BMBAD BJESR Mühendislik Bilimleri ve Araştırmaları Dergisi
Journal of Engineering Sciences and Researches

Cooperative Spectrum Sensing Using Reptile Search Algorithm in Cognitive Radio

Bilişsel Radyoda Sürüngen Arama Algoritması Kullanarak İşbirlikçi Spektrum Algılama

[1]Burcu KETENCİ, [2]Necmi TAŞPINAR, [3]Tareq M. SHAMİ

[1]*Erciyes University, Institute of Natural and Applied Science, Kayseri, Turkey*
[2]*Erciyes University, Department of Electrical and Electronics Engineering, Kayseri, Turkey*
[3]*University of York, Department of Electronic Engineering, U.K.*

[1]burcuketenci23@gmail.com, [2]taspinar@erciyes.edu.tr,
[3]tareq.al-shami@york.ac.uk

Araştırma Makalesi/Research Article

ARTICLE INFO

Article history

Received : 25 August 2023
Accepted : 26 September 2023

Keywords:

Cognitive Radio, Reptile Search Algorithm, Weight Coefficients Optimization, Detection Performance

ABSTRACT

Given the growing requirement for wireless communication and the limited nature of the spectrum, cognitive radio technology plays a crucial role in optimizing the use of the radio frequency spectrum. Spectrum sensing is the core function of the cognitive radio network. In this paper, the recently developed Reptile Search Algorithm (RSA) is used to increase detection capabilities in cooperative spectrum sensing for cognitive radio systems. Weight assignments were made to secondary users with the help of soft fusion scheme and Reptile Search Algorithm was used to ensure that these assignments gave the highest detection results. The results were compared with the other two optimization algorithms, Particle Swarm Optimization (PSO) and Aquila Optimizer (AO), and it was seen that Reptile Search Algorithm provides better results than the other algorithms.

MAKALE BİLGİSİ

Makale Tarihleri

Gönderim : 25 Ağustos 2023
Kabul : 26 Eylül 2023

Anahtar Kelimeler:

Bilişsel Radyo, Sürüngen Arama Algoritması, Ağırlık Katsayıları Optimizasyonu, Algılama Performansı

ÖZET

Kablosuz iletişim için giderek artan gereksinim ve spektrumun sınırlı doğası göz önüne alındığında, bilişsel radyo teknolojisi radyo frekansı spektrumunun kullanımının optimize edilmesinde çok önemli bir rol oynamaktadır. Spektrum algılama, bilişsel radyo ağının temel işlevidir. Bu makalede, yakın zamanda geliştirilen Sürüngen Arama Algoritması (RSA), bilişsel radyo sistemleri için işbirlikçi spektrum algılamada tespit yeteneklerini artırmak amacıyla kullanılmıştır. Yumuşak füzyon şeması yardımıyla ikincil kullanıcılara ağırlık atamaları gerçekleştirildi ve bu atamaların en yüksek tespit sonuçlarını vermesini sağlamak için Sürüngen Arama Algoritmasını kullanıldı. Sonuçlar diğer iki optimizasyon algoritması olan Parçacık Sürü Optimizasyonu (PSO) ve Aquila Optimizer (AO) ile karşılaştırılarak Sürüngen Arama Algoritmasının diğer algoritmalara göre daha iyi sonuçlar sağladığı görülmüştür.

ORCID ID: [1]0000-0002-9936-9785
[2]0000-0003-4689-4487
[3]0000-0002-0159-4985

1. INTRODUCTION

The radio frequency spectrum is utilized as a critical resource in wireless technologies, including radio and television broadcasting, cellular networks, Wi-Fi, satellite communications, Bluetooth and much more. As the interest and demand for wireless services grow day by day, the proper allocation and utilization of spectrum become increasingly essential. Due to the limitations of the fixed spectrum allocation approach in fully utilizing the spectrum's capacity, cognitive radio technology is employed to achieve more efficient spectrum utilization [1]. Cognitive radio enables unlicensed users to adaptively use frequency bands when licensed users with priority rights are not actively occupying the spectrum, using the concept of dynamic spectrum access [2]. The users who have a license in the spectrum are considered primary users (PUs), while the users who do not have a license are considered secondary users (SUs). One of the critical stages in cognitive radio is spectrum sensing, which refers to the process of analyzing and detecting the occupation or availability of radio frequency bands. The successful execution of the spectrum sensing stage is vital because if the presence of primary users is not precisely determined, secondary users may cause detrimental interference to the other users, which is highly undesirable [3-4].

In the literature, research on spectrum sensing algorithms has been evolving and depending on the system requirements and characteristics, various methods such as energy detection [5], matched filter [6], cyclostationary detection [7] are used [8]. Cooperative spectrum sensing schemes are proposed to mitigate the impact of different challenges such as fading, noise variations and to increase the reliability of spectrum sensing. [9] In these schemes, multiple secondary users come together to perform the sensing task cooperatively. Each secondary user senses the spectrum locally, and then the information obtained from these users is combined at a fusion center to generate an ultimate conclusion. This combining process in the fusion center can be applied with three different techniques: Hard Decision Fusion, Soft Decision Fusion and Softened Hard Decision Fusion [10-13]. In this study, the soft decision fusion technique is used, which is known to have better detection performance than hard decision fusion. In this technique, secondary users report their detection results in the form of probability distributions. These reports provide statistical information about the spectrum state and the fusion center merges this information to estimate the presence/absence of the PU in the spectrum.

Several metaheuristic algorithms have been investigated in the literature for the implementation of spectrum sensing. In [14], to enhance the detection accuracy in cooperative spectrum sensing, PSO and five additional PSO variants were employed to optimize the weight vector, and a comparative study was conducted to evaluate their performance. An soft decision fusion (SDF)-based cognitive radio network based on GA is introduced in [15] and the results show that it performs better compared to HDF and traditional schemes. In [16], an evolutionary optimization approach using the Imperialistic Competitive Algorithm (ICA) is presented for the effective selection of weighting coefficients for each secondary user in the cooperative sensing scheme. The ICA-based method has been compared to Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and SDF-based methods, demonstrating that it surpassed other SDF-based techniques in terms of performance. In [17], the efficient adaptive artificial bee colony (EA-ABC) algorithm was developed, and the proposed EA-ABC algorithm was adapted for cooperative spectrum sensing. The results have shown that a higher detection probability is achieved compared to ABC, PSO, and modified PSO algorithms with the same false alarm probability. Three distinct bio-inspired techniques, namely, PSO, firefly algorithm, and fish school search, were employed to assess the optimal weighting vector utilized in the fusion center in [18]. Numerical findings demonstrate that bio-inspired techniques outperform traditional algorithms commonly used for spectrum sensing and allocation. In this paper, our focus is on enhancing spectrum sensing performance. In line with this objective, we aim to achieve maximum efficiency in detection performance by leveraging the functionality of intelligent optimization techniques rather than traditional methods for assigning weights to users in the soft fusion scheme. Our goal is to harness the power of intelligent optimization techniques to enhance detection performance and consequently improve the overall quality of service in cognitive radio networks, addressing the growing demand for spectrum resources while minimizing interference and ensuring more efficient spectrum utilization. In cognitive radio (CR) systems, weight coefficients are utilized to merge the individual sensing reports from multiple secondary users (SUs) during the cooperative spectrum sensing process, and they play a critical role in the detection performance. Each SU may be exposed to different channel conditions, noise levels, and fading effects, which makes all sensing reports not equally reliable. By assigning higher weights to secondary users with more reliable sensing capabilities, they have a greater influence on the final combined decision. This way, the cognitive radio system makes more accurate and informed decisions about the primary user (PU) activity, reducing the likelihood of harmful interference caused by secondary users. Ultimately, by intelligently combining the sensing reports using weight coefficients, the cognitive radio system can better utilize underutilized spectrum bands, leading to improved spectrum efficiency and increased capacity. Various optimization algorithms are used to search for the optimal set of weights that maximize the detection accuracy. Towards this goal, the recently emerged Reptile Search Algorithm (RSA) has been adapted to the cooperative spectrum sensing scheme, aiding in determining suitable weight coefficients. We selected the reptile search algorithm because of its effective balance between exploration and exploitation mechanisms, thus facilitating our efficient discovery of optimal weights. This adaptability of the algorithm allows it to dynamically adapt to environmental changes and intelligently explore uncharted regions of the parameter space. In the context of cognitive radio networks, where spectrum dynamics can change rapidly, this adaptability is highly valuable. The obtained results have been compared with other optimization algorithms such as Particle Swarm Optimization

(PSO) and Aquila Optimizer (AO). This paper is divided into the following sections: A summary of the system model we used is presented in Section 2. In Section 3 RSA and weight optimization performed using RSA are explained. The simulation parameters and simulation results are presented in Section 4. The overall results of this paper are given in Section 5.

2. SYSTEM MODEL

Figure (1) illustrates the proposed framework for cooperative spectrum sensing. Soft fusion technique has been used in this study. M number of SU have been used to transmit local observations to a fusion center (FC). The local individual decision of each SU is forwarded to the FC according to the binary hypothesis given in (1).

$$\begin{cases} X_i[n] = W_i[n], & for\ H_0 \\ X_i[n] = g_i S[n] + W_i[n], & for\ H_1 \end{cases} \qquad i = 1,2,3,\ldots,M \tag{1}$$

In this hypothesis, H_0 represents that there is no active primary user in the spectrum, indicating that the spectrum is vacant. H_1, on the other hand, signifies that the spectrum is occupied by a primary user and is not vacant. In (1), the received signal is symbolized by $X_i[n]$. The channel gain between the primary user and i^{th} secondary user is signified by g_i. While $W_i[n]$ represents the additive white Gaussian noise (AWGN) $W_i[n]{\sim}N(0,\sigma_{W_i}^2)$, s[n] denotes the signal of the primary user. The channel gain of the secondary user-fusion center link is represented by h_i. $N_i[n]$ represents the AWGN characterized by a mean value of zero and a variance of $\delta_i^{\cdot 2}$. The signals received from the secondary users are denoted as $Y_i[n]$. Z_i stands for the energy accumulated by the fusion center from the i^{th} secondary user. Z is the ultimate test statistic computed by the fusion center before the decision-making block. At the fusion center, the energy of every secondary user is multiplied by a weight and then all the weighted energies are summed together. Subsequently, a constant threshold value, dependent on a fixed false alarm probability P_f, is compared with this sum to make a decision between hypothesis H_0 or H_1. The probability of detection equation that we want to maximize in this study is given below:

$$P_d(\omega) = Q\left(\frac{Q^{-1}(P_f)\sqrt{\omega^T \varphi_{H_0}\omega} - \omega^T\theta}{\sqrt{\omega^T \varphi_{H_1}\omega}}\right) \tag{2}$$

where, $Q(x) = \int_x^{\infty} \frac{1}{2\pi} exp\left(-\frac{t^2}{2}\right) dt$, $\theta_i = \sigma_S^2 K P_{R,i} |h_i|^2 |g_i|^2$, σ_S^2 is the variance of the primary user signal, K corresponds to the total number of samples, $P_{R,i}$ represents the transmitting power of the i^{th} secondary user. The covariance matrices for the H_0 and H_1 hypothesis are denoted as φ_{H_0} and φ_{H_1}. The weight vector $\omega = [\omega_1, \omega_2, \omega_3, \ldots, \omega_M]^T$ and Reptile Search Algorithm is employed to find the appropriate weight coefficients. The detailed equations used in this study can be found in [14].

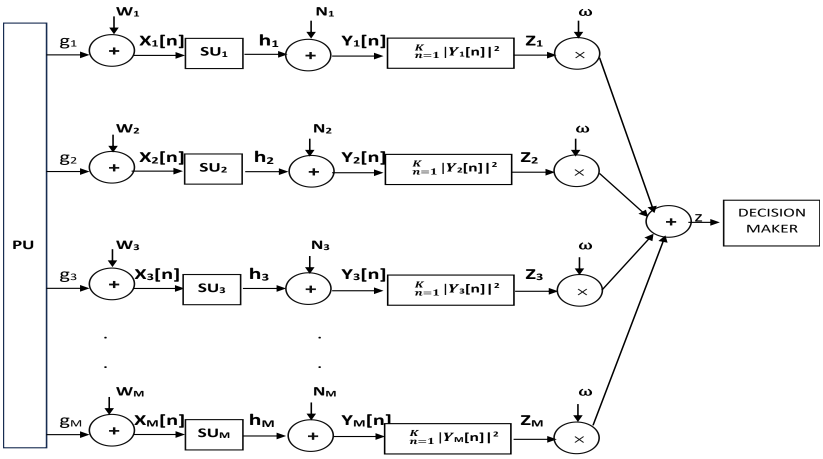

Fig.1. Illustration of cooperative spectrum sensing architecture.

3. REPTILE SEARCH ALGORITHM BASED APPROACH FOR SENSING OPTIMIZATION

The reptile search algorithm (RSA), introduced by Abualigah et al.[19], is an innovative optimization algorithm that replicates the encirclement and hunting actions exhibited by crocodiles. The RSA starts by assigning a random solution to the variable x_{ij} within the minimum and maximum values. In order to harness the inherent behavior of crocodiles, RSA divides its total iterations into four stages. The first two stages specifically emphasize exploration, employing the encircling strategy that encompasses high and belly walking actions. During the encircling process, crocodiles initiate a search in the area, enabling a comprehensive exploration of the solution area, which can be represented in the following manner:

$$x_{(i,j)}(t+1) = \begin{cases} Best_j(t) \times -\eta_{(i,j)}(t) \times \beta - \mathrm{R}_{(i,j)}(t) \times rand, & t \leq \frac{T}{4} \\ Best_j(t) \times x_{(r_1,j)} \times ES(t) \times rand, & t \leq 2\frac{T}{4} \; and \; t > \frac{T}{4} \end{cases} \tag{3}$$

Where t corresponds to the current iteration while T signifies the maximum number of iterations. $Best_j(t)$ represents the i^{th} position in the currently best solution. $rand$ denotes a random number generator. The hunting parameter is denoted by $\eta_{(i,j)}$ and is calculated utilizing (4). β, set to a constant value, controls the exploration accuracy. The reduce function $\mathrm{R}_{(i,j)}$ is computed according to (5). r_1 represents a randomly chosen value from the range [1 N], where N is the count of candidate solutions, $x_{(r_1,j)}$ denotes a randomly selected location from the i^{th} solution. The Evolutionary Sense (ES) is a probability ratio, calculated using (6).

$$\eta_{(i,j)} = Best_j(t) \times \mathrm{P}_{(i,j)} \tag{4}$$

$$\mathrm{R}_{(i,j)} = \frac{Best_j(t) - x_{(r_2,j)}}{Best_j(t) + \epsilon} \tag{5}$$

$$ES(t) = 2 \times r_3 \times \left(1 - \frac{1}{T}\right) \tag{6}$$

Where, ϵ is a small amount. r_2 represents a random value and r_3 represents a random integer number within the range of -1 to 1. Equation (7) is used to determine the difference parameter $\mathrm{P}_{(i,j)}$. The accuracy of exploration is controlled by α. The average positions of the i^{th}solution, denoted by $M(x_i)$, are determined using (8).

$$\mathrm{P}_{(i,j)} = \alpha + \frac{x_{(i,j)} - M(x_i)}{Best_j(t) \times (UB_{(j)} - LB_{(j)}) + \epsilon} \tag{7}$$

$$M(x_i) = \frac{1}{n} \; {}_{j=1}^{\;n} \, x_{(i,j)} \tag{8}$$

During the final two phases, RSA employs exploitation to carry out the local search, utilizing two approaches: hunting coordination and cooperation. The solution's value can be updated using (9) throughout the exploitation phase [20].

$$x_{(i,j)}(t+1) = \begin{cases} Best_j(t) \times \mathrm{P}_{(i,j)}(t) \times rand, & t \leq 3\frac{T}{4} \; and \; t > 2\frac{T}{4} \\ Best_j(t) - \eta_{(i,j)}(t) \times \epsilon - \mathrm{R}_{(i,j)}(t) \times rand, & t \leq T \; and \; t > 3\frac{T}{4} \end{cases} \tag{9}$$

In our study, the size of the weight vector is equal to the number of secondary users, which corresponds to the population size in RSA. At the beginning of RSA, random solutions are generated, and during the iteration cycles, RSA's search mechanisms explore possible locations of solutions close to the optimum. Each solution adjusts its positions based on the processes proposed by RSA and ultimately finds the most suitable weight coefficients that maximize the detection probability given in (2), which corresponds to the best solution obtained. Accordingly, (3), (5), (7), (8) and (9) have been updated as follows,

$$\omega_{(i,j)}(t+1) = \begin{cases} Best_j(t) \times -\eta_{(i,j)}(t) \times \beta - \mathrm{R}_{(i,j)}(t) \times rand, & t \leq \frac{T}{4} \\ Best_j(t) \times \omega_{(r_1,j)} \times ES(t) \times rand, & t \leq 2\frac{T}{4} \; and \; t > \frac{T}{4} \end{cases} \tag{10}$$

$$\mathrm{R}_{(i,j)} = \frac{Best_j(t) - \omega_{(r_2,j)}}{Best_j(t) + \epsilon} \tag{11}$$

$$\mathrm{P}_{(i,j)} = \alpha + \frac{\omega_{(i,j)} - M(\omega_i)}{Best_j(t) \times (UB_{(j)} - LB_{(j)}) + \epsilon} \tag{12}$$

$$M(\omega_i) = \frac{1}{n} \; {}_{j=1}^{\;n} \, \omega_{(i,j)} \tag{13}$$

$$\omega_{(i,j)}(t+1) = \begin{cases} Best_j(t) \times \mathrm{P}_{(i,j)}(t) \times rand, & t \leq 3\frac{T}{4} \; and \; t > 2\frac{T}{4} \\ Best_j(t) - \eta_{(i,j)}(t) \times \epsilon - \mathrm{R}_{(i,j)}(t) \times rand, & t \leq T \; and \; t > 3\frac{T}{4} \end{cases} \tag{14}$$

4. SIMULATION RESULTS

In this section, simulation studies aimed at maximizing the detection probability given by equation (2) are presented. The simulation parameter values used throughout this study are defined in Table 1. For the reptile search algorithm, α and β parameter values that control the exploration accuracy are selected as 0.1. The values for noise and channel gain are chosen at random within a certain range in order to simulate sub-optimal SNR scenarios. We assessed the sensing performance using detection probability metric, which quantifies the reliability of correctly identifying the existence of PUs' signals when they are indeed present. To provide a comprehensive assessment, we contrasted the RSA approach with two other metaheuristic techniques: Particle Swarm Optimization and Aquila

Optimizer. PSO, inspired by social behavior patterns, iteratively refines solutions by mimicking the movement of particles in a multidimensional search space. On the other hand, AO, simulates four different hunting tactics observed in the hunting behavior of Aquila, navigating through a multidimensional search space to find optimal or near-optimal solutions. Fig. 2 depicts the average detection probabilities of weight schemes obtained using PSO, AO, and RSA. The population size is taken as 20 for all three algorithms. The obtained results are for a fixed false alarm probability value of 0.24. At the beginning of iterations, all three algorithms exhibited similar behavior. The following is the provided pseudo code for the suggested system:

Algorithm 1: The pseudo code of the reptile search algorithm for optimizing $P_d(\omega)$

Initialize the population $\omega_i(i = 1,2,3, \dots M)$, M:Number of Secondary Users, and parameters α, β
While $(t < T)$ **do**
Compute the fitness values of every potential solution
Save the best solution obtained so far
Update ES according to (6)
for ($i = 1 - \mathrm{M}$) **do**
    for $(j = 1 - \mathrm{M})$ **do**
        η, R, P are updated using (4),(11) and (12)
        If ($t \leq \frac{T}{4}$) **then**
        $\omega_{(i,j)}(t+1) = Best_j(t) \times -\eta_{(i,j)}(t) \times \beta - \mathrm{R}_{(i,j)}(t) \times rand,$
        else if $(t \leq 2\frac{T}{4}$ and $t > \frac{T}{4})$ **then**
        $\omega_{(i,j)}(t+1) = Best_j(t) \times \omega_{(r_1,j)} \times ES(t) \times rand$,
        else if $(t \leq 3\frac{T}{4}$ and $t > 2\frac{T}{4})$ **then**
        $\omega_{(i,j)}(t+1) = Best_j(t) \times \mathrm{P}_{(i,j)}(t) \times rand$,
        else
        $\omega_{(i,j)}(t+1) = Best_j(t) - \eta_{(i,j)}(t) \times \epsilon - \mathrm{R}_{(i,j)}(t) \times rand,$
        end if
    end for
end for
$t = t$ +1
end while
Return the solution with the highest fitness

However, after surpassing a certain iteration, RSA outperformed PSO and AO significantly in terms of average probability of detection(P_d) values. While the average P_d value of RSA exceeded 0.9, AO remained approximately 0.78 and PSO remained around 0.81. The convergence speed of RSA has shown improvement after around 370 iterations.

The simulation curves shown in Fig. 3 and Fig. 4 are used to evaluate the detection probability values of PSO, AO and RSA for various false alarm probability values. In these receivers operating characteristic (ROC) curves, the value of probability of false alarm (P_f) is changed at each iteration, instead of being set to a fixed value. The probability of false alarm is systematically varied between 0 and 1, with increments of 0.1. For each probability value, the corresponding probability of detection is calculated to construct the ROC curve, illustrating the trade-off between false alarm rate and detection rate. The performance of RSA is compared with PSO and AO and the results have shown that the detection performance of PSO and AO are approximately close to each other, while the detection performance of RSA has outperformed both of them. Additionally, to observe the impact of the number of secondary users on the detection performance, in Fig. 3, the number of secondary users was set as 20, while in Fig. 4, the number was increased to 24. The results indicate that as the number of secondary users increases, the detection performance also improves. For example, when the P_f value is 0.1, in the cognitive radio system with 20 users, the detection probability for RSA is 0.79, while with 24 users, it increases to approximately 0.82. For AO, it rises from around 0.60 to 0.65, and for PSO, it increases from around 0.59 to 0.61. When the P_f value is 0.2, in the cognitive radio system with 20 users, the detection probability for RSA is approximately 0.84, while with 24 users, it increases to approximately 0.86. For AO, it rises from 0.71 to 0.78, and for PSO, it increases from about 0.73 to around 0.77. With an increasing number of secondary users, the cooperative spectrum sensing process becomes more robust due to the diversity in sensing reports from multiple users. This diversity enhances the accuracy of detecting PU signals. As more secondary users participate, more accurate decisions can be made regarding the occupancy or availability of the frequency band. The simulation results underscore the effectiveness of the proposed RSA-based cooperative spectrum sensing approach in cognitive radio systems. The obtained results presented in this section demonstrate that the weight optimization performed with the help of RSA significantly boosts the sensing accuracy in spectrum sensing and is superior to the other two meta-heuristic optimization algorithms.

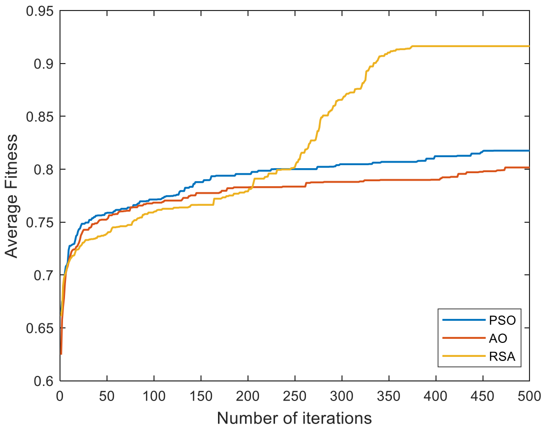

Fig. 2. Comparison of average fitness values for PSO, AO and RSA.

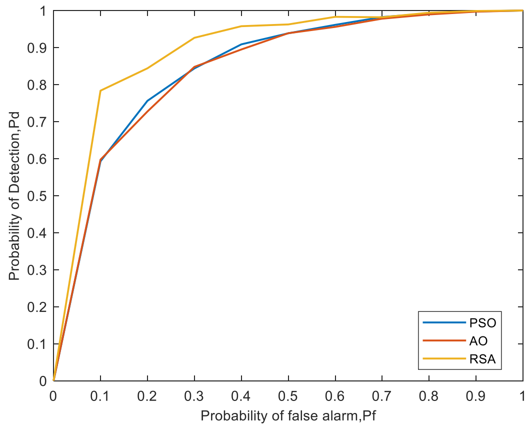

Fig. 3. P_f vs P_d for 20 secondary users.

Table 1. Simulation parameters.

Variable	Value
Number of SUs (M)	20
Probability of False Alarm	0.24
Sensing time, Bandwidth	28 μsec, 6 MHz
SU-FC channel noise variance	-60 dBm$\leq \delta_i^2 \leq -47$ dBm
PU-SU channel gain	-50 dBm $\leq gi \leq -40$ dBm
SU-FC channel gain	-40 dBm $\leq h \leq -30$ dBm
Transmit power (PU)	25 dBm
Transmit power (SU)	12 dBm

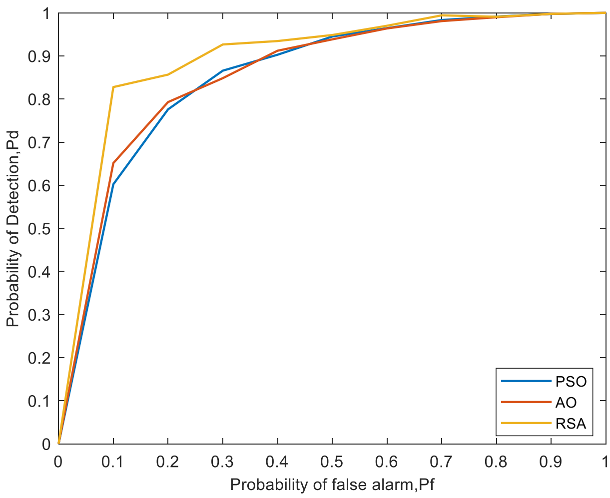

Fig. 4. P_f vs P_d for 24 secondary users.

5. CONCLUSION

Cognitive radio is a technology that offers an opportunistic solution to the spectrum scarcity issue caused by the increasing number of wireless communication devices. Spectrum sensing is a vital process of cognitive radio. In this paper, we focused on adapting different metaheuristics algorithms to the soft fusion scheme to enhance the effectiveness of cooperative spectrum sensing systems in cognitive radio. We used RSA, PSO and AO to perform weight optimization. Compared to PSO and AO, RSA offers better performance in terms of detecting spectrum holes and determining the presence of primary users, which are measures of detection probability.

Acknowledgment

This work was supported by Erciyes University Scientific Research Projects Coordination Unit (Project No: FYL-2022-12479).

Author's Contribution

Burcu Ketenci contributed to the implementation of the research, analysis of the result, and writing; Tareq M. Shami provided support for the coding part of the study, and Necmi Taşpınar contributed to the review of the manuscript.

Statement of Conflict of Interest

Authors have declared no conflict of interest.

REFERENCES

[1] S. Haykin "Cognitive radio: Brain-empowered wireless communications," IEEE Journal on Selected Areas in Communications, vol. 23, no. 2, pp. 201–220, 2005.

[2] B. Wang, K.J.R. Liu "Advances in Cognitive radio networks: A survey," IEEE Journal of Selected Topics in Signal Processing, vol. 5, no. 1, pp. 5–23, 2011.

[3] P.Verma, B.Singh "On the decision fusion for cooperative spectrum sensing in cognitive radio networks," Wireless Networks, vol. 23, no. 7, pp. 2253–2262, 2016.

[4] I.F. Akyildiz, W.-Y. Lee, M.C. Vuran, and S. Mohanty "NeXt generation/dynamic spectrum access/cognitive radio wireless networks: A survey," Computer Networks, vol. 50, no. 13, pp. 2127–2159, 2006.

[5] W. Zhang, R. Mallik, and K. Letaief "Optimization of cooperative spectrum sensing with energy detection in cognitive radio networks," IEEE Transactions on Wireless Communications, vol. 8, no. 12, pp. 5761–5766, 2009.

[6] R. Vadivelu, K. Sankaranarayanan, and V. Vijayakumari "Matched filter based spectrum sensing for cognitive radio at low signal to noise ratio," Journal of Theoretical and Applied Information Technology , vol. 62, no. 1, 2014.

[7] K. Kim, I.A. Akbar, K.K. Bae, J.-S. Um, C.M. Spooner, and J.H. Reed "Cyclostationary Approaches to Signal Detection and Classification in Cognitive Radio," 2nd IEEE International Symposium on New Frontiers in Dynamic Spectrum Access Networks, pp. 212-215, 2007.

[8] Y.-C. Liang, K.-C. Chen, G. Y. Li, and P. Mahonen, "Cognitive radio networking and communications: an overview," IEEE Transactions on Vehicular Technology, vol. 60, no. 7, pp. 3386–3407, Sep. 2011.

[9] Z. Quan, S. Cui, H. Vincent Poor, and A.H. Sayed "Collaborative wideband sensing for cognitive radios," IEEE Signal Processing Magazine, vol. 25, no. 6, pp. 60–73, 2008.

[10] Z. Quan, S. Cui, and A.H. Sayed "Optimal Linear Cooperation for Spectrum Sensing in Cognitive Radio Networks," IEEE Journal of Selected Topics in Signal Processing, vol. 2, no. 1, pp. 28–40, 2008.

[11] J. Ma, G. Zhao, and Y. Li "Soft combination and detection for cooperative spectrum sensing in cognitive radio networks," IEEE Transactions on Wireless Communications, vol. 7, no. 11, pp. 4502–4507, 2008.

[12] H. Sakran, M. Shokair "Hard and softened combination for cooperative spectrum sensing over imperfect channels in cognitive radio networks," Telecommunication Systems, vol. 52, no. 1, pp. 61–71, 2011.

[13] D. Teguig, B. Scheers, and Vincent Le Nir "Data fusion schemes for cooperative spectrum sensing in cognitive radio networks," 2012 Military Communications and Information Systems Conference (MCC), pp. 1–7, Gdansk,Poland, 2012.

[14] T.M. Shami, A.A. El-Saleh, and A.M. Kareem "On the detection performance of cooperative spectrum sensing using particle swarm optimization algorithms," IEEE 2nd International Symposium on Telecommunication Technologies, pp. 110–114, Langkawi, Malaysia, 2014.

[15] A.A. El-Saleh, M. Ismail, and M.A.M. Ali "Genetic algorithm-assisted soft fusion-based linear cooperative spectrum sensing," IEICE Electronics Express, vol. 8, no. 18, pp. 1527–1533, 2011.

[16] M. Akbari, M. Ghanbarisabagh "A novel evolutionary-based cooperative spectrum sensing mechanism for cognitive radio networks", Wireless Personal Communications, vol. 79, no. 2, pp. 1017-1030, 2014.

[17] X. Li, L. Lu, L. Liu, G.Li, X.Guan "Cooperative spectrum sensing based on an efficient adaptive artificial bee colony algorithm", Soft Computing, vol. 19, no. 13, pp. 597-607, 2015.

[18] F. Azmat, Y. Chen and N. Stocks "Bio-inspired collaborative spectrum sensing and allocation for cognitive radios", IET Communications, vol. 9, no. 16, pp.1949-1959, 2015.

[19] L. Abualigah, M. A. Elaziz, P. Sumari, Z. W. Geem, and A. H. Gandomi "Reptile Search Algorithm (RSA): A nature-inspired meta-heuristic optimizer," Expert Systems with Applications, vol. 191, p. 116158, 2022.

[20] I. Al-Shourbaji, N. Helian, Y. Sun, S. Alshathri, and M. Abd Elaziz "Boosting Ant Colony Optimization with Reptile Search Algorithm for Churn Prediction," Mathematics, vol. 10, no. 7, p. 1031, 2022.