A Novel Grasshopper Optimization-based Particle Swarm Algorithm for Effective Spectrum Sensing in Cognitive Radio Networks

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Abstract

In CRNs, SS is of utmost significance. Every CR user generates a sensing report during the training phase beneath various circumstances, and depending on a collective process, either communicates or remains silent. In the training stage, the fusion centre combines the local judgments made by CR users by a majority vote, and then returns a final conclusion to every CR user. Enough data regarding the environment, including the activity of PU and every CR's response to that activity, is acquired and sensing classes are created during the training stage. Every CR user compares their most recent sensing report to the previous sensing classes during the classification stage, and distance vectors are generated. The posterior probability of every sensing class is derived on the basis of quantitative data, and the sensing report is then classified as either signifying the presence or absence of PU. The ISVM technique is utilized to compute the quantitative variables necessary to compute the posterior probability. Here, the iterations of SVM are tuned by novel GO-PSA by combining GOA and PSO. Novel GO-PSA is developed since it overcomes the problem of computational complexity, returns minimum error, and also saves time when compared with various state-of-the-art algorithms. The dependability of every CR user is taken into consideration as these local choices are then integrated at the fusion centre utilizing an innovative decision combination technique. Depending on the collective choice, the CR users will then communicate or remain silent.

Keywords: Effective Spectrum Sensing; Cognitive Radio Networks; Improved Support Vector Machine; Grasshopper Optimization-based Particle Swarm Algorithm

1. Introduction

To make better usage of the electromagnetic frequency spectrum, CR was first introduced in 1999 [1]. On the one hand, certain spectrum bands face overuse, which reduces their bandwidth availability, while on the other hand, remaining bands, such those allotted to TV channels, may suffer underuse, which wastes network resources [2]. For instance, mobile cellular networks, which are capacity constrained, are designed to support an increase in users and data traffic [3]. PU and SU are two distinct user kinds that have been added to the CR idea in order to alleviate the bandwidth shortage in wireless communication networks [4]. The former, a licensed user, has first dibs on the spectrum, but the latter, an unlicensed user, can utilize it as they see fit [5] [6].

The traditional CR spectrum access procedure consists of four stages: spectrum sensing, spectrum sharing, spectrum decision, and spectrum mobility [7] [8]. When there are numerous channels available, SUs pick one of them to connect with, during the spectrum choosing phase [9] [10] [11]. The latter describes a situation in which the sensed bandwidth exceeds the channel's coherence bandwidth. As a result, NB sensing techniques must make a trade-off between the higher count of accessible bands and a specific bandwidth [12]. Owing to their ignorance of the occupancy circumstances of the spectrum bands that need to be felt, existing CR spectrum access approaches have been crude and ineffective. Moreover, present spectrum access methods are incapable of detecting network modifications or even taking into account the needs of unlicensed users, which results in a worse QoS and unnecessary latency [13]. Future wireless communication networks will heavily rely on user-specific strategies; therefore, the traditional CR spectrum access has to be upgraded to be more efficient and quicker.

The paper contribution is.

- To provide a trustworthy SS method using a novel machine learning technique.
- To perform the classification stage using ISVM, where the iterations are tuned by novel hybrid optimization algorithm.
- To propose a novel form of hybrid optimization algorithm called GO-PSA for enhancing the classification stage and to compare the proposed method with existing algorithms to describe the superiority.

Machine learning has recently been applied to spectrum sensing to increase sensing sensitivity [14]. After extracting features in the spectrum sensing method, the classifier in machine learning-oriented approaches can use either soft or hard combining methods to make decisions. Although much work has been done to develop the effectiveness of machine learning-oriented SS approaches, very little of it has taken into account mobility impacts and various fading channel types, which we predict would have a significant influence on the outcomes [15].

The paper organization is as follows: Section I is the introduction of SS in CRNs. Section II is literature survey. Section III is system model and CRN for the proposed model. Section IV is SS and effective SS for the proposed model. Section V is ISVM and proposed GO-PSA for the developed effective SS in CRNs. Section VI is results. Section VII is conclusion.

2. Literature Survey

An extensive literature survey of critical and recent methods has been carried out and the findings have been comprehensively presented in **Table 1**.

Table 1. Comparison of existing methods

Literature Work	Methodology	Merits	Demerits
Thilina et al. (2013) [16]	KNN based CSS for spectrum detection	➢ Better Classification accuracy	➢ Time consuming as determination and analysis of ROC for each sensing cycle is quite complex
Zhang et al. (2018) [17]	Distributed Reinforcement learning approach	➢ Adaptable to dynamic scenario ➢ Scalable	➢ Network construction is complex ➢ Requires immense prior knowledge of channel state information
Ozturk et al. (2019) [18]	ANN based Narrow band sensing approach	➢ Learning based and hence better classification possible ➢ Quite suited for dynamic approaches where prior knowledge of channel continuously changes	➢ Accuracy depends on the meticulous planning of design of ANN layers. ➢ Not suitable for 5G networks characterized by wide bandwidth ➢ Increased latency incurred due to slow learning curve
Liu et al. (2019) [19]	Bayesian learning based CSS coupled with K-means	➢ Extremely flexible towards scalable and changing dynamic channel state information (CSI) ➢ Improved prediction on presence/absence of PU activity observed from the experimental results	➢ No proper methodology available for selection of right kind of prior CSI leading to inaccuracies.
Kant et al. (2021) [20]	Manta Ray foraging approach based spectrum sensing	➢ Improved accuracy in detection due to optimal selection of features of CSI	➢ Well-suited for large bandwidth networks like 5G, 6G etc. underutilization may occur in narrow band sensing.
Shamim et al. (2021)	SVM based spectrum sensing	➢ Able to distinguish PU mitigation	➢ Reduced detection accuracy at the cost of

[21]		attacks in a more effective manner.	increased PU mitigation attacks. ➢ Increased latency also observed.
Ahmed et al. (2021) [22]	CR-IoTNet based spectrum sensing	➢ Is better able to locate the spectrum spaces in the channel thus reducing the waiting time of the SUs.	➢ Increased complexity as the energy levels of nodes in the IoT network also have to be considered with their associated optimal routing issues
Wang et al. (2022), [23]	Adversarial learning based spectrum sensing.	➢ Detection based on learned features hence reducing dependency on the SNR.	➢ Not suitable for dynamic scenarios where the nature of SNRs may vary. ➢ Also not suited when high noise is encountered in received signal
Paul et al. (2022) [24]	SVM based DQN model for detection	➢ Improved energy efficiency over conventional detection models	➢ Increased false alarm probability in cases where noise is predominant in the receiver channel
Abusubaih et al. (2022) [25]	Rule based KNN based spectrum detection	➢ Improved true positives in cases of increasing noise in the channel	➢ Rule based and not quite suited for dynamic scenarios.

Limitations in existing methods:

- ➢ Most of methods provide good detection accuracies. However, they depend on extensive and meticulous design of learning architectures.
- ➢ Most of the methods especially exhibit slow learning characteristics in contrast to rapidly changing dynamic scenario of the receiver channel which increases latency and even high false alarm probabilities.
- ➢ Some methods are rule based and hence there is a need to continuously monitor and modify the rules as per changing dynamic scenario.
- ➢ Selection of optimal features for the classification/detection process is always and has been observed to be a challenging issue.

3. System model and Cognitive Radio Network for the proposed model

3.1 System Model

The utilized quantization technique and the energy detection technique are detailed in this part. This section describes the creation of the sensing report that is utilized in the spectrum sensing program's training and classification phases [26]. If the FC determines that there is a spectral hole, the CR user transmits data. Users of CR work in half-duplex mode, which allows them to either send or receive at any one moment. Users of CR are presumptively near to the PU and away from remaining PUs. **Fig. 1** depicts the system model.

CSS creates spatial diversity, whereas mini slotting the sensing slot creates temporal diversity. The ideal length of a sensing slot was explored by the authors in [27]. The length of a poor sensing slot is taken into account in this study. When fading and shadowing events are prevalent, the sensing outcome might alter. By detecting the spectrum times during the sensing window, temporal diversity mitigates these effects. The sensing slot is again split into mini slots in this research. The spectrum is separately detected in every mini slot.

The sensing ability can be enhanced by increasing the count of mini slots and subsequently the sensing time, however this reduces the transmission slot duration [27]. [27] asserts that the introduction of diversity reception into the sensing procedure occurs when the channel is separately sensed in mini slots during the similar sensing period. The outcomes of these mini slots are merged in the suggested method to create a sensing report, which is then utilized in the classification stage. To determine every CR user's level of confidence in a CRN that is being attacked by hostile users, the sensing reports were actually employed in [28].

The sensing data in this study are utilised to train the classifiers and are next employed to categorise the most recent sensing report. This presents a half-duplex CR user framework where no CR users communicate during the sensing slot. The CR users communicate in the transmission slot if it is determined during the sensing slot that the PU is not present; else, they stay neutral. The CR users perceive the spectrum once more after the time frame's lifetime, comes to an end. Every mini slot makes advantage of energy detection. The energy that the j^{th}CR user acquired in the ω^{th} sensing slot in the l^{th}mini slot $Y_{l,\omega,j}$ may be represented as

$$Y_{l,\omega,j} = \sum_{k=1}^{O_0}\left[f_{l,\omega,j}(k)\right]^2 \tag{1}$$

Here, O_0 shows the total count of samples, denoted by $l \in \{1,2,3,\cdots,o\}$and $o$shows the total count of minislots, $f_{l,\omega,j}(k)$shows the k^{th}energy sample obtained at the l^{th}mini slot of the ω^{th}sensing slot. The detection time Uas well as the signal bandwidth C is both expressed in Hertz. The bandwidth linked with the detected spectrum as well as the sensing duration determine how many samples are received in a certain minislot. The received signal$f_{l,\omega,j}(k)$, is presented in both the existence of PU (I_1) and lack of PU (I_0)as below.

$$f_{l,\omega,j}(k) = \begin{cases} w_{l,\omega,j}(k); & I_0 \\ t_{l,\omega,j}(k) + w_{l,\omega,j}(k) & I_1 \end{cases} \tag{2}$$

Here, $t_{l,\omega,j}(k)$ shows the k^{th}sample of the PU signal received at the l^{th}minislot of the ω^{th}sensing slot by the j^{th}CR user, and $w_{l,\omega,j}(k)$ shows zero-mean Additive White Gaussian Noise (AWGN). The pdf of the energy of the received signal at the j^{th}CR user $Y_{l,\omega,j}$ continues to follow a central chisquare distribution having mean μ_0 and variance σ_0^2 if the primary signal is unavailable, and a noncentral chisquare distribution having mean μ_1 and variance σ_1^2 if the primary signal is present.

$$\begin{aligned} \mu_0 &= O_0 \\ \sigma_0^2 &= 2O_0 \\ \mu_1 &= O_0(\gamma_j + 1) \\ \sigma_1^2 &= 2O_0(2\gamma_j + 1) \end{aligned} \quad (3)$$

Here, γ_j shows the SNR of the j^{th} CR user's received signal. The energy signal received $Y_{l,\omega,j}$ beneath both hypotheses I_0 and I_1 can be roughly represented by a Gaussian random variable when the total count of samples, O_0, is high. The energy signal at every minislot in this approach is quantized into distinct zones.

The slotted-frame architecture, in which a frame becomes single unit of accessibility to the spectrum, is explored in the study. Every frame's first slot, also known as the detecting slot, is utilized to sense the spectrum and determine whether or not the PU is active. Usually, they don't say anything during the entire transmission window. The CR users will begin detecting the spectrum once the broadcast slot has ended.

Since wireless channels fluctuate quickly, the spectrum is felt more than once rather than just once in order to take the channel's shifting behaviour into account. The detecting slot in the work is split into minislots to accomplish this. Every minislot's spectrum is individually felt, and a sensing report is created on the basis of the findings. Based on the quantized decision of every minislot, conveyed by Eq. (4), a sensing report is created that will be utilized in the subsequent classification phase.

There are four quantization levels in this project, or $N = 4$. $A_1, A_2, A_3, and\ A_4$ represents quantization zones or tese levels, respectively. In contrast to zones A_3 and A_4, which signify strong energy or the existence of the PU, zones A_1 and A_2 stand for low energy or the lack of the PU. These are the quantized energy zones:

$$v_{l,\omega,j} = \begin{cases} I_0 \begin{cases} A_1; & Y_{l,\omega,j} \le \lambda_{A_1} \\ A_2; & \lambda_{A_1} < Y_{l,\omega,j} \le \lambda_{A_2} \end{cases} \\ I_1 \begin{cases} A_3; & \lambda_{A_2} < Y_{l,\omega,j} \le \lambda_{A_3} \\ A_4; & Y_{l,\omega,j} > \lambda_{A_3} \end{cases} \end{cases} \quad (4)$$

Here, $v_{l,\omega,j}$ stands for the quantized energy for the l^{th} minislot of the ω^{th} sensing slot of the j^{th} CR user, and $\lambda_{A_1}, \lambda_{A_2}, \lambda_{A_3}, and\ \lambda_{A_4}$ describes the thresholds. The group of quantization zones is comprised of $r \in \{A_1, A_2, A_3, A_4\}$, while the group of thresholds is made up of $\lambda \in \{\lambda_{A_1}, \lambda_{A_2}, \lambda_{A_3}, \lambda_{A_4}\}$. Equation (4) indicates that the average received energy at the j^{th} CR user at the l^{th} sensing slot $(Y_{l,\omega,j})$ can be quantized into either A_1 or A_2, and in the event of I_0, $Y_{l,\omega,j}$ is quantized into either A_3 or A_4. The quantization system interprets A_1 and A_2 as I_0, whereas A_3 and A_4 as I_1.

A sensing report made up of symbols from r is created at every sensing slot. Sensing report refers to the report for the j^{th} CR user at the ω^{th} sensing slot and is expressed by $S_{j,\omega}$, which has o items from r. This information is utilised by the machine learning algorithm as a feature vector. This data is categorised into a sensing class during the training stage on the basis of the global decision and the ACK.

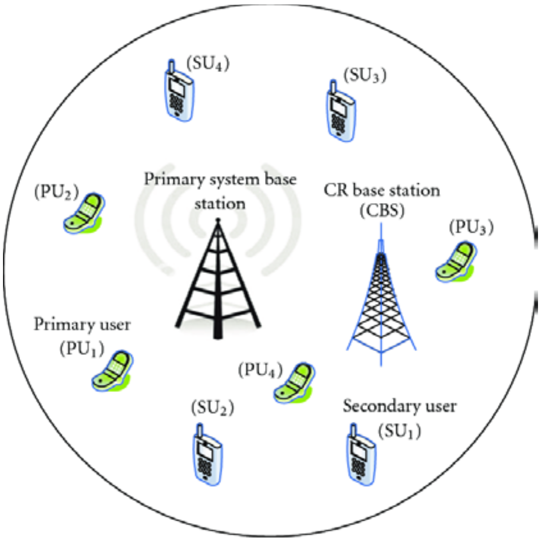

Fig. 1. System Model

3.2 Cognitive Radio Network

As long as PU communication is unaffected, CR users have unrestricted access to the spectrum [29] [30]. The spectrum is regularly checked for PU activity to make sure of this. Spectrum sensing may also be utilized to find spectrum openings and allow CR users to communicate when there exists a good opportunity. Through the usage of CSS, which entails numerous CR users working together to find spectral gaps, a CR state's performance gain is again increased.

While matched filtering works better than alternative methods like the use of cyclo stationary detection and energy detection, its complexity renders it problematic for spectrum sensing because of several systems. The easiest approach is energy detection in light of the constrained resources (such as energy and cognitive average CR users' power). CSS uses spatial variety, hence need maintaining of PU restrictions [31]. In CSS, each CR user provides data to a FC, which integrates local reports to reach a judgement at the global level. The real quantity of energy received, which has not been quantized into different levels, can be reported by CR users. This technique, known as a soft-decision pair, produces the best detection accuracy but, potentially, uses an infinite amount of bandwidth. As an option, CR users can decide definitively on the basis of the energy received [32]. Hard reporting uses less bandwidth but delivers less effective outcomes than soft reporting. Almost similar performance exists for likelihood ratio tests and linear soft combinations [33].

Here, the energy range can be quantized, as in [34], a mix of both soft and hard choices can be employed to optimize performance as well as bandwidth efficiency. The measured energy is quantized into four regions utilizing two bits in employing what is known as a "softened hard combination technique," with every zone being denoted by a label. This strikes a fair balance among the information lost during the quantization procedure and the enhanced performance brought on by smart reporting.

For example, an AND rule increases spectral hole identification but reduces the PU main criterion while an OR rule produces high PU protection but has the lowest spectral hole exploration capabilities [35]. Similar to this, the kout-N decision combination rule performs worse when there is poor sensing and/or malevolent CR users. PU protection and spectral hole discovery are improved by more complex combination methods, but they also demand previous knowledge that may not always be present in a single CR scenario [36].

The idea of CRs includes the idea of learning from the surroundings. Users of CR are bound to maintain an eye on their surroundings and adjust their operational parameters (transmitting power, operating frequency, etc.) to the shifting circumstances. Numerous writers have thought about machine learning methods to help CR users learn from the surroundings [37] [38] [39] [40] [41] [42]. SS cannot accurately establish the PU state on the basis of the current sensing slot alone since fading and shadowing can make it difficult to estimate the channel state [37]. Spectrum sensing on the basis of machine learning may, nevertheless, indirectly learn about the surrounding world. One benefit of machine learning-oriented spectrum sensing describes its ability to accurately identify PU activity without the need for prior environmental knowledge.

4. Spectrum Sensing and effective spectrum sensing for the proposed model

4.1 Spectrum Sensing

The suggested spectrum sensing method seeks to enhance PU detection performance in various situations to enhance spectral hole identification [43]. The next objective effectively takes use of spectrum access options to let the CR user transfer data. The energy vector is used to determine the channel accessibility for the j^{th} CR user during the ω^{th} sensing slot$\left(S_{j,\omega}\right)$. It is necessary to study the behaviour of the PU in order to accurately map $S_{j,\omega}$, to PU activities. But in this situation, the energy vector is comparable to a feature vector in the area of machine learning.

A training step is required to build a classifier, which will categorise the current sensing report into channel available (I_0) or channel busy (I_1) classes. Energy vectors of size X are stored by every CR user, in which X shows the length of the training or training step. The slotted-frame architecture is employed in the training stage, and each one-time slot contains two phases: a sensing stage and a transmission stage. X places are available throughout the training period. The classifier accepts these vectors as input during the classification stage, which determines whether the current sensing report is in the I_0 or I_1 category based on comparisons with pre recorded sensing reports.

In the suggested method, the sensing reports—which are created quantized energy vectors—are mapped to the precise condition of the PU so that the CR users may first understand how the PU behaves. Using ACK and a trustworthy mix of local decisions made by CR users that are decided by the FC, the real condition of the PU is discovered. The CR user's role during the training stage is distinct from its role during the classification stage. During the training stage, sensing reports are categorised into sensing classes based on the PU's real activity and the CR user's behaviour.

Training Stage: The j^{th} CR user creates a sensing report $S_{j,\omega}$, generates a local determination on the basis of the average received energy in the active sensing slot, transmits the local determination to the FC, and then designates the sensing report to a sensing class on the basis of the FC's decision and the ACK's status. Assume a description of the energy received at the j^{th}CR user's ω^{th}sensing slot$Z_{j,\omega}$, where

$$Z_{j,\omega} = \frac{\sum_{l=1}^{o} Y_{l,\omega,j}}{o} \tag{5}$$

Here, $Y_{l,\omega,j}$ is provided by Eq. (1). In the training stage, the local choice for the j^{th}CR user at the ω^{th}sensing slot is denoted by $r_{j,\omega}$and supplied by [31].

$$r_{j,\omega} = \begin{cases} I_0\begin{cases} A_1; & Z_{j,\omega} \leq \lambda_{A_1} \\ A_2; & \lambda_{A_1} < Z_{j,\omega} \leq \lambda_{A_2} \end{cases} \\ I_1\begin{cases} A_3; & \lambda_{A_2} < Z_{j,\omega} \leq \lambda_{A_3} \\ A_4; & Z_{j,\omega} > \lambda_{A_3} \end{cases} \end{cases} \quad (6)$$

The FC receives the local choice and delivers a global judgement by combining the local decisions of entire CR users. Each component of the report relates to r, as can be observed. Each sensing slot for each CR user generates a sensing report (the current sensing report is denoted by$S_{j,\omega}$), and the local decision is made in accordance with Eq. (6).

The global choice is then given back to the CR users. Users of the CR can choose to transmit or not, depending on the collective judgement. The ACK signal can be used to confirm whether the CR global decision is I_0or not. There exists no interference to the PU transmissions since the overlay Cognitive Radio Network is taken into consideration. The PU communication only affects the ACK signal when the SS outcome is incorrect and the actual ground truth isI_1. The following are the list of probable situations and findings.

Finding 1: The global choice is alsoA_1, as shows the local decision $(r_{j,\omega})$. The CR user transmits its data. Receiving an ACK indicates that the sensing outcome was accurate and that the PU's real state wasI_0. The actual state of the PU is determined via the ACK signal. When this choice $(S_{j,\omega})$ is made, the sensing report associated with it is placed in a class known asS_1, but when there is no ACK signal, it is placed inS_2.

Finding 2: Whether the global choice and the local decision $(r_{j,\omega})$ are A_1 or A_2, respectively, depends on the local decision A_1. If the ACK is not returned after the CR user transmits, the sensing judgement was incorrect and the PU was accessible. The CR user will save $S_{j,\omega}$in a class called $S_2$with the value. When an ACK signal is received, S_1will store it. This method will also record $S_{j,\omega}$ if the local choice is $A_1$and the global decision is A_3orA_4.

Finding 3: The local choice $(r_{j,\omega})$ isA_2, and A_2also applies to the global decision. The CR users follow the steps outlined in finding 1 for this operation. If ACK is obtained, the sensing choice was made correctly, and the PU is not available; else, the data $S_{j,\omega}$is saved in the S_4class.

Finding 4: The global decision is either A_1or A_2, while the local decision is A_2. When a CR user transmits, if an ACK is not returned, the class $S_{j,\omega}$is labelled S_4; else, the class is labelled S_3. Again, $S_{j,\omega}$will be saved in the class designated as S_4if the local choice is $A_2$and the global decision is either A_3or A_4.

Finding 5: The local choice is A_3, and so is the overall decision. In this situation, there won't be any transmission. Therefore, it is impossible to ascertain the PU's real condition. $S_{j,\omega}$ will be enrolled in a class with the designation S_5. If the global choice is $A_4$and the local decision is A_3, the sensing report will likewise be kept in class S_5.

Finding 6: The global choice is either A_1or A_2, whereas the local choice is A_3. The user of the CR will send. $S_{j,\omega}$ will be saved in a class with the designation S_6if ACK is returned; else, it will be saved in S_5.

Finding 7: The local and global choices are both A_4. There will be no transmission, and $S_{j,\omega}$will be kept in the class S_7if the local decision is Z4 and the worldwide choice is Z3. $S_{j,\omega}$will also be kept in S_7if the local decision is $A_4$and the global decision is A_3.

Finding 8: The global decision is either A_1or A_2, whereas the local decision is A_4. The user of the CR will send. If an ACK is obtained, $S_{j,\omega}$will be kept in class S_8. In the absence of an ACK, $S_{j,\omega}$will be kept in S_7.

The ACK signal is utilised when the global decision isI_0, as shown in the findings above. The CR users do not broadcast when the global decision isI_1, therefore the ACK signal cannot be utilised to determine the reality on the ground. As a result, when $I_1$is the FC's overall decision, the CR users store the current sensing report in classes $S_5$and S_7since there exists no other method to verify the current sensing choice without running the danger of interfering with the PU transmission.

These findings provide CR users past data that they may utilise in combination with their present sensing behaviour to more accurately forecast the PU state, as well as information regarding the environment around them and how it affects human behaviour. This method may be viewed as cooperative learning in which the influence of other CR users is included via the global choice in addition to the individual CR user's consideration. This increases the learning system' geographic variety by allowing a receiver having superior SNR settings to influence the behaviour of CR users having lower SNR circumstances.

The training process is continued till the CR user has received sufficient training in the environment's behaviour, comprising adjusting the SNR circumstances and the PU's behaviour. As a result of the constantly evolving sensory environment, fading can also have a short-term impact on the signal and corresponding energy received.

During the training stage, local training data is gathered from every CR user. The length of the training stage affects how well machine learning algorithms operate. Efficiency increases as training volume increases. A bigger region is encompassed by the PU as the count of CR users rises. The training stage can precisely predict how CR users would behave in response to PU activity since the modelling approach integrates the global decision by behaving in accordance with it and also via the ACK signal. With a significant training stage, the responses of CR users to different PU activity types may also be correctly predicted. The training stage of traditional machine learning approaches can collect enough training data to understand the surroundings. Since both the wireless channel and PU activity are random, it is almost impossible to determine their precise nature.

Classification stage: Information was obtained about the operating context and CR user behaviour in reaction to the dynamic world in the preceding step. The structure of CR networks makes it particularly difficult to learn the environment. Users of CR only get partial observations of the configuration files due to the noisy different characteristics. Users of CR are also required to send data. Therefore, limited sensing time and incomplete quantitative measurements make learning more difficult. A PU's status as an autonomous entity constitutes a third restriction. A CR user might not be familiar with the PU's behaviour, its operational parameters, the interference levels, RF environment, or the distribution of noise power.

Partial observability is dealt with by include the actions of the worldwide CR community into the learning experience decision. The ACK assists CR users in learning the split the sensing information according to the operational environment better properly into their various groups. The education strategy is effective and doesn't need any previous knowledge.

The present instance is precisely classified into one among the sensing classes using improved SVM, a machine learning algorithm, which effectively detects PU activity.

4.2 Effective Spectrum Sensing

The local choices are sent to The FC as E_j in which $= ,3, \cdots, O$. Due to the fact that different CR users in CSS have different sensing capacities, different local sensing outcomes are produced [44]. We employ a weight-oriented decision combination at the FC in the suggested approach. Depending on their effectiveness, every CR user is given a weight. A partial global decision is taken at FC, denoted by $M_{H,j}$, by eliminating the j^{th}CR user's response as

$$M_{H,j} = \begin{cases} I_0 & O_{I_0}^j > O_{I_1}^j \\ I_1 & otherwise \end{cases} \tag{7}$$

Here, $O_{I_0}^j$ shows the count of CR users reporting I_0that do not include the j^{th} CR user's local choice and is stated as

$$O_{I_0}^j = \sum_{j=1, j\neq j}^{O} J_0(E_j = I_0) \tag{8}$$

And the indicator function $J_0(E_j = I_0)$for I_0 is provided by

$$J_0(E_j = I_0) = \begin{cases} 1; & E_j = I_0 \\ 0; & E_j \neq I_0 \end{cases} \tag{9}$$

On the other side, $O_{I_1}^j$ indicates the proportion of j^{th}CR users who reported I_1but did not provide their local decision.

$$O_{I_1}^j = \sum_{j=1, j\neq j}^{O} J_0(E_j = I_1) \tag{10}$$

Here, the indicator function for I_1 is provided by and $J_0(E_j = I_1)$ is provided.

$$J_0(E_j = I_1) = \begin{cases} 1; & E_j = I_1 \\ 0; & E_j \neq I_1 \end{cases} \tag{11}$$

For entire CR users, partial global decisions are discovered. The majority vote is then used to integrate local choices as $M_{H,all}$, and may be expressed as

$$M_{H,all} = \begin{cases} I_0 & O_{I_0} > O_{I_1} \\ I_1 & otherwise \end{cases} \tag{12}$$

Here, the count of CR users who reported I_0 is O_{I_0} and the count of CR users who reported I_1 is O_{I_1}. The weight for every CR user α_j is derived on the basis of Eq. (7) and Eq. (12).

$$\alpha_j = \begin{cases} \alpha_j + 1 & M_{H,j} \neq M_{H,all} \\ \alpha_j & M_{H,j} = M_{H,all} \end{cases} \tag{13}$$

Next, the cumulative weight for every hypothesis β_b, in which $b \in \{I_0, I_1\}$is determined as follows:

$$\beta_b = \sum_{j=1}^{O} \alpha_j J_0(E_j = b) \quad b \in \{I_0, I_1\} \tag{14}$$

Here, $J_0(E_j = b)$ is shown by

$$J_0(E_j = b) = \begin{cases} 1; & E_j = b \\ 0; & otherwise \end{cases} \tag{15}$$

The final global decision is shown by M_H and is computed as

$$M_H = \begin{cases} I_0 & \beta_{I_0} > \beta_{I_1} \\ I_1 & otherwise \end{cases} \tag{16}$$

The CR users receive the global decision back, and they next broadcast or remain silent in accordance with the global decision. Consider $\beta = \sqrt{2\gamma \sum_{l=1}^{o} |i_l|^2 + 1}$ in which i_l be the channel gain among the primary user and the j^{th} CR user during the l^{th} minislot, and assume γ be the mean SNR obtained from the PU. When nonfading channels are used, the system's probability of false alarm is expressed as [27] if it is considered that the state's coefficients are known.

$$Q_g^T = R\left(\beta R^{-1}\left(\overline{Q_e}\right) + \sqrt{O_0}\gamma \sum_{l=1}^{o} |i_l|^2\right) \tag{17}$$

Here, $\overline{Q_e}$ shows the system goal probability of detection and $R(\cdot)$ shows the complementary distribution function of the standard Gaussian, which is $R(X) = (1/2\pi) \int_y^\infty exp(-u^2/2)du$. The goal probability of detection for effective spectrum sensing may be expressed as [45]

$$\overline{Q_e} = \prod_{n=1}^{N} \left\{ \left(O - \underbrace{\sum_{t=1}^{m} O_{A_t}}_{O_{Cn}} \right) \left(Q_{I_1}(A_n) \right)^{O_{A_n}} \right\} \tag{18}$$

Here, O_{A_n} shows the percentage of CR users who have made a local sensing choice in the zone A_n, m shows the greatest integer less than n, and $Q_{I_1}(A_n)$ seems to be the likelihood that a local sensing decision was made in the quantization zone A_n beneath I_1. The system's likelihood of detection can be expressed as [27].

$$Q_e^T = R\left(\beta R^{-1}\left(\overline{Q_g}\right) + \sqrt{O_0}\gamma \sum_{l=1}^{o} |i_l|^2\right) \tag{19}$$

Here, $\overline{Q_g}$ shows the system goal false alert probability and is provided by [46].

$$\overline{Q_g} = \prod_{n=1}^{N} \left\{ \left(O - \underbrace{\sum_{t=1}^{m} O_{A_t}}_{O_{Cn}} \right) \left(Q_{I_0}(A_n) \right)^{O_{A_n}} \right\} \tag{20}$$

Here, $Q_{I_0}(A_n)$ shows the likelihood that the local sensing decision in the quantization zone A_n will be less than I_0.

5. Improved SVM and Proposed GO-PSA for the developed effective spectrum sensing in cognitive rdio networks

5.1 Improved SVM

The improved SVM is used for the classification process of the developed effective spectrum sensing in CRN model. SVM represents a supervised learning technique for both classification as well as regression problems. To differentiate between the two classes of data points, one might pick from a variety of possible hyper-planes. The Eq. (1) may be used to locate the hyper-plane.

$$\vec{x} \cdot \vec{y} + c = 0 \tag{21}$$

Here, $\vec{y}$ shows the collection of points and $\vec{x}$ shows the normal vector to the hyperplane. The margin's width is $(2/|x|)$. The fact why SVM struggles to effectively function with large training sets is due to the fact that as the number of training vectors rises, so do the storage and computing needs. Thus, performance may be increased, and calculation time decreased by using improved SVM. Here, the iterations in SVM are tuned by novel GO-PSA, thus referred as improved SVM.

5.2 Proposed GO-PSA

The proposed GO-PSA is used for optimizing the iterations of SVM for the developed spectrum sensing in CRN model. The PSO technique was developed to simulate the behavioural patterns of a flock of birds, but once the algorithm was modified it was discovered that the individuals, here referred to as particles, were really engaged in optimisation. The PSO approach places the particles at random locations in the search space and then has them move in randomly chosen directions. A particle's trajectory is then progressively adjusted such that it will begin to migrate in the direction of its own and its competitors' best prior locations. As it searches in their neighbourhood, it will ideally find even better places with relation to some fitness metric. The PSO algorithm has several advantages such as better efficiency, simplicity, etc. But, it limits from the drawback of high computational complexity. Hence, to overcome the drawbacks, GOA is integrated into it and the so formed algorithm is referred as GO-PSA. This GO-PSA reduces the computational complexity as well as solves all forms of optimization related problems.

The core principle of the GOA swarm during the larval stage is the grasshoppers' sluggish mobility and short steps. In comparison, the adult swarm's primary characteristic is long-distance, rapid movement. Another crucial aspect of the grasshopper swarm is the search for food sources. The search agents are urged to move quickly during exploration, while they usually move slowly during exploitation. In addition to target finding, grasshoppers naturally carry out these two tasks. Thus, if we can represent this behaviour scientifically, we can create a brand-new algorithm that draws its inspiration from nature.

In the proposed GO-PSA algorithm, the process takes place using random-based concept. Therefore, if $rand \leq 0.5$, the update takes place using GOA as below.

$$Y_j^e = d\left(\sum_{\underbrace{k=1}_{k\neq j}}^{O} d\,\frac{ub_e - lb_e}{2}\, t\left(\left|y_k^e - y_j^e\right|\right)\frac{y_k - y_j}{e_{jk}}\right) + \widehat{U_e} \tag{22}$$

Here, Y_j shows the position of the j^{th} grasshopper, e_{jk} shows the distance among the j^{th} and k^{th} grasshopper, d shows the decreasing coefficient that minimizes the comfort zone, $\widehat{U_e}$ shows the value of the E^{th} dimension in the target, lb_e shows the lower bound in the E^{th} dimension, and ub_e shows the upper bound in the E^{th} dimension respectively.

Otherwise, if $rand > 0.5$, then the update takes place by PSO as below.

$$\vec{y} \leftarrow \vec{y} + \vec{w} \tag{23}$$

Here, the position of particle is shown by $\vec{y}$ and the velocity of particle is shown by $\vec{w}$ respectively. The pseudo code of novel GO-PSA is shown in algorithm 1.

Algorithm 1: Proposed GO-PSA

Start
Population initialization
Parameter initialization
Fitness calculation
While $iter < iter_{max}$
    If $rand \leq 0.5$

$$Y_j^e = d\left(\sum_{\substack{k=1 \\ k\neq j}}^{O} d\frac{ub_e - lb_e}{2} t(|y_k^e - y_j^e|)\frac{y_k - y_j}{e_{jk}}\right) + \widehat{U_e}$$

    else

$$\vec{y} \leftarrow \vec{y} + \vec{w}$$

    End if

$$iter = iter + 1$$

End
Stop

6. Results

6.1 Experimental Procedure

In this part, we examine the behavior of the suggested scheme and evaluate it against various schemes using system factors including the probability of detection, probability of spectral holes exploitation, and probability of error. The CR user will have more possibilities to transmit if the PU's idle probability is raised. The system's performance during the training phase is significantly impacted by the development of the sensing classes throughout this phase. The larger this phase, the more training instances there will be, increasing the count of reports that the current sensing report may match with. The description and the optimization parameters for GOA and PSO are shown in **Table 2** below.

Table 2. Optimization parameters

Methods	Parameters	Description
GOA	Population size	10
	Chromosome length	2
	Number of iterations	25
PSO	Population size	10
	Chromosome length	2
	Number of iterations	25

6.2 Simulation Parameters

The simulation parameters considered for the proposed spectrum sensing in CRNs using improved machine learning-based optimization model is shown in **Table 3**.

Table 3. Simulation parameters

Parameters	Description
Number of iterations	500
Number of CR user	4
Sampling frequency	250 kHz
Sensing slot duration	0.5 ms
Idle probability of PU	0.3
Number of energy samples	500
SNR range	-20 to -10 dB

6.3 Probability of detection analysis

The system detection performance for the developed and the current models is shown in **Fig. 2**. The suggested plan operates better than the competition. The detection probability attained from the analysis showed that the proposed method shows better outcomes over the provided number of counts at various SNR levels, revealing its superiority.

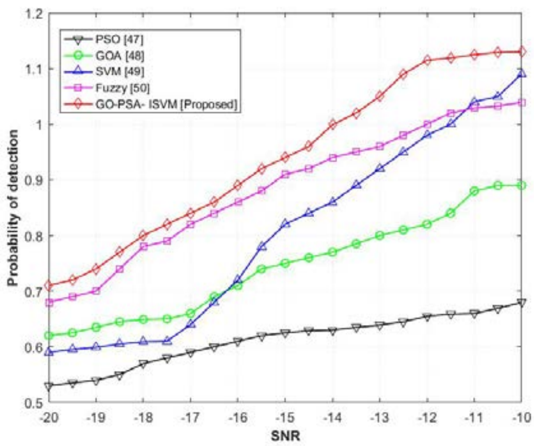

Fig. 2. Probability of Detection Analysis

The explanation is because under low SNR regimes, the sensing reports are not far off from one another. The energies received in the low SNR for both theories have minimal difference between either sensing than normal plans. The suggested technique produces more dependable spectrum as the SNR increases.

6.4 Probability of error analysis

The error performance is shown in the **Table 4**. The suggested system has a low likelihood of error even in the low SNR zone, as can clearly be observed in this figure and table. The error probability defines the rate of occurrence of an error in a hypothetical infinite repetition of the process. Here, it is clearly elaborated that the developed model shows lesser error rate of occurrence than the considered existing methods, thus demonstrating its betterment. The approach demonstrates that the suggested strategy can produce more accurate spectrum sensing than previous methods.

Table 4. Probability of error analysis

SNR	Probability of error				
	PSO [47]	**GOA [48]**	**SVM [49]**	**Fuzzy [50]**	**GO-PSA-ISVM**
-20	0.15	0.16	0.12	0.11	0.03
-17.5	0.13	0.09	0.14	0.07	0.02
-15	0.08	0.11	0.06	0.05	0.02
-12.5	0.03	0.06	0.04	0.05	0.01
-10	0.02	0.05	0.04	0.03	0.01

6.5 Probability of spectral holes exploitation analysis

The effectiveness of the suggested technique to utilize spectral gaps is shown in **Table 5**. Utilizing chances for data transmission is of utmost importance from the viewpoint of a CR user. The suggested system enables CR users to take advantage of data transmission possibilities even in poor SNR circumstances. The sensing reports that are created are better reflections of the PU's activity in the region with high SNR. Because the PU signal will take up a bigger fraction of the received signal than the random noise, the sensing performance can be enhanced in the high SNR regimes. The secondary users exploit the presence of spectrum holes in an opportunistic manner for enhancing the spectrum usage. At various SNR levels, the probability of exploitation of spectral holes shows improved performance with developed methods than the traditional approaches, thereby demonstrating its effectiveness. These figure and table demonstrate how the suggested system may both more effectively secure PU data and offer more chances for data exchange.

Table 5. Probability of Spectral holes exploitation analysis

SNR	Probability of spectral holes exploitation				
	PSO [47]	**GOA [48]**	**SVM [49]**	**Fuzzy [50]**	**GO-PSA-ISVM**
-20	0.22	0.31	0.53	0.68	0.70
-17.5	0.28	0.43	0.61	0.65	0.72
-15	0.42	0.53	0.72	0.69	0.80
-12.5	0.76	0.82	0.79	0.91	0.94
-10	0.82	0.87	0.95	0.93	0.98

6.6 Average delay analysis

The time required to determine the channel availability for various classifiers is shown in the **Fig. 3**. More precisely, even while the values of the decision parameters fluctuate significantly with the count of training energy vectors, the count of decision parameters does not vary. Results showed that when the training samples of PU is higher than that of SUs, the average delay of SUs in the queue and the chance of SU packet loss are worse; however, when the training sample of both users is equal, performance is better. Hence, it can be clearly demonstrated that the proposed model returns less delay than the considered existing methods.

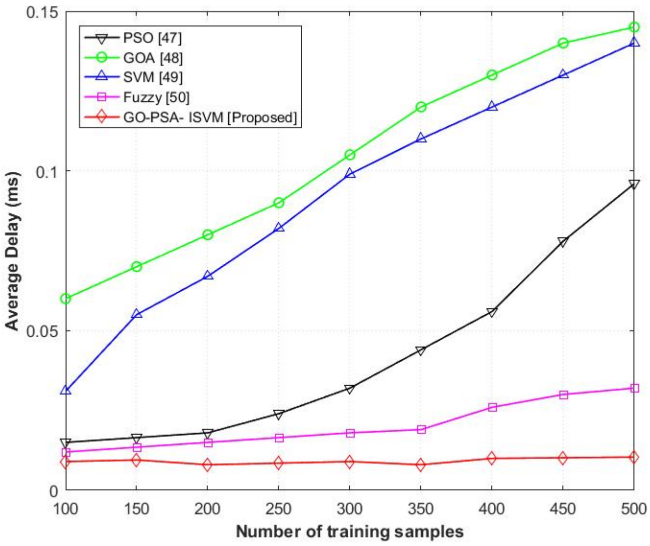

Fig. 3. Average Delay Analysis

6.7 Detection Time analysis

The detection time in this article, when the count of CRs is constant, is significantly quicker than the detection times in the remaining approaches, as shown in **Fig. 4**. The difficulty of computing rapidly rises as the count of CR users rises. The developed technique makes it feasible to see the whole spectrum situation at any one time. As the CR user count increases, the detection time gets lesser for the introduced model than the other state-of-the-art methods, thus revealing its superiority.

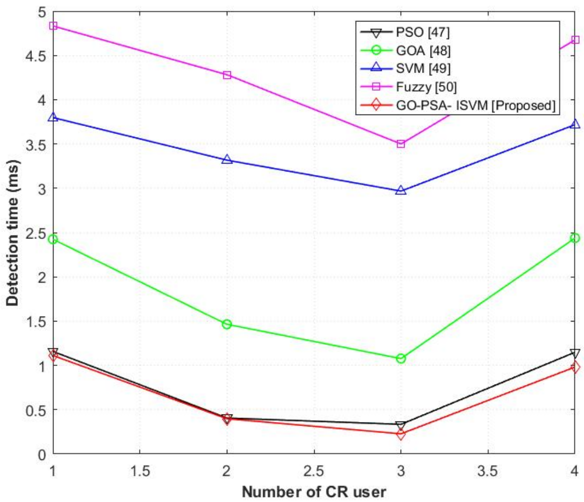

Fig. 4. Detection time Analysis

The suggested strategy, nevertheless, employs a cutting-edge machine learning technique to lessen the disturbance from rogue users to nearby users. On detection time, the quantity of malicious users has less of an impact. Consequently, in a large-scale CRN, the suggested approach has high detection efficiency.

6.8 Convergence analysis

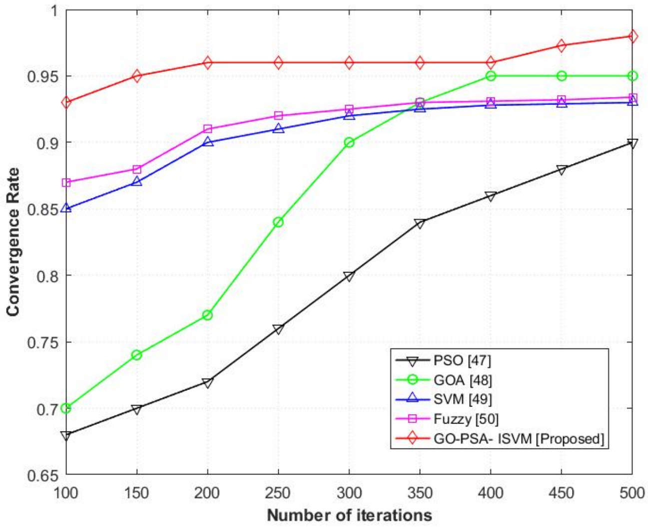

Fig. 5. Convergence Analysis

The convergence analysis of various algorithms for the developed spectrum sensing in CRN model is shown clearly in the **Fig. 5**. A total of 500 iterations are considered for running the convergence analysis process. The introduced model reveals better convergence outcomes than other conventional methods at various iteration reveals, thus demonstrating the betterment of the proposed method. It can be clearly demonstrated that the proposed model achieves faster convergence rate than all the considered state-of-the-art methods respectively at various iteration counts.

7. Conclusion

A trustworthy spectrum sensing approach based on novel machine learning was suggested in this research. The suggested system adapts to its surroundings by taking into consideration the actual state of the PU. The current sensing report was classified into one among the sensing classes once the sensing reports have been stored in the relevant sensing classes. The status of the PU was determined by the classification outcome. An innovative decision combination system at the FC that took into consideration the dependability of the CR users combines local decisions. Effective spectrum sensing was ensured by both CR level and FC level mechanisms. According to simulation findings, the suggested approach outperforms traditional approaches in terms of various measures. Some limitations observed are significant waiting time for the convergence to occur especially in case of dense networks. considerable complexity in the construction of the hybrid evolutionary model is another limitation which needs to be worked on.

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