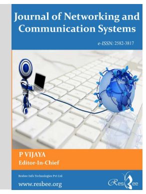
Vol.8 Issue 2 April 2025

Journal of Networking and Communication Systems

Received 24 March, Revised 28 April, Accepted 29 May



CGOA: CAViaR Goat Optimization Algorithm based Cooperative Spectrum Sensing in Cognitive Radio Network

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Abstract: Cognitive radio (CR) is a modern technology that enhances the usage of the radio spectrum. Cooperative spectrum sensing (CSS) is a core component of CR technology. However, due to various factors, detection performance may degrade, making accurate spectrum sensing challenging. Recently, various CSS techniques have been developed. However, these methods are model-driven and depend on prior data. Also, spectrum sensing performance is degraded when the system assumptions are inexact or when previous information is difficult to obtain. In this research, the CAViaR Goat Optimization Algorithm (CGOA) is introduced for CSS in the Cognitive Radio Network (CRN). Here, the received signal is taken as an input, and then, the extraction of signal components is performed. The extracted signal components are cyclostationary features, eigen statistics, matched filters, and signal energy. Afterward, the fusion process of extracted signal components is carried out in the fusion center, and thus, a decision is acquired. In addition, weight determination is performed using a newly designed CGOA. However, CGOA is devised by integrating Conditional Autoregressive Value at Risk (CAViaR) with the Goat Optimization Algorithm (GOA). Furthermore, CGOA has achieved a maximum probability of detection of about 0.932, as well as minimal sensing time and a probability of false alarm of about 253.304 sec and 0.598.

Keywords: Cooperative Spectrum Sensing, Cognitive Radio Network, Cyclostationary Features, Conditional Autoregressive Value at Risk, Goat Optimization Algorithm.

Nomenclature

Abbreviations	Description
CR	Cognitive Radio
CRN	Cognitive Radio Network
PU	Primary User
SU	Secondary User
CSS	Cooperative Spectrum Sensing
SPU	Second Priority User
FPU	First Priority User
CGOA	CAViaR Goat Optimization Algorithm
GOA	Goat Optimization Algorithm
CAViaR	Conditional Autoregressive Value at Risk
CNN	Convolutional Neural Network
LSTM	Long Short Term Memory
NN	Neural Network
SNR	Signal to Noise Radio
AUC	Area Under Curve

1. Introduction

The quick development of wireless applications regularly increases requests for high data rates, settling allocation policies, and fixed properties of the spectrum to test. To efficiently enhance the static spectrum usage policy, a beneficial attribute of CR is developed based on the dynamic spectrum. CR is one of the capable methods that solves the spectrum insufficiency problems by optimizing the spectrum. The primary purpose of CR is to monitor the spectrum and its environments while accurately employing its radio parameters [1]. CR is developed as a vital technology to lessen the shortage of cooperative spectrum resources. A temporally available spectrum for the primary user (PU) is accessible by the secondary user (SU) in CRN. Hence, a major responsibility of CR is to identify PU's existence. In addition, the spectrum sensing technology is a fundamental part of CR [2]. Spectrum management, sharing, or mobility, as well as spectrum sensing, completely rely on CRN. Spectrum sensing is categorized into three types such as non-cooperative detection, interference detection, and cooperative detection [3]. In CSS, various Second Priority Users (SPU) decide to sense an idle channel by distributing data regarding accessible channels amongst every SPU for superior performance of First Priority Users (FPU) while lessening probability values [1].

During the process of spectrum sensing, CRs collaborate to recognize the activities of PU. The local detection outcomes are reported to a fusion center that later combines every local decision and provides the final decision [4]. The spectrum sensing techniques are classified into two types, namely non-parametric and parametric sensing models [5]. A parametric sensing technique requires some previous data on PU signals; however, preceding data based on PU activities is complex to acquire practically. Hence, a non-parametric detection model is highly appropriate in CR systems. Several parametric sensing models are being developed present days, including matched filter algorithm, energy detection algorithm, periodogram-based algorithm, likelihood detection algorithm, and cyclostationary detection [6]. Machine Learning (ML)-enabled methods offer an attractive choice to tackle complicated issues with decreased time and effort. Currently, several ML-enabled techniques are being developed to solve energy-efficiency problems of a distributed CSS. It is accomplished by employing Q-learning for instructing learning sensor selection models for energy efficiency by embedding data from the graph structures into a Neural Network (NN) [4]. With the rapid growth of Deep Learning (DL) algorithms, several types of research based on DL models for CSS are designed [7] [2]. Furthermore, deep cooperative sensing that utilizes a Convolutional Neural Network (CNN) is devised for achieving CSS [8] [2]. Therefore, the implementation of efficient models for CSS is significant in improving the reliability, effectiveness, and accuracy of spectrum detection in CRN.

A significant intention is to present CGOA for spectrum sensing in CRN. CR is an important technology to enhance the use of the radio spectrum, and it has gained more attention from various researchers. Furthermore, CSS has an invaluable position in the domain of CR and also, and it is studied expansively. In this research, the received signal is considered as an input. Then, signal components, namely signal energy, cyclostationary features, eigen statistics, and matched filter, are extracted. Thereafter, the fusion process of extracted signal components is accomplished in the fusion center, and thus, a decision is obtained. To enhance this fusion process, weights are determined by CGOA, which is an integration of CAViaR with GOA.

- ❖ **Proposed CGOA-based spectrum sensing in CRN:** CSS is considered an important method in the CR system, as it is capable of enhancing spectrum sensing. In this research, the extracted signal components are combined in a fusion center, and their weight determination is carried out by CGOA. This method leverages the predictive strength of CAViaR and the exploration capabilities of GOA to improve decision-making. However, the newly designed CGOA is an incorporation of CAViaR with GOA.

The organization of the following sections is: Section 2 interprets the literature overview of classical models and their disadvantages, Section 3 reveals the system model, the methodology of CGOA is explained in Section 4, Section 5 describes the outcomes of CGOA, and Section 6 illustrates the conclusion of CGOA.

2. Motivation

In CRN, the CSS offers the strongest way to increase throughput, energy efficiency, and spectral efficiency. However, more counts of SUs increase energy consumption, thereby decreasing energy efficiency. This creates a trade-off between detection performance and power consumption. Therefore, an energy-efficient algorithm for CSS is designed in this research by reviewing various methods. The goal is to retain high detection accuracy while minimizing unnecessary energy expenditure. This section presents the collected conventional techniques along with their challenges.

2.1 Literature Survey

L. Li., *et al.* [6] developed Long-Short-Term Memory and CNN (LSTM-CNN) for spectrum sensing in CRN. It enhanced the reliability of the spectrum sensing, but still, this model led to increased bandwidth consumption and probable latency problems. While LSTM-CNN showed promise, it failed to address real-time constraints in bandwidth and latency. K. Arshid., *et al.* [1] designed SPU transmission model for CSS. This scheme was reliable based on optimized energy efficiency, and minimized handoff delay and sensing performance. However, it failed to distribute consistent data about the channels among SPUs. The lack of data consistency among SPUs limited the model's scalability in more dynamic environments. Q. Wu., *et al.* [4] introduced NN for energy-effectual spectrum sensing. This technique was robust even with varying global necessities, even though energy-efficient decentralized spectrum sensing was not considered. The model, while effective, lacked a comprehensive approach to decentralized operations and energy optimization across nodes. M. Xu., *et al.* [2] presented a Multifeatures Combination Network for spectrum sensing in CRN. It enhanced sensing consistency by combining local data from diverse sensing nodes. Nevertheless, it was not validated using a more complicated and larger database. Validation using real-world, large-scale data sets remains a gap in the approach.

2.2 Challenges

The challenges confronted by traditional CSS models are described below.

- The model developed in [1] was not enhanced by considering extra unoccupied spectra accessible for transmission and also, and it resulted in additional energy consumption. A lack of dynamic spectrum availability consideration resulted in inefficient energy use.
- In [2], the Multifeatures Combination Network achieved efficient performance, though it did not concentrate on minimizing computational complexity while sustaining the validity of a model. Reducing computational complexity without compromising model accuracy remains a challenge.
- CR refers to the practical method to overcome spectrum inadequacies by sensing and using spectrum holes across an extensive spectrum. However, it is still challenging to balance energy effectiveness as well as superior sensing performance in classical CSS systems. A key challenge remains optimizing both energy efficiency and sensing accuracy in large-scale, real-world scenarios. Thus, an effective algorithm is essential for spectrum sensing in the CRN.

3. System Model of Cooperative Spectrum Sensing in CRN

Fig. 1 shows a system model of the spectrum sensing in CRN. In CSS [9], every CR measures a licensed spectrum and makes decisions independently. Generally, CRN contains various PUs as well as SUs, wherein SU intends to distribute multichannel spectrum resources along with the PU without disturbing PUs. As the channel state is not known, SU is only capable of making decisions after an individual tries to sense diverse channels. In addition, an individual synchronizes with a certain time slot. A structure of time slots is categorized into two types of periods: data transmission period and sensing period. At an early stage of the sensing period, every SU senses the slots independently. Thereafter, SU transfers its information to other users and incorporates it with acquired data. Lastly, decisions are transferred by the individual SU. Moreover, there is an acknowledgement (ACK) signal for sending confirmed data based on unsuccessful or successful transmission before ending a sensing period.

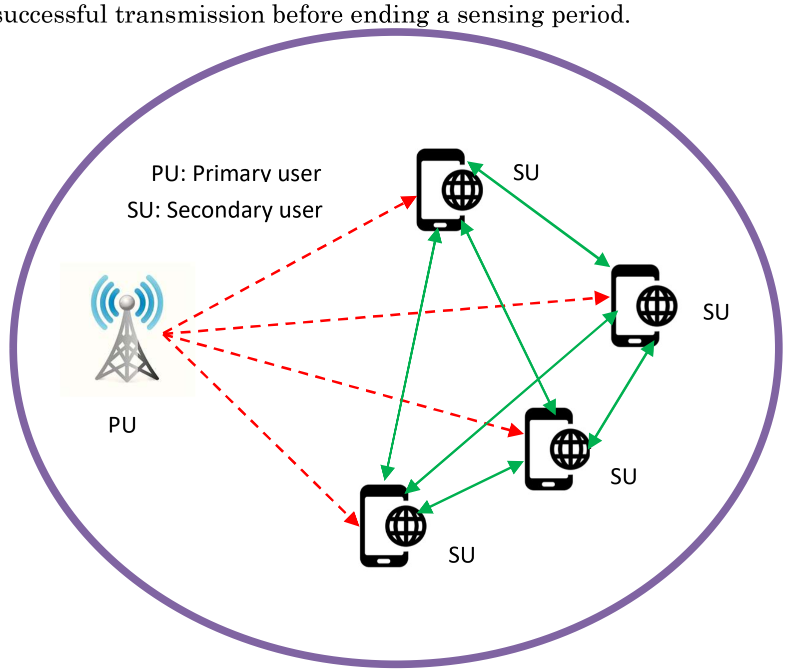


Fig. 1. *System model of spectrum sensing in the CRN*

4. Proposed CAViaR Goat Optimization Algorithm based on cooperative spectrum sensing in CRN

Presently, CSS plays an important part in effective 5G communication. The spectrum sensing method is more applicable owing to its efficient and fast performance. In this context, CGOA is newly presented for spectrum sensing in CRN. Initially, the received signal is considered as an input. Next, signal components, namely eigen statistics, matched filter, cyclostationary features, and signal energy, are extracted. Afterward, the fusion process of signal components is conducted in a fusion center, and thus, the decision is attained. Furthermore, weights are determined using CGOA, which is derived by integrating CAViaR with GOA. This hybrid model is designed to optimize the decision fusion process by assigning more accurate weights to each sensing component. Fig. 2 delineates the graphical illustration of CGOA-based cooperative spectrum sensing in CRN.

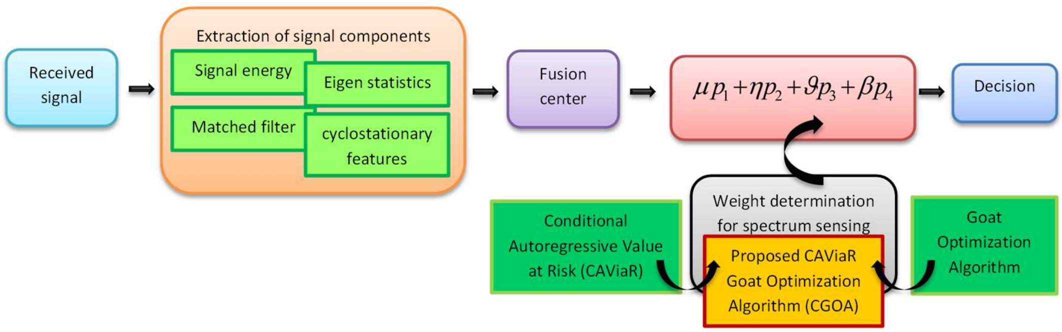


Fig. 2. *Graphical illustration of CGOA-based spectrum sensing in CRN*

4.1 Extraction of Signal Components

A received signal V is taken as an input, and then, signal component extraction is performed. The extraction of signal components refers to a process of identifying and isolating PU signals from received composite signals at SUs. Here, signal components considered for extraction are eigen statistics, cyclostationary features, matched filter, and signal energy.

4.1.1 Signal Energy and Eigen Statistics

A data sample matrix Q is developed utilizing samples obtained by sensors from certain transmitters. An expression of the matrix Q can be modeled by,

$$Q = \left[Q_{uv}\right]_{r\times z}; \quad (1 \le u \le r); \quad (1 \le v \le z) \tag{1}$$

Here, Q_{uv} this relates to v^{th} data samples received utilizing u^{th} sensors in the CR; overall, data samples z are received employing sensors. Moreover, Q the matrix is developed utilizing channel gain, thermal noise, and transferred signals. The purpose of transmitters is the transmission of signals, and these signals are arranged as a signal matrix indicated by W . Hence, the transferred signal matrix can be represented by,

$$W = \left[W_{lv}\right]_{w\times z} \tag{2}$$

where, w implies the overall count of transmitters, whereas z signifies overall data samples, and W_{lv} denotes signal from l^{th} the transmitter. An expression of the data sample matrix is illustrated by,

$$Q = \left[H * K\right] + X \tag{3}$$

Here, channel gain is specified by H and X refers to the thermal noise matrix. A channel matrix can be modeled as,

$$H = \left[H_{ul}\right]_{r\times w} \tag{4}$$

Here, the channel gain between l^{th} the transmitter and u^{th} sensor is symbolized by H_{ul} . A thermal noise matrix can be given as,

$$R = \left[R_{uv}\right]_{r\times z} \tag{5}$$

where, R_{uv} signifies thermal noise that acquires data from u^{th} the sensor. A received signal's ensemble covariance matrix is calculated as,

$$J = Expected\left[Q \;\; Q^{+}\right] \tag{6}$$

Here, $Expected[\ ]$ the expected value operator, Q^{+} reveals the conjugate and the transpose of Q. The ensemble covariance matrix modified with maximum likelihood estimate (MLE) to represent a sample is given by,

$$J = \frac{1}{z}\left[Q\ Q^{+}\right] \tag{7}$$

where J signifies the covariance matrix. An eigenvalue of J is depicted by,

$$\left\{\omega_1 \geq \omega_2 \geq \ldots \omega_r\right\} \tag{8}$$

Hence, energy statistics [10] can be illustrated by,

$$p_1 = \frac{\omega_1}{\frac{1}{r}\sum_{u=1}^{r}\omega_u} \tag{9}$$

where ω_u implies the eigenvalue of u^{th} the sensor, and the eigenstatistics [10] can be modeled by,

$$p_2 = \frac{1}{w \times \tau^2}\sum_{u=1}^{r}\omega_u \tag{10}$$

Here, τ the thermal noise factor.

4.1.2 Matched Filter

Matched filter sensing [11] is an optimum method of sensing as it requires only less count of samples to achieve the best detection performance. These methods compare a received signal with the pre-assigned as well as pilot samples captured from equivalent transmitters. These samples are utilized for computing test statistics, and it is given as,

$$p_3 = \frac{1}{Y}\sum_{y=1}^{Y} x(y)\, m_i^{*}(y) \tag{11}$$

Here, Y implies overall samples, x signifies a vector of the samples, whereas m_i denotes pilot samples and p_3 specifies extracted matched filter.

4.1.3 Cyclostationary Features

The signal's statistical parameters, namely carrier frequency and modulation rate, are naturally periodic, and then it is considered a cyclostationary feature [12]. If ACF and the mean of the received signal are periodic, then the signal is termed a cyclostationary signal. A signal's periodicity of ACF and mean are utilized by cyclostationary features-enabled detectors for accomplishing sensing tasks. The periodicity of ACF and mean can be mathematically defined by,

$$P_h^{\partial}(\hbar) = P_h^{\partial}(s + S_0, \hbar) \tag{12}$$

$$v_h(s) = E\left[h(s)\right] = v_h(s + \hbar) \tag{13}$$

$$v_h(s) = \sum_{s=1}^{S=1}\left[h[s]\, e^{-\alpha 2\pi \partial s}\right] \tag{14}$$

$$P_h^{\partial}(\hbar) = E\left[h[s]^{*}\, h[s+\hbar]\, e^{\alpha 2\pi \partial s}\right] \tag{15}$$

Here, $E[.]$ indicates an expectation operator, S_0 denotes the time interval of the received signal, $\hbar$ depicts the time interval, ∂ mentions cyclic frequency, $P_h^{\partial}(\hbar)$ and implies autocorrelation operation, whereas $v_h(s)$ reveals the mean of the received signal $h[s]$ and extracted cyclostationary features are symbolized as p_4.

4.2 Fusion Center

The fusion center refers to a processing node or system that integrates several signal components from various sources to produce a comprehensive and accurate representation of an underlying signal. An expression to fuse all extracted signal components in the fusion center based on weights can be computed by,

$$F = \mu\, p_1 + \eta\, p_2 + \vartheta\, p_3 + \beta\, p_4 \tag{16}$$

Here, p_1 implies signal energy, p_2 depicts eigen statistics, p_3 specifies matched filter, and p_4 represents cyclostationary features, whereas $\mu, \eta, \vartheta\ \ \beta$ denotes weights.

4.3 Determination of weight for spectrum sensing using CAViaR Goat Optimization Algorithm

Weight determination refers to a process of assigning appropriate weights to each signal component after they have been fused from various sources. Here, the determination of weights is accomplished by CGOA, which is derived by combining CAViaR with GOA.

4.3.1 Solution Encoding

Solution encoding involves a formulation of a structured representation that encapsulates the assigned weights to the individual signal component. This encoding enables the CGOA to optimize each component's contribution during the fusion process. Fig. 3 displays the solution encoding for the determination of weights.

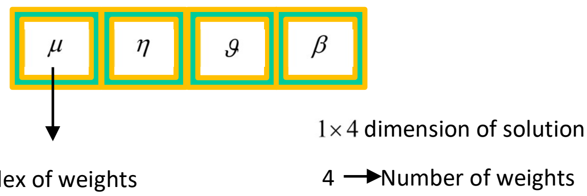


Fig. 3. *Solution encoding for the determination of weights*

4.3.2 Fitness Function

The fitness function for weight detection of signal components is calculated based on the area under the curve (AUC). AUC [13] is defined as a quantitative measure acquired by incorporating the fused signal over a certain domain or interval. AUC can be formulated by,

$$A = \int_0^1 \mathrm{P}_T \, d\mathrm{P}_\ell \tag{17}$$

Here, P_T and P_ℓ indicates detection as well as false alarm probabilities.

4.3.3 Algorithmic Steps of CAViaR Goat Optimization Algorithm

The major intention of weight determination is to optimize the influence of individual signal components in subsequent processing or decision-making phases, thereby improving the accuracy, interpretability, or robustness of fused signal components. Here, CGOA is used to determine the weights of individual signal components. In addition, the newly designed CGOA is derived by integrating CAViaR with GOA.

CAViaR [14] is the framework model for estimating the dynamic evolution of Value at Risk (VaR) by directly deriving a quantile of the return distribution as an operation of prior data. The flexibility of CAViaR enables more accurate weight determination based on the nature of combined signals.

GOA [15] is designed by an inspiration on adaptive characteristics of goats. Based on their moving patterns, capability to avoid parasites and foraging strategies, GOA is devised to balance exploitation as well as exploration efficiently. GOA can obtain the best convergence speed, improved global search efficacy, and enhanced solution accuracy.

CGOA effectively handles fused signal components with varying attributes and captures subtle features and relationships within particular data for exact weight determination. The algorithmic steps of CGOA are described as follows.

Step 1: Solution initialization

Initially, each goat in the population is initialized randomly, and it can be given by,

$$G = \{G_1, G_2, ..., G_c, ..., G_t\} \tag{18}$$

Here, G_c implies c^{th} a candidate solution and G_t symbolizes the total variables in a population G

Step 2: Computation of the objective function

An objective measure is calculated by AUC based on detection and false alarm probabilities utilizing Eq. (17).

Step 3: Adaptive foraging strategy

An individual goat explores a search space in this stage by moving randomly in diverse directions, enthused by its foraging behaviors. The newer location of individual goats can be updated by,

$$G_c^{a+1} = G_c^a + \gamma . q . (U - L) \tag{19}$$

Incorporating CAViaR with GOA can lead to a highly effective exploration of the search space for optimum weights. The standard expression of CAViaR can be given by,

$$G_c^a = \varsigma_0 + \sum_{o=1}^{j} \varsigma_o G_c^{a-o} + \sum_{o=1}^{\varepsilon} \varsigma_g f\left(G_c^{a-\varepsilon}\right) \tag{20}$$

Let us assume $j = \varepsilon = 2$ and therefore the equation is modeled as,

$$G_c^a = \varsigma_0 + \varsigma_1 G_c^{a-1} + \varsigma_2 G_c^{a-2} + \varsigma_1 f\left(G_c^{a-1}\right) + \varsigma_2 f\left(G_c^{a-2}\right) \tag{21}$$

Substitute Eq. (21) in Eq. (19), and therefore, an updated equation of CGOA is mentioned.

$$G_c^{a+1} = \left[\varsigma_0 + \varsigma_1 G_c^{a-1} + \varsigma_2 G_c^{a-2} + \varsigma_1 f\left(G_c^{a-1}\right) + \varsigma_2 f\left(G_c^{a-2}\right)\right] + \gamma . q .(U - L) \tag{22}$$

Here, γ indicates the exploration coefficient, q symbolizes a random variable acquired from a Gaussian distribution, U and L denotes upper and lower bounds, whereas ς depicts a constant.

Step 4: Movement against the superior goat

For refining solutions, the goats slowly move against better solutions thus far, imitating the capability of goats to travel toward optimum grazing regions. This stage can be modeled by,

$$G_c^{a+1} = G_c^a + \xi .\left(G_b^a - G_c^a\right) \tag{23}$$

Here, G_b^a signifies the best-performing goat at a^{th} iteration, whereas ξ indicates the exploitation coefficient.

Step 5: A jumping strategy for escaping the local optima

A vital feature of GOA is its capability to escape the local optima utilizing sudden jumps, enthused by the distinctive movement capabilities of goats in rough terrains. It can be represented by,

$$G_c^{a+1} = G_c^a + M .\left(G_n^a - G_c^a\right) \tag{24}$$

Here, M signifies the jump coefficient and G_n^a denotes a randomly chosen goat from the population.

Step 6: Avoidance of parasites and solution filtering

The goats automatically avoid all areas affected by parasites to maintain solution quality, and this stage is expressed by,

$$G_c^{a+1} = L + \left(U - L\right).\Re\left(k\right) \tag{25}$$

where $\Re$ implies a random value.

Step 7: Re-estimation of fitness measure

The best fitness value is obtained by re-evaluating a fitness measure computed using Eq. (17)

Step 8: Termination

The outcomes of CGOA are continuously carried out until acquiring optimum solution and then the process is terminated.

5. Results and Discussion

The outcomes of CGOA devised for CSS are revealed in this section, along with the experiment setup and performance metrics.

5.1 Experiment Setup

The designed CGOA is implemented in the MATLAB tool using simulation.

5.2 Evaluation Metrics

The metrics considered for assessing CGOA are sensing time, probability of false alarm, and probability of detection.

5.2.1 Probability of Detection

The probability of detection refers to the likelihood that SUs correctly determine the existence of a PU signal in a certain frequency band.

5.2.2 Probability of False Alarm

The probability of a false alarm can be stated as the likelihood that a cooperative sensing mechanism imprecisely determines PU's existence when the spectrum is truly free.

5.2.3 Sensing Time

Sensing time is specified as a duration assigned by SU for monitoring a particular frequency band to identify the absence or presence of PU.

5.3 Comparative Techniques

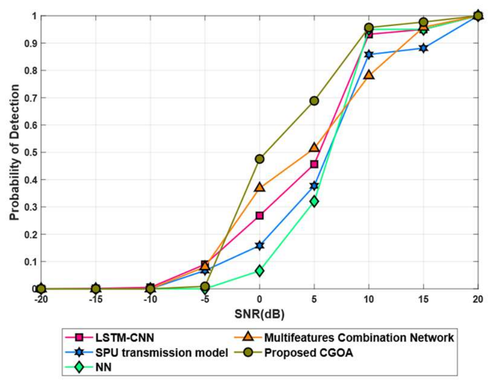
LSTM-CNN [6], SPU transmission model [1], NN [4] ,and Multifeatures Combination Network [2] are the traditional approaches considered to compare with CGOA to validate its effectiveness.

5.4 Comparative Evaluation

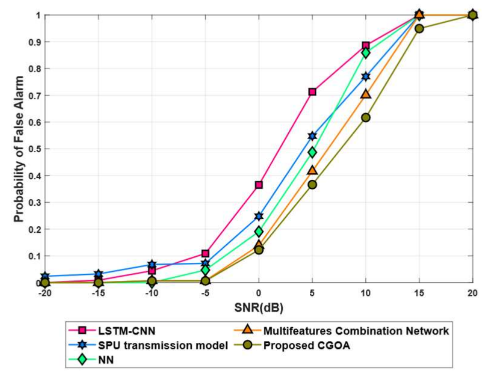
The estimations of CGOA are performed based on setups like the Rayleigh channel and the Nakagami channel.

5.4.1 Analysis based on the Rayleigh channel

Fig. 4 specifies the analysis of CGOA by varying SNR values. Here, the values obtained by CGOA and existing methods for SNR=10dB are explained. Fig. 4a) interprets the estimation of CGOA concerning the probability of detection. CGOA achieved a probability of detection of about 0.957, whereas LSTM-CNN, SPU transmission model, NN, and Multifeatures Combination Network obtained 0.932, 0.858, 0.950, and 0.780. Assessment of CGOA considering the probability of false alarms is shown in Fig. 4 b). CGOA acquired a 0.617 probability of false alarm, whereas LSTM-CNN, SPU transmission model, NN, and Multifeatures Combination Network attained 0.886, 0.770, 0.859, and 0.701. Fig. 4c) delineates the estimation of CGOA in terms of sensing time. LSTM-CNN, SPU transmission model, NN, and Multifeatures Combination Network obtained sensing time of 326.858sec, 324.517sec, 321.671sec, and 305.097sec, whereas CGOA acquired 269.472sec of sensing time.



(a)



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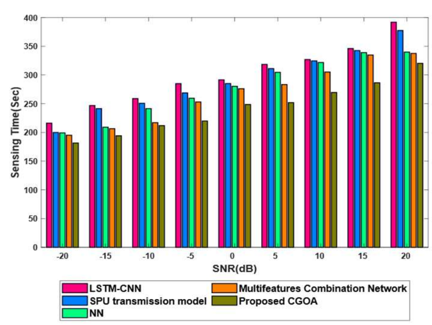
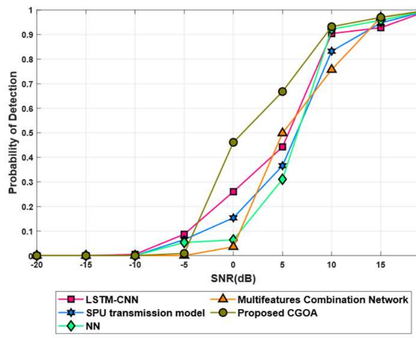


(c)

Fig. 4. *Analysis of CGOA based on Rayleigh channel, a) Probability of detection, b) Probability of false alarm, c) Sensing time*

5.4.2 Analysis based on Nakagami Channel

Assessment of CGOA considering metrics by varying SNR is demonstrated in Fig. 5. The analysis values acquired by CGOA and other methods while considering SNR=10dB are interpreted in this section. Fig. 5 a) describes the evaluation of CGOA based on the probability of detection. CGOA achieved a 0.932 probability of detection, whereas LSTM-CNN, SPU transmission model, NN, and Multifeatures Combination Network obtained a probability of detection of about 0.904, 0.832, 0.922, and 0.757. Estimation of CGOA concerning the probability of false alarms is revealed in Fig. 5 b). LSTM-CNN, SPU transmission model, NN, and Multifeatures Combination Network acquired a probability of false alarm about 0.913, 0.785, 0.821, and 0.679, whereas CGOA obtained 0.598. Fig. 5 c) depicts the analysis of CGOA about sensing time. The sensing time obtained by CGOA is 253.304 sec, whereas LSTM-CNN, SPU transmission model, NN, and Multifeatures Combination Network achieved sensing times of 307.246 sec, 305.046 sec, 302.371 sec, and 286.791 sec.



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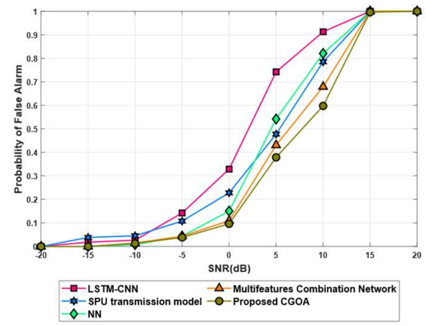

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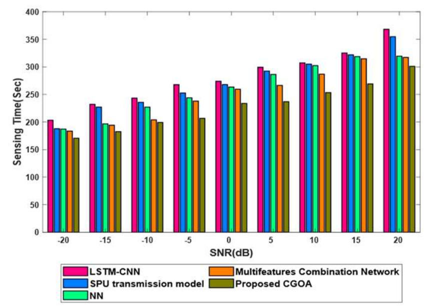

(c)

Fig. 5. *Analysis of CGOA based on Nakagami channel, a) Probability of detection, b) Probability of false alarm, c) Sensing time*

5.5 Comparative Discussion

Table 1 explicates the evaluation values achieved by CGOA and other reviewed schemes. When SNR=10dB, CGOA acquired a 0.932 probability of detection, whereas LSTM-CNN, SPU transmission model, NN, and Multifeatures Combination Network attained probabilities of detection of about 0.904, 0.832, 0.922, and 0.757. A maximum probability of detection indicates that CGOA reduced the probability of missed detection. For SNR=10dB, LSTM-CNN, SPU transmission model, NN, and Multifeatures Combination Network obtained a probability of false alarm about 0.913, 0.785, 0.821, and 0.679, whereas CGOA acquired 0.598. A low probability of false alarm indicates that CGOA results in an effective spectrum sensing procedure and minimizes interference. The sensing time acquired by CGOA is 253.304sec while considering SNR=10dB, whereas LSTM-CNN, SPU transmission model, NN, and Multifeatures Combination Network obtained sensing times of 307.246sec, 305.046sec, 302.371sec, and 286.791sec. The minimal sensing time obtained by CGOA enables CRN to operate more effectively and efficiently. It can be acknowledged that CGOA is an effective algorithm for CSS. Moreover, CGOA attained a high probability of detection of about 0.932 as well as a minimal probability of false alarm and sensing time of about 0.598 and 253.304 sec for the Nakagami channel when SNR=10 dB.

Table 1. *Comparative discussion of CGOA*

Setups	Metrics/ Methods	LSTM-CNN	SPU transmission model	NN	Multi-feature Combination Network	Proposed CGOA
Rayleigh channel	Probability of detection	0.932	0.858	0.950	0.780	0.957
	Probability of false alarm	0.886	0.770	0.859	0.701	0.617
	Sensing time (sec)	326.858	324.517	321.671	305.097	269.472
Nakagami channel	Probability of detection	0.904	0.832	0.922	0.757	**0.932**
	Probability of false alarm	0.913	0.785	0.821	0.679	**0.598**
	Sensing time (sec)	307.246	305.046	302.371	286.791	**253.304**

6. Conclusion

CSS can enhance spectrum sensing performance by introducing spatial diversity in CRN. However, delay is also introduced by this cooperation to report sensing information. The traditional methods assume that cooperative SU reports its local data to a fusion center successively. It causes a reporting delay due to a larger count of the cooperative SUs and eventually affects CSS performance. In this research, CGOA is newly designed for spectrum sensing in CRN. Firstly, the received signal is considered as an input. After that, signal components, namely eigen statistics, matched filter, signal energy, and cyclostationary features, are extracted. Next, the fusion of extracted signal components is done in the fusion center, and therefore, the decision is acquired. Moreover, the weights of extracted signal components are determined utilizing CGOA. However, CGOA is modeled by incorporating CAViaR with GOA. Additionally, CGOA has obtained a high probability of detection of about 0.932 as well as a minimum value of probability of false alarm about 0.598, and a minimum value of sensing time about 253.304 sec. In the future, several 5G signal parameters and more diverse channel conditions will be considered to prove the best performance of the introduced model.

Compliance With Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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