International Research Journal of Multidisciplinary Scope (IRJMS), 2025; 6(1):189-198

Original Article | ISSN (O): 2582-631X DOI: 10.47857/irjms.2025.v06i01.02442

Optimization of Quantized Cooperative Sensing Using Multi-Objective JAYA Algorithm

Keraliya Divyesh Rudabhai*, Mehta Rahul Dhirendrabhai, Loriya Hitesh Thakarshibhai

Electronics and Communication Department, Government Engineering College, Rajkot, Gujarat, India. *Corresponding Author's Email: drkeraliya@gmail.com

Abstract

Cognitive radio (CR) is the new era of wireless technology having objective is to effective utilization of available spectrum. The primary function of cognitive radio is to sense the available free spectrum. The effectiveness of cooperative spectrum sensing (CSS) for searching available free spectrums in network of cognitive radio (CR) has been executed by receiving sensing data from surrounding node which is called CR. The data senses by CR node are transmitted at the central/common node named fusion center using either soft combining techniques or standard hard combining technique. These two combining techniques have a trade-off between performance and data required to sense the channel. The primary factor that decides the quality of sensing spectrum depends on weightage given to the coefficient used in softened data combing strategy in CSS. In this paper, optimal sensing framework using Multi-Objective JAYA (MOJAYA) algorithm is presented which use optimality criterion of the Neyman-Pearson, as an effective tool to search the optimal coefficients vector so that sensing quality is preserved with less overhead. The performance of the presented framework which is based MOJAYA algorithm is thoroughly evaluated and compared with a conventional soft combining strategy as well as hard combining by using computer for simulation. The results show that the presented MOJAYA based performance is almost near to the conventional soft combining scheme i.e., equal gain combiner (EGC) with less overhead and bandwidth, which confirms the validation of presented framework.

Keywords: Cognitive Radio, Cooperative Sensing, Hard Combination, Multi-Objective JAYA, Soft Combination.

Introduction

The radio spectrum is currently being used inefficiently, with a significant percentage of the spectrum that have licenses not being fully utilized. The Federal Communications Commission is now considering allowing opportunistic access to the licensed spectrum by secondary users, as long as it should not have any adverse effect/disturbance to the primary users or license holders (1). In a network of CR user, the SUs must possess the ability to detect presence or absence of user who have license. For the objective to prevent interference with licensed users, primary user (PU) signal consistently experiences significant signal degradation caused by propagation loss and interference from secondary users (SUs). This is demonstrated in Figure 1. To mitigate the fading issue, we can employ diversity gained by deploying many secondary users (SUs) to detect the spectrum in a cooperative manner. The significance of this research is to improve the spectral efficiency of the cognitive radio so that overall quality of voice communication as well as data communication service will be improved without disturbing the Primary user or a license user using limited resources. The SUs in a spectral sensing for cooperative type system provide their data to a fusion centre (FC), which then determines the global presence or absence of primary users (PUs) based on a specified rule. When SUs transmits all received signals to common receiver which is called fusion centre (FC) without making any decisions, this is known to as soft combination (2). Alternatively, when secondary users transmit their choice information to the fusion centre using a 1-bit piece of information; which is referred to as HDF (3). Generally, cooperative spectrum sensing using soft combination yields superior performance compared to using hard combination. Nevertheless, the soft combination necessitates a higher volume of traffic for secondary users (SUs) because substantial

(Received 16th September 2024; Accepted 18th January 2025; Published 27th January 2025)

amount of data required for better sensing quality. Conversely, the HDF requires a mere single bit of additional data for every SU. The spectrum efficiency is clearly challenging. This study assumes that each secondary user utilizes energy detection as the method for sensing. The mechanism by which the local choice is sent to the FC is crucial in cooperative schemes, particularly in spectrum sensing the context. Optimization of a quantized cooperative spectrum sensing is a very sensitive task and crucial task in cognitive radio because compressing sensing data of the reporting channel at fusion center will degrade the spectrum sensing efficiency as well as create the interference with primary user.

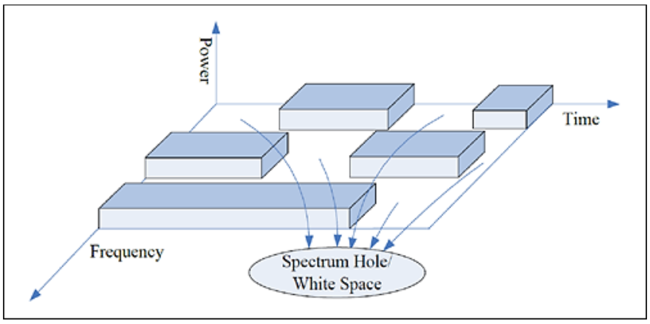

Figure 1: Spectrum White Space (Holes) Utilization

Using this optimization strategy, accommodation of more dedicated communication channel of emergency medical service is possible in the context of the real-world impacts. Cooperation spectrum sensing techniques with quantization have been suggested in several literatures. It was found that there is a trade-off between the quantity of information of sensing and the count of cooperative users (4). In the study of spectrum sensing approach, it was found that Welch's periodogram and Dempster-Shafer theory is used for effect sensing mechanism in the cooperative mechanism but it required larger number of iterations (5). In the study of the Lloyd-Max approach for optimization it is concluded that this method is used to find the optimal quantizer with the least amount of error and it is not stable for larger number of nodes (6). In the study of the application of the use of the Neyman-Pearson criteria it is found that this method has a raise in the complexity of system due to the use of log-likelihood due to complex architecture (6,7). To maximize the likelihood of detection while preserving a predetermined false alarm rate, it was found that two-bit quantization method is not sufficient to preserve sensing information (7). Still, we need to need to optimize the right settings. The organization of research paper is in given manner. In Section II, basic theory of CSS is introduced. Section III is dedicated to proposed optimal sensing framework pertaining to searching of spectrum in cooperative manner using softend data fusing method and the associated optimization problem. Section IV presents the multi-objective JAYA (MOJAYA) based solution for the given optimization problem. The simulation findings are given in section V which also provides a comparison between our optimized model and conventional method and finally conclusive remarks is described in Section VI.

Cooperative Spectrum Sensing

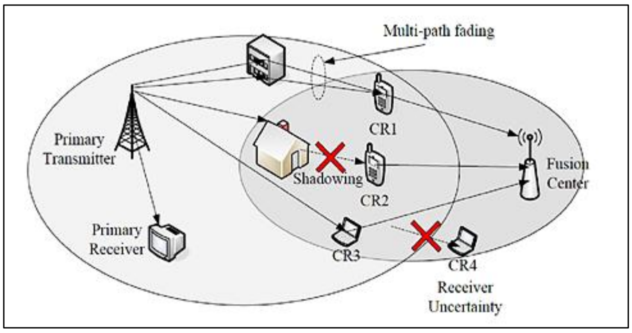

Figure 2: Cooperative Spectrum Sensing Scenario

Assume that total no of SU is N and a Frequency Coordinator (FC) in the CR network, as illustrated in Figure 2. Secondary users (SUs) independently perceive the information of spectrum in their immediate vicinity and transmit their binary determinations to a fusion centre. The central/common base station then makes a conclusive determination as to whether a licensed user (PU) exists or vacant. The objective of sensing of spectrum is to differentiate among two hypotheses: H_0, which assumes that signal, is no communicated, and H_1, which assumes that a signal is being, conveyed (8). Regarding sensing of spectrum, there are two primary probabilities that are commonly linked: the false alarm rate (P_f), which is the likelihood of signal detecting even when it is not present, and the detection rate (P_d), which is the likelihood of correctly detecting a signal.

$$x(t) = \{n(t) \qquad H_0\; hs(t) + n(t) \quad H_1 \qquad [1]$$

It was found that the false rate, average detection rate, and average missed detection rate for AWGN channel are as follows (9).

$$P_d = P\{H_1\} = Q(\beta, \lambda) \qquad [2]$$

$$P_f = P\{H_0\} = \frac{\Gamma(TW, \frac{\lambda}{2})}{\Gamma(TW)} \qquad [3]$$

$$P_m = 1 - P_f \qquad [4]$$

The variables in question are λ, which represents the energy detection threshold; γ, which represents the instantaneous SNR of CR; and TW, which represents the full form of the multiplication of the two-factor bandwidth and time. The function for gamma is denoted by Γ(.), the incomplete function of gamma is denoted by Γ (.,), and the generalized function is denoted by Q(.,..). Marcum the Q-function is defined as follows:

$$Q_u(a, b) = \int_b^\alpha \frac{x^u}{a^{u-1}} e^{-\frac{x^2+a^2}{2}} I_{u-1}(ax)dx \qquad [5]$$

According to the Neyman-Pearson criterion, the i[th] CR's threshold is determined as

$$\lambda^* = 2\Gamma^{-1}(P_f, TW) \qquad [6]$$

Substituting the aforementioned threshold into the likelihood of detection equation yields the ROC for a specified false alarm rate. The conventional receiver uses the mean probability of each cognitive radio (CR) to determine the false rate and the detection rate in sensing of spectrum for the case of cooperative manner. The probability of a false alert is computed by reference (10);

$$Q_f = \sum_{k=n}^{N} \binom{N}{k} P_f{}^k (1 - p_f)^{N-k} = prob\{H_1/H_0\} \qquad [7]$$

Also, cooperative detection rate is presented by following;

$$Q_d = \sum_{k=n}^{N} \binom{N}{k} P_d{}^k (1 - p_d)^{N-k} = prob\{H_0/H_1\} \qquad [8]$$

The detection rate in averaging form can be achieved by calculating the average of the P_d in the scenario of AWGN environment, considering the distribution of SNR for fading case.

$$P_d = \int Q_u(\beta, \lambda) f_\beta(x) dx \qquad [9]$$

When many plane waves make up the composite received signal in certain scattering scenarios, the distribution of the received signal conforms to a Rayleigh distribution (10). In the environment of Rayleigh fading, the random variable γ follows an exponential distribution.

$$f(\beta) = \frac{\beta}{\underline{\beta}} exp\; exp \left(\frac{\beta}{\underline{\beta}}\right), \beta \geq 0 \qquad [10]$$

In this scenario, expression in the form of compact for the likelihood of detection can be derived (with some manipulation) by replacing f (γ) in the equation above with given

$$P_{dRay} = e^{-\frac{\lambda}{2}} \sum_{k=0}^{u-2} \frac{1}{k!} \left(\frac{\lambda}{2}\right)^k . + \left(\frac{1+\underline{\beta}}{\underline{\beta}}\right)^{u-1} \left(e^{\frac{\lambda}{2(1+\beta)}} - e^{-\frac{\lambda}{2}} \sum_{k=0}^{u-2} \frac{1}{k!} \left(\frac{\lambda\underline{\beta}}{2(1+\underline{\beta}}\right)^k\right) \qquad [11]$$

The data fusion center receives a one-bit judgment from each cognitive user on the primary user's idle or active in hard combing-based fusion. Its low bandwidth requirement is its key benefit. The common node can use "AND", "OR", and "MAJORITY" to make binary judgments. Cognitive users send 1 for signal presence and 0 for absence. Instead of making judgments locally, CR users in soft combing-based fusion communicate all sensing results to the fusion centre, which then utilizes suitable data gathering technique like equal weightage is apply to each node (EGC), selection combining and maximal weightage given based on SNR (MRC) to make a conclusion. Despite the increased bandwidth requirements of the reporting control channel, soft combination outperforms hard combination (10). There is more work involved than with the hard combination method β.

Methodology

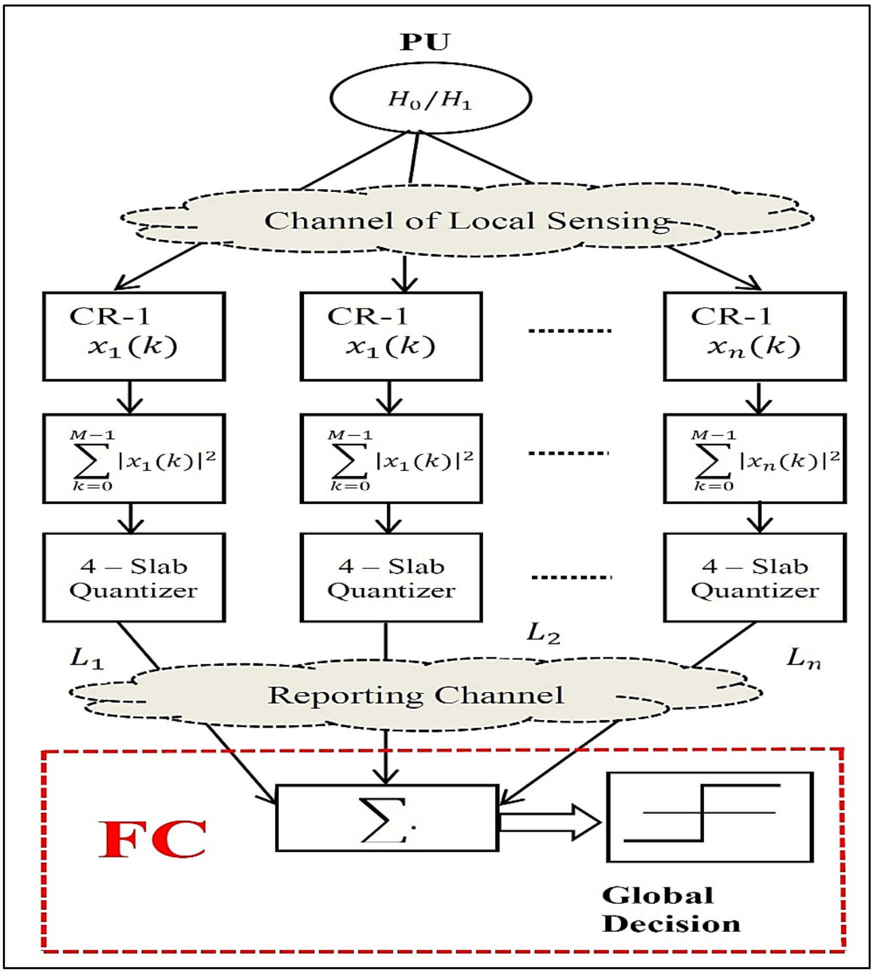

Figure 3: Multi-Objective JAYA Based Optimal Framework

Figure 3 depicts the optimal spectrum sensing framework system model optimal spectrum sensing framework based softend CSS approach. Every secondary user that is working together searches the available spectrum in its immediate vicinity and transmits bit of information known as quantized data of measurement of local channel, represented as L_n (indicating the level of quantization), to the common/central base station (FC) located at the centrally. The FC makes a worldwide judgement which is depends on the index (L_n) and weight given to the relevant energy level. While date fusion for the case of Soft combining method exhibits superior detection performance, it necessitates a significant amount of extra/redundant information for every cognitive radio (CR) user to periodically broadcast the sensing result. On the contradictory, the traditional hard combination approach necessitates only a single bit of additional data for each CR user. However, it experiences a decline in performance because information being loss resulting from HDF. In our approach, we have used a softened hard which is known as quantization of energy level combining strategy having 2-it extra required for every cognitive radio (CR) user. We call it overhead. This technique gives efficient detection performance while minimizing complexity. The Soft combination-based data fusion approach achieves detection of spectrum by assigning varying weights to all available cognitive radio (CR) users based on their SNR. In the traditional one-bit hard combining strategy for data gathering at common data centre i.e. AND, OR etc., a single threshold is set as benchmark function to partition the entire measured energy level into two distinct zones. Consequently, all CR users beyond this level are assigned equal importance, irrespective of any potentially significant variations in their measured energies. A refined binary hard combination data fusion approach improves detection performance by partitioning the measured energy level into multiple regions and assigning distinct weights to every zone.

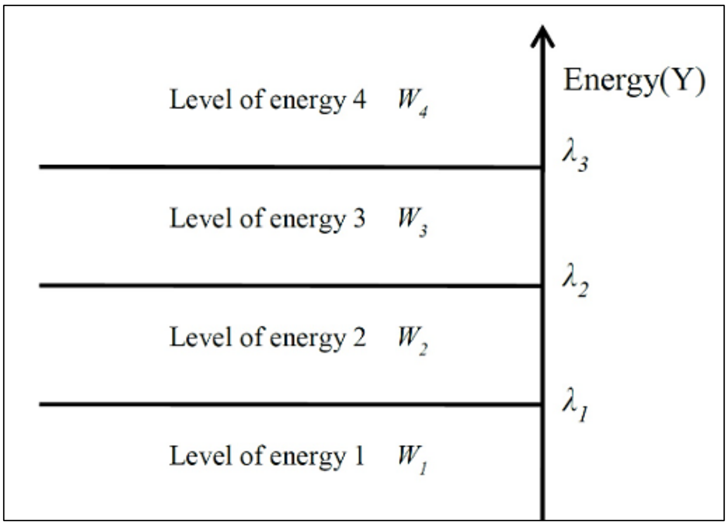

Figure 4: Principle of two-bit Softend Method

Fundamental concept of the data gathering method at central/common receiver is demonstrated in Figure 4 which is fundamentally based on a two-bit hard combination with a softened approach. While for the case of traditional one-bit strategy that utilizes single threshold, the proposed two-bit method uses three thresholds, namely λ_1, λ_2, and λ_3, to partition the entire range of measured energy into four distinct zones. Every secondary user that is working together search the available free slot and transmits its 2-bit pieces of information which is called as "quantized data" to the FC at the central node or base station, indicating the specific location where it's seen energy is located. The central node/common receiver (FC) centre makes a worldwide decision based on its measurement of a 2-bit value. The probabilities of observing data in the relevant regions under the hypotheses H_1 and H_0, in the vicinity of channel for AWGN case, are as follows.

$$P_{dn} = \{1 - P_d(\lambda_j) \quad if\ j \\ = 1\ P_d(\lambda_{j-1}) \quad if\ j \\ = n\ P_d(\lambda_{j-1}) - P_d(\lambda_j) \quad else \qquad [12]$$

In the proposed method, the weight vector and threshold values are used to establish the global selection. Here, the energy level, rather than the reporting nodes, receives the weight distribution. A 2-bit softened hard combination strategy is used by this data fusion system. With the use of quantified measures, the fusion centre is able to precisely determine the user count.

$$\vec{N} = \ [n_1 n_2\, n_3 n_4\,] \qquad [13]$$

$$\vec{W} = [w_1 w_2 w_3 w_4] \qquad [14]$$

The Evaluation of decision is executed by utilizing the number of users across all energy levels and weight given to that region.

$$f(\overrightarrow{weıght}) = \{1 \quad if\ \vec{N}.\overrightarrow{weıght} \\ > 0\ 0 \quad else \qquad [15]$$

For the above case, the total is calculated by following

$$N_c = \sum_{i=0}^{3} w_i . N_i \qquad [16]$$

WhereN_i= the total amount of energy that were detected in area.Then the value of N_c is make comparison with cut off, N_T If N_c≥N_T, main signal is deemed to be available; if not, it is deemed to be absent. In addition, we analyze the Rayleigh channel, which encompasses multipath phenomena. The probability of collaborative detection for the case channel being Rayleigh is estimated using a technique termed softened data fusion combining strategy, as described in (10).

$$P_d = \sum_{i=1}^{4} \sum_{j=1}^{4} P_T(H_1) \qquad [17]$$

$$P_d = \sum f(\vec{w}) \sum_{i=1}^{4} \left(\frac{N - \sum_{j=1}^{i-1} N_j}{N_i}\right) (1 - P_{d1})^{n_1} (P_{d1} - P_{d2})^{n_2} (P_{d2} - P_d \qquad [18]$$

$$P_d = \sum f(\vec{w}) \left(\frac{N}{n_1}\right) \left(\frac{N - n_1}{n_2}\right) \left(\frac{N - n_1 - n_2}{n_3}\right) \left(\frac{N - n_1 - n_2 - n_3}{n_4}\right) (1 - P_{d1})^{n_1} (P_{d1} - P_{d2})^{n_2} (P_{d2} - P_{d3})^{n_3} (P_{d4})^{n_4} \qquad [19\ ]$$

$$P_d \propto f(\vec{w}) \qquad [20]$$

Differentiating between the two possibilities that the channel state is empty, H0, or that it is in use, H1 is the main goal of spectrum detection. The best way to determine which selections are the most ideal goal of Neyman-Pearson optimality is to increase the likelihood of signal detection. The enhancement of $(\vec{w})$ vector according to the following optimality is necessary for the suggested data fusion technique and decision logic. Problem of Optimization: $Maximize\ P_d\ suject\ to\ P_f \leq \alpha$

Multi-Objective Jaya (Mojaya) Based Solution

Multi-objective JAYA (MOJAYA) algorithm is the upgraded edition of the normal JAYA algorithm. It was found that specified optimization methodology is a straightforward yet efficient technique for tackling both limited and unconstrained optimization issues (11). In a cooperative spectrum sensing environment, the fading effect is time dependent and continuous changing due to wireless channel characteristic the static parameter dependent algorithm is not suitable for optimization of weighting coefficient vector. MOJAYA algorithm adapted to the optimization problem due to its free from parameter feature and higher convergence efficiency. It was found that the algorithm's main idea is to guide the solution towards the best possible solution while avoiding the worst solution (12). Multi-objective JAYA has no any parameter of algorithm itself, making it free from parameter algorithms. It only requires a few control parameters. It was found that the multi-objective JAYA algorithm is characterized by its parameter-less nature, which is unique to optimization methods (13, 14). Unlike TLBO, which has only one step, the Multi-objective JAYA algorithm is relatively easier to implement. The algorithm's objectives are to succeed (i.e., get to the best answer) and prevent failure (i.e., stay away from the worst option). The algorithm successfully executed to obtain the highest value by reaching the most favorable solution, so it is referred to as Jaya, a term derived from Sanskrit meaning triumph. To optimize the objective function f(x), it is essential to consider 'm' design parameters (j = 1,2, 3..., m) at each iteration 'i' and a population size of ‘n' (k = 1,2, 3..., n). The fitness computation is conducted for every potential solution, and the most suitable option is allocated the optimal value of f(x), denoted as $f(x)_{best}$. Similarly, the candidate with the lowest performance, denoted as $f(x)_{worst}$ is allocated the minimum value of f(x). Following are the basic equation of JAYA algorithm based on which multi-objective JAYA is derived. This equation is also utilized in our optimization problem to compute the revised value of $x'_{j,k,i}$

$$y'_{j,k,i} = y_{i,j,k} + t_{1,j,i}\left(y'_{j,best,i} - |y_{j,k,i}|\right) - t_{2,j,i}\left(y'_{j,worst,i} - |y_{j,k,i}|\right) \quad [21]$$

If $y'_{j,k,i}$ yields a best function value, it is retained and acceptable. All the approved function values are retained at the last iteration. The values mentioned before are used as the input for the following iteration. The results have shown that the Multi-objective JAYA technique performs exceptionally well when applied to constrained optimization problems. The statistical testing has also demonstrated the recital superiority of the proposed technique. The Multi-objective JAYA algorithm is used to determine the weight, w_i as depicted in given algorithm is shown in Figure 5.

```
Algorithm: Multi-objective JAYA based optimization of weight
I/O: CR User, type of channel, SNR, Iteration, Threshold value
O/P: Detection rare P_d, Optimal weight vector w⃗
Initialize the iteration and size of population
While (number of generation is not reached)
    For i = 1 to N
        For j = 1 to D
            Set t1 ∈ (1,0)
            Set t2 ∈ (1,0)
            y'_j^i = y_j^i + t1 X ( y_j^1 − y'_j^i ) − t2 X (y_j^N − y_j^i)
        End loop of For
        If f(x'^i) ≤ f(x^i) then
            y'^i = y'^i {udpate Process}
        End loop of If
    End loop of For
End loop of While
```

Figure 5: MOJAYA Pseudo code

Result and Discussion

An evaluation has been conducted via a simulation to measure the performance of Muti-objective JAYA algorithm based 2-bit softened fusion scheme used in CSS. The detection probability for the ROC is determined in which a comparison between conventional soft combining rule like giving equal weightage to every node (EGC) and conventional hard combining rules i.e. Half VOTING, MAJORITY, OR etc., is made. In computer simulation, the fitness function is the detection rate for spectrum sensing and it is defined as P_d. Following Table 1 illustrated the value of parameters set for simulation in the optimal spectrum sensing framework having no malicious node and the idle channel is assumed

Table 1: Simulation Parameter List

Sr.	Parameter	Value/ Range
01	Time Bandwidth Product	5
02	Channel	AWGN, Rayleigh
03	SNR	10dB
04	Total CR Nodes	10
05	Samples of signal (M)	2u
06	Threshold range	10 to 60
07	Population Size	20
08	Frame duration T	100ms
09	Number of noisy reporting channel	0
10	Number of Malicious Node	0

Comparative analysis of decision logic performance depends on the optima weight vector using the MOJAYA algorithm in the vicinity of the channel of AWGN and the channel of Rayleigh channel is mentioned in Table 2 and Table 3 respectively. From this simulation result, the performance of presented the proposed 2-bit quantized cooperative is almost the same as the conventional scheme i.e. EGC which required a lager bandwidth for EGC method, so it validate the robustness of our proposed technique.

Table 2: Comparative Table of Proposed Method for AWGN Channel

$P_F \backslash P_D$	OR	MAJ	AND	EGC	MO-JAYA
0	0.24	0.32	0.32	0.42	0.41
0.10	0.44	0.54	0.64	0.82	0.81
0.20	0.53	0.64	0.74	0.82	0.81
0.30	0.61	0.75	0.81	0.86	0.85
0.40	0.66	0.79	0.84	0.89	0.88
0.50	0.68	0.81	0.85	0.91	0.91
0.60	0.68	0.86	0.85	0.94	0.94
0.70	0.74	0.90	0.89	0.95	0.95
0.80	0.80	0.92	0.93	0.98	0.98
0.90	0.91	0.94	0.96	0.99	0.99
1.00	1.00	1.00	1.00	1.00	1.00

Table 3: Comparative Table of Proposed Method for Rayleigh Channel

$P_F \backslash P_D$	OR	MAJ	AND	EGC	MO-JAYA
0	0.22	0.30	0.30	0.40	0.39
0.10	0.42	0.52	0.61	0.80	0.79
0.20	0.51	0.61	0.72	0.81	0.80
0.30	0.6	0.71	0.79	0.81	0.80
0.40	0.64	0.74	0.81	0.86	0.85
0.50	0.67	0.80	0.81	0.90	0.89
0.60	0.68	0.83	0.84	0.93	0.93
0.70	0.72	0.88	0.88	0.94	0.94
0.80	0.78	0.90	0.91	0.97	0.97
0.90	0.89	0.92	0.93	0.98	0.98
1.00	1.00	1.00	1.00	1.00	1.00

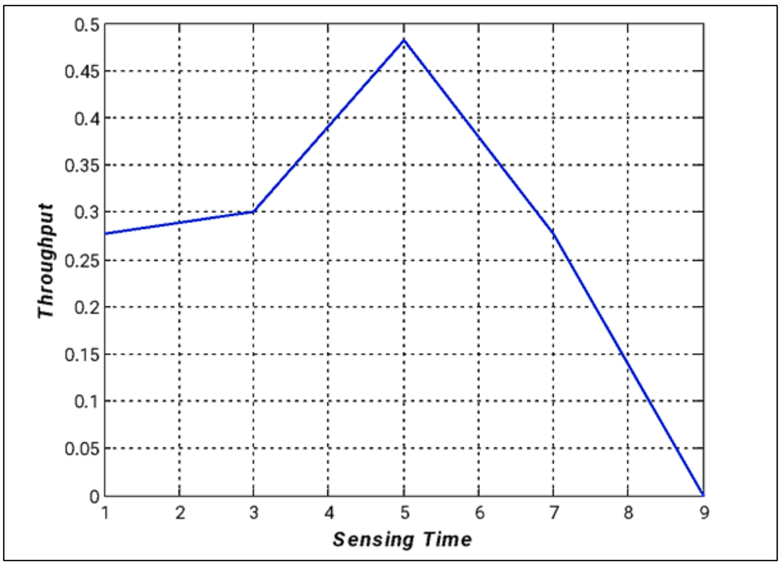

Figure 6: Curve of time of Sensing (ms) Relative to Throughput

A secondary user (SU) network's normalized throughput was examined in a performance study shown in Figure 6. The graph demonstrates that as the sensing time grows, the throughput of the SU user network also increases. However, beyond a certain optimal point, the throughput starts to drop, validating and satisfying the sensing-throughput trade-off of a proposed multi-objective JAYA based method. It is demonstrated from the simulation result that the maximum throughput is reached when the time of sensing time is on the verge of 5 ms which confirms the improvement of 25% efficiency as compared to other optimization algorithms. The extended duration of the time of sensing time leads to a decline in the efficient transmission of data rate of the secondary user network since it raises the likelihood of the single PU arriving during the sensing period.

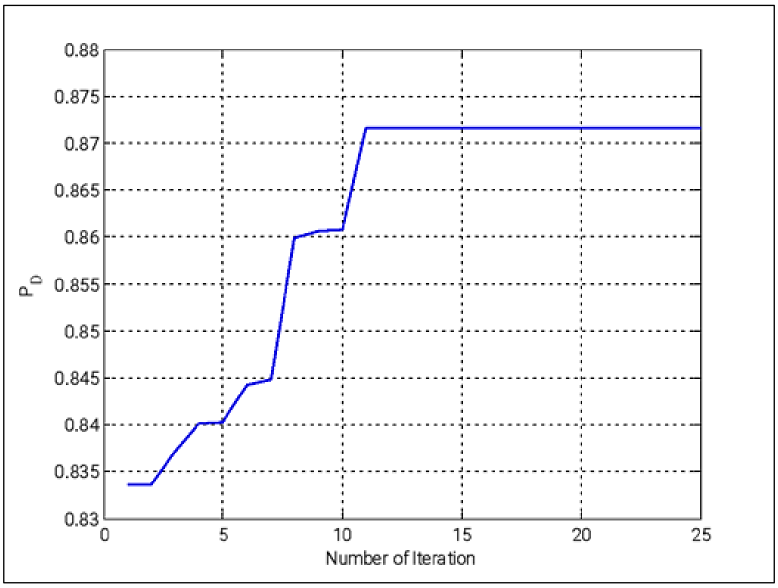

Figure 7: Rate of Convergence for MOJAYA Based Technique

The rate of convergence for the proposed multi-objective JAYA based solution of a 2-bit softened decision based fusion scheme for false alarm rate $P_f = 0.01$ is illustrate in Figure 7. According to the simulation outcome, the suggested technique achieves convergence after 12 rounds, demonstrating a really rapid pace to suit the requirement of the real-time wireless communication for sensing of spectrum in CR user. The algorithm used in the given method is free from parameters, so it also ensures to meet the overall less computation complexity requirement in the sensing of spectrum. According to the simulation outcome, all over various obtained detection probability after 12 iterations can be insignificant which validates that the multi-objective JAYA-based solution is also pretty stable as compared to similar kind of other solution.

Conclusion

Spectrum sensing has emerged as a crucial component of cognitive radio to enhance spectrum utilization effectively. We examined traditional methods of combining data, specifically soft data fusion (SDF) as well as hard decision fusion (HDF), for sensing in cooperative manner (CSS). Our simulation revealed a trade-off between quality and overhead. In order to minimize the additional costs, we employ a cooperative spectrum sensing (CSS) technique that utilizes energy detection and softens the hard quantization. This paper proposes the utilization of the multi-objective JAYA algorithm as a prominent technique to optimize the vector of weighting factors for the measured energy level of the information sensing. According to the simulation outcome, it is very cleared that the suggested multi-objective JAYA-based softend CSS technique is reliable, efficient and resilient. It provides Enhanced output with comparison to conventional CSS methods and is nearly as efficient as SDF-based CSS, while having minimal additional costs. Additionally, the multi-objective JAYA based framework exhibits improved convergence output, which indicates reduced computation time and complexity, as it is not dependent on specific parameters. This research expands the scope of future work with some suggestions and new paths for investigation. It is possible to assess the suggested approach using user mobility, and the cooperative spectrum sensing framework based on MOAYA may be expanded to include several cognitive networks. Adding the impact of noise uncertainty (NU) on the main user's receiver to the sensing-throughput trade-off dilemma is another potential addition for the future.

Abbreviation

Nil.

Acknowledgement

The author would like to express their gratitude to their mentor, parents and Lord for their support as well as motivation during entire process.

Author Contributions

All the authors are equally contributed.

Conflict of Interest

The authors declare that they have no conflict of interest.

Ethics Approval

This work does not need ethical approval.

Funding

This work does not receive any funds to carry out the work.

References

1. Haykin S. Cognitive radio: Brain-empowered wireless communications, Journal of Communication. 2005; 23(2): 201–220.
2. Moha J, Zhao GD, Ye L. Soft combination and detection for cooperative spectrum sensing in cognitive radio networks, IEEE Transactions on Wireless Communications. 2008;7(11): 4502- 4507.
3. Oh DC, Lee HC, Lee YH, Linear hard decision combing for cooperative spectrum sensing in cognitive radio systems, IEEE 72nd Vehicular Technology Conference. 2010; 5(2):1-5.
4. Mustonen M, Matinmikko M, Mammela A. Cooperative spectrum sensing using quantized soft decision combining, in CognitiveRadio Oriented Wireless Networks and Communications, 2009. CROWNCOM'09. 4th International Conference on. 2009; 3(7):1–5.
5. Nguyen TN, Koo I. Evidence-theory-based cooperative spectrum sensing with efficient quantization method in cognitive radio, Vehicular Technology, IEEE Transactions on Communication. 2011;60(1):185– 195.
6. Nguyen TN, Koo I. Log-likelihood ratio optimal quantizer for cooperative spectrum sensing in cognitive radio, IEEE Communications Letters. 2011;15(3):317–319.
7. Zahabi S, Tadaion A, Aissa S. Neyman-pearson cooperative Spectrum sensing for cognitive radio networks with fine quantization at local sensors, Communications, IEEE Transactions on communication. 2012; 60(6): 1511–1522.
8. Ghasemi A, Sousa ES. Collaborative spectrum sensing for opportunistic access in fading environments, International DySPAN conference. 2005; 2(5):131–136.
9. Wei Zhang, Ranjan K, Khaled Letaief. Optimization of Cooperative Spectrum Sensing with Energy Detection in Cognitive Radio Networks, IEEE transactions on wireless communications. 2009; 8(12):112-121.
10. Zhi Quan, Shuguang Cui, Vincent Poor, Sayed AH. Collaborative wideband sensing for cognitive radios, IEEE Signal Processing Magazine. 2008; 25(6): 63–70.
11. Rao RV, More KC, Coelho LS, Mariani VC. Multi-objective optimization of the stirling heat engine through self-adaptive jaya algorithm. 2017; 9(3):33-53.
12. Berrouk F, Bouchekara HREH, Chaib AE, Abido MA, Bounaya K, Javaid MS. A new multi-objective jaya algorithm for solving the optimal power fow problem. Journal of Electrical System. 2018;14(3):165–181.
13. Srinivasarathnam C, Yammani Chandrasekhar, Maheswarapu Sydulu. Multi-objective jaya algorithm for optimal scheduling of dgs in distribution system. Journal of electrical system. 2019;7(1):59–78.
14. Rao RV, Keesari HS. Novel algorithms for multi-objective optimization of selected thermodynamic cycles. Engineering with Computers. 2021; 37(4):09-37.