International Journal of Science and Research (IJSR)
ISSN: 2319-7064
SJIF (2022): 7.942

Enhancing Node Activation in Sensor Networks Using MOCL - RFSA for Maximized Coverage, Connectivity, and Minimized Interference

R. Christal Jebi[1], S. Baulkani[2]

[1]Research Scholar, Department of Information and Communication Engineering, Anna University, Chennai, Tamil Nadu, India
Corresponding Author E- mail: *jebijewish[at]gmail.com*

[2]Professor, Department of Electronics and Communication Engineering, Government College of Engineering, Tirunelveli, Tamil Nadu, India
E- mail: *ramabaulkani[at]yahoo.co.in*

Abstract: ***Wireless Sensor Networks (WSNs) can be used for surveillance, smart agriculture, and healthcare. However, WSNs face several challenges, such as coverage, connectivity, and interference issues that affect network performance. Therefore, a novel approach called the Multi objective Chaotic Learning based Red Fox Selective Activation algorithm (MOCL - RFSA) is proposed. The MOCL - RFSA method introduces six objective functions to maintain network performance. The objective function is formulated to guide the fox towards the areas of interest or target area, ensuring that nodes are activated optimally with maximum coverage, maximum connectivity, and minimum interference. The fox may leave the herd due to lack of food or be shot down by hunters. This behaviour is adapted in the proposed MOCL - RFSA algorithm to deactivate the unnecessary nodes (shot down) that cause coverage overlap in the network. This improved the network lifetime. Moreover, the proposed MOCL - RFSA algorithm introduces opposition learning and chaotic mechanism to overcome problems like local optima and premature convergence. The performance of MOCL - RFSA is estimated using simulation experiments, and the outcomes indicate that the proposed MOCL – RFSA outperforms the existing methods with better network lifetime, residual energy, throughput, coverage, connectivity, and interference ratio.***

Keywords: Coverage, Connectivity, Interference, Optimization, Selective Activation

1. Introduction

WSNs are a collection of small devices (sensors) that can interconnect with each other wirelessly to form a network. These sensors are equipped with various sensing and processing capabilities, and they can be deployed in different environments to collect data and perform various tasks [1 - 3]. However, the major challenges in WSN design is to maximize coverage, connectivity, and minimize interference. The key objective of WSN design is to maximize coverage, which means ensuring that the sensors can monitor the entire area of interest with sufficient accuracy and density [4, 5]. This is particularly important in applications such as healthcare, surveillance, and environmental monitoring, where accurate data collection is critical. Maximizing coverage ensures that the sensors can cover the entire area of interest and collect sufficient data [6].

Maximizing connectivity ensures that the sensors can communicate with each other to share information and cooperate to perform tasks. Achieving connectivity requires designing the network topology and communication protocols carefully [7, 8]. Minimizing interference ensures that the sensors can avoid collisions and maintain a reliable communication link. Interference can be caused by various factors, such as channel contention, radio frequency interference, and overlapping sensor coverage [9, 10]. These three objectives are interrelated, and achieving them requires a careful design of the network topology and communication protocols.

The contributions of the paper are as follows:

- The red fox leaves the herd in case of danger. This behavior is adapted in the proposed MOCL - RFSA algorithm to reduce coverage overlap.
- Opposition - based learning and chaotic mechanism is introduced in the proposed MOCL - RFSA algorithm to prevent the solution from trapping in local optimum and prevent premature convergence.
- The interference is minimized and the coverage and connectivity are maximized by introducing six objective functions.
- The proposed MOCL - RFSA algorithm is implemented using NS2 - network simulator and the performance is compared with the existing techniques.

2. Related Works

Sah and colleagues [11] developed an effective solution known as the Constrained Relay Harvesting Node Placement (CRHNP) method. This method relies on effective coverage responsiveness and facilitates efficient management among sensors using geometric - based technique. The CRHNP is applied depending on the selection of relay harvesting nodes and operates in a sleep/awake manner, whereby only the necessary nodes are made active. In their study, Shivalingegowda and Jayasree [12] presented a hybrid model called Gravitational Search algorithm - social ski - driver (GSA - SSD) approach for target oriented WSNs. It aims to optimize both connectivity and coverage. The performance is enhanced by incorporating the SSD’s dynamic behaviour. However, the convergence is slow and the connectivity is poor.

Priyadarshini and Sivakumar [13] developed a method called Minimum Connected Dominating Set based Multi - hop Information (MCDS - MI) algorithm to select a cluster head (CH). The process has two phases, where Bi - Partite Graph (BG) is employed to select the dominator in the first phase. Then a tree cycle technique is utilized to determine the subsequent CH. However, the energy consumption and interference are high. In their study, ABOLADE et al. [14] introduced an enhanced version of Low Energy Adaptive Clustering Hierarchy (LEACH) method, aimed at enhancing connectivity and the lifespan of the network. The authors put forth a new approach that modifies the CH election process for greater flexibility, taking into account the current energy levels, instead of relying on a fixed energy requirement. However, the coverage is poor.

Jebi and Baulkani [15] introduced the multi - objective randomized Grasshopper Optimization Algorithm based Selective Activation (MORGOA - SA) algorithm to improve the network lifetime of the WSN without affecting coverage and connectivity. Similarly, other nature inspired algorithm based algorithms such as Genetic Algorithm (GA), Improved Genetic Algorithm (IGA), Improved Artificial Bee Colony (IABC), Particle Swarm Optimization (PSO), Biogeography Based Optimization (BBO), and Gravitational Search Algorithm (GSA) have been proposed by various researchers [15, 16] to enhance the network performance. However, the interference of these methods are high. Jebi and Baulkani [17] proposed a Multi objective adaptive Horse herd optimization algorithm selective activation (MOAHOA - SA) to improve coverage, connectivity, & minimize interference in the WSN. This method improves the network lifetime, but the convergence is slow.

3. Proposed Multi objective Learning based Red Fox Selective Activation (MOCL - RFSA)

The assumptions are made in the proposed MOCL - RFSA approach are taken from paper [15]. The proposed MOCL - RFSA algorithm has six objectives that includes minimizing the number of nodes that are active (F_1), minimizing coverage overlap (F_2), minimizing the interference (F_3), maximizing connectivity (F_4), maximizing the coverage (F_5), and maximizing the residual energy (F_6). The fitness F_1, F_2, F_4, F_5, & F_6 are computed using the equations used in [15]. Selection of nodes with minimum interference, F_3 is computed using Eqn. (1).

$$F_3 = \frac{1}{k} \sum_{a=1}^{k} \sum_{b=a+1}^{k} \phi_{ab} \tag{1}$$

where k number of locations of the deployed nodes and ϕ_{ab} denote the sensing interference which is computed using Eqn. (2).

$$\phi_{ab} = \begin{cases} 1 & dist(N_a, N_b) \le 2 \times R_S, \ \forall a, \forall b, 1 \le a, b \le k \\ 0 & otherwise \end{cases} \tag{2}$$

Where *dist* (N_a, N_b) denotes the distance between node N_a and N_b, R_s denote the sensing range.

The fitness function of the solution is determined by Eqn. (3).

$$\text{Fit} = min\,(w_1F_1 + w_2F_2 + w_3F_3) + max\,(w_4F_4 + w_5F_5 + w_6F_6) \tag{3}$$

Where w_1, w_2, ..., w_6 denotes the weights such that $w_1 + w_2 + w_3 + w_4 + w_5 + w_{6=1}$.

The Red Fox Optimization (RFO) [18] is adapted in this paper to selectively activate the nodes in the WSN. The RFO algorithm incorporates the behaviour of red foxes searching for food in their territories. This behaviour is represented as the exploration stage (global search). In the subsequent phase, the foxes move within the territory to approach their prey before attacking it, which is represented as the exploitation stage (local search).

In the proposed MOCL - RFSA algorithm, the fox represents the sensor nodes in the network, and the food represents the areas of interest or the target zones that need to be monitored. The objective function is formulated to guide the fox towards the areas of interest (food), ensuring that nodes are activated optimally (maximize coverage, maximize connectivity, and minimize interference) to maintain network performance. However, the fox might die due to lack of food or shot down by hunters. This behaviour is adapted in the proposed MOCL - RFSA algorithm to deactivate the unnecessary nodes that cause coverage overlap in the network. This improves the network lifetime of the network.

The population of the individuals are moved toward the best one using Eqn. (4).

$$\left(\bar{y}^j\right)^t = \left(\bar{y}^j\right)^t + \beta sign\left(\bar{y}^{best}\right)^t - \left(\bar{y}^j\right)^t \tag{4}$$

The fox's hunting radius is defined by Eqn. (5).

$$s = \begin{cases} b\dfrac{\sin(\psi_0)}{\psi_0} & if\ \psi_0 \ne 0 \\ \rho & if\ \psi_0 = 0 \end{cases} \tag{5}$$

where $b \in (0, 0.2)$, $\psi_0 \in (0, 2\pi)$, and $\rho \in (0,1)$

The reallocation is modelled using Eqn. (6).

$$\begin{cases} y_0^{new} = bs \cdot cos(\psi_1) + y_0^{act} \\ y_1^{new} = bs \cdot sin(\psi_1) + bs \cdot cos(\psi_2) + y_1^{act} \\ y_2^{new} = bs \cdot sin(\psi_1) + bs \cdot sin(\psi_2) + bs \cdot cos(\psi_3) + y_2^{act} \\ \vdots \\ y_{m-2}^{new} = bs \cdot \sum_{l=1}^{m-2} sin(\psi_l) + bs \cdot cos(\psi_{m-1}) + y^{act}_{m-2} \\ y_{m-1}^{new} = bs \cdot sin(\psi_1) + bs \cdot sin(\psi_2) + \cdots + bs \cdot sin(\psi_{m-1}) + y_{m-1}^{act} \end{cases} \quad (6)$$

where $\psi_1, \psi_2, \cdots, \psi_{m-1} \in (0, 2\pi)$

The new fox (solution) are updated or replaced by Eqn. (7).

$$s = \begin{cases} new individual & if\ \lambda \geq 0.45 \\ alpha\ couple\ reproduction & if\ \lambda < 0.45 \end{cases} \quad (7)$$

Where $\lambda \in (0, 1)$. The two best solutions are reproduced using Eqn. (8).

$$(\bar{y})^{t(rep)} = \lambda \frac{(\bar{y})^{t(1)} + (\bar{y})^{t(2)}}{2} \quad (8)$$

While the RFO algorithm [18] performs better than other methods in solving optimization problems, it may still fall short of achieving the optimal results due to issues such as getting stuck in local optima, premature convergence, and lower consistency. To address these challenges, this paper introduces two enhancements to the method with a jump rate R_J.

To expand the exploration capabilities of the algorithm, one proposed modification is to incorporate the opposition - based learning (OBL). The OBL posits that every possible location in the search region has an opposite position. By generating the opposite position of each solution using Eqn. (9), the algorithm can better explore the search region.

$$\left((\bar{y})^j\right)^t_{opp} = \left((\bar{y})^j\right)^t_L + \left((\bar{y})^j\right)^t_U - \left((\bar{y})^j\right)^t \quad (9)$$

where $\left((\bar{y})^j\right)^t, \left((\bar{y})^j\right)^t_{opp} \in \Re^j$. The second alteration focuses on incorporating chaotic learning to improve the quality of the optimal solution over the course of iterations. The existing approach has a limitation where the best individual may be stuck in a local optimum, leading to premature convergence. To overcome this issue, chaotic sequence is introduced to improve the quality of the solution. Specifically, the logistic map in Eqn. (10) and Eqn. (11) are used to introduce chaos.

$$\alpha_{n+1} = 4\alpha_n(1 - \alpha_n) \quad (10)$$

$$\eta_{n+1} = 4\eta_n(1 - \eta_n) \quad (11)$$

where n signifies the iteration count $\alpha_n, \eta_n \in (0, 1)$. The search process continues until the minimum nodes are activated without affecting coverage, connectivity, and interference or when the termination condition is met. The flowchart of the MOCL – RFSA method is depicted in Fig.1.

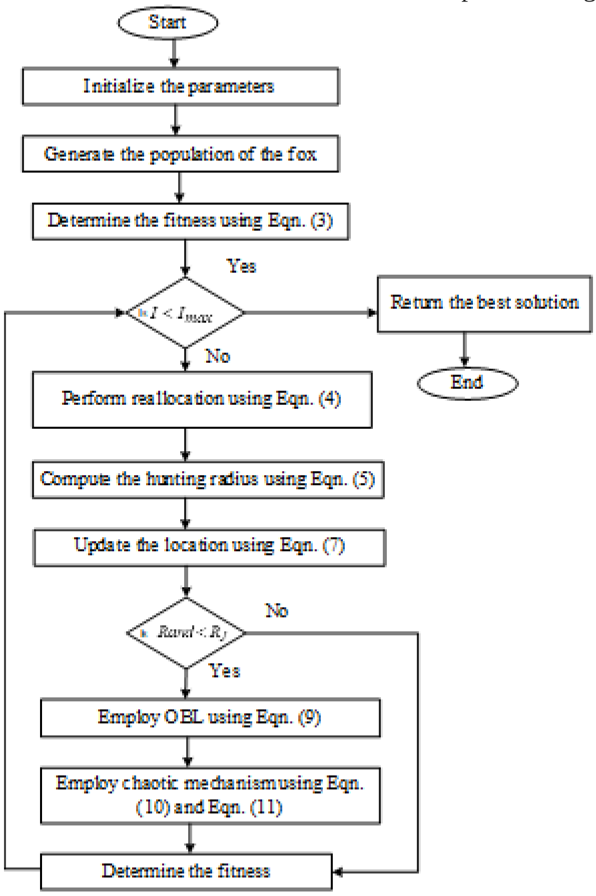
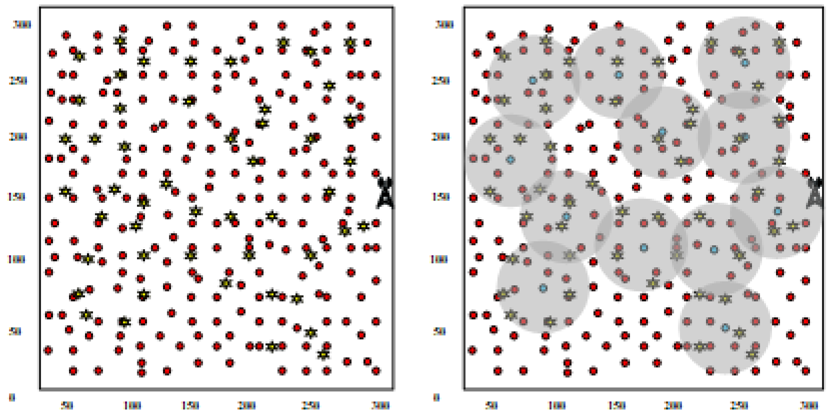


Figure 1: Flowchart of the proposed MOCL - RFSA

4. Simulation Results and Analysis

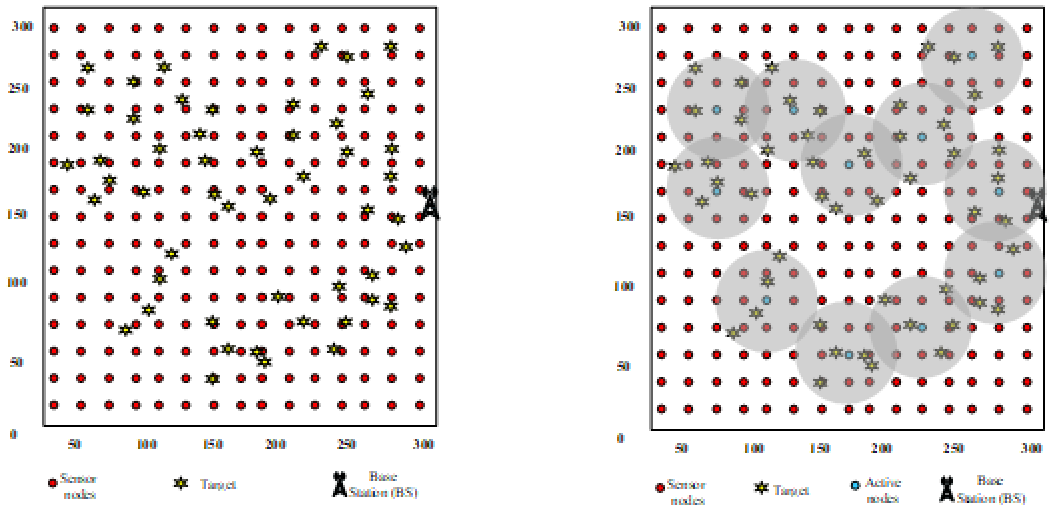
The proposed MOCL - RFSA method is implemented using the NS - 2 network simulatorin $300 \times 300 m^2$ area. The other parameter setup is similar to the setup used in [15]. Fig.2 and Fig.3provides the selective activation results of the proposed MOCL - RFSA based activation under two different scenarios.

International Journal of Science and Research (IJSR)
ISSN: 2319-7064
SJIF (2022): 7.942



(a) (b)

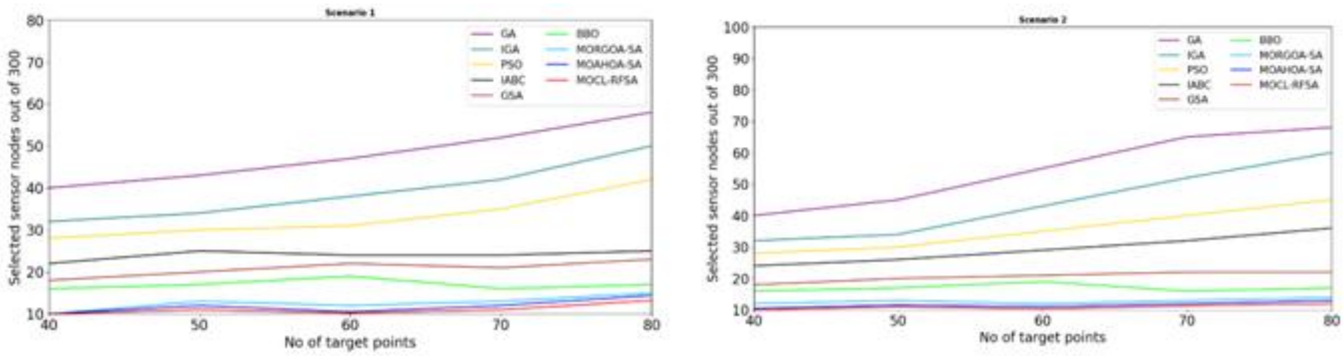
Figure 2: Scenario 1 (a) Random Node deployment (b) Proposed MOCL - RFSAbased activation



(a) (b)

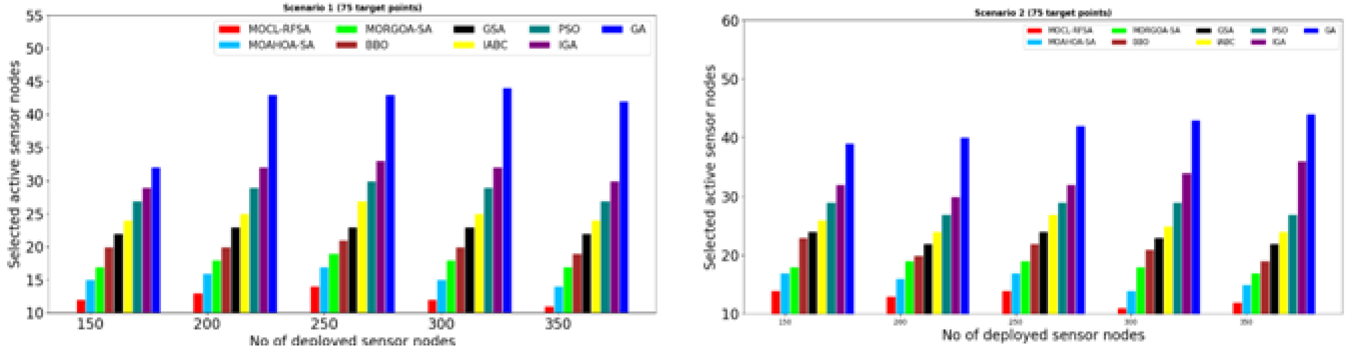
Figure 3: Scenario 2 (a) Random Node deployment in 15*15 grid (b) Proposed MOCL - RFSA based activation

Fig.4 and Fig.5 gives the activation analysis by varying the target points and sensors, respectively. The outcomes demonstrate that the proposed MOCL - RFSA (for scenario 1) has activated minimum sensors of 14 nodes than GA, IGA, IABC, PSO, GSA, BBO, MORGOA - SA, and MOAHOA - SA methods. This is due to the selection of the fittest solution by the proposed MOCL - RFSAalgorithm that considers the minimum activation of nodes as one of the objective functions.



(a) (b)

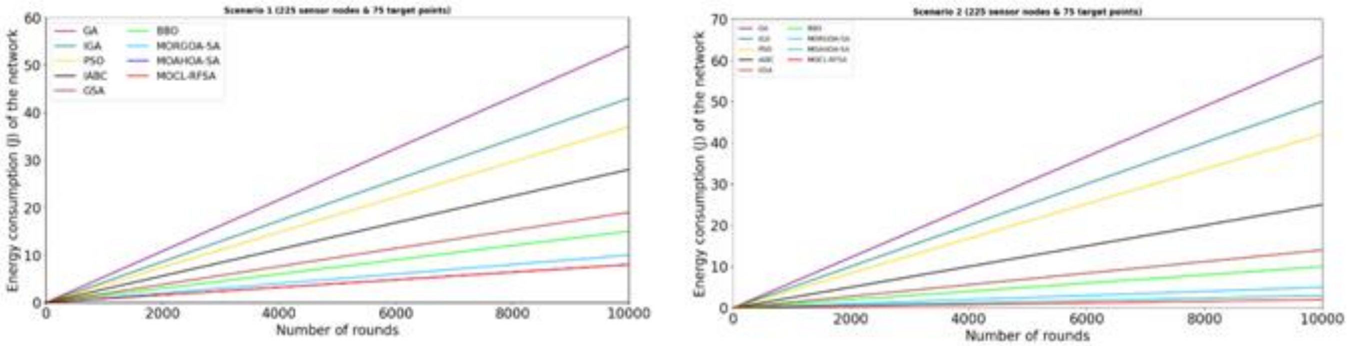
Figure 4: Activation analysis by varying targets (a) scenario 1 (b) scenario 2



(a) **(b)**

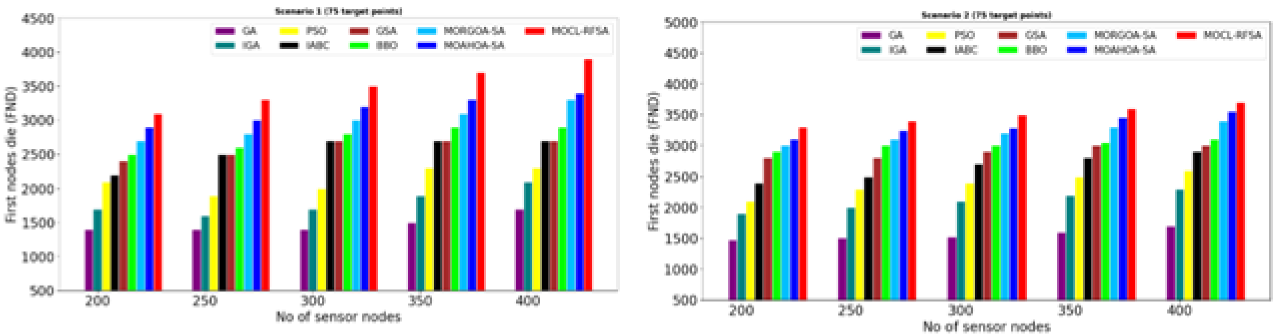
Figure 5: Activation analysis by varying the sensor count (a) scenario 1 (b) scenario 2

Fig.6 and Fig.7 gives the energy consumed and connectivity results obtained under two different scenarios. The outcomes indicate that theproposed MOCL - RFSA has less energy consumption of 4 J than GA (54 J), IGA (43 J), IABC (28 J), PSO (37 J), GSA (19 J), BBO (15 J), MORGOA - SA (10 J), and MOAHOA - SA (8J) methods as well as high connectivity. This is due to the fact that MOAHOA - SA deactivates the sensors that cause coverage overlap without affecting connectivity. This moderates the consumed energyas well as improves the connectivity.



(a) **(b)**

Figure 6: Energy consumption (a) scenario 1 (b) scenario 2



(a) **(b)**

Figure 7: Connectivity (a) scenario 1 (b) scenario 2

Also, from Fig.8, it can be seen that the residual energy of the network drops to a minimum only after 14, 000 rounds. Since the proposed MOCL - RFSA algorithm activates the nodes that has higher residual energy, lifetime of the network is improved than GA, IGA, IABC, PSO, GSA, BBO, MORGOA - SA, and MOAHOA - SA methods.

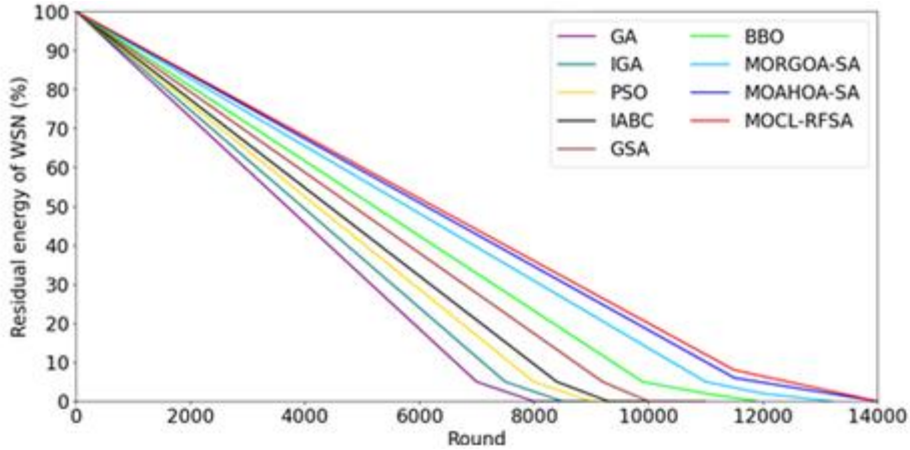


Figure 8: Residual Energy

Fig.9 gives the throughput results. The analysis show that the throughput of the proposed MOCL - RFSA is higher (200 kbps) than the existing techniques like GSA (151 kbps), IABC (114 kbps), PSO (95 kbps), GA (68 kbps), IGA (78 kbps), MORGOA - SA (181 kbps), MOAHOA - SA (195 kbps), and BBO (160 kbps). The throughput is high for MOCL - RFSA because the connectivity is improved by the fitness evaluation. Moreover, from Fig.10, it can be noted that the introduction of opposition learning and chaotic mechanism in the proposed MOCL - RFSA algorithm increases the convergence speed compared to the existing algorithms. The interference ratio of the MOCL - RFSAtechnique is also reduced to 0.37 % which can be observed from Fig.11. This is due to the activation of nodes with minimum interference (F_3) by the proposed MOCL - RFSA algorithm.

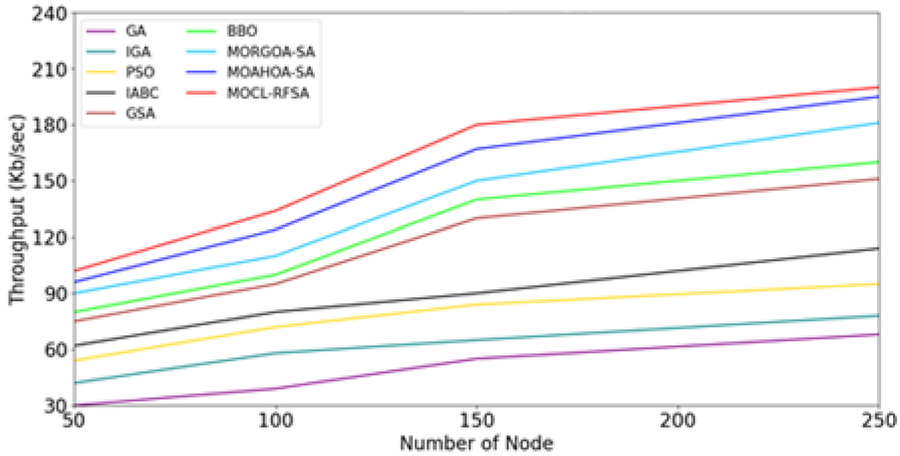


Figure 9: Throughput

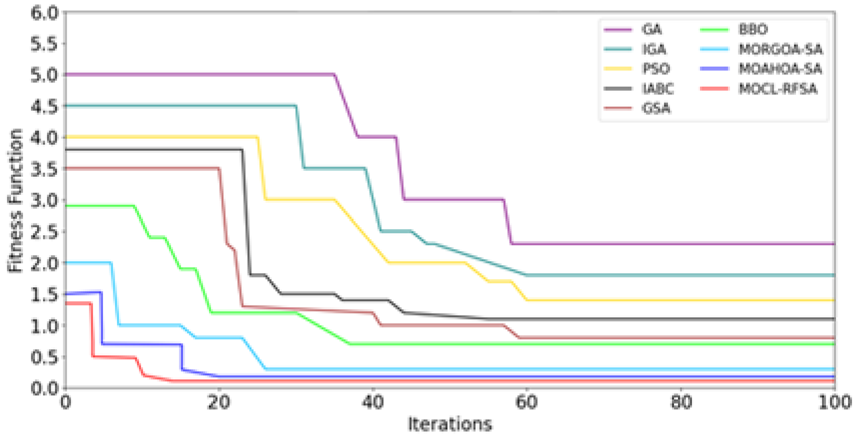


Figure 10: Convergence

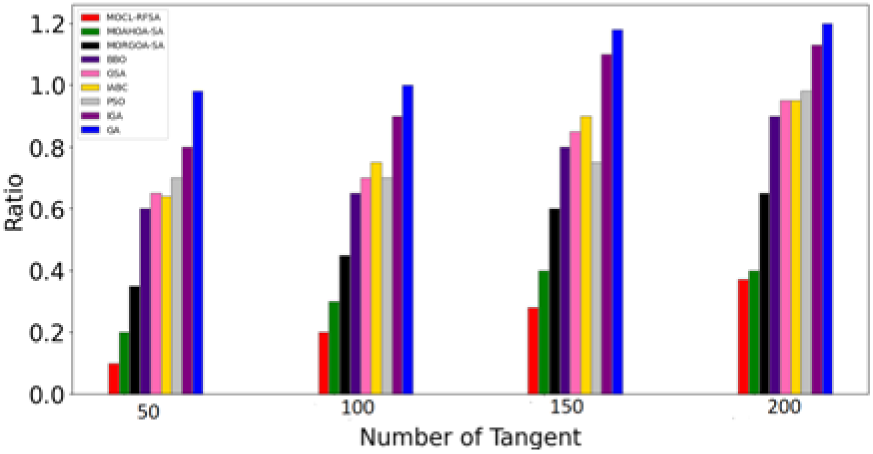
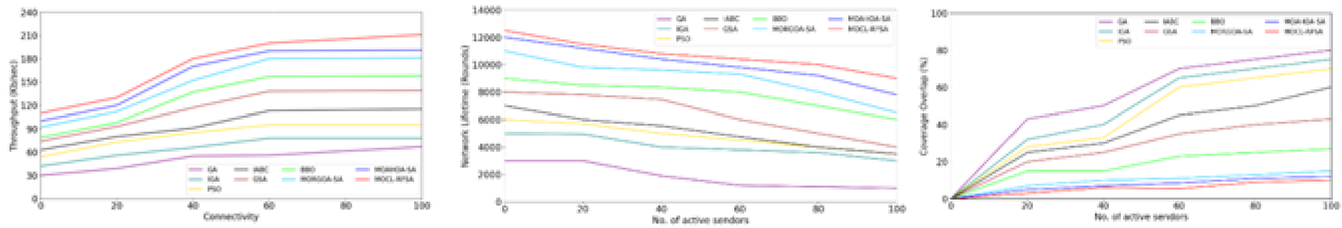


Figure 11: Interference Analysis

The proposed MOCL – RFSA method is also tested under various conditions in Fig.12. The results show improved results compared to the existing techniques like GSA, IABC, PSO, GA, IGA, MORGOA - SA, MOAHOA - SA, and BBO under all the conditions with high coverage, high throughput, high network lifetime, and low coverage overlap.



(a) (b) (c)

Figure 12: Performance analysis under various conditions (a) throughput, (b) Network lifetime and (c) coverage overlap

5. Conclusion

In conclusion, the MOCL - RFSA method has been proposed to minimize the activation of sensors. It also addresses the local optima and premature convergence issues that can arise in traditional RFO algorithm. This has been achieved through the introduction of opposition learning and chaotic mechanisms. Additionally, the method introduces six objective functions, which improve coverage, connectivity, and minimize interference, leading to improved performance. The performance analysis of the MOCL - RFSA method demonstrated that it outperformed existing techniques in terms of network lifetime, residual energy, throughput, coverage, connectivity, and interference ratio. Overall, the MOCL - RFSA method presents a promising direction for future research in WSN for a range of applications, including smart cities and environmental monitoring. However, the security can be improved in future works.

References

[1] H. T. T. Binh, N. T. Hanh, L. Van Quan, N. D. Nghia, and N. Dey, "Metaheuristics for maximization of obstacles constrained area coverage in heterogeneous wireless sensor networks, " Applied Soft Computing, vol.86, p.105939, Jan.2020

[2] S. Harizan and P. Kuila, "Evolutionary Algorithms for Coverage and Connectivity Problems in Wireless Sensor Networks: A Study, " Design Frameworks for Wireless Networks, pp.257–280, Aug.2019

[3] A. H. Imani, M. Eslami, J. Haghighat, and M. Noori, "Effect of fading on the k-coverage of wireless sensor networks, " Transactions on Emerging Telecommunications Technologies, vol.31, no.7, Jun.2020

[4] H. ZainEldin, M. Badawy, M. Elhosseini, H. Arafat, and A. Abraham, "An improved dynamic deployment technique based - on genetic algorithm (IDDT - GA) for maximizing coverage in wireless sensor networks, " Journal of Ambient Intelligence and Humanized Computing, vol.11, no.10, pp.4177–4194, Jan.2020

[5] Moorthi and R. Thiagarajan, "Energy consumption and network connectivity based on Novel - LEACH - POS protocol networks, " Computer Communications, vol.149, pp.90–98, Jan.2020

[6] Dande B, Chang CY, Liao WH, Roy DS. MSQAC: maximizing the surveillance quality of area coverage in wireless sensor networks. IEEE Sensors Journal.2022 Jan 27; 22 (6): 6150 - 63.

[7] Upreti R, Rauniyar A, Kunwar J, Haugerud H, Engelstad P, Yazidi A. Adaptive pursuit learning for energy-efficient target coverage in wireless sensor networks. Concurrency and Computation: Practice and Experience.2020 Aug 25: e5975.

[8] Devi S, Sangwan A, Sangwan A, Mohammed MA, Kumar K, Nedoma J, Martinek R, Zmij P. The Use of Computational Geometry Techniques to Resolve the Issues of Coverage and Connectivity in Wireless Sensor Networks. Sensors.2022 Sep 16; 22 (18): 7009.

[9] Zrelli A, Ezzedine T. A new approach of WSN deployment, K - coverage and connectivity in border area. Wireless Personal Communications.2021 Dec; 121 (4): 3365 - 81.
[10] Mohanty SK, Udgata SK. Minimizing the maximum receiver interference in wireless sensor networks using probabilistic interference model. Engineering Applications of Artificial Intelligence.2020 May 1; 91: 103563.
[11] Sah DK, Srivastava S, Kumar R, Amgoth T. An energy efficient coverage aware algorithm in energy harvesting wireless sensor networks. Wireless Networks.2022 Nov 18: 1 - 21.
[12] Shivalingegowda C, Jayasree PV. Hybrid gravitational search algorithm based model for optimizing coverage and connectivity in wireless sensor networks. Journal of Ambient
[13] Priyadarshini RR, Sivakumar N. Cluster head selection based on minimum connected dominating set and bi - partite inspired methodology for energy conservation in WSNs. Journal of King Saud University - Computer and Information Sciences.2021 Nov 1; 33 (9): 1132 - 44.
[14] ABOLADE O, OKANDEJI A, OYEDEJI A, OSIFEKO M, ONAIFO F, Peter AL. Dynamic advanced node selection for wireless sensor networks for improved network life and packet transmission. Scientific African.2021 Jul 1; 12: e00753.
[15] R. C. Jebi and S. Baulkani, “Mitigation of coverage and connectivity issues in wireless sensor network by multi - objective randomized grasshopper optimization based selective activation scheme, ” Sustainable Computing: Informatics and Systems, vol.35, p.100728, Sep.2022
[16] Naik C, Shetty DP. Optimal sensors placement scheme for targets coverage with minimized interference using BBO. Evolutionary Intelligence.2022 Sep; 15 (3): 2115 - 29.
[17] R. Christal Jebi, S. Baulkani, "Maximizing coverage and connectivity in WSNs with MOAHOA - SA: A selective activation approach with minimum interference", International Journal of Science and Research (IJSR), Volume 12 Issue 3, March 2023
[18] D. Połap and M. Woźniak, “Red fox optimization algorithm, ” Expert Systems with Applications, vol.166, p.114107, Mar.2021

Author Profile

Christal Jebi R is enriching her Ph. D. at Department of Information and Communication Engineering, Anna University, Chennai, India. In 2015, she joined as a Lecturer at Department of Electronics and Communication Engineering, St. Judes polytechnic college, Tamilnadu, India. She received her M. E. degree in Applied Electronics from Bethlahem Institute of Engineering (affiliated Anna University, Chennai) Karungal, Tamilnadu, India, in 2014 and B. E. degree in Electronics and Communication Engineering from Noorul Islam College of Engineering (affiliated Anna University, Chennai), Kumaracoil, Tamilnadu, India, in 2012. Her present research is about Networking, Sensor Networks, Internet of Things, Soft Computing and Artificial Intelligence.

S. Baulkani M. E., Ph. D., MISTE is a professor in the Department of Electronics and Communication Engineering, Government College of Engineering, Tirunelveli, Tamil Nadu, India. She completed her Ph. D in 2009 under anna university, Chennai – 600 025. In 1998, she completed her M. E programme in Computer Science and Engineering at Government College of Technology, Coimbatore –641 013. She completed her under graduate programme B. E in Electronics and Communication Engineering in the year 1986. Her research focus is on Image Processing, Pattern Recognition, Distributed Computing, Wireless Networks and VLSI.