Enhancing Cognitive Radio WSN Communication through Cluster Head Selection Technique

Shraddha Panbude
Dr. Babasaheb Ambedkar Technological University, India
shraddha.panbude@gmail.com

Prachi Deshpande
Department of Computer Science & Engineering, Shreeyash College of Engineering & Technology, India
hod.cse@sycet.org

Brijesh Iyer
Dr. Babasaheb Ambedkar Technological University, India
brijeshiyer@dbatu.ac.in (corresponding author)

A. B. Nandgaonkar
Dr. Babasaheb Ambedkar Technological University, India
abnandgaonkar@dbatu.ac.in

Received: 23 December 2023 | Revised: 19 January 2024 | Accepted: 28 January 2024

ABSTRACT

The demand for frequency spectrum is increasing rapidly with the wide growth of wireless communications. Spectrum sensing issues present in Cognitive Radio Sensor Networks (CRSN) are detected dynamically using spectral sensing techniques, which also help to utilize frequency bands more effectively. The study proposes a novel Cosine Sand Cat Optimization (CSCO) protocol to address spectral sensing problems by selecting the optimal Cluster Head (CH) in a CRSN. The CRSN is simulated, and spectral allocation is performed using LeNet to extract signal components. Then, Primary User (PU) aware optimal CH selection is performed using the proposed CSCO by taking account of multi-objective fitness parameters. Finally, data communication is performed between nodes after CH selection using the CSCO protocol. The simulation results of CSCO were validated to determine its superiority concerning Secondary User (SU) density, and it attained residual energy, network lifetime, Packet Delivery Ratio (PDR), normalized throughput, and delay of 69.457 J, 77, 75.89%, 74.473, and 4.782ms, respectively.

Keywords-cosine sand cat optimization; sine cosine algorithm; sand cat swarm optimization; LeNet

I. INTRODUCTION

Cognitive Radio (CR) is an intelligent radio device that adapts itself to activities within its Radio Frequency (RF) environment [1]. Spectrum scarcity issues are effectively addressed by CR technologies, which also provide a solution to increase spectrum utilization by intelligently using temporarily unused spectrums [2]. Today, CR techniques have overcome the limitations encountered by conventional Wireless Sensor Networks (WSNs) to create Cognitive Radio Sensor Networks (CRSNs) [3-4]. In general, idle time slots or other resources are utilized by CR if they are not used by the Primery User (PU) or licensed users. CR uses frequency resources when the connection is used by a Secondary User (SU) or an unlicensed user [5]. CR performs dynamic variation in operating parameters, spectrum sensing, and the estimation of vacant bands. In general, CR has two objectives: efficient utilization of spectrum resources and maintaining permanent and reliable communication [5]. Several methods have been proposed for the effective utilization of unused spectrum [6]. In general, spectrum sensing is performed by a few of the received signal features to effectively distinguish the signal from noise. PU signals are accurately detected by various spectral sensing approaches. The approaches used for spectrum sensing are categorized into blind and non-blind techniques. Blind spectrum sensing approaches do not utilize information on PU signals, such as pulse shape, carrier frequency, modulation, etc. Wireless links are generally affected by different channel impairment issues, such as receiver impairments, multipath fading, and shadowing. These imperiments may cause loss of unpredictable signals resulting in spectrum sensing degradation. Moreover, hidden node issues affect spectrum sensing based on a single cognitive user and create shadowing issues. Thus, it becomes difficult for an SU to detect PU. Cooperative Spectrum Sensing (CSS) has been introduced to provide solutions in challenging scenarios by increasing the reliability of spectrum sensing [7]. CRSN performance has been improved by grouping adjacent nodes into clusters using cluster routing protocols, inter-cluster relay, and intra-cluster aggregation using multi-hop data delivery [8-9]. Thus, the clustering routing protocol introduced for CRSNs has become a trending research topic. CRSN assumes perfect spectrum sensing while designing cluster routing protocols. However, this assumption is suitable only for designing simple routing protocols that do not consider the original perceptual performance of CRSN nodes [9].

CRSNs also perform intracluster data transmission that applies to clustering protocols. This involves communication between clusters and inter-cluster data transmission and helps to increase scalability by reducing energy consumption and promoting communication between the sink and the cluster. The predetermined CHs present in intercluster communication help to transmit data to the sink. In CRSN, CHs are selected mostly among available sensor nodes that are highly vulnerable to energy depletion issues. This is due to the burden caused while performing functions related to CR, such as channel assignment and sensing, data forwarding, and data aggregation. In general, CH experiences high energy consumption while performing single-hop communication. The lifetime of CRSN is increased by performing multi-hop routing. However, the residual energy of CHs near the sink severely decreases due to frequent traffic relaying [10]. Therefore, the energy consumption of the end users is considered the critical parameter of CRSNs. In addition, artificial intelligence techniques, such as machine learning and deep learning approaches, are employed to provide solutions to CH-related problems in CRSNs. Several studies have been conducted based on the use of neural networks to design and optimize wireless communication systems [11-12].

Currently, several clustering algorithms are employed to form a fully connected topology of the network. However, the algorithms only paid minimum attention to problems based on ensuring maximum energy efficiency. CRSN is introduced by integrating CR capacity into sensor networks [13] and helps reduce high contention delays, eliminate collisions, and deploy multiple overlaid sensor networks. This aspect motivated the present study, which selected the optimal CH in a CRSN using the CSCO protocol. The CRSN was initially simulated and was further allowed for spectrum allocation using LeNet by extracting various signal components, such as energy, test statics, eigenstatistics, wavelet transform, and matched filter. Then, optimal PU-aware CH selection was performed on the allocated spectrum using CSCO by taking into account different multiobjective fitness parameters, such as trust factor, energy, delay, and distance. Later, in the data communication phase, the selected CH carried out data communication by transferring data packets to other nodes.

II. THE PROPOSED CSCO PROTOCOL FOR OPTIMAL CH SELECTION IN CSRN

This study presents the CSCO protocol for the selection of optimal CH in CRSN. Initially, the CRSN simulation is performed, followed by the allocation of the spectrum. Spectrum allocation is performed by extracting signal components using LeNet [14]. The different signal components, such as energy, eigenstatistics, test statics, matched filter, and wavelet transform, are extracted. The allocated spectrum is allowed for PU-aware optimal CH selection, which is performed using the CSCO protocol by considering multiobjective fitness parameters, such as trust factor, energy, delay, and distance. CSCO was designed by integrating the SCA [15] and SCSO [16] algorithmic approaches. Finally, the selected CH performs data communication by transferring data packets from one node to another. Figure 1 shows the diagrammatic view of the CSCO protocol used for optimal CH selection in CRSN.

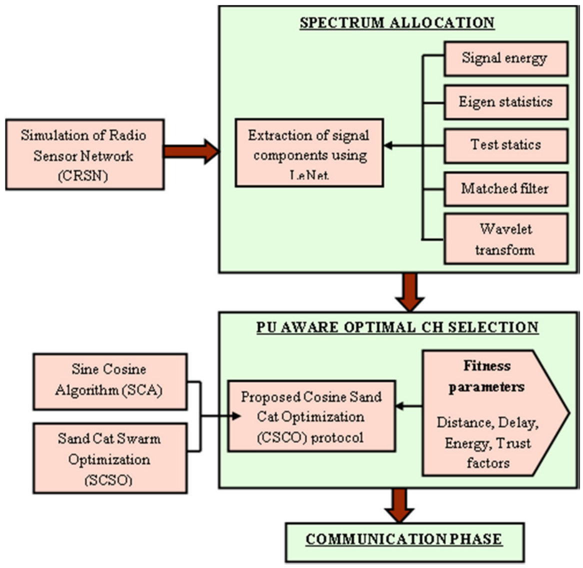

Fig. 1. Schematic diagram of CSCO protocol for optimal CH selection in CRSN.

A. *Test Statistic*

The test statistic [17] was used to observe null and alternative hypotheses in binary hypothesis testing problems with the presence and absence of PU.

B. *LeNet Architecture*

LeNet [14], a Convolutional Neural Network (CNN) gradient-based learning method, was applied for the spectrum allocation in CRSN. The extracted signal components are fed into the input layer and the output from the final layer is received. The LeNet comprises deep layers that help to accurately allocate spectrum in less execution time. It consists of convolutional, pooling, fully connected, and softmax layers. The total parameters used for training are effectively reduced by utilizing fully connected layers in LeNet.

C. CH Selection Using the CSCO Protocol

The optimal CH is selected using the proposed CSCO protocol, which is designed by integrating the SCA [15] and SCSO [16] techniques. SCSO is a metaheuristic algorithm designed to consider the natural survival behavior of sand cats. In general, sand cats live in stony and sandy deserts. The low-frequency noises are easily heard by sand cats through their extraordinary hearing sense. SCSO is designed based on two distinct characteristics of a sand cat, such as foraging and attacking the prey. Extraordinary features are used by sand cats to easily locate their prey. The SCSO effectively controls transitions in a balanced manner, which also effectively determines optimal solutions using few parameters in the exploitation and exploration phases. Similarly, SCA is a population-based optimization algorithm designed by considering the effects of sine and cosine. In this algorithm, the solution is repositioned in a cyclic pattern of sine and cosine functions. The SCA effectively converges to the global optimum and identifies promising regions of the search space. The SCA is incorporated with SCSO to exploit promising regions of the search space and promote the best approximation of local optimum. The mathematical modeling of CSCO is described below.

1) Phase 1: Population Initialization

The solution of each cat is randomly initiated, given by:

$$Y = [y_1, y_2, y_3, \ldots, y_e] \quad (1)$$

The upper and lower boundaries are considered to locate Y, and a candidate matrix is generated by considering the population of sand cats and based on the problem size ($\theta_P \times \theta_e$).

2) Phase 2: Fitness Computation

Equation (16) is used for the computation of the fitness function during the selection of the optimal CH after the solution is initiated.

3) Phase 3: In search of Prey

Sand cats consider the emission of low-frequency noise to execute prey search mechanisms. The sensitivity ranges of sand cats are considered to start from 2 kHz to 0 during prey search, where the sensitivity range is determined by:

$$\vec{S}_A = Z_h - \left(\frac{2 \times Z_h \times Iter_P}{Iter_{Max}}\right) \quad (2)$$

where $\bar{S}_A$ denotes the general sensitivity range, Z_h represents the hearing characteristics of a sand cat, the present iteration is signified as $Iter_P$, and the maximum iteration is indicated as $Iter_{Max}$. The final parameter is initialized to control the transition between the exploration and exploitation phase, which is given by:

$$\vec{\tau} = 2 \times \vec{S}_A \times R[0,1] - \vec{S}_A \quad (3)$$

where τ represents the parameter vector initialized for transitions control and $R[0, 1]$ signifies a random number set to [0, 1]. The sensitivity range of each sand cat is expressed as:

$$\vec{S} = \vec{S}_A \times R[0,1] \quad (4)$$

The best-candidate position is considered by each sand cat to update its position $\vec{X}_P$, sensitivity range $\vec{S}$, as well as the present best position $\vec{X}_B$. Then, the best prey position is determined by sand cats as:

$$\vec{X}(f+1) = \vec{S}.\left(\vec{X}_B(f) - R[0,1].\vec{X}_P(f)\right) \quad (5)$$

where $\vec{X}_B$ signifies the best-candidate position of the sand, $\vec{S}$ denotes sensitivity range, and the present position of the sand cat is indicated by $\vec{X}_P$. Let us consider, $\vec{X}(f+1) = X(f+1)$, $\vec{X}_B(f) = X_B(f)$, $\vec{S} = S$, and $\vec{X}_P(f) = X(f)$. Thus, (5) becomes:

$$X(f+1) = S.\left(X_B(f) - R[0,1].X(f)\right) \quad (6)$$

SCA [15] is incorporated with SCSO [16] for the exploitation of promising regions of the search space and to promote the best approximation of local optimum. From SCA:

$$X(f+1) = X(f) + y_1 * cos(y_2) * |y_3 u_D - X(f)| \quad (7)$$

where y_1, y_2, and y_3 are random numbers, u_D is the position of the destination in the D^{th} dimension, and $X(f)$ signifies the position of the present solution. Assuming $u_D > X(f)$, (7) becomes:

$$X(f) = \frac{X(f+1) - y_1 * cos(y_2) * y_3 u_D}{(1 - y_1\, cos(y_2))} \quad (8)$$

Substituting (8) into (6) gives:

$$X(f+1) = S.\left(X_B(f) - R[0,1].\left[\frac{X(f+1) - y_1 * cos(y_2) * y_3 u_D}{(1 - y_1\, cos(y_2))}\right]\right) \quad (9)$$

Thus, the updated equation of CSCO is given by:

$$X(f+1) = \frac{1}{(1 - y_1\, cos(y_2) + S.R[0,1])}\,[S.X_B(f)(1 - y_1\, cos(y_2)) + S.R[0,1].y_1 * cos(y_2) * y_3 u_D] \quad (10)$$

4) Phase 4: Attacking the Prey

Based on its hearing ability, the sand cat effectively determines the prey, and the distance between its present and best positions is determined. The random position ensures that the position of the cat is near to the prey and is expressed as:

$$\vec{X}_R = \left|R.\vec{X}_B(f) - \vec{X}_P(f)\right| \quad (11)$$

where $\vec{X}_R$ symbolizes the random position of the sand cat. Moreover, the local optimum trap is avoided and the direction of movement is identified using a random angle when the sensitivity range of the sand cat is supposed to be a circle. Thus, the modified prey position based on the direction of movement is given by:

$$\vec{X}(f+1) = \vec{X}_B(f) - R.\vec{X}_R.Cos(\theta) \quad (12)$$

5) Phase 5: Solution Feasibility Check

The reevaluation of fitness is performed using (4) to identify the optimal solution to select optimal CH in CRSN. If any new solutions are identified to be more efficient than the current one, the solution can be replaced. Thus, the CSCO protocol effectively selects the optimal CH in the PU-aware CRSN system from the allocated spectrum by considering multi-objective fitness parameters.

III. RESULTS AND DISCUSSION

The NS2 simulator was used to implement the CSCO protocol for optimal CH selection in a CRSN. Figure 2 shows the simulation results obtained by the CSCO protocol during the selection of optimal CH. Figure 2 shows the simulation results obtained for 0.002 s and 6.028 s. In Figure 2(a), the algorithm does not declare a clear CH, while Figure 2(b) shows the CH selected with the black triangular spot.

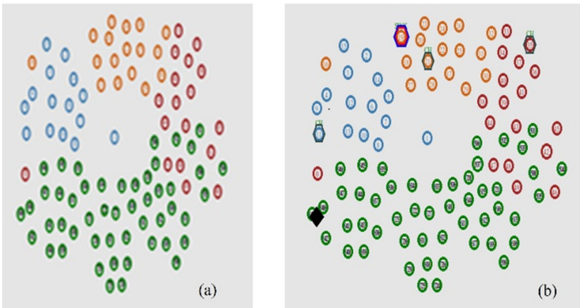

Fig. 2. Experimental simulation results of CSCO: (a) 0.002 s, (b) 6.028 s.

A. Evaluation Parameters

The following parameters, concerning SU density, were used to evaluate the performance of CSCO in CH selection.

Residual energy is the remaining energy presented in the nodes after the transmission of data packets in CRSN, and it is calculated by:

$$Residualenergy = 1 - W_R(K) \tag{13}$$

where $W_R(K)$ denotes consumed energy.

Network lifetime is computed by considering the death of the sensor node, showing the ability of the model to prolong the network functioning during data transmission.

Throughput is the total data packets sent to the destination by the nodes at the stipulated period, expressed as:

$$Throughput = \frac{\eta}{\iota} \tag{14}$$

where ι denotes the time duration taken by the nodes and η indicates the total number of node counts.

PDR is the proportion of total packets delivered to the total packets transmitted to the destination, formulated as:

$$PDR = \frac{\rho}{\sigma} \tag{15}$$

where ρ represents the total packets delivered, and σ indicates the total packets passed to the destination.

Delay is the time taken by the data packets to reach the destination, and is determined using (5).

B. Comparative Analysis

The effectiveness of the CSCO protocol in CH selection was validated by comparing its performance with that of traditional protocols, namely ISSMCRP [9], ESAUC [10], sensing-after prediction scheme [18], and Dynamic Fuzzy-based PU aware Clustering (DFPC) [19]. Comparative validation of the designed CSCO protocol in CH selection was performed for 1000 rounds. Figure 3 shows the analysis of the CSCO for the optimal selection of a CH with 1000 rounds. Figure 3(a) shows the analysis of the CH selection protocols using residual energy, where CSCO recorded maximum residual energy of 60.983J for an SU density of 200. The residual energy measured by existing models, such as ESAUC, the sensing-after prediction scheme, ISSMCRP, and DFPC was 50.297 J, 51.831 J, 53.187 J, and 56.765 J, respectively.

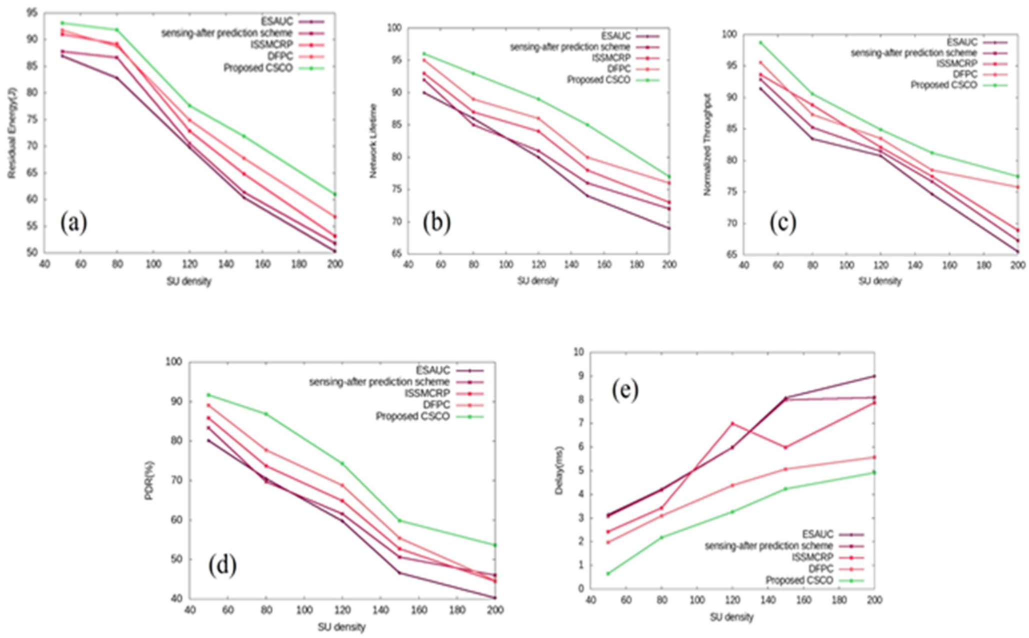

Fig. 3. Analysis of CSCO with 1000 rounds based on: (a) Residual energy, (b) network lifetime, (c) normalized throughput, (d) PDR, and (e) delay.

Figure 3(b) presents the validation using the network lifetime of the CH selection protocols. For an SU density of 200, the network lifetime obtained by ESAUC was 69, for the sensing-after prediction scheme was 72, for the ISSMCRP was 73, for the DFPC was 76, and for the proposed CSCO protocol was 77. Figure 3(c) shows an analysis of various CH selection models used in CRSN using normalized throughput. For an SU density of 200, the CSCO protocol recorded a maximum normalized throughput of 77.438, and the prevailing techniques, such as ESAUC, sensing-after prediction scheme, ISSMCRP, and DFPC measured a normalized throughput of 65.529, 67.255, 68.914, and 75.748, respectively. Figure 3(d) shows the PDR obtained by the various CH selection methods. For an SU density of 200, the maximum PDR of 53.64% was recorded by the proposed CSCO protocol, and PDRs of 40.27, 46, 44.475, and 44.764% were obtained by ESAUC, sensing-after prediction scheme, ISSMCRP, and DFPC, respectively. Figure 3(e) shows the validation of the performance of different CH selection protocols using delay. For an SU density of 200, the delays recorded by the existing models were 9 ms by ESAUC, 8.089 ms for the sensing-after prediction scheme, 7.874 ms for ISSMCRP, and 5.563 ms for DFPC. The proposed CSCO protocol obtained a minimum delay of 4.910 ms.

IV. CONCLUSIONS AND FUTURE WORK

This paper presented the CSCO algorithmic model for optimal CH selection to effectively perform CH-based communication in CRSNs by reducing the energy consumption of the network. The experimental results obtained showed that CSCO outperformed previous approaches. The CSCO achieved superior performance compared to previous techniques, having a residual energy of 69.457 J, a network lifetime of 77, a normalized throughput of 74.473, a PDR of 75.894%, and a delay of 4.782 ms. In the future, the performance of the proposed CSCO algorithm can be studied in various real-world applications. The use of various technologies to schedule subclusters to increase the energy efficiency of spectrum sensing in CRSN can also be studied.

REFERENCES

[1] O. P. Awe, D. A. Babatunde, S. Lambotharan, and B. AsSadhan, "Second order Kalman filtering channel estimation and machine learning methods for spectrum sensing in cognitive radio networks," *Wireless Networks*, vol. 27, no. 5, pp. 3273–3286, Jul. 2021, https://doi.org/10.1007/s11276-021-02627-w.

[2] S. Haykin, "Cognitive radio: brain-empowered wireless communications," *IEEE Journal on Selected Areas in Communications*, vol. 23, no. 2, pp. 201–220, Feb. 2005, https://doi.org/10.1109/JSAC.2004.839380.

[3] H. Luo, Z. Huang, and T. Zhu, "A Survey on Spectrum Utilization in Wireless Sensor Networks," *Journal of Sensors*, vol. 2015, Mar. 2015, Art. no. e624610, https://doi.org/10.1155/2015/624610.

[4] O. B. Akan, O. B. Karli, and O. Ergul, "Cognitive radio sensor networks," *IEEE Network*, vol. 23, no. 4, pp. 34–40, Aug. 2009, https://doi.org/10.1109/MNET.2009.5191144.

[5] Y. Cui, X. jun Jing, S. Sun, X. Wang, D. Cheng, and H. Huang, "Deep learning based primary user classification in Cognitive Radios," in *2015 15th International Symposium on Communications and Information Technologies (ISCIT)*, Jul. 2015, pp. 165–168, https://doi.org/10.1109/ISCIT.2015.7458333.

[6] M. Höyhtyä *et al.*, "Spectrum Occupancy Measurements: A Survey and Use of Interference Maps," *IEEE Communications Surveys & Tutorials*, vol. 18, no. 4, pp. 2386–2414, 2016, https://doi.org/10.1109/COMST.2016.2559525.

[7] M. K. Giri and S. Majumder, "Eigenvalue-based cooperative spectrum sensing using kernel fuzzy c-means clustering," *Digital Signal Processing*, vol. 111, Apr. 2021, Art. no. 102996, https://doi.org/10.1016/j.dsp.2021.102996.

[8] K. B. Vikhyath and N. A. Prasad, "Combined Osprey-Chimp Optimization for Cluster Based Routing in Wireless Sensor Networks: Improved DeepMaxout for Node Energy Prediction," *Engineering, Technology & Applied Science Research*, vol. 13, no. 6, pp. 12314–12319, Dec. 2023, https://doi.org/10.48084/etasr.6542.

[9] A. Rajab, "Genetic Algorithm-Based Multi-Hop Routing to Improve the Lifetime of Wireless Sensor Networks," *Engineering, Technology & Applied Science Research*, vol. 11, no. 6, pp. 7770–7775, Dec. 2021, https://doi.org/10.48084/etasr.4484.

[10] T. Stephan, F. Al-Turjman, S. J. K, and B. Balusamy, "Energy and spectrum aware unequal clustering with deep learning based primary user classification in cognitive radio sensor networks," *International Journal of Machine Learning and Cybernetics*, vol. 12, no. 11, pp. 3261–3294, Nov. 2021, https://doi.org/10.1007/s13042-020-01154-y.

[11] G. K. Walia, M. Kumar, and S. S. Gill, "AI-Empowered Fog/Edge Resource Management for IoT Applications: A Comprehensive Review, Research Challenges and Future Perspectives," *IEEE Communications Surveys & Tutorials*, 2023, https://doi.org/10.1109/COMST.2023.3338015.

[12] M. Zhang *et al.*, "Exploiting Deep Learning for Secure Transmission in an Underlay Cognitive Radio Network," *IEEE Transactions on Vehicular Technology*, vol. 70, no. 1, pp. 726–741, Jan. 2021, https://doi.org/10.1109/TVT.2021.3050104.

[13] Z. Chen and W. Yue, "Differential Space-time Block Coding Based Cooperative Spectrum Sensing over Fading Environments in Cognitive Radio Sensor Networks," *Journal of Information*, vol. 9, no. 15, pp. 4599–4606, 2012.

[14] G. Wei, G. Li, J. Zhao, and A. He, "Development of a LeNet-5 Gas Identification CNN Structure for Electronic Noses," *Sensors*, vol. 19, no. 1, Jan. 2019, Art. no. 217, https://doi.org/10.3390/s19010217.

[15] S. Mirjalili, "SCA: A Sine Cosine Algorithm for solving optimization problems," *Knowledge-Based Systems*, vol. 96, pp. 120–133, Mar. 2016, https://doi.org/10.1016/j.knosys.2015.12.022.

[16] A. Seyyedabbasi and F. Kiani, "Sand Cat swarm optimization: a nature-inspired algorithm to solve global optimization problems," *Engineering with Computers*, vol. 39, no. 4, pp. 2627–2651, Aug. 2023, https://doi.org/10.1007/s00366-022-01604-x.

[17] A. Patel, H. Ram, A. K. Jagannatham, and P. K. Varshney, "Robust Cooperative Spectrum Sensing for MIMO Cognitive Radio Networks Under CSI Uncertainty," *IEEE Transactions on Signal Processing*, vol. 66, no. 1, pp. 18–33, Jan. 2018, https://doi.org/10.1109/TSP.2017.2759084.

[18] P. Kumar, N. Chauhan, M. Kumar, and L. K. Awasthi, "Clustering based opportunistic traffic offloading technique for device-to-device communication," *International Journal of System Assurance Engineering and Management*, vol. 14, no. 3, pp. 827–839, Jul. 2023, https://doi.org/10.1007/s13198-021-01136-5.

[19] S. Panbude, B. Iyer, A. B. Nandgaonkar, and P. S. Deshpande, "DFPC: Dynamic Fuzzy-based Primary User Aware clustering for Cognitive Radio Wireless Sensor Networks," *Engineering, Technology & Applied Science Research*, vol. 13, no. 6, pp. 12058–12067, Dec. 2023, https://doi.org/10.48084/etasr.6279.