Maximizing Coverage and Connectivity in WSNS with Moahoa-Sa: A Selective Activation Approach with Minimum Interference

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

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

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

Abstract: ***Wireless Sensor Network (WSN) consists of small autonomous devices, called sensor nodes that are capable of sensing, computing, and wireless communication. In order to monitor targets or detect events, sensors are deployed at specific Point of Interest (PoI), and then the data was transmitted to the Base Station (BS) or sink. Maximizing coverage and connectivity with minimal sensing interference is a critical issue in WSN. To address these concerns, we propose a Multi-Objective Adaptive Horse Herd Optimization Algorithm-based Selective Activation (MOAHOA-SA) scheme to select minimum active nodes at the PoI in WSN. The MOAHOA-SA approach solves the multi-objective problem using the adaptability factor. An improved fitness function is mathematically formulated with six objectives such as coverage maximization, ensuring connectivity, coverage overlap minimization, high residual energy node selection, active sensor node minimization, and interference minimization. Hence, the MOAHOA-SA scheme maximize the target coverage and connectivity with minimum sensor interference while selecting minimum active sensors to be placed at the PoI. Under random and grid deployment scenarios, the performance results of the MOAHOA-SA approach achieves better performance than other optimization algorithms.***

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

1. Introduction

With the development of low-cost and low-power wireless devices, Wireless Sensor Networks (WSNs) are becoming increasingly popular for various applications, such as military, agriculture, healthcare, automation and so on [1-2]. In WSN, target coverage, connectivity, and interference are essential factors that determine the network's overall performance and efficiency. The target coverage was referred as the ability to detect and cover a specific area of interest from the deployment of the sensor nodes. The concept of Point of Interest (PoI) was critical in WSNs because it helped define the area of interest and the sensors' role in monitoring events in that area. It can also be used to optimize the performance of the network by selectively activating sensors in the PoI based on the type of event being monitored. This can help conserve energy and prolong network lifespan [3-4]. Then the connectivity was referred as the ability to maintain communication with each other and to ensure reliable data transfer from the deployment of the sensor nodes. It is influenced by factors such as network topology, routing protocols, and transmission power [5]. Finally, interference refers to the occurrence of overlapping transmissions in the network that can cause interference and affects the network performance. Interference can occur due to various factors, such as the active nodes, transmission power, and channel bandwidth [6-7]. In WSNs, minimizing interference is crucial to ensuring the accuracy and reliability of data transmission. These factors are interrelated and influenced by various factors such as node deployment, transmission range, network topology, routing protocols, transmission power, and channel bandwidth [8]. Several traditional optimization methods such as greedy algorithms [9], clustering algorithms [10], Genetic algorithms (GA) [11], Particle Swarm Optimization (PSO) [12], and Simulated Annealing (SA) [13] were effective in optimizing the target coverage, connectivity, and interference in WSNs. However, they have several limitations, such as low handling scalability, limited energy resources, high interference, and dynamic nature of the network. Therefore, there is a need for an advanced optimization technique to address these challenges.

Main contributions:

- We present an efficient MOAHOA-SAscheme for reducing the number of selective active nodes leads to an optimized solution with maximum target coverage and connectivity and, minimum interference in WSN.
- An adaptability factor allows the HOA algorithm to dynamically adjust the balance between exploration and exploitation and improve the efficiency of the algorithm in finding high-quality solutions to complex optimization problems.
- Performance results of the MOAHOA-SA approach obtains better results than other optimization algorithms when simulated on random and grid based deployment scenarios.

The remaining article is structured as follows: section 2 reviewed the recent works of optimization algorithms in the domain of WSN. Section 3 explains the proposed methodology in detail. Section 4 presents the performance comparison results of proposed and existing approaches. The overall conclusion is summarized in Section 5.

2. Related Works

Several recent works carried out in the domain of WSN using optimization algorithms for avoiding network problems are discussed as follows:

Studying optimization problems in WSN can lead to improvements in network coverage, reduced sensor node interference, lower energy consumption, extended network lifetime, and improved overall connectivity. To achieve these objectives, various traditional algorithms such as GA Gupta et al. [14], Improved GA (IGA) Harizan and Kuila [15], PSOThiagarajan [16], Improved ABC (IABC) Yue et al. [17], Gravitational Search Algorithm (GSA) Shivalingegowda and Jayasree [18], multi-objective randomized Grasshopper Optimization Algorithm-based Selective Activation (MORGOA-SA) Jebi and Baulkani [19] and, Biogeography Based Optimization (BBO) Naik and Shetty [20] have been employed to improve the efficiency of WSNs. Zhang et al. [21], presented a combination of Grey Wolf Optimization (GWO) with the SA algorithm (SA-GWO) to overcome the drawbacks of the GWO algorithm, which can suffer from slow convergence and premature convergence, leading to suboptimal solutions. Simulation results shows promising results in optimizing the coverage of WSN. However, the hybrid algorithm may still suffer from premature convergence in some cases (i.e., it may converge to a suboptimal solution before finding the global optimal solution). Whereas in another authors Deepa and Venkataraman et al. [22], introduced a combination of Whale Optimization Algorithm (WOA) with the Levy Flight technique (LWOA) to optimize the coverage of WSN. This approach aims to overcome some of the limitations of traditional optimization algorithms by introducing a more efficient search strategy that mimics the behaviour of the Levy Flight pattern, which is known to improve exploration capabilities in search processes. The experimental results showed that the LWOA approach achieved better coverage with a lower number of sensors compared to the other algorithms. However, this method has high computational complexity thus leads to more challenging to find optimal solutions.

Furthermore, Wei et al. [23] developed a Simplified Slime Mould Algorithm (SSMA) for optimizing the coverage of WSN. The SSMA algorithm is designed to simulate the foraging behaviour of the slime mould, which involves finding the shortest path between food sources. One of the advantages of the SSMA approach is that it is able to provide a more efficient solution for the WSN coverage optimization problem. This is achieved by utilizing the slime mould's foraging behaviour, which enables the algorithm to efficiently explore and exploit the search space to find the optimal sensor placement. But SSMA algorithm has improper parameter settings thus leads to suboptimal solutions or slow convergence. Another author Jiao et al. [24], developed a new approach to optimize the coverage of WSN with random deployment using an improved version of the Flower Pollination Algorithm (FPA). The improved FPA algorithm is designed to simulate the pollination behaviour of flowers, which involves exchanging information between different flowers to improve their reproductive success. The FPA approach has the advantage of being able to balance target coverage and energy consumption. However, FPA approach may not be able to provide diverse solutions, as the algorithm tends to converge towards a single optimal solution. This may limit the algorithm stability to explore the search space and find alternative solutions.

From the overall reviewed articles, it has been concluded that the existing methods suffers from (a) Absence of diversity: existing optimization algorithms tend to converge towards a single optimal solution, which can limit their ability to explore the search space and find alternative solutions. This may result to high complexity to solve the optimization problems; (b) uncertainty and variability: WSNs are subject to environmental uncertainties and variability, which can make it challenging to develop optimization models that accurately capture the network behaviour. This can lead to unreliable solutions. These leads to increased energy consumption, high interference and coverage issues to exchange data between nodes in WSN. Hence, there is a need to develop an improved optimization algorithm for addressing these concerns in WSN.

3. Proposed MOAHOA-SA based Active Selection Method

In this paper, we proposed an active selection method namely MOAHOA-SAto reduce the number of active nodes, resulting in an optimised solution with maximum target coverage and connectivity and minimal interference in WSN.

Consider that the sensor nodesin the targetnetwork area of the WSN are used to monitor it either periodically or continuously. The network assumptions are taken from paper [19].

3.1 Derivation of Fitness Function

The proposed work used six derivatives to evaluate the fitness function, as some of the objective functions were mathematically described and taken fromthe paper [19]. First five objective such as Coverage maximization, Ensuring connectivity, Coverage overlap minimization, High residual energy node selection and Active sensor nodes minimization are taken from that paper.

Objective 6: Interference minimization

In a WSN, multiple sensor nodes are deployed in a target area to perform sensing tasks. When multiple nodes sense the same phenomenon at the same time and location, they may interfere with each other and produce inaccurate or inconsistent readings. Sensing Interference Ratio (SIR) is a metric used in WSN to measure the level of interference between sensor nodes during sensing operations. SIR measures the level of interference caused by the simultaneous sensing of multiple nodes in the network.

SIR is defined as the ratio of the average power of the desired signal (i.e., the sensed phenomenon) to the average power of the interfering signals (i.e., signals from other nodes sensing the same phenomenon). A high SIR value indicates low interference and high accuracy in sensing, while a low SIR value indicates high interference and low accuracy. Therefore, minimizing interference among sensor nodes is an essential design consideration in WSNs to achieve reliable and accurate sensing. The underlying formula to minimize the SIR is expressed as follows:

$$MAX\ f_6' = 1 - \frac{1}{l} \sum_{m=1}^{l} \sum_{n=m+1}^{l} \delta_{mn} \qquad (1)$$

$$\text{OR } MIN\ f_6' = \frac{1}{l} \sum_{m=1}^{l} \sum_{n=m+1}^{l} \delta_{mn} \qquad (2)$$

where δ_{mn} is the sensing interference, and l represents the number of positions selected for deploying sensor nodes.

Thus the fitness function is estimated by the equation (3):

$$Fitness = MAX\left(W_1, f_1' + W_2 f_2' + W_4 f_4' + W_6 f_6'\right) + MIN\left(W_3 f_3' + W_5 f_5' + W_6 f_6'\right) \qquad (3)$$

where the weight values (W_1, W_2, W_3, W_4, W_5 and W_6), are determined through multiple rounds of testing with various combinations of weight values. The condition for these weight values is that their sum must equal one (i.e. $W_1 + W_2 + W_3 + W_4 + W_5 + W_6 = 1$).

3.2 Multi-Objective Adaptability HOA Approach

HOA is a meta-heuristic algorithm [25] which is capable of effectively addressing both simple and complex single-objective high-dimensional problems. The HOA algorithm offers several benefits in terms of exploration and exploitation, enabling it to identify the optimal solution for even the most complicated problems. The optimization is done by using three phases: movement phase (i.e updating the position of the horses based on their current position and the positions of other horses), interaction phase (i.e, updating the fitness values of the horses based on their new positions) and final phase (i.e., the best solution in the population is identified, and the algorithm returns it as the solution to the optimization problem) based on the behaviour of horses. Here, the horse position (deployment of sensor nodes) in the intelligence represents the best solution (i.e., selective active nodes with low interference in sensing and best connectivity and coverage). In HOA, adaptability, which refers to how the behaviour of the horse herd changes or adapts. This term describe the ability of the herd to detect and respond to changes in the WSN environment. The MOAHOA-SA scheme flowchart is shown in the Figure 1.

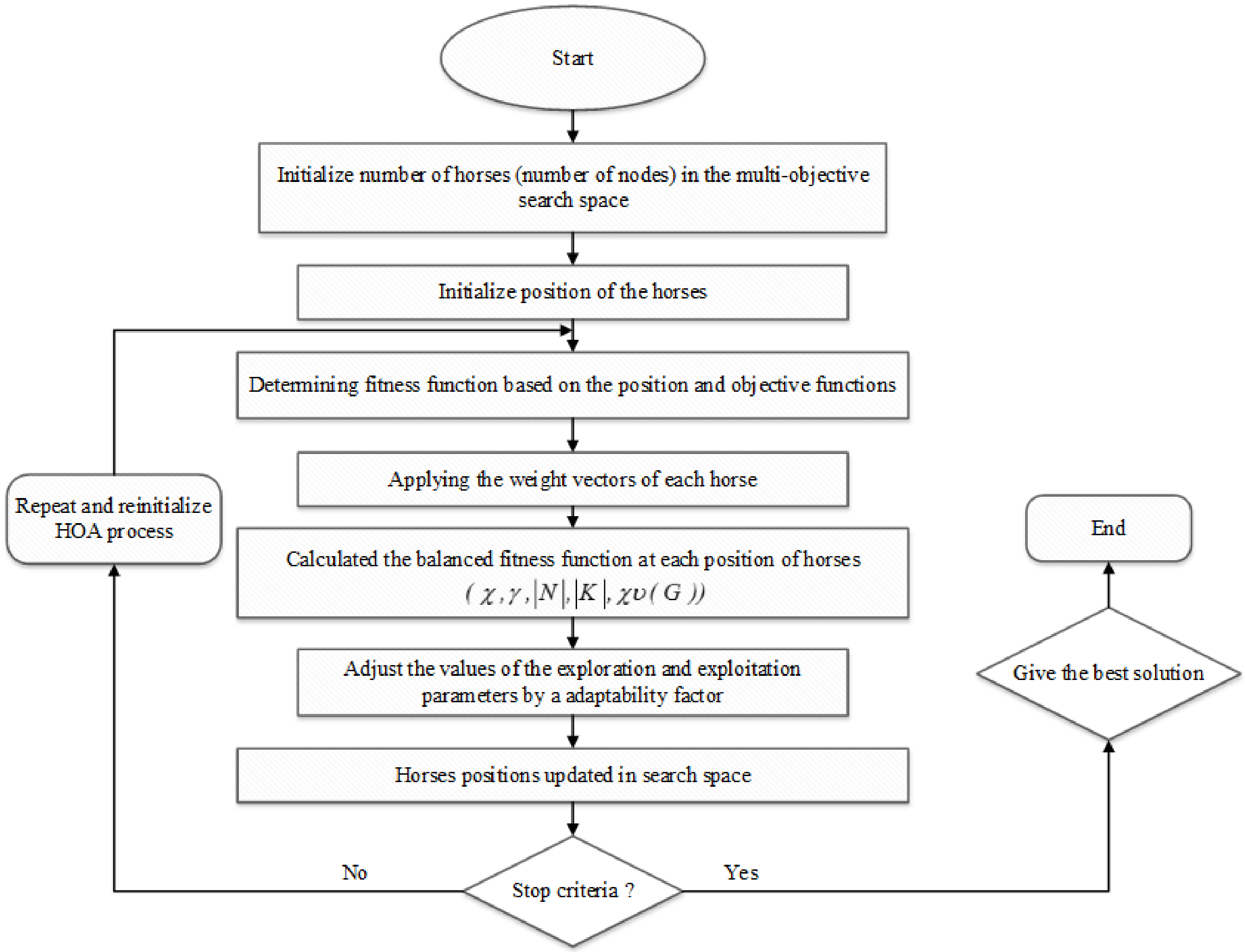


Figure 1: Flowchart of the MOAHOA-SA method

Mathematically, a minimization problem can be used to describe a multi-objective optimization problem given by:

$$\begin{aligned} &MIN \quad : f_O(x), \qquad o=1,2,....,O \\ &Subject : g_c(x) \geq 0, \quad c=1,2,....,C \\ &H_e(x)=0, \qquad e=1,2,.......,E \\ &B_i \leq x_i \leq D_i, n \quad i=1,2,.......,n \end{aligned} \tag{4}$$

where the number of objectives is denoted by O, the number of limiting inequalities is denoted by C, the number of limiting equalities is denoted by E, and $[B_i, D_i]$ denotes the boundaries of the i^{th} variable.

A general objective function with a weight vector based on Equation (5) is used by the AHOA algorithm to search the multi-objective search space. The objective function combines the objectives of each horse into a single objective represented by O, allowing the algorithm to identify the relationship between horses, given by:

$$W(x_i) = \frac{1}{O}\sum_{j=1}^{O} w_i(x_i) \tag{5}$$

The probability of selecting an objective from a set of objectives can be determined by Equation (6).

$$P_i = {}^{1}\!/_{T_i} \tag{6}$$

where the total number of neighbourhoods for the i^{th} solution is indicated by T_i.

The Equation (7) is utilized as a multi-objective function for selecting active node features. However, simply minimizing the number of active node features leads to an optimized solution. As such, a specific threshold value exists for each objective, which varies depending on the given problem. Consequently, achieving an appropriate balance between the objectives is necessary. Hence, the balanced fitness function is expressed as:

$$F = \chi\upsilon(G) + \gamma\frac{|K|}{|N|} \tag{7}$$

where the active features within the PoI are quantified by the value $|N|, |K|$ indicates the node selection for multi-linearity, $\chi\upsilon(G)$ denotes the leadership coefficient and, χ and γ describes the significance of network quality and node subset length, respectively.

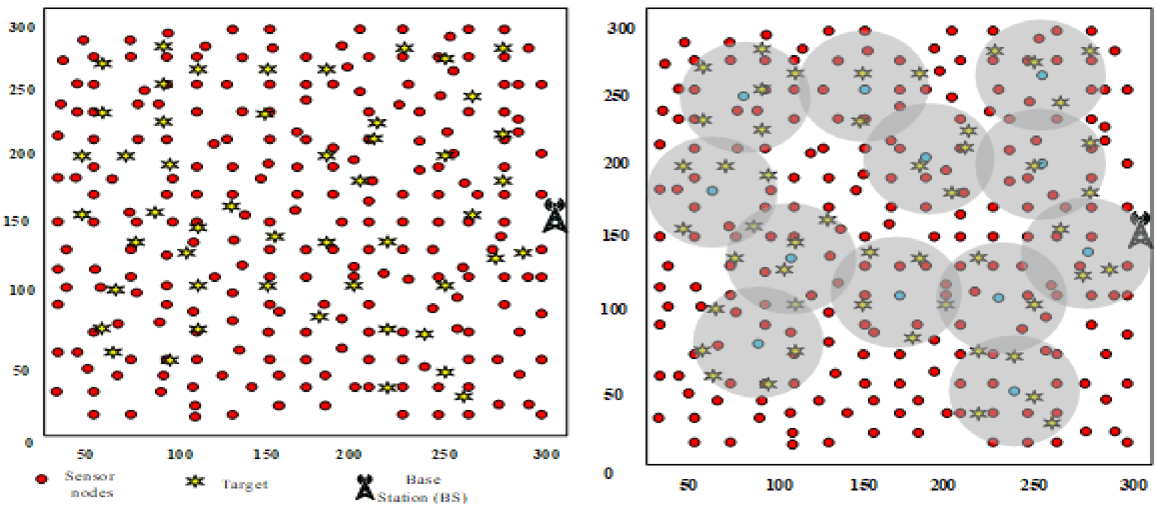
The adaptability equation in HOA is used to adjust the values of the exploration and exploitation parameters based on the current state of the optimization process. The adaptability equation in HOA is given by:

$$\alpha = 2 - I_C \cdot (2/I_{max}) \tag{8}$$

where α is the adaptability factor, I_c is the current iteration or generation number, and I_{max} is the maximum number of iterations or generations. The adaptability factor α is used to adjust the values of the exploration and exploitation parameters in the algorithm. These parameters include the leadership coefficient, which control the movement of the horses in the search space. In light of the current stage of the optimization process, the adaptability equation in HOA enables the algorithm to dynamically change the ratio of exploration to exploitation. This helps to avoid premature convergence and improve the efficiency and effectiveness of the algorithm in solving difficult optimization issues with best solution.

4. Experimental Results and Analysis

This section examines the criteria for assessing network efficiency results, comparing them with existing models to demonstrate the improvement achieved by MOAHOA-SA approach. The subsequent sub-sections provide an analysis of the simulation setup, evaluation metrics, and performance comparison results. The simulation parameters were taken from the paper [19]. The illustrative diagram for two scenarios are shown in Figures 2 and 3.



(a) (b)

Figure 2: Scenario 1: (a) Random deployment of nodes and target points; (b) Selective active nodes using MOAHOA-SA approach

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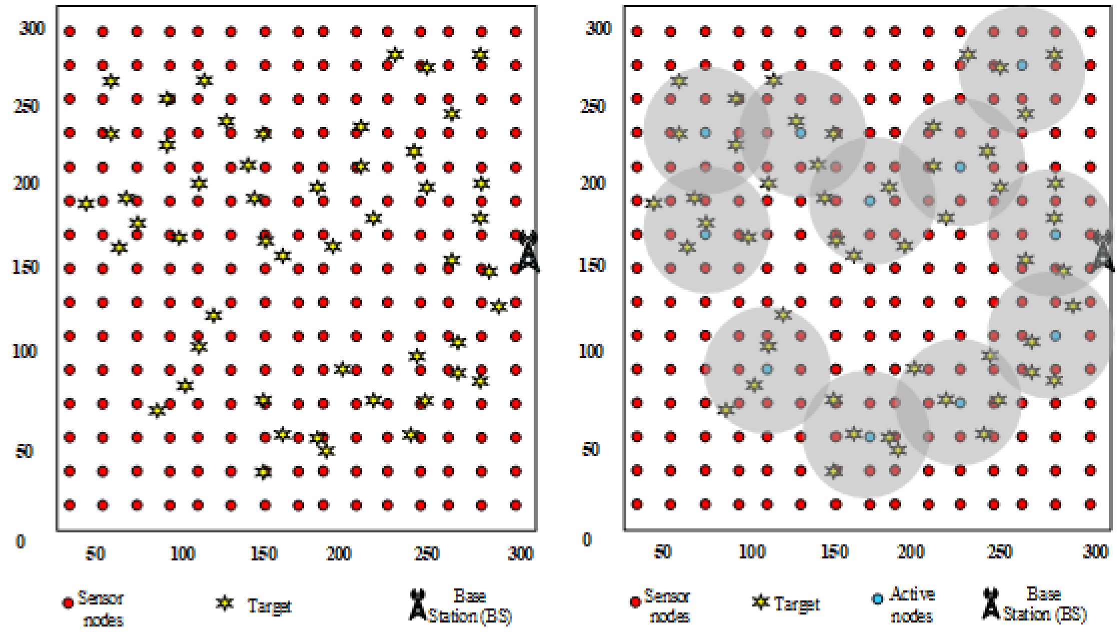
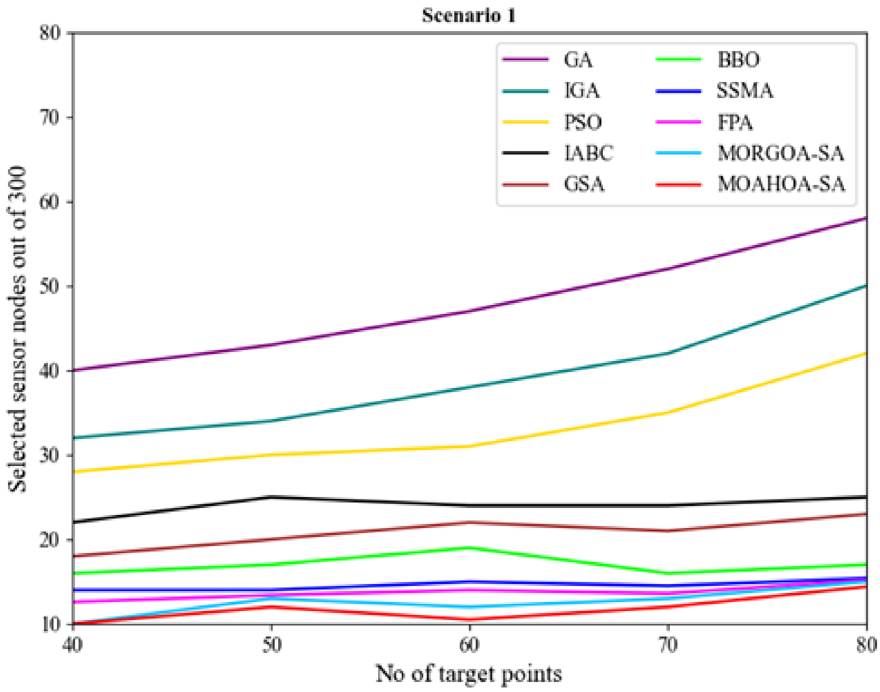


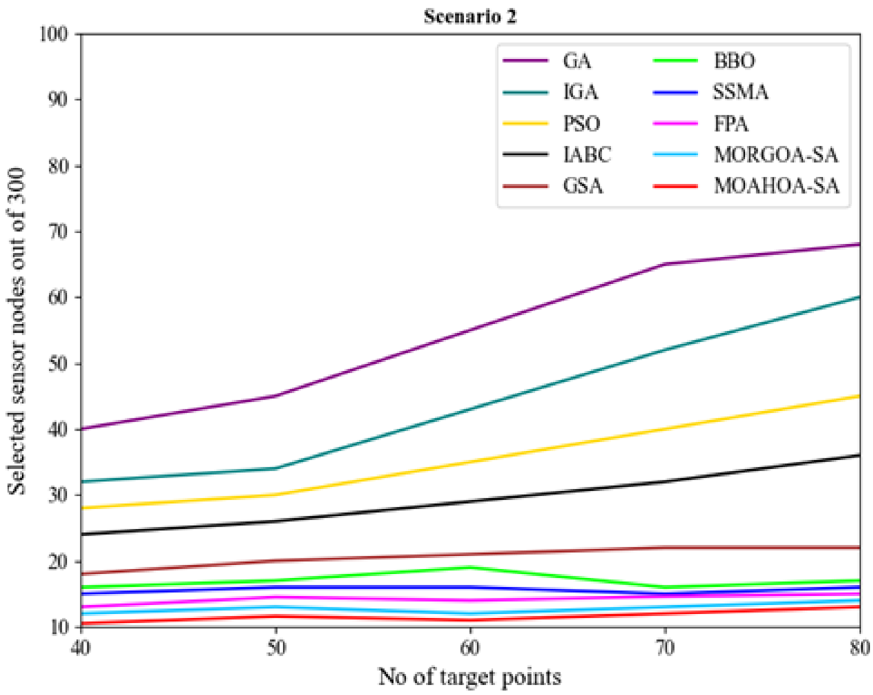
Figure 3: Scenario 2: (a) Grid based deployment of nodes and target points; (b) Selective active nodes using MOAHOA-SA approach

4.1 Performance Comparison Results

The performance of the MOAHOA-SA approach is compared with existing optimization methods such as GA [14], IGA [15], PSO [16], IABC [17], GSA [18], BBO [20], SSMA [23], FPA [24], and MORGOA-SA [19] in terms of varying active nodes under two scenarios.



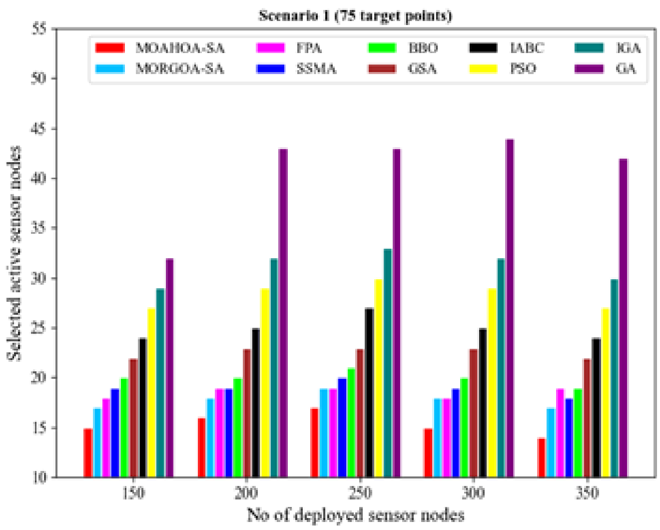
(a) Scenario 1



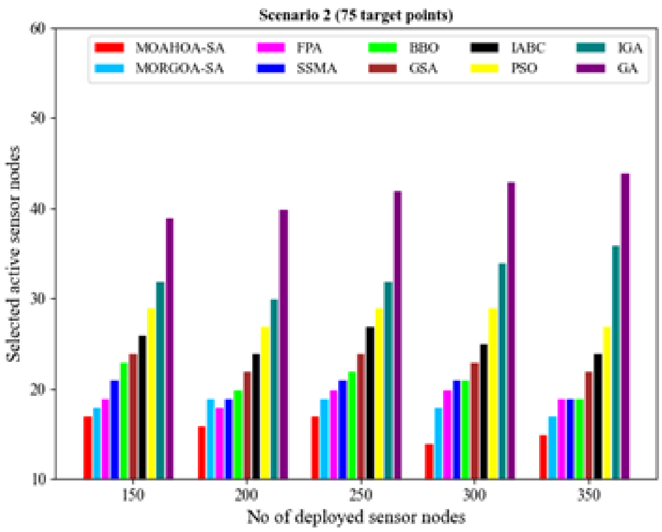
(b) Scenario 2

Figure 4 (a) and (b): Performance results of active nodes versus target points for both scenarios

The Figures 4 (a) and 4 (b) shows the results of the activation obtained from two scenarios using the MOAHOA-SA method and existing methods. As the number of targets varied from 40 to 80, the MOAHOA-SA approach achieves lower selection of active nodes out of 300 nodes. According to the target point 40, the nodes has been selected constant as the plotted points are gradually decreased. For target point 80, the selected active nodes are gradually increased but still performing good selective activation than other methods. From the overall observed results, the existing optimization methods activate a greater number of sensors (ranging from 15 to 40), shown in Figure 4 (a) and (b). Thus the MOAHOA-SA technique maintains high coverage and connectivity by reducing the number of activated sensors at the PoI.



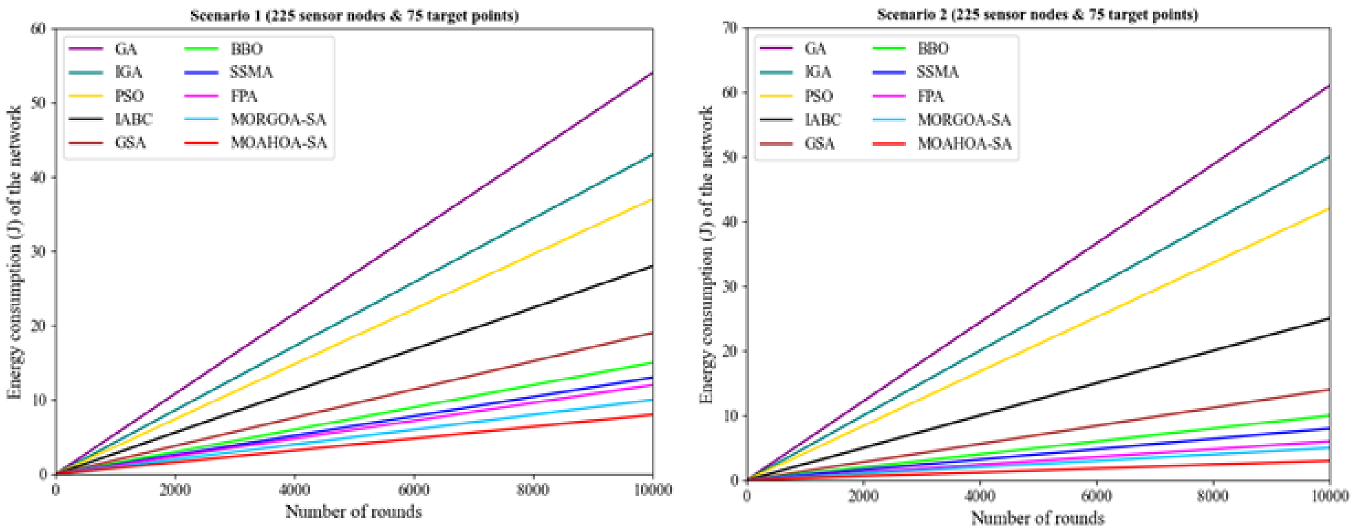
(a) Scenario 1



(b) Scenario 2

Figure 5 (a) and (b): Performance results of active sensor nodes versus deployed nodes for both scenarios

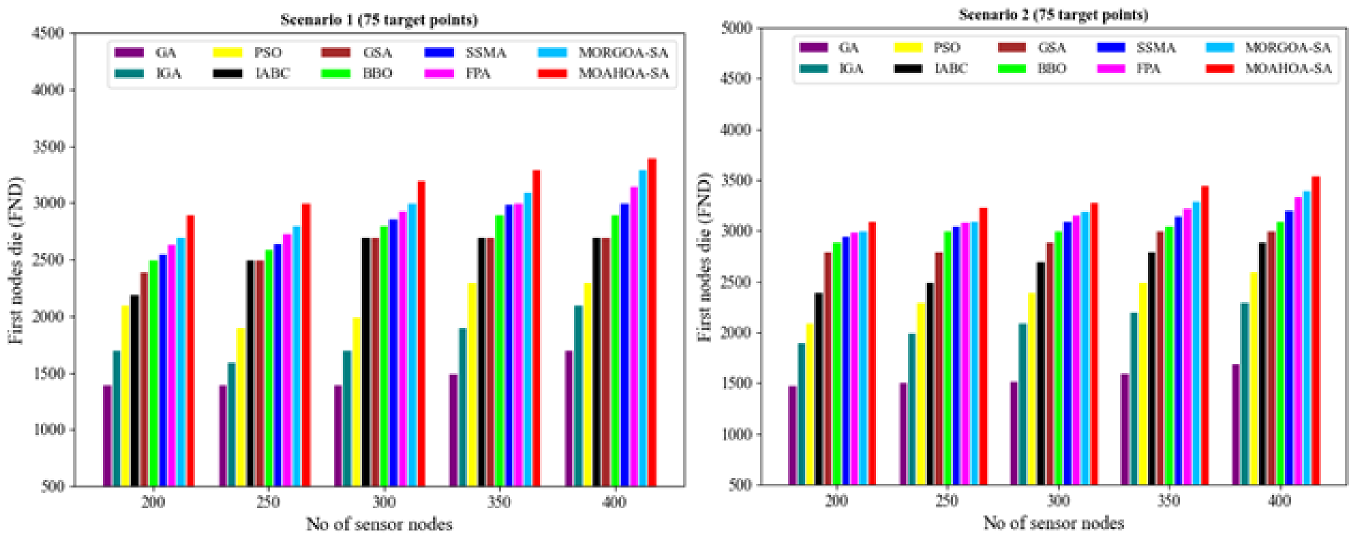
As the deployment nodes varied from 150 to 350, the MOAHOA-SA method achieves lower selected active nodes when the target point is 75, shown in Figures 5 (a) and 5 (b). When sensor node is deployed to 250, the selected active nodes are only 17 than other optimization methods. Existing methods activate the selected nodes in the range of 20 to 30 sensors. Hence findings reduced the number of selected active nodes for both scenarios.



(a) Scenario 1 **(b) Scenario 2**

Figure 6 (a) and (b): Performance results of energy consumption for both scenarios

Consider the number of deployment nodes is 255 and target point is 75 for both scenarios. According to the number of rounds varied from 0 to 10000, lower energy consumption is achieved by using MOAHOA-SA approach, is shown in the Figures 6 (a) and 6 (b). This can be attributed to the MOAHOA-SA algorithm's ability to activate fewer nodes while maintaining maximum coverage and connectivity. It is also evident that activating fewer sensors consumes less energy than larger number of sensors for both scenarios. Thus the MOAHOA-SA approach minimizes the number of rounds required to complete the sensing task (i.e., consumes less energy) while ensuring that the data is accurately collected and transmitted.



(a) Scenario 1 **(b) Scenario 2**

Figure 7 (a) and (b): Performance results of connectivity for both scenarios

Figures 7(a) and (b) show the number of nodes that die in relation to the number of rounds for both scenarios. As the number of nodes varied from 200 to 400, the deployed nodes took more time to die for the MOAHOA-SA approach when the target point was 75, where the FND metric is measured in seconds. Communication is interrupted when the first sensor loses power. When every sensor is operational, the network is most connected. Connectivity is determined by how long it takes for the first sensor to die because if a lot of sensors die rapidly, there won't be any nearby sensors to transmit packets. The number of rounds required for the first node to perish also rises as the number of nodes increases. In comparison to other optimization schemes, the MOAHOA-SA scheme under consideration requires more rounds before the first sensor expires. Scalability refers to the MOAHOA-ability SA's ability to function effectively even as the WSN changes over time and obtains greater performance than other optimization algorithms, as shown in Figures 7(a) and 7(b).

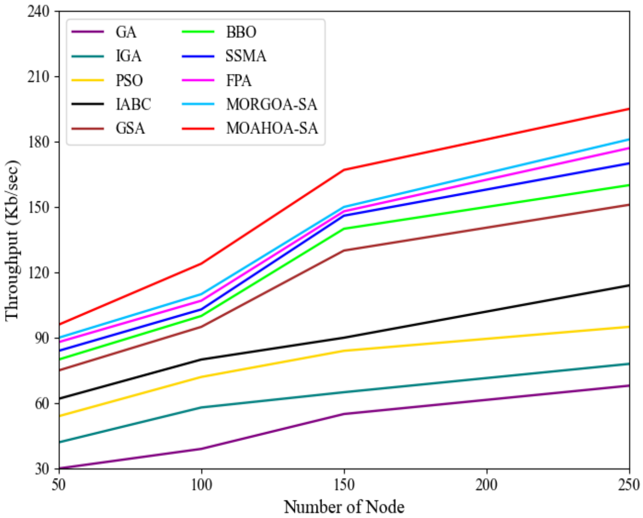


Figure 8: Performance results of throughput

As the number of nodes increased from 50 to 250, the MOAHOA-SA approach obtains higher throughput than other optimization methods, is shown in Figure 8. Overall, increasing the throughput in a WSN using MOAHOA-SA optimization of coverage and connectivity parameters to achieve a balance between the network performance metrics such as energy efficiency and reliability. From the plotted results, the MOAHOA-SA algorithm has highest throughput of 195 kb/sec than other optimization methods. Throughput increases as a result of the MOAHOA-SA algorithm choosing the best routing route with less selective active nodes.

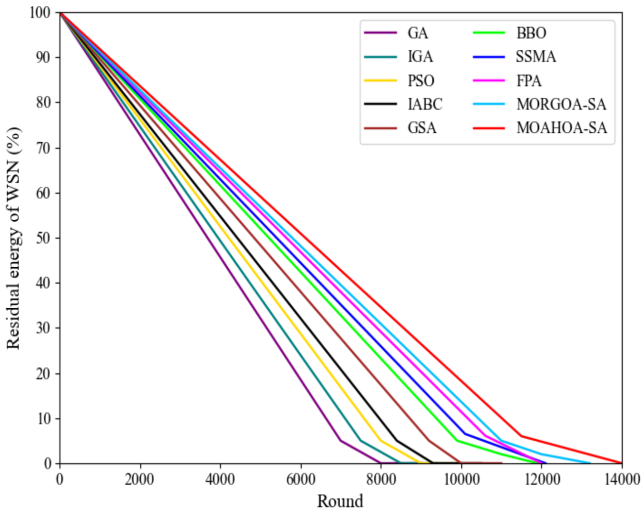


Figure 9: Performance results of residual energy

The analysis of residual energy is shown in Figure 9. Comparing the MOAHOA-SA approach and existing optimization methods, it has the greatest residual energy. After 14,000 cycles, the MOAHOA-SA algorithm-controlled network runs out of remaining energy. However, after 8,000 cycles, the MORGOA-SA algorithm-controlled network exhausts its remaining energy. Hence the MOAHOA-SA approach achieves high residual energy thus reducing coverage overlap and turning off idle nodes in WSN.

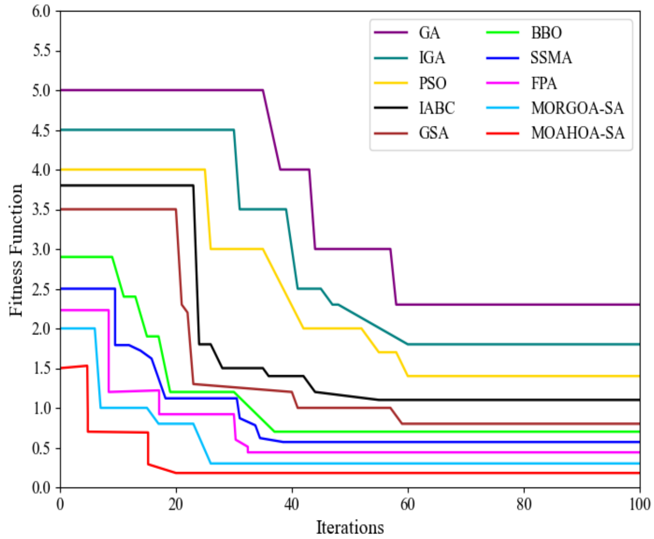


Figure 10: Performance results of convergence

The findings of the convergence analysis are shown in Figure 10. The rate of convergence for MOAHOA-SA method is performed by improved fitness functions and other methods was examined by the same fitness function. The findings indicate that even when using the improved fitness function, the MOAHOA-SA method has a faster rate of convergence than the other optimization methods. The MOAHOA-SA approach outperforms other algorithms in terms of improved fitness value.

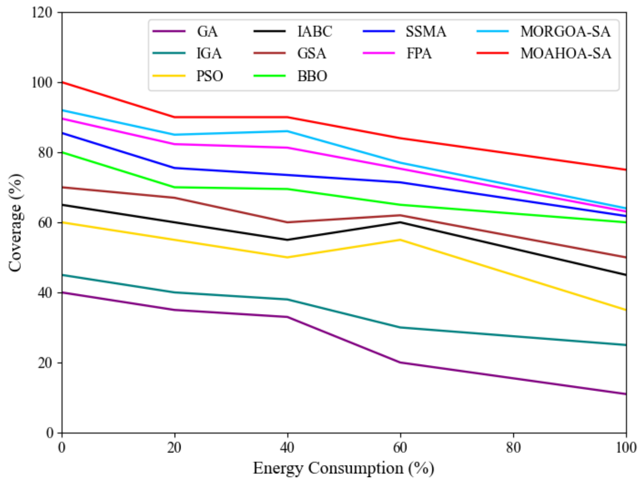


Figure 11: Performance results of energy consumption versus coverage in percentage

Figure 11 compares the MOAHOA-SA method to recent optimization methods. According to the findings, the MOAHOA-SA method improves target coverage when energy consumption is low. This is because the MOAHOA-SA algorithm only activates the sensors that minimize coverage overlap, providing a larger coverage area than the existing approaches.

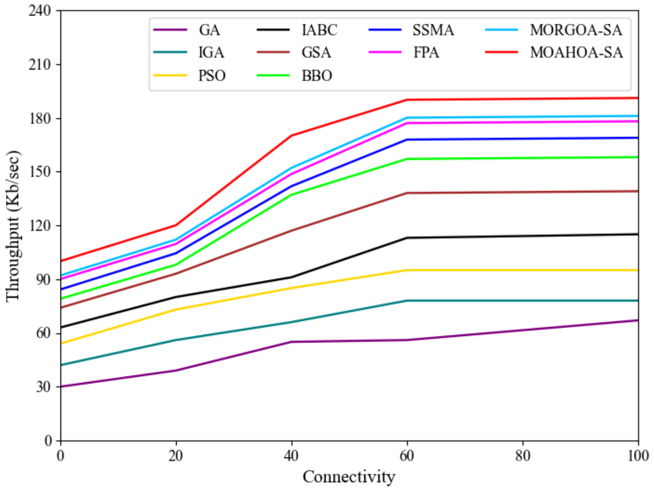


Figure 12: Performance results of throughput versus connectivity

Results for the MOAHOA-SA method are displayed in Figure 12 as throughput verses network connectivity in percentage. According to the results, better network connectivity results in greater throughput. Comparing the MOAHOA-SA algorithm to the existing optimization methods reveals that it has a better throughput. This is because the MOAHOA-SA method achieves high throughput by selectively activating sensors with optimal connectivity and delivering data through the shortest path.

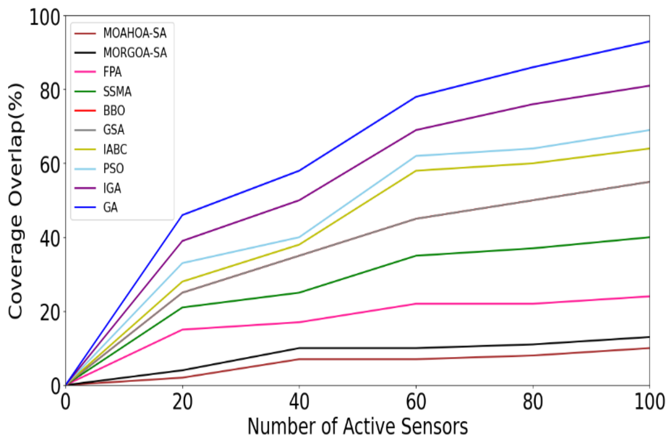


Figure 13: Performance results of coverage overlap versus active sensors

Figure 13 shows the coverage overlap for the MOAHOA-SA and existing optimization methods as the number of active sensors varied from 0 to 100. The coverage overlap of the MOAHOA-SA algorithm is considerably smaller than that of other optimization techniques. When 100 sensors are active, the MOAHOA-SA algorithm only has a 10 % coverage overlap, as compared to the 13 % overlap of the MORGOA-SA method, according to the findings that have been observed in Figure 13. This is due to the MOAHOA-SA method's ability to carefully activate the necessary sensors, which minimizes coverage overlap.

5. Conclusion

Network optimization have become a major problem in WSN, as these types of coverage, connectivity and interference factors consumes more energy, lower network lifetime, high interference and coverage issues to exchange data between nodes. For this purpose, an optimal MOAHOA-SA scheme is proposed with maximum target coverage and connectivity and minimum interference while reducing the selective active nodes leads to an optimized solution in WSN. An improved fitness function is formulated for MOAHOA-SA scheme and weight vector with adaptability factor for solving highly complex optimization problems. Experimental results are conducted to evaluate the performance of various metrics on both grid and random scenarios. In addition, a comparison between the MOAHOA-SA scheme and other optimization schemes was carried out, which confirmed its superiority over them with respect to minimizing energy loss caused by interference. Furthermore, MOAHOA-SA demonstrated better performance in terms of achieving high coverage, high connectivity, and low interference ratio than other optimization schemes.

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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.