better detection threshold, sensing time, and transmission power values by compromising energy efficiency and interference immunity. However, only a single PU was considered in this method. Zhang *et al.* designed, in [16], a kernel-based sensing approach for CRNs. It maps the input signal matrix to the higher dimensional of features through a non-linear Gaussian function and generates the test statistics in the feature space. It achieved better performance when faced with interference and Gaussian noise, but it proved sensitive to the level of Gaussian noise. Liu *et al.* [4] developed a deep neural network (DNN) based model for exploring test statistics in CRN. It used a covariance matrix as the CNN input for the sensing process, to increase performance. It achieved higher detection and false alarm probability rates, but faced greater computational complexity issues.

Eappen *et al.* [7] designed a hybrid particle swarm optimization with gravitational search algorithm (PSO–GSA) for detecting spectrum holes by analyzing energy usage. It effectively detects the holes by finding optimal values of transmission power, sensing bandwidth, and power spectral density. It increased energy efficiency, but its higher population value increases computational complexity.

Pan *et al.* [22] designed a spectrum sensing model with deep learning and the cycle spectrum mechanism in CRN. It analyzes cyclic autocorrelation of the OFDM signal by relying on the cyclic spectrum captured through the time domain fast Fourier transform (FFT) algorithm. Cyclic spectrum was normalized to the gray scale dispensation in order to form the gray scale image. Deep features were learned through CNN and the sensing process was performed in the cyclic spectrum. Performance was increased in the presence of noise, but different issues were faced with single feature inputs.

Jothiraj *et al.* [23] modeled an optimized sensing model using the dragonfly algorithm. It increased the usage of spectrum by allocating the free spectrum to unlicensed or SUs in the network. It used the adaptive threshold factor to detect spectrum holes. This model outperforms other techniques in terms of efficiency and detection accuracy. Reddy *et al.* [25] designed an improved whale optimization algorithm for spectrum sensing in CRN. The weight function for CNN was computed to analyze its accuracy performance. It increased the performance in terms of such measures as energy consumption, delivery ratio, and delay.

Some of the issues faced by the conventional approaches include the following:

- The use of machine learning in the resource allocation mechanism results in outstanding performance, better than that of other simple convex algorithms relied upon in the dual decomposition model, with the consideration of imperfect channel state information (CSI). However, considering different application-related requirements in cooperative CRN settings, the significant difficulties continue to be faced [21].
- The use of machine learning in the resource allocation mechanism results in outstanding performance, better than that of other simple convex algorithms relied upon in the dual decomposition model, with the consideration of imperfect channel state information (CSI). However, considering different application-related requirements in cooperative CRN settings, the significant difficulties continue to be faced [21].
- MOMGWO is an efficient method for defining multi-objective functions with the best Pareto front. Nevertheless, it continues to face problems related to the computational time required [6].
- Kernel-based detection is not effective in terms of certain factors concerning Gaussian mixture noise, but its efficiency was improved by increasing the number of receiver antennas, samples and by modifying the signal-to-noise-ratio (SNR) [16].
- DNN achieved higher efficiency, but it faced issues related to signal-to-noise-ratio complexity [4].
- The extreme population size increases computational complexity of optimization algorithms [7].

3. System Description

The cooperative spectrum sensing approach used for detecting PUs in multiple-input multiple-output (MIMO) systems is modeled as a binary hypothesis corresponding to the absence and presence of PUs [29]. The CRN contains a fusion center with X_a receiver antennas and X cooperating SUs with X_b antennas for every cooperating user. Let us consider $p_{d,m}$ as probability of detection, and $p_{f,m}$ as probability of a false alarm of a local decision rule of the *m*–th user. When the *m*–th secondary node made the decision, the node transmits the set of A vectors $G_m(h) \in \Re^{X_b \times 1}, 1 \leqslant h \leqslant A$ corresponding to the local decision concerning the absence or presence of the PU, to the fusion center. Matrix G_m is generated by stacking all sets of A vectors $g_m(h), 1 \leqslant h \leqslant A$ corresponding to the decision, as:

$$G_m(h) = [g_m(1), g_m(2), \ldots, g_m(A)]^B \in \Re^{A \times X_b}.$$

Next, matrix G_m is sent towards the fusion center to get the values of $G_m = P_0$ or $G_m = P_1$ corresponding to the decision regarding the absence $\aleph_0$ or presence $\aleph_1$ of PUs, respectively. Under a non-antipodal signal with $A = 2$ and $X_b = 2$, matrix $P_0 = 0_{2\times2}$ and P_1 is selected as an orthogonal matrix $P = 0_{2\times2}$ and P_1 is selected as an orthogonal matrix $[1 \;\; 1, 1 \, -1]_{2\times2}$ with $P_1 P_1^B = AC_2$. Accordingly, local performance for the *m*–th secondary user, i.e. $p_{d,m}$ and $p_{f,m}$, is:

$$p_{d,m} = \mathrm{pr}(G_m = P_1 | \aleph_1), \tag{1}$$

$$1 - p_{d,m} = \mathrm{pr}(G_m = P_0 | \aleph_1), \tag{2}$$

$$p_{f,m} = \mathrm{pr}(G_m = P_1 | \aleph_0), \tag{3}$$

$$1 - p_{d,m} = \mathrm{pr}(G_m = P_0 | \aleph_0). \tag{4}$$

It is assumed that the number of antennas located at the PU, as well as detection mechanism utilized at every cooperating SU are chosen arbitrarily. Accordingly, signal $J_m(h) \in \Re^{X_a \times 1}$ received at the fusion center and corresponding to vector

$g_m(h)$ sent by the m–th $(1 \leqslant m \leqslant X)$ SU at the m–th $(1 \leqslant h \leqslant A)$ instant over the orthogonal MAC is specified as:

$$J_m(h) = \mathbf{B}_m\, g_m(h) + q_m(h), \tag{5}$$

where $\mathbf{B}_m \in \Re^{X_a \times X_b}$ denotes the MIMO channel matrix and every element $k_m(x, y)$ of matrix $\mathbf{B}_m$ shows a fading coefficient between the y–th transmitting antenna of the m–th SU and the x–th receiving antenna of the fusion center. The l–th row of channel matrix $\mathbf{B}_m = [k_{m,1}, k_{m,2}, \ldots, k_{m,X_a}]^B$ is defined by $k^B_{m,l} \in \Re^{1\times X_b}$ and vector $q_m(h) \in \Re^{X_a\times 1}$ denotes circularly symmetric additive white Gaussian noise that is showed as identically separated and independent with the value of zero mean, such that the covariance matrix is represented as $\mathbf{S}_q = E\{q_m(h)q^B_m(h)\} = \lambda^2 C_{X_a}$. The received signal $v_{m,l}(h)$ at the l–th receive antenna of the fusion center $(1 \leqslant l \leqslant X_a)$ is modeled as:

$$v_{m,l}(h) = k^B_{m,l}\, g_m(h) + q_{m,l}(h), \tag{6}$$

where vector $J_m(h)$ in Eq. (5) is represented as $J_m(h) = [v_{m,1}(h), v_{m,2}(h), \ldots, v_{m,X_a}(h)]^T \in \Re^{X_a\times 1}$ and the term $q_{m,l}(h)$ implies the l–th element of noise vector. Figure 1 illustrates the model of a cooperative MIMO CRN.

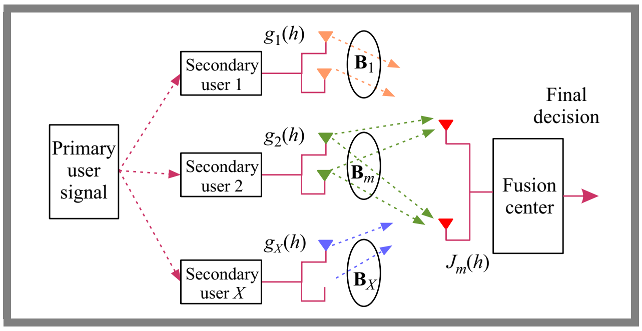

Fig. 1. Model of a cooperative MIMO cognitive radio network.

4. Proposed Adam GD Algorithm for Spectrum Sensing

To enable detecting availability of the free spectrum and to allocate the licensed bands to SUs, a spectrum sensing framework based on the Adam GD algorithm has been designed, relying on the fusion center mechanism. At first, few signal components are collected and next they are fuse based on the weights assigned to specific signal components by the Adam GD algorithm. A block diagram of the proposed model is presented in Fig. 2.

The first step is to define the signal received at the antenna with the use of a mathematical expression in order to further extract signal components needed to perform the fusion strategy required for making the final decision. The signal received at the l–th antenna of the fusion center for a set of A concatenated transmitted vectors that corresponds to the decision of the m–th SU is expressed as:

$$J_{m,l}(h) = G_m\, k_{m,l} + q_{m,l}\,, \tag{7}$$

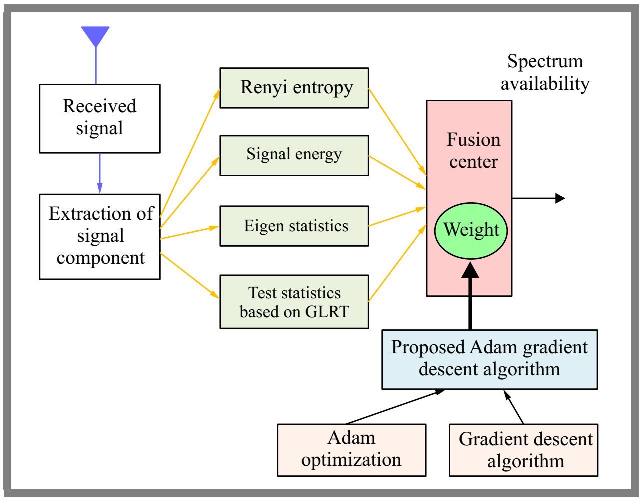

Fig. 2. Block diagram of the proposed, fusion center–based method.

where $J_{m,l} = [v_{m,l}(1), v_{m,l}(2), \ldots, v_{m,l}(A)]^B \in \Re^{A\times 1}$. The stacked noise vector $q_{m,l} \in \Re^{A\times 1}$ is generated as $q_{m,l} = [u_{m,l}(1), u_{m,l}(2), \ldots, u_{m,l}(A)]^B$.

4.1. Extraction of Signal Components

After receiving signal $J_{m,l}$, other signal components, such as Renyi entropy, signal energy, eigen statistics, and test statistics based on GLRT need to be extracted. Let us assume a CRN scenario with r transmitters and s receivers or sensors, such that each transmitter is engaged in communication within the CRN radio network. To enable communication between the transmitter and the sensor, there must exist a free channel in the CR environment. The proposed framework for determining channel availability relies on the following measures.

Renyi entropy measure for extracting a signal component is defined as:

$$RE = \frac{1}{1 - J_{m,l}} \ln \sum_{m=1}^{X} \sum_{l=1}^{X_a} J_{m,l}\,, \tag{8}$$

where denotes the Renyi entropy.

Signal energy and eigen statistics – this measure uses information obtained by receivers from transmitters [28] to generate data matrix **D** as:

$$D = [D_{cn}]_{M\times N}\,,\ 1 \leqslant c \leqslant M\,,\ 1 \leqslant n \leqslant N\,, \tag{9}$$

where D_{cn} implies n–th data received by c–th receiver in the CRN and N denotes the total number of signals received by sensors. Accordingly, matrix **D** is made up of the transmitted signals, thermal noise, and channel gain. A signal matrix **S** is formed by the signals that are sent by the transmitter and is specified as:

$$S = [S_{zn}]_{r\times N}\,, \tag{10}$$

where r implies the total number of transmitters, and N shows all data samples, S_{zn} represents the signal obtained from the z–th transmitter. Hence, communication is established through the radio channel and is processed with the use of an unoccupied channel. The data sample matrix is represented as:

$$D = [R * Q] + L\,, \tag{11}$$

where R is channel gain, $\mathbf{L}$ indicates noise matrix, and Q represents desired data. The channel matrix is estimated as:

$$R = [R_{cz}]_{s\times r}\,, \tag{12}$$

where R_{cz} denotes channel gain between the c–th receiver and the z–th transmitter. In general, signals transmitted by radio channels in CRN are degraded by noise, such that noise L is assumed while creating channel matrix $\mathbf{D}$ and thermal noise matrix is specified as:

$$K = [K_{cn}]_{M\times N}\,, \tag{13}$$

where K_{cn} is the thermal noise of the channel used to receive information from the c–th sensor. Next, the data sample matrix is utilized for calculating the signal energy and eigen statistics. The covariance matrix $\mathbf{H}$ is calculated from $\mathbf{D}$, in which the binary hypothesis test is considered. The ensemble covariance matrix of the received signal is represented as:

$$H = \text{expected}\,[D\,D^{+}]\,, \tag{14}$$

where expected[.] is the expected operator value and D^{+} implies the conjugate or the transpose of $\mathbf{D}$. At first, the ensemble covariance matrix is not known. Therefore, it is replaced with the maximum likelihood estimate (MLE) for specifying the sample as:

$$H = \frac{1}{p}\,[D\,D^{+}]\,. \tag{15}$$

By considering covariance matrix $\mathbf{H}$, signal energy and Renyi entropy, eigen statistics and test statistics based on GLRT are used for estimating spectrum availability. The eigen values of $\mathbf{H}$ are estimated as:

$$\{\gamma_1 \geqslant \gamma_2 \geqslant \ldots \gamma_r\}\,. \tag{16}$$

The energy statistics are:

$$\gamma = \frac{\gamma_1}{\frac{1}{s}\sum\limits_{c=1}^{M}\gamma_c}\,, \tag{17}$$

where γ_c shows the eigen value of the c–th sensor. The eigen statistics are:

$$I = \frac{1}{r\times\eta^2}\sum_{c=1}^{M}\gamma_c\,, \tag{18}$$

where η indicates the thermal noise factor.

GLRT-based test statistics [29] for local detection of the respective users are:

$$TS = \sum_{m=1}^{X}\sum_{l=1}^{X_a} J_{m,l}^{B}\,\alpha\,J_{m,l}\,, \tag{19}$$

where TS denotes the test statistics and the parameter α is given as:

$$\alpha = C - \mu\,, \tag{20}$$

where μ shows the projection matrix.

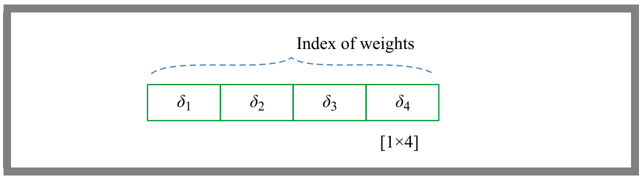

Fig. 3. Solution encoding.

4.2. Fusion Center

After extracting individual components from the received signal, they need to be fused. The fusion mechanism relies on combining all signal components with applicable weight values assigned thereto:

$$F = \delta_1\gamma + \delta_2 I + \delta_3 TS + \delta_4 RE\,, \tag{21}$$

where F denotes probability of detection, $\delta_1 \ldots \delta_4$, are the weight factors, RE shows signal component obtained through the Renyi entropy measure, I shows the eigen statistics value, γ is the signal energy and TS represents test statistics based on GLRT.

4.3. Proposed Adam GD Algorithm

The optimal weight for the fusion process is determined using the Adam GD algorithm derived through the incorporation of the GD algorithm from [27] with the Adam optimization technique from [26]. The GD algorithm is a popular optimization algorithm, also referred to as the black box optimizer, since its strengths and weaknesses are hard to explain. It is mainly used to determine the cost function based on the θ parameter for a training set. Each update process requires that a gradient for the entire dataset be computed. When the dataset does not fit to memory, it becomes slow and it is also intractable. The Adam algorithm is an effective stochastic optimization method that needs a first order gradient and is characterized by limited memory usage. It calculates the adaptive learning rate for different factors by estimating the first and the second moments of gradients. The benefits of Adam optimization are that it updates the magnitude factor such that it is invariant to gradient rescaling and it works well with sparse gradients. The solutions are encoded in the form of a vector, as $\delta_1, \delta_2, \delta_3$, and δ_4 with the dimension of $[1\times 4]$ (Fig. 3). Four different weight factors are determined using the proposed algorithm.

The proposed Adam GD algorithm is divided into the following steps:

Initialization. It defines the parameters for the entire training set in order to perform the updating process.

Fitness measure. Fitness is measured based on the area under the receiver operating characteristic (ROC) curve, i.e. a quantitative metric used for comparing various detectors. It is an expression used to determine optimal solution during iteration [**?**] and is expressed as:

$$F = \int_0^1 P_d(t)dp_f(t)\,\mathrm{d}t\,, \tag{22}$$

where t represents the specific detector, p_d is the probability of detection, and p_f signifies the probability of a false alarm.

Update solution. The update vector of the GD algorithm is formulated as:

$$Y_w = \beta\, Y_{w-1} + \chi \nabla_\theta\, Z(\theta)\,, \tag{23}$$

The standard expression of Adam optimization is specified as:

$$Y_w = Y_{w-1} - \frac{\tilde{\omega}.\hat{i}_w}{\sqrt{\hat{j}_w + \varepsilon}}\,, \tag{24}$$

$$Y_{w-1} = Y_w + \frac{\tilde{\omega}.\hat{i}_w}{\sqrt{\hat{j}_w + \varepsilon}}\,, \tag{25}$$

By substituting Eq. (25) to Eq. (23) we get:

$$Y_w = \beta\left(Y_w + \frac{\tilde{\omega}.\hat{i}_w}{\sqrt{\hat{j}_w + \varepsilon}}\right) + \chi \nabla_\theta\, Z(\theta)\,, \tag{26}$$

$$Y_w = \beta Y_w + \left.\frac{\beta.\tilde{\omega}.\hat{i}_w}{\sqrt{\hat{j}_w + \varepsilon}}\right) + \chi \nabla_\theta\, Z(\theta)\,, \tag{27}$$

$$Y_w - \beta Y_w = \left.\frac{\beta.\tilde{\omega}.\hat{i}_w}{\sqrt{\hat{j}_w + \varepsilon}}\right) + \chi \nabla_\theta\, Z(\theta)\,, \tag{28}$$

$$Y_w(1-\beta) = \left.\frac{\beta.\tilde{\omega}.\hat{i}_w}{\sqrt{\hat{j}_w + \varepsilon}}\right) + \chi \nabla_\theta\, Z(\theta)\,, \tag{29}$$

$$Y_w = \frac{1}{1-\beta}\left[\left.\frac{\beta.\tilde{\omega}.\hat{i}_w}{\sqrt{\hat{j}_w + \varepsilon}}\right) + \chi \nabla_\theta\, Z(\theta)\right], \tag{30}$$

$$Y_w = \frac{\beta.\tilde{\omega}.\hat{i}_w + \chi \nabla_\theta\, Z(\theta)\sqrt{\hat{j}_w + \varepsilon}}{\sqrt{\hat{j}_w + \varepsilon}\,(1-\beta)}\,, \tag{31}$$

where $\varepsilon = 10^8$, β represents the momentum term and equals 0.9, χ specifies the size of the steps taken to reach the minimum, $Z(\theta)$ signifies the objective function, w indicates the time step and $\hat{i}_t = \frac{i_t}{1-\rho_t}$. Here ρ_t denotes the decay rate within the $0 \ldots 1$ range.

Evaluating feasibility. The fitness of each solution is computed based on the fitness measure function such that the optimal solution shows the best value for specific weight factors.

Termination. The above steps are repeated until the optimal solution is attained. Algorithm 1 summarizes the proposed method.

Algorithm 1. Pseudo code of proposed model.

1: Input: Momentum term, decay rate, and step size.
2: Output: Y_w.
3: Initialize the factors.
4: Compute fitness measure.
5: Derive update solution of Y_w using Eq. (31).
6: Evaluate feasibility.
7: Return best solution.

5. Results and Discussion

The proposed model is evaluated using Matlab and is compared with existing approaches, such as kernel-based spectrum sensing [16], DNN [4], cooperative reinforcement learning [22], and deep learning [23] to show the extent of the improvements achieved.

Figure 4 analyzes the detection probability for a Rayleigh channel. At SNR of 5 dB, detection probability achieved by kernel-based spectrum sensing, DNN, cooperative reinforcement learning, deep learning, and the Adam GD algorithm is 0.47, 0.39, 0.33, 0.53, and 0.71, respectively (Fig. 4a). A false alarm probability analysis is shown in Fig. 4b. For SNR of 5 dB, the probability measure for kernel-based spectrum sensing, DNN, cooperative reinforcement learning, deep learning, and the Adam GD algorithm is 0.76, 0.58, 0.52, 0.44, and 0.39, respectively. Figure 4c shows an analysis of ROC. For the probability of detection equaling 0.6, the false alarm probability rate obtained by kernel-based spectrum sensing, DNN, cooperative reinforcement learning, deep learning, and Adam GD algorithm is 0.47, 0.42, 0.32, 0.18, and 0.50, respectively. Figure 5 shows the results of a detection probability analysis for a Rician channel. For SNR of 10 dB, the detection probability of kernel-based spectrum sensing, DNN, cooperative reinforcement learning, deep learning, and the Adam GD algorithm is 0.93, 0.86, 0.95, 0.78, and 0.96, respectively (Fig. 5a). Results of the false alarm probability are shown in Fig. 5b. For SNR of 5 dB, the probability measure for kernel-based spectrum sensing, DNN, cooperative reinforcement learning, deep learning, and the Adam GD algorithm is 0.79, 0.51, 0.58, 0.46, and 0.40, respectively. Analysis of ROC for a detection value of 0.7 gives a false alarm probability for kernel-based spectrum sensing, DNN, cooperative reinforcement learning, deep learning, and the Adam GD algorithm of 0.27, 0.53, 0.55, 0.66, and 0.78, respectively (Fig. 5c).

Figure 6 presents the results of a detection probability analysis for a Gaussian channel. When SNR=10 dB, the detection value for kernel-based spectrum sensing, DNN, cooperative reinforcement learning, deep learning, and the Adam GD algorithm is 0.78, 0.67, 0.86, 0.89, and 0.91, respectively. The false alarm probability shown in Fig. 6b for SNR of 10 dB for kernel-based spectrum sensing, DNN, cooperative reinforcement learning, deep learning, and the Adam GD algorithm is 0.92, 0.83, 0.94, 0.72, and 0.64, respectively. Figure 6c shows the ROC. For a detection value of 0.8, the false alarm probability for kernel-based spectrum sensing, DNN, cooperative reinforcement learning, deep learning, and the Adam GD algorithm is 0.64, 0.55, 0.69, 0.80, and 0.87, respectively. Table 1 summarizes the results of all analyses performed.

6. Conclusion

Spectrum sensing is a key technology used in CRNs. The objective of this research is to determine the availability of free spectrum using the proposed Adam GD algorithm. Here, the signal received at the receiver end is used to extract individual signal components, such as energy, Renyi entropy, test statistics, and eigen statistics. Accordingly, the signal's components are fused at the fusion center by applying weight factors determined using the Adam GD algorithm. The proposed approach achieves the maximum probability of detection and the minimum probability of a false alarm equaling 0.7099 and 0.3892, respectively, for a Rayleigh channel.

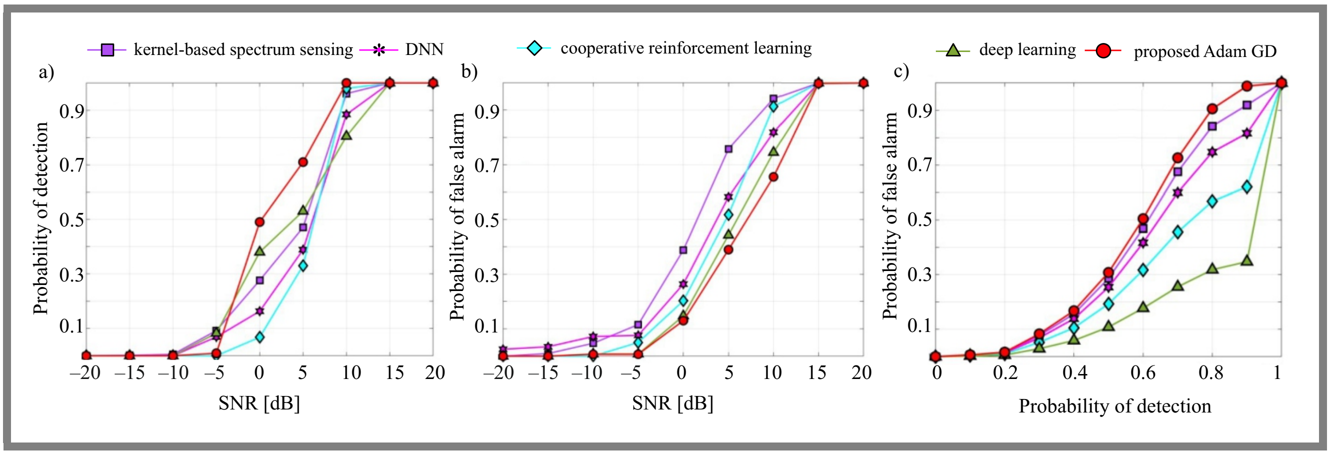

Fig. 4. Rayleigh channel analysis results: a) probability of detection, b) probability of false alarm, and c) ROC.

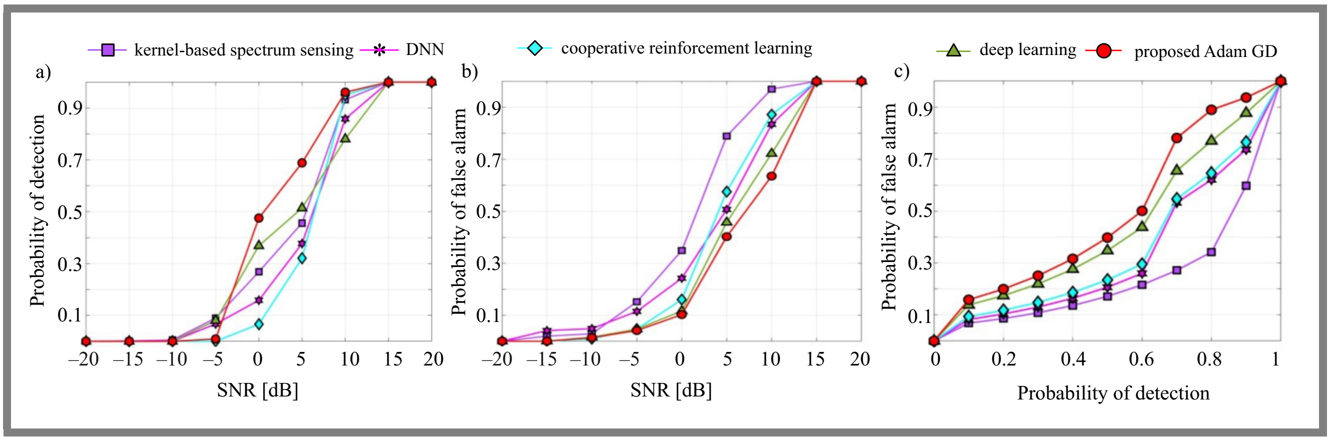

Fig. 5. Rician channel analysis results: a) probability of detection, b) probability of false alarm, and c) ROC.

Tab. 1. Analysis summary for SNR = 5 dB.

Channel type	Metrics	Kernel-based spectrum sensing	DNN	Cooperative reinforcement learning	Deep learning	Proposed Adam GD algorithm
Rayleigh	Probability of detection	0.4704	0.3889	0.3303	0.5300	0.7099
	Probability of false alarm	0.7578	0.5820	0.5173	0.4423	0.3892
Rician	Probability of detection	0.4563	0.3772	0.3204	0.5141	0.6886
	Probability of false alarm	0.7888	0.5077	0.5759	0.4578	0.4029
Gaussian	Probability of detection	0.5967	0.5105	0.5319	0.6693	0.6909
	Probability of false alarm	0.7781	0.4570	0.5723	0.4656	0.4097

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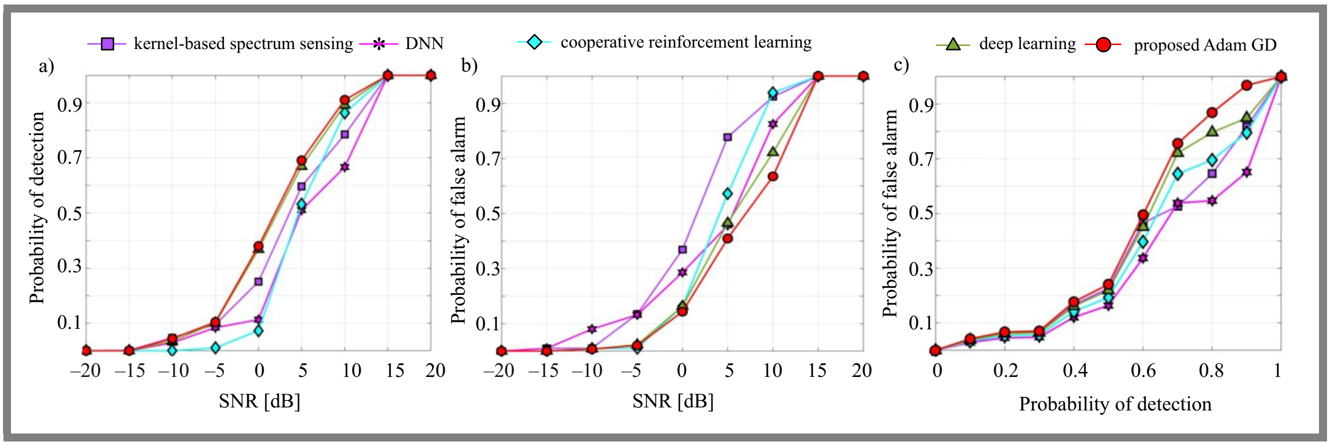

Fig. 6. Gaussian channel analysis: a) probability of detection, b) probability of false alarm, and c) ROC.

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