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ADVANCED NUMERICAL COOPERATIVE SPECTRUM SENSING USING MAYFLY OPTIMIZATION ALGORITHM

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ABSTRACT:-

The expected development and expansion of remote and wireless networks with specific network standards are needed to enhance the range of communications, power utilization, interoperability and clients' requests for higher information rates and better nature of administration. Spectrum sensing (S.S.) to overcome these issues based on a May Fly optimization (MFO). Here, the Cognitive Radio Network (CRN) weight vectors are optimized using an optimization algorithm, namely May Fly optimization (MFO). Finally, Secondary users (SUs) are provided with the adequate optimum solution. The execution of the suggested method was simulated with the CRNS-2 (Cognitive Radio Network Simulator). Then proposed modified mayfly algorithm implementation with different parameters was analogized with the existing Particle Swam Optimization (PSO). MFO Algorithm provides lower delay, higher delivery ratio, lower drop, lower Overhead, higher network lifetime, and higher throughput are superior compared with implemented methods. That proposed modified Mayfly Algorithm provides both bandwidth and power-efficient optimization solutions.

Keywords: word: *Spectrum Sensing (S.S.), Cognitive Radio Network (CRN), Particle Swam Optimization (PSO).May Fly optimization (MFO), secondary user (SU), Primary user (PU), and Fusion centre (F.C.).*

1. INTRODUCTION

The tremendous development of wireless communication requirements, there was a very big challenge to accommodate different cellular networks and IoT architecture and to satisfy communication between other remote devices .there is a huge demand for the intelligent network to control day-to-day traffic to improve higher data-rated and good quality of services (QoS). To enhance spectrum utilization in wireless networks, cognitive Radio(C.R.) is the best solution to improve spectrum efficiency by allocating unutilized or unoccupied spectrum bands to the Secondary users (SUs) whenever the primary user is idle. The spectrum holes are rationed to the unlicensed users without interfering to the licensed users) (Hoque et al.,2014)

Spectrum sensing is the one of the important function of the cognitive radio. Sensing can be accomplished by implementing various algorithms which identify frequency holes; these unused spectrum bands are assigned to the unsliced users called Secondary users.

Spectrum Sensing is broadly categorized into two major mechanisms: Cooperative and Non-cooperative spectrum sensing.

Cooperative sensing of the radio environment collects information on the various nodes (central / distributed) (Cao & Pan, 2020). In cooperative sensing, information is shared with the fusion centres (F.C.), and hard and soft decisions are implemented based on data. Hard decisions are implemented using (logic operations like) and soft decision are implemented using linear combining, square-law combining (and maximal ratio combining (MRC) are popularly implemented to simplify hard ware requirements, hidden node problem, data processing operations it does not require, at the same time cooperative sensing implementation require more energy consumption, sensing time causes delay in the network reduction implementation requires more energy to implement.

The spectrum sensing operating procedure is represented in different steps. (1) spectrum sensing, (2)reporting info to the coordinator(FC), (3) Decision making at Fusion center and (4) Information (decision) transmission (Biglieri et al.,2013)(shen et al.,2018). In the local sensing step, at each node spectrum sensing mechanism implemented to collect primary user status information forwarded to fusion centre, F.C. takes decisions (Biglieri et al., 2011) based on collected information, In the reporting step, S.U.s local decisions and observations are forwarded to the fusion centre (F.C.). The F.C. decides the decisions regarding the presence /absence of the PUs based on the locally collected database information (Thimmapuram et al., 2022). There is an interesting compromise between spectrum utilization, sensing and reporting. Spectrum holes detection is directly proportional to sensing time; sensing time reduces the probability of false alarm and transmission time. Less sensing time leads to an increase in the transmission time duration. This leads to secondary user interference with the primary user, which increases false detection. Similarly, increasing the number of S.U.s in the spectrum sensing number of bits required increases in reporting the probability detection of P.U.s to the fusion centre. Increasing bit size takes a long time for reporting and leads to more transmission time and inefficient spectrum utilization.

This manuscript proposes a Numerical cooperative Spectrum Sensing Optimization Algorithm from the improved Mayfly Optimization algorithm. The CRN weight vectors are optimized using the Improved May fly optimization algorithm. The optimization results are used to spectrum utilization efficiency improved at the fusion center (sonti et al., 2021).

This manuscript includes a brief introduction to Cognitive Radio (C.R.), and chapter 2 explains about literature review. Chapter 3 explains spectrum sensing optimization using Particle Swam Optimization Method (PSO), Chapter 3 explains Improved May Fly Optimization Algorithm (IMFOA), and the consequences of PSO and IMFOA are compared in chapter 4 and chapter 5 deals with the conclusion.

2. LITERATURE REVIEW

Some of the recent pieces of literature related to this research work are referred here as follows:

The energy efficient strategy for cognitive radio spectrum sensing proposed by (Cao & Pan, 2020) particle swarm optimization technique used for local optimization and Cauchy mutation method used to find fitness function which helps to improve throughput and energy efficiency.

Spectrum sensing using flower pollination algorithm was proposed (Asfandyar, Gul,Rasool & Elahi,2019) for calculation of optimum weights based on the weights decisions will be taken at the fusion canter. the signal to noise ratio of proposed algorithm improved compared with different gain combining techniques.

Proposed method (C. Liu & Z. Wang, 2011)explains different adaptive weights mixing in cooperative spectrum sensing techniques helps to improve probability of error, data rate and over head on the channel.

Proposed solution for spectrum sensing optimization and solution for hidden node problem using new may fly optimization algorithm (Thimmapuram, Laxmaiah, & Sreelatha, 2022) addressed solution for different challenges of spectrum sensing like hidden node problem, delay, improvement in throughput, etc.

The drawbacks of artificial neural network was proposed by (Sonti & Prasad, 2021) and solution for computation complexity at the time of training data because of large amount of hidden layers was addressed with optimum fruit fly optimization algorithm and proposed with optimum results hidden node problem with improves accuracy and reduced false alarm probability.

The proposed method to improve the primary user energy efficiency technique (Cao & Pan, 2020) using amplify and forward and decode and forward .Proposed multi phase cooperation ,parameters utilization, spectrum allocation strategies to the secondary users without interfering to the primary users.

3. RELATED WORK

Optimization technique based on Particle Swam Optimization (PSO) method for spectrum sensing:

The most popularly used stochastic optimization techniques used for the network intelligence where decisions are optimized based on previous results is Particle Swam Optimization. PSO implementation is on the social behaviour of birds (particles) or fish schooling. PSO is a computational method to discover an optimal resolution (Wu et al., 2011). Each particle movement in the search space is represented as simple mathematical formulas based on that position and Velocity in each iteration. The best optimum position calculated after K number of iterations like Local Best Position (LBP) and Global Best Position (Xie et al., 2022)

Steps involved in PSO optimization:

1. Initialization of particles
2. Fitness function
3. Updating Velocity
4. Updating Position
5. Termination.

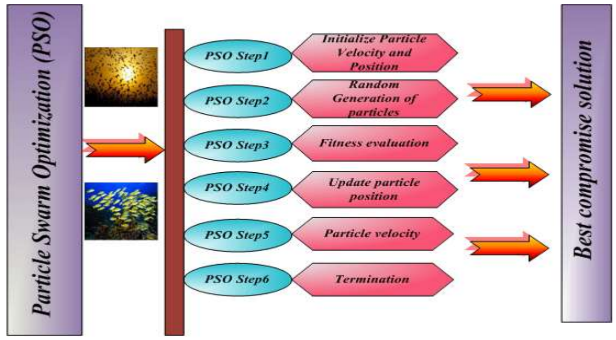

Fig1: Flow Chart of PSO

Mathematical Analysis:

Position:

$P_1^d = [P_1^d,\ Y_1^d]$

$P_2^d = [P_2^d,\ Y_2^d]$

$P_i^d = [P_i^d,\ Y_i^d,\ Z_i^d\ - - -]$ (1)

Velocity Updating:

Next velocity=Current velocity+ Personal Best Solution+ Global Best Solution

$v_i^{d+1} = 2\gamma_1 v_i^d + 2\gamma_2 (t_i^d - x_i^d) + 2\gamma_3 (G^d - x_i^d)$ (2)

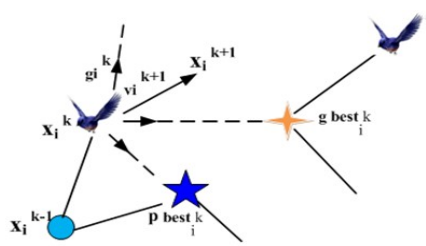

Fig2: Position & Velocity updating in PSO

Based on Velocity next position of the particle is calculated.

$\boldsymbol{P_i^{d+1} = P_i^d + P_i^{d+1}}$ (3)

In PSO optimization, every solution for a given problem was considered a particle.

$\boldsymbol{V_i^{t+1} = w\, v_i^d + C_1\gamma_2 (t_i^t - W_i^t) + C_1\gamma_3 (G^t - W_i^t)}$ (4)

Updated position (Global best position of the particle) = Inertia+ Individual Cognitive

component +Social Component.
The particle's position was real vectors at different time instant representing possible solutions trying to optimize the velocities. It represents how the particle was trying to get a better optimal solution obtained in view of the previous position and velocities of the particles updated , difference between the current particle position and the historical position of the particle. Termination is used in the flow chart to stop the criteria execution of the optimization algorithm. The current strategy enhancement procedure given Particle Swam Optimization (PSO) technique results are implemented by simulating related spectrum sensing code using cognitive radio network simulator tool on a personal computer and obtained results are analyzed with the proposed method.

4. PROPOSED TECHNIQUE

Spectrum optimization using Improved May Fly Optimization Algorithm for spectrum sensing:

The problem with the hidden nodes in cognitive radio networks addressed by the Improved May Fly Algorithm reduces with proper spectrum allocation to the secondary users whenever spectrum hole exist in the network. This algorithm also addresses the false alarm probability and missed detection in a noisy environment. In this manuscript, Additive white Gaussian noise is considered (AWGN), and spectrum utilization efficiency is maximized.

Mayflies are insects; based on the life cycle (behaviour, matting process) inspired to implement continuous, discrete, and optimization problems. The proposed solution optimizes both local search and global search.[1].

Initialization

The initial populations of the may fly were initialized as the populations of the may pass were denoted as

$W = (W_1, W_2, \ldots W_{\dim ension})$

Mayfly generation (random generation)

May flies are initializations considered as a random function finite number of both male and female may flies are initialized. Optimal weight vectors estimation require to assign frequency spectrum to the secondary user, the behaviour of the mayflies helps to estimate weight vectors at the data fusion center.

Calculation of cost function:

The life spans or based on fitness of the mayfly is considered as variable to allocate spectrum to the secondary user without primary user in conjunction with optimum weights calculation at data fusion centre. The mathematical equation for reliable communication is given below The parameter is chosen to minimize the shadowing of the primary user because of the probability of error in the communication channel.

$$Costfunction = Minimize\{\varpi_{fa,r}, \varpi_{m,r}, h_{optimal,}\} \quad (5)$$

Consider channel as the AWGN. The function

Here, it h is represented as the AWGN. This function $h_{optimal}$ is considered as the optimal solution. This helps to address problem with the hidden nodes.

Where probability mean for error function was represented as $\varpi_r^{'}$, false alarm probability is represented as $\left(\varpi_{fa,r}\right)$ in CSS and the missed detection probability represented as $\left(\varpi_{m,r}\right)$ above all parameters are designed for spectrum sensing (Cao & Pan, 2020).

Step 4: Spectrum sensing and allocation

The spectrum allocation strategy for secondary users based on the spectrum vacancy the matting behaviour of the may flies heuristics optimization algorithm can be implemented in multiple levels like uni model and multi model can be represented fixed and variable dimensions. This may be the solution for both local and global searching optimization calculation. The unused spectrum holes allocation to the secondary users with less hidden node problem..

Step 5: Hidden node problem reduction

Based the way male mayflies attracts female mayflies with the nuptial dance just few meters above the water .the flying flies mate , drops eggs before they die. Each may fly have its own characteristic this based on this behaviour algorithm designed to allocate unused frequency spectrum which is hidden due to environmental conditions and reduces the hidden node problem. The mathematical equations which address the hidden node problem given below.

The velocity of the may flies

$$R_a^{t+1} = R_a^t + \beta_r$$

$$R_a^0 \approx \left(h_{optimal\ mim}, R_{\max}\right) \tag{7}$$

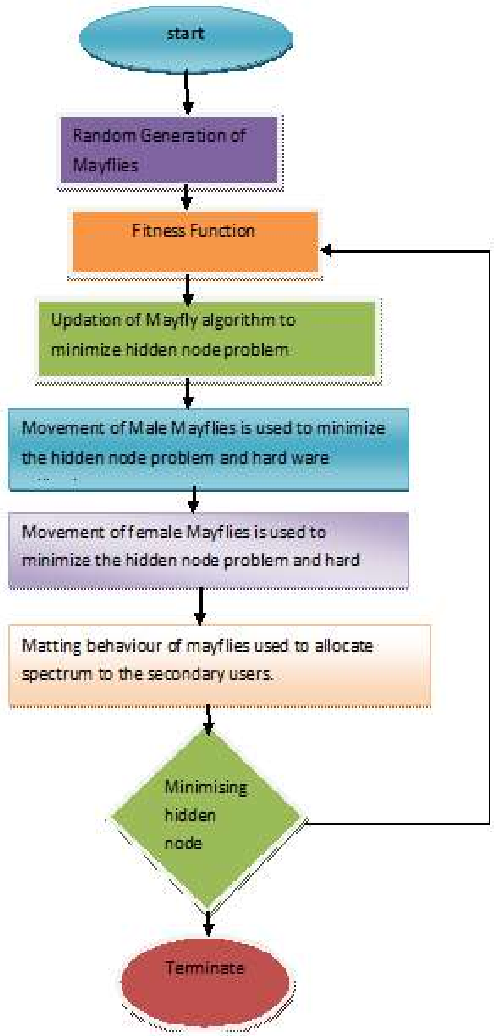

Fig3: Mayfly algorithm

Based on the received information from different local centers the fusion center takes decision in the favour of the unlicensed users

The optimum spectrum allocation calculation is as follows

$$h_{optimal} = mimimize\left(R, \left[\frac{R}{1+\beta_r}\right]\right) \tag{8}$$

Where $\beta_r = \dfrac{\ln \dfrac{pb_{af}}{1-pb_m}}{\ln \dfrac{pb_m}{1-pb_{af}}}$

The position of the vacant place represented with R in the above equation

The mayflies current position represented by R_a^t and the random movement of the may flies

with respect to time is $t+1\ \beta_r$.
Spectrum sensing time minimized by increasing the speed of transmission of the licensed user by calculating optimal solution.
The mathematical formula is.

$$L_{bestab} = \begin{cases} O_a^{t+1},\ if\ \ h\left(O_a^{t+1}\right) < hL_{bestab} \\ \quad otherwise\ same \end{cases} \qquad (9)$$

h It is represented as the function for efficiently transmitting primary users and allocating the unlicensed users to occupy vacant place.
Then the optimal equation is given in equation (10)

$$\left\|O_a - O_b\right\| = \sqrt{\sum_{b=1}^{m} \left(O_{ab} - Q_{ab}\right)^2} \qquad (10)$$

The position of the mayflies represented as $O_{ab}\ Q_{ab}$

Step 7: Minimization of allocation time

Female mayflies

Female Mayflies will minimize the problem n the sensing allocation time by reducing the delay with efficient bandwidth. This process is estimated by the movement of the Mayflies in the breeding process. Then the minimization equation is given (11)

$$V_{ab}^{t+1} = \begin{cases} O_{ab}^{t+1} + h_{optimal\,2} Z^{-\delta r_{n2}^2}\left(O_{ab}^t - Q_{ab}^t\right), if h\left(Q_a\right) \geq h\left(O_a\right) \\ V_{ab}^t + h * Random, \qquad if\ \ h\left(Q_a\right) \geq h\left(O_a\right) \end{cases} \qquad (11)$$

The female mayfly velocity is represented by V_{ab}^{t+1}, for optimal spectrum sensing of the secondary users h is minimized, $h * Random$ is described as the coefficient of random walk.

Step 8: Spectrum allocation to the secondary users.

Spectrum allocation to the secondary users used to allocate.
The characteristic behavior of the mayflies based on fitness
Function and the equation is given as (12-13

$$May_{offspring} 1 = O_{\max} * May_{maleaparent} + \left(1 - O\right) * May_{female} \qquad (12)$$

$$May_{offspring} 2 = O_{\max} * May_{femaleaparent} + \left(1 - O\right) * May_{male} \qquad (13)$$

Spectrum utilization allocated to the licensed users represented as $R_{\max}$ in the spectrum, the initial velocity $May_{offspring}$ of the mayflies initialized as zero.

5. RESULT AND DISCUSSION

Current section focused on the simulation results of the proposed Improved May Fly optimization algorithm frame work carried to improve spectrum optimization in the cognitive radio networks and results are compared with the performance of particle swarm optimization. These simulations are conducted on personal computer with the following specifications Intel core i5,16GB RAM processor with windows 10 ,the tool used for simulation is cognitive radio network simulator -2.

Performance Metrics:

This section discusses calculation of different performance metrics which are usefull to design communication system.

Delay:

Delay represents time taken for transmission of packets from transmitter receiver.
It is calculated as follows

$$delay = d_S - d_R \quad (14)$$

it d_S represented as message sending time and d_R expressed as message receiving time.

The simulation parameters of the IMFO are shown in Table 1below.

Parameter	Value
Target area	1500m
Users	40,80,120,160,200
Packet size	1K bytes
Nodes	200
Size of the population	100
Processing Time	3000s
Range of transmission	150m
No of nodes	100

Table 1: The simulation parameters

Delivery ratio:

The delivery ratio can be determined calculated as follows (15)

$$DR = \frac{Number\ of\ packets\ received}{Number\ of\ packets\ sent} \quad (15)$$

Drop:

Drop is represents loss of data in the packet transmission. It is calculated as follows (16)
DROP=Ratio of (Total No of data packets-Total number of data packets received/Total Number of packets) (16)

Overhead:

Every transmission comprises supplementary, Overhead information necessary to the data transmission to the appropriate destination.

Network lifetime:

Network lifetime can be determined by the equation (17)

$$Network\ Lifetime = \frac{E_{initial\,energy}}{E_{consumed\,energy}} \times S_{cycle} \quad (17)$$

Where $E_{initial\,energy}$ e initial energy $E_{consumed\,energy}$ represents the consumed energy S_{cycle} in the time cycle.

Throughput:

Throughput is the reliable transmission over a network channel. The mathematical formula for throughput is given as follows (18)

Throughput = Ratio of (Number of packets delivered successfully * Average Packet size)/(Total time required to provide the data)(18)

Simulation: **The Performance comparison of a modified mayfly with swarm optimization and grey wolf algorithm.**

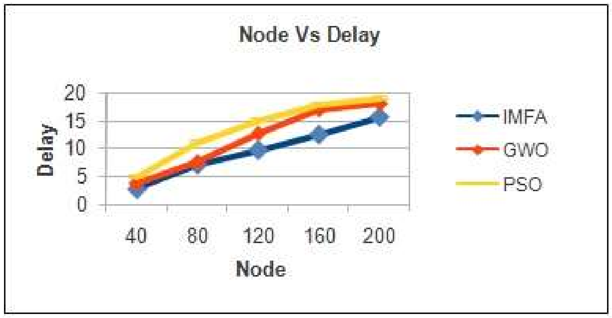

Fig 4: Simulation of Node Vs Delay

From the simulation results comparison shown in the above figure. IMFO provides lesser delay compared to GWO and PSO Respectively.

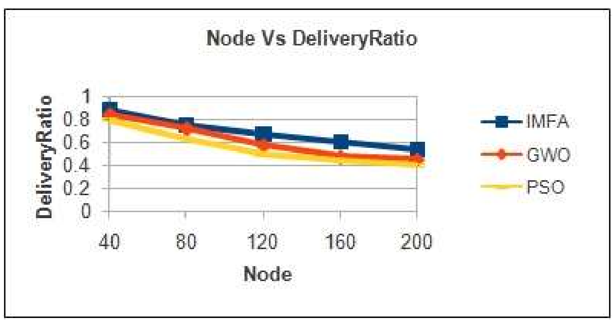

Fig 5: Simulation of Node Vs Delivery Ratio

From the simulation results comparison shown in the above figure. Delivery ratio of IMFO higher compared with existing methods like GWO and PSO, respectively. At node 100, the proposed IMFO method provides 26.17% delivery ratio higher compared with GWO and PSO.

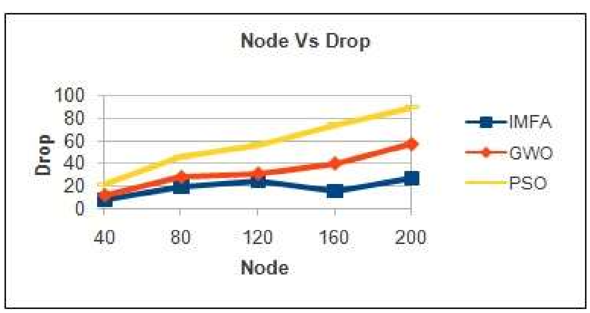

Fig 6: simulation of Node Vs Drop

From the simulation results comparison shown in the above figure .Proposed method drop rate

69.66% lower compared methods like GWO and PSO, respectively.

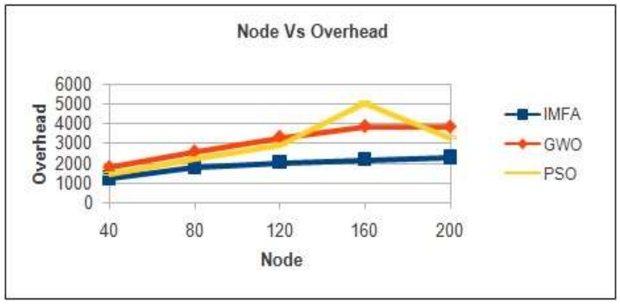

Fig 7: Simulation of Node Vs Overhead

From the simulation results comparison shown in the above figure The proposed IMFO method provides 30% lower Overhead compared with GWO and PSO, respectively.

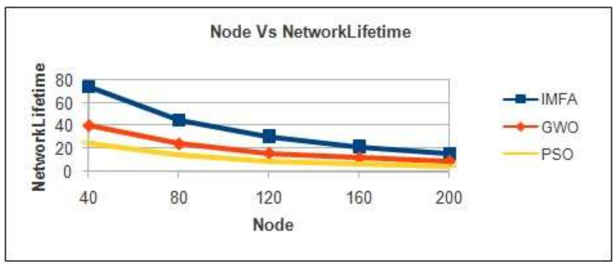

Fig 8: Simulation of Node Vs network lifetime.

Figure shows the implementation analysis of the Network lifetime with various methods. The proposed IMFO method provides 68.18% larger network lifetime compared with GWO and PSO respectively.

5. CONCLUSION:

This research work successfully implemented the Improved May Fly optimization (IMFO) algorithm. The problem with the hidden nodes in the Cognitive Radio networks was successfully addressed using IMFO. Optimum weight vectors are calculated at the fusion center based on spectrum allocated to secondary users with less interference. Then the proposed IMFO algorithm provided solution for different parameters optimization compared with an existing algorithm such as Intelligent Particle Swarm Optimization Algorithm and gray wolf optimization algorithm.

References:

1. Thimmapuram, S., Laxmaiah, M., & Sreelatha, M. (2022). Cooperative Spectrum Sensing Optimization in Cognitive Radio networks based on a Hybrid (MFO-GDO) Heuristic Search Algorithm. 2022 First International Conference on Electrical, Electronics, Information and Communication Technologies (ICEEICT). https://doi.org/10.1109/iceeict53079.2022.9768560

2. Sonti, S. R., & Prasad, M. (2021). Deep belief network with FOA-based cooperative spectrum sensing in cognitive radio network. International Journal of Communication Networks and Distributed Systems, 27(3), 323. https://doi.org/10.1504/ijcnds.2021.118128

3. Xie, X., Zheng, J., Feng, M., He, S., & Lin, Z. (2022). Multi-Objective Mayfly Optimization Algorithm Based on Dimensional Swap Variation for RFID Network Planning. *IEEE Sensors Journal*, *22*(7), 73117323. https://doi.org/10.1109/jsen.2022.3151932

4. Zhao, J., & Gao, Z. (2020). The regrouping mayfly optimization algorithm. 2020 7th International Forum on Electrical Engineering and Automation (IFEEA). https://doi.org/10.1109/ifeea51475.2020.00214

5. Zhao, J., & Gao, Z. (2020a). The fully informed mayfly optimization algorithm. International Conference on Big Data. https://doi.org/10.1109/icbase51474.2020.00101

6. Cao, Y., & Pan, H. (2020). Energy-Efficient Cooperative Spectrum Sensing Strategy for Cognitive Wireless Sensor Networks Based on Particle Swarm Optimization. IEEE Access, 8, 214707–214715. https://doi.org/10.1109/access.2020.3037707

7. Cai, J., Peng, P., Huang, X., & Xu, B. (2020). A Hybrid Multi-phased Particle Swarm Optimization with Sub Swarms. *International Conference on Artificial Intelligence*.https://doi.org/10.1109/icaice51518.2020.00026

8. Guo, M., Wang, J., Zhu, L., & Xie, W. (2020). An Improved Grey Wolf Optimizer Based on Tracking and Seeking Modes to Solve Function Optimization Problems. *IEEE Access*, *8*, 69861–69893. https://doi.org/10.1109/access.2020.2984321

9. Arora, S., Singh, H., Sharma, M., Sharma, S., & Anand, P. (2019). A New Hybrid Algorithm Based on Grey Wolf Optimization and Crow Search Algorithm for Unconstrained Function Optimization and Feature Selection. *IEEE Access*, *7,* 26343–26361. https://doi.org/10.1109/access.2019.2897325

10. Chuan-Qing, L., & Zhi-Ming, W. (2011). Adaptive weighted algorithm of cooperative spectrum sensing in cognitive radio networks. Journal of Jishou University. Jishou University. https://doi.org/10.1049/cp.2011.0860

11.Shen, Y., Li, Y., Kang, H., Zhang, Y., Sun, X., Chen, Q., . . . Wang, H. (2018). Research on Swarm Size of Multi-swarm Particle Swarm Optimization Algorithm. *IEEE International Conference Computer and Communications*. https://doi.org/10.1109/compcomm.2018.8781013

12. Cao, B., Mark, J. W., Zhang, Q., Lu, R., Lin, X., & Shen, X. (2013). Optimal Communication Strategies in Cooperative Cognitive Radio Networking. In *Springer briefs in electrical and computer engineering*. Springer International Publishing. https://doi.org/10.1007/978-3-319-32881-2_4

13. Ahmad, A., Ahmad, S., Rehmani, M. H., & Hassan, N. U. (2015). A Survey on Radio Resource Allocation in Cognitive Radio Sensor Networks. IEEE Communications Surveys and Tutorials, 17(2), 888–917. https://doi.org/10.1109/comst.2015.2401597

14. Hoque, K. A., Ullah, S. N., Hasan, M. M., Shakil-Al-Monsur, Mostaqim, M., Arnab, B., . . . ForhadulAlam, A. S. M. (2014). *Proper allocation and utilization of spectrum by using cognitive radio networks: Bangladesh perspective*. https://doi.org/10.1109/icget.2014.6966663

15.Biglieri, E., Goldsmith, A. J., Greenstein, L. J., Mandayam, N. B., & Poor, H. V. (2013). *Principles of Cognitive Radio*. Cambridge University Press.

16. Shen, Y., Li, Y., Kang, H., Zhang, Y., Sun, X., Chen, Q.,Wang, H. (2018b). Research on Swarm Size of Multi-swarm Particle Swarm Optimization Algorithm. IEEE International Conference Computer and Communications. https://doi.org/10.1109/compcomm.2018.8781013

17. Wu, X. (2011). A density adjustment based particle swarm optimization learning algorithm for neural network design. *International Conference on Electrical and Control Engineering*. https://doi.org/10.1109/iceceng.2011.6057937.