SSRG International Journal of Electronics and Communication Engineering
ISSN: 2348-8549/ https://doi.org/10.14445/23488549/IJECE-V12I8P103

Volume 12 Issue 8, 22-39, August 2025

Original Article

Genetic Algorithm-Based Coverage Maximization and Connectivity Preserving Approach using Computational Geometry for 3-Dimensional Directional Sensor Networks

Sharmila Devi[1], Anju Sangwan[2]

[1,2]*Department of Computer Science and Engineering, Guru Jambheshwar University of Science and Technology, Hisar, India.*

[1]*Corresponding Author : shar02chahal@gmail.com*

Received: 02 June 2025 Revised: 03 July 2025 Accepted: 03 August 2025 Published: 30 August 2025

Abstract *- Directional Sensor Networks (DSNs) are a vital advancement in sensor technology, offering targeted, efficient and precise data collection as compared to traditional omnidirectional sensors. Sensing area overlapping problem in DSNs arises due to factors such as improper sensor placement, environmental changes, fixed orientations and high sensor density. This problem results in inefficiencies in data collection, energy consumption and communication. Optimizing sensor orientation can help mitigate these issues and improve overall network performance. This paper presents a three-dimensional mathematical model designed to detect various overlapping types among sensor nodes in the DSNs using Computational Geometry. The proposed model aims to optimize the sensing coverage area, mainly applied in fields where coverage is a primary concern, such as with cameras or infrared detectors. Coverage overlap can lead to redundant data collection, unnecessary energy depletion and potential communication interference; all these factors can significantly affect the network's overall efficiency. A Genetic Algorithm (GA)-based approach has been introduced for maximizing area coverage. By selecting the most effective cover set from numerous possible combinations, the approach emphasizes directional sensing while minimizing coverage overlap. A fitness function is developed to assess the degree of overlap and maximize the covered area to reduce coverage overlap. Comprehensive simulations have been carried out to validate the efficiency of our proposed method. Results indicate that the degree of overlap decreases and the coverage fraction improves as the algorithm iterates through more generations. Moreover, the proposed GA-based optimization method outperforms existing state-of-the-art approaches.*

Keywords *- Directional Sensor Network, Genetic Algorithm, Computational geometry, Angle of view, Coverage maximization, Connectivity preservation.*

1. Introduction

In the past few years, coverage optimization has been the main research area in Wireless Sensor Networks (WSNs). WSNs are generally divided into two kinds of models, i.e., omnidirectional models and directional models. The use of omnidirectional sensor networks makes the process of data collection from the surroundings very easy, especially in areas such as humidity, temperature, and forest fires. Under the complicated and varying environmental conditions, Directional Sensor Networks (DSNs) have emerged with [1] powerful communication and management capabilities. In the case of omnidirectional sensors, the sensing field is a complete sphere with radius 'r', while in the case of a directional model, the sensor has a fixed angle of view. In DSNs, every sensor can rotate about its axis with a limited angle of sensing range, i.e. work in a specified direction [2]. Due to their lower energy consumption and rotation flexibility, DSNs have become an important field of research. In addition, each sensor possesses the capability to alter its sensing direction and subsequently communicate with other directional sensors in the network [3]. Due to the distinctive qualities of DSNs, like rotatable sensing direction and limited sensing range, certain challenges are envisaged, such as coverage and energy optimization. Coverage of sensors reflects the capability of how effectively the defined region is observed by sensors, which is a very basic issue in WSNs [4]. In random deployment scenarios, a directional sensor's detection range is determined by its position, sensing radius and orientation angle, and all these factors define the sensor's Angle Of View (AOV). Coverage issues can be divided into three types depending on the nature of the target: barrier coverage, target coverage and area coverage. The main impetus of area coverage is on the challenge of monitoring many points within a specified region. Its purpose is to enhance coverage with a minimum number of sensors so that the whole area is covered completely. Target coverage focuses on monitoring specific, limited points inside a defined region. Barrier coverage aims to minimize the risk of unauthorized intrusion by detecting potential invaders attempting to breach a secure perimeter. Despite the increasing interest in DSNs due to their energy efficiency and targeted monitoring capabilities, several challenges remain insufficiently explored.

Methods for detecting overlapping sensing regions and strategies for optimizing sensor nodes' movement to minimize such overlap have received limited attention. Most existing solutions rely on heuristics or simplified models, which often result in inaccurate coverage estimations in complex environments. Although Computational Geometry offers a promising avenue for accurately and efficiently identifying overlapping areas within DSNs, its application is still in its early stages. Notably, the integration of Genetic Algorithms presents a captivating approach for dynamically adjusting the orientation of directional sensors, enabling reduced overlap with minimal sensor rotation.

In this paper, a three-dimensional mathematical model is presented to characterize and analyze various scenarios in the case of overlapping sensing areas in a DSN. This model will help to understand the communication among nodes to find overlapping and rotation of working direction with some angle using Computational Geometry.

Mathematical modelling of different cases of overlapping provides a structured way to define how the sensing range of nodes intersects in each area. A Genetic Algorithm (GA)-based approach has been suggested to recognize the optimal cover set from multiple possible sets for overlapping minimization. To reduce coverage overlapping, a fitness function is designed to assess the degree of overlapping. The key offerings of this work can be outlined as mentioned below:

- A three-dimensional model is developed to identify some special cases of overlapping for DSNs. The study formulates a coverage optimization problem to maximize coverage area with minimum rotation of the sensor node's working direction using Computational Geometry.
- A coverage overlapping detection algorithm for 3D DSNs is presented to identify sensors whose coverage overlaps and suggest movement of their directional antenna.
- To find an optimal cover set from multiple possible sets for enhancing the network's coverage, GA is applied to select an optimal cover set to reduce coverage overlapping by defining chromosome, selection, crossover and mutation operators.
- Analytical derivation of coverage, connectivity and energy consumption in 3D- DSN is presented.
- Comparative performance of the proposed approach with state-of-the-art approaches is presented.
- Analytical results of the coverage are validated with the simulation results.

This paper comprises eight parts, and the rest of this paper is structured as follows: Section 2 consists of two parts, i.e. relevant literature of Computational Geometry-based two-dimensional and three-dimensional algorithms for coverage enhancement in DSNs. The metaheuristic approach-based area coverage model is highlighted in Section 3, and Section 4 describes the overlapping detection algorithm. Section 5 presents the design of GA to create a cover set for the coverage overlapping problem. Section 6 presents an analytical study, followed by a comparison of the proposed algorithm's simulation results with existing methods in Section 7. The conclusions of the study are summarized in Section 8.

2. Related Work

In the ongoing section, we are providing previous works related to coverage enhancement in DSNs. Coverage of DSNs not only depends on the location of a node but also on the direction of the angle of view. So, DSNs cannot use the solution used for standard wireless sensor networks. Adjustment of the working direction of a sensor is an effective way to improve coverage in DSNs [2-4].

2.1. Computational Geometry-Based Two-Dimensional Algorithms for Coverage Enhancement in DSNs

Research on DSNs has mostly been conducted on 2D planes. The Prioritized Geometric Area Coverage approach, which is based on Voronoi, has been proposed in [5]. This approach is used to reduce overlapping and maximize network life span. Authors in [6] proposed a distributed greedy algorithm that is based on the Voronoi Diagram. To implement this algorithm, they have used the concept of Direction Adjustable DSNs with the help of the Voronoi Diagram. They used three principles: Intra and Inter-cell Working Direction Selection and Out of Field Coverage Avoidance to select the working direction of sensors, which is based on Voronoi vertices. This algorithm removes overlapping and provides better sensing quality. A method in [7] is used for the redeployment of sensors. To improve the network coverage, the authors used the Distributed Voronoi-Based Self-Redeployment Approach (DVSA), which uses directional sensors. Their work did not use any GPS support to change the sensor's location. With the help of the Voronoi Diagram, they found the largest included angle of the Voronoi Vertex and then moved the sensor to that node. They compared their approach with other methods and proved that their work is better in coverage enhancement. Liang [8] presented two distributed greedy approaches, i.e. least overlapping area first, then updated priority with rotatable sensor to enhance coverage in DSNs. In case two sensors overlapped, they defined the intersection point and tangency point. Based on the distance between two sensors, the authors explained how to find the candidate point of rotation.

In [9], the authors proposed a coverage hole detection algorithm that is based on Delaunay Triangulation. They used the LEACH protocol for node communication. They divided their approach into Coverage Hole Detection and estimation of these holes for Wireless Underground Sensor Networks. Basically, the authors have provided a mathematical model that saves energy and finds all existing coverage holes in each region of interest. The work in [10] projected a concept of sensing connected subgraph for DSNs to improve the coverage of a given area. In this approach, the sensing area is partitioned into different groups using a sensing-connected subgraph. A multi-layered convex hull is formed for every sensing-connected subgraph, and then they rotated the sensing direction of directional nodes. Their work provided a reduced overlap in a two-dimensional sensing network. Authors in [11] considered the problem of connectivity of directional antennas in wireless sensor networks. They considered the beam width ϕ and radius r to study the problem of connectivity in WSNs. They further provided an approximate algorithm for a different range of ϕ and fixed r to achieve connectivity. However, there are still some coverage holes that can only be tackled through node movement as proposed by the authors in [12]. They developed a system for event monitoring to cover targets that projected a concentrated coverage distribution heuristic repetition to deploy sensor nodes. To enable efficient deployment, it is necessary to consider that a sensor's position can be repositioned to eliminate coverage holes in the designated area. Authors in [13] suggested two-stage node deployment schemes for static and mobile sensor nodes to reduce total network cost. They used an enhanced particle swarm algorithm to determine the effective working direction of a static directional sensor. In the case of mobile nodes, they used the Sparrow search algorithm to optimize energy. The study in [14] introduced a cluster-based greedy algorithm for heterogeneous DSNs, where sensors are different in rotation speed, radius and field of view. By prioritizing cost-effectiveness in sensor deployment and orientation, the proposed method achieves an improvement in target coverage over traditional distributed approaches. An improved Genetic Algorithm is used in [15] to address the maximal exposure path problem in heterogeneous directional WSNs. By redefining the problem through sensing field intensity rather than traditional Euclidean metrics, they enhanced the accuracy and scalability of the solution. The proposed improved Genetic Algorithm demonstrated polynomial complexity and reliable convergence. Experimental evaluations confirmed effectiveness in optimizing coverage paths while maintaining energy efficiency and minimizing traversal distance.

2.2. Computational Geometry-based Three-Dimensional Algorithms for Coverage Enhancement in DSNs

In the existing research, most of the work is done on two-dimensional sensor networks and uses the concept of mobility; only a few papers are available that are related to three-dimensional sensor networks. In [16], the authors proposed an approach that is based on Dynamic Adjustment Optimization in three-dimensional DSNs. They enhanced network lifetime and improved coverage by using a spherical sector model. Based on an improved Voronoi Diagram, they designed the approach to adjust the direction of the sensor. Their work improves the traditional virtual force algorithm to gain node utilization and enhance network coverage. Authors in [17] presented a three-dimensional coverage model with tunable orientations in directional sensors. They used directional sensor ability and designed a rotatable three-dimensional model to describe a target-detecting scenario. This study focuses on enhancing coverage through the deployment of rotatable sensors. It applies a virtual force analysis technique to improve initial coverage following random sensor placement. For global optimization, the Simulated Annealing (SA) algorithm is being utilized. Additionally, research cited in [18] introduces a probabilistic 3D directional sensor model that overcomes limitations found in conventional virtual potential field algorithms. To optimize rotation, a coverage impact factor is calculated to discard ineffective movements and a cross-set test is implemented to detect overlaps in sensing regions. The proposed method significantly improves coverage compared to standard virtual potential field approaches and achieves better energy efficiency. In [19], deployment issues related to heterogeneous wireless DSNs are considered to optimize coverage in 3-dimensional urban terrain on uneven ground. They used two types of nodes, i.e., sensor and relay nodes, to monitor and store data, respectively. They deployed relay nodes and placed them near the sink node in a relatively small area to avoid the path loss problem. They mainly focused on relay nodes rather than sensor nodes. Modified differential evolution algorithm and polynomial-based mutation have been defined in [20]. They chose parents for crossover and mutation from the whole generation to avoid premature convergence or local optima. They used message passing interface parallelism to enhance the operation speed. For efficiency purposes, they used the fixed grouping concept and assigned variables with the same property by using an evolutionary technique. The research in [21] demonstrated that the proposed Reinforcement Learning-driven Hunter-Prey Optimization algorithm is used for coverage performance enhancement in three-dimensional underwater sensor networks. By using Q-learning with a nonlinear convergence factor, they effectively balanced exploration and exploitation phases. The addition of the Nelder-Mead simplex strategy enhanced adaptability and prevented premature convergence.

3. Meta-Heuristic Approach Based on Area Coverage

Maximizing coverage area with minimum rotation of the sensor node's working direction is an NP-complete problem [22, 23]. As a result, in recent years, researchers have focused primarily on metaheuristic-based solutions to solve these problems. Most of the traditional algorithms get stuck in the local optima trap in the early iterations and provide a solution that is far away from the optimum value. Authors in [22, 24] proposed the Particle Swarm Optimization (PSO) technique to optimize area coverage and minimize energy usage for DSNs. An area coverage optimization model was developed to enhance coverage efficiency, and a cluster head selection optimization framework was introduced. The proposed study also focuses on determining the minimum degree of overlap using a Metaheuristic Genetic Algorithm.

3.1. System Model

This section presents a three-dimensional directional sensor model designed to cover a specific region of interest. Each node is assumed to sense within its field of view, defined as a spherical sector area. The directional model illustrated in Figure 1 can be represented using four-tuples (Si(xi,yi,zi),θ,α,β,γ, r) where Si(xi, yi, zi) represents location coordinates of a nodes, 2θ is the angle of view, (α,β,γ) represent the angles formed with (x, y, z) axis respectively, r is the radius of sensing range, ϕ is the angle of sensing direction with positive x-axis, all these notations are also defined in Table 1. For simplicity in the design of DSNs, certain properties of the nodes are assumed:

- Nodes are isomorphic, i.e., every sensor is of the same radius and angle of view.
- Sensor nodes are distributed randomly across the designated area.
- The locations of all nodes are known with the help of existing Global Positioning System (GPS) technology.
- Every node can rotate in any direction.

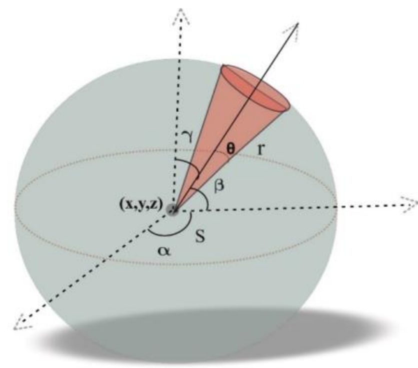


Fig. 1 Three-dimensional directional sensor model

Table 1. Notations used

Symbolization	Explanation	Symbolization	Explanation
N	Total sensor node deployed	m	Number of overlapping nodes
R	Sensing range	O_k	Degree of overlapping
M_i	Neighboring nodes	IP	Initial chromosome population
2θ	Angle of view	C_i	i^{th} chromosome
Φ	Angle of sensing direction with the positive x-axis	A(O)	Area overlap of two nodes
x, y, z	Location coordinates of a node	F_j	Fitness value of j^{th} chromosome
Ds	Distance between two nodes		

3.2. Theoretical Analysis of the Proposed Problem

When sensor nodes are deployed randomly, there may be an overlap in the sensing area of two or more sensors. Our main aim is to escalate the coverage by reducing overlaps with the help of rotation. There are different types of overlapping in the case of three-dimensional DSNs. In this research, we are considering some specific cases of overlap between two nodes, S1 and S2. To validate the problem analytically, we are suggesting five lemmas as follows.

Lemma 1: If both sensors are outside the sensing area of one another and the distance between these two sensors is r<ds<S1S1' or r<ds<S2S2', then there is an overlap.

Proof: Let two sensor nodes S1 and S2 with some overlapping area as shown in Figure 2. ϕ1, ϕ2 are the angles made by nodes S1 and S2 with the axes. The distance between two sensor nodes is ds=S1S2. To clearly understand Lemma 1, we are using Figure 3. The larger angle from (ϕ1-θ, 180-ϕ2-θ) is λ, which is selected to make an isosceles triangle and to find the distance, i.e. if ϕ1-θ>180-ϕ2-θ then λ = ϕ1-θ; otherwise λ =180-ϕ2-θ. The larger angle should be less than π/2.

S1O=S2O'=r
S1 S1'=2rcosλ
S2 S2'=2rcosλ

By implementing the Genetic Algorithm technique, the degree of overlap between sensor coverage areas can be effectively minimized, as shown in Figure 4.

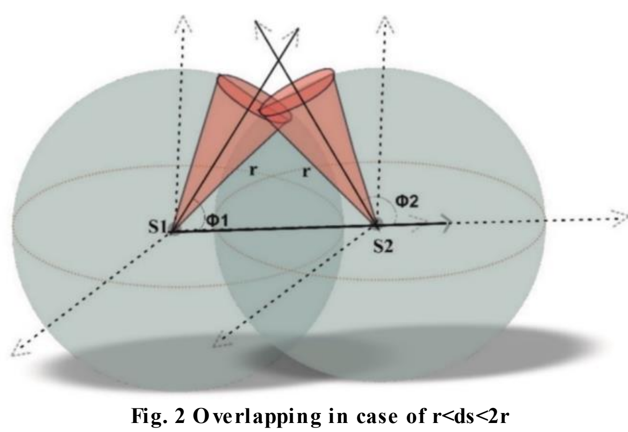


Fig. 2 Overlapping in case of r<ds<2r

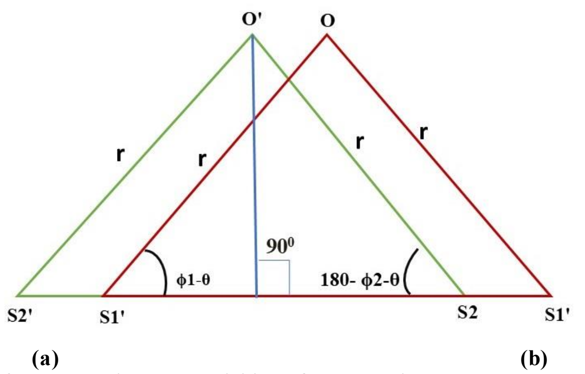


Fig. 3 Representing the possibility of overlapping when sensors are outside the sensing area of each other and r<ds<2r

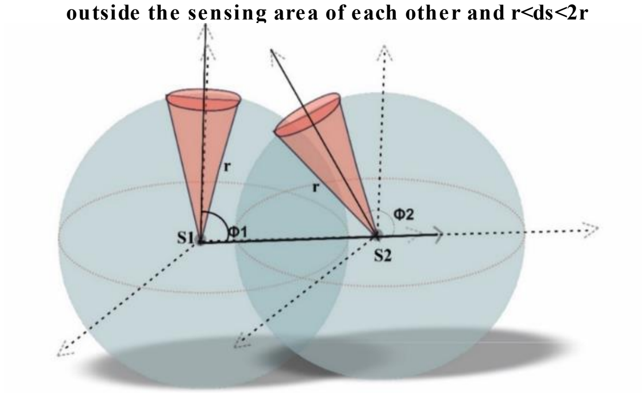


Fig. 4 Overlapping removed after rotation of node S1

Lemma 2: If both sensors are outside the sensing area of one another and the distance between them is ds>=2r, then there is no overlapping.

Proof: Let two neighbouring nodes S1 and S2, whose distance ds = 2r (this is the special case of Lemma 1 where ds=2rcos), as shown in Figure 5. Additionally, as illustrated in Figure 6, there is no overlap because there is no intersecting edge between sensors S1 and S2 when the distance between the two sensors exceeds 2r.

Lemma 3: If sensor S2 lies within the sensing range of another sensor S1, then there is an overlap.

Proof: Let sensor S2 be in the sensing area of sensor S1; there is an overlap as shown in Figure 7. To check for overlapping, we must check two conditions:

1) $\phi 1-\theta<0$ and $\phi 1+\theta>0$
2) ds<=r

Overlapping exists only if both conditions are satisfied; otherwise, there is none. Overlapping can be removed by rotating node S1 as shown in Figure 8.

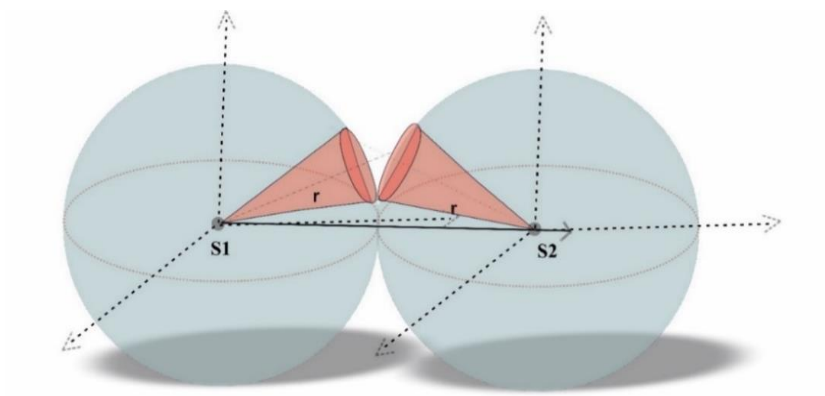


Fig. 5 No overlapping when ds=2r

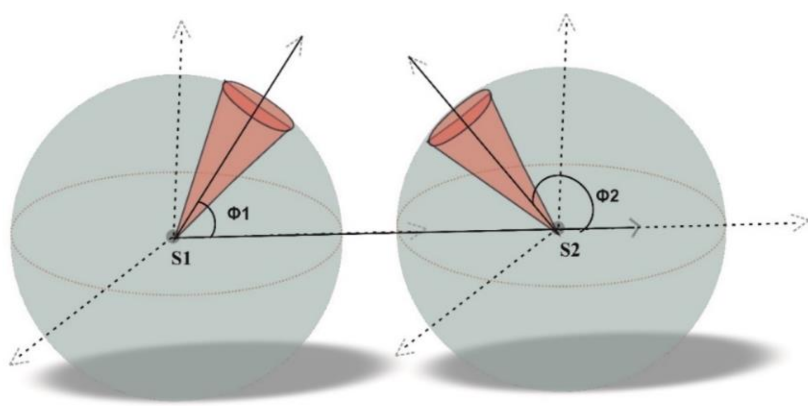


Fig. 6 No overlapping when ds>2r

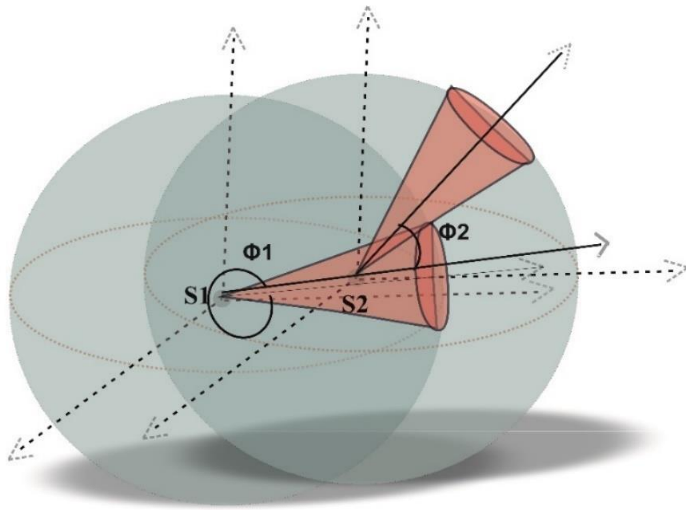


Fig. 7 Overlapping in the case where sensor S_2 is in S_1's sensing area

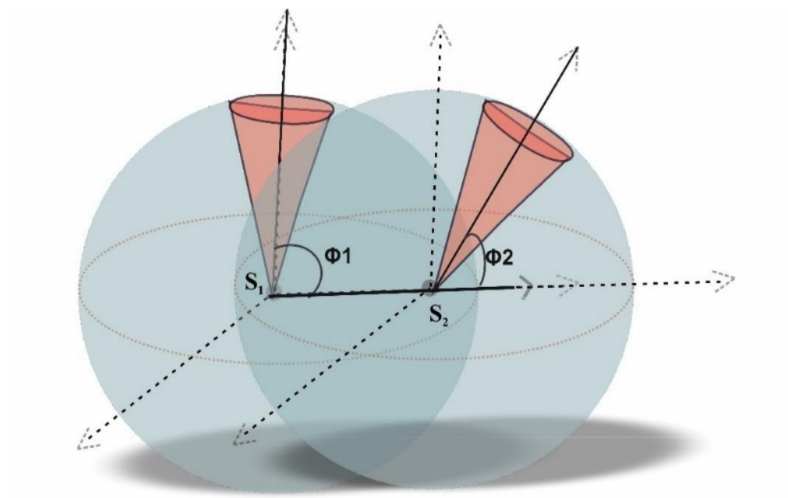


Fig. 8 Overlapping removed after rotation of node S_1.

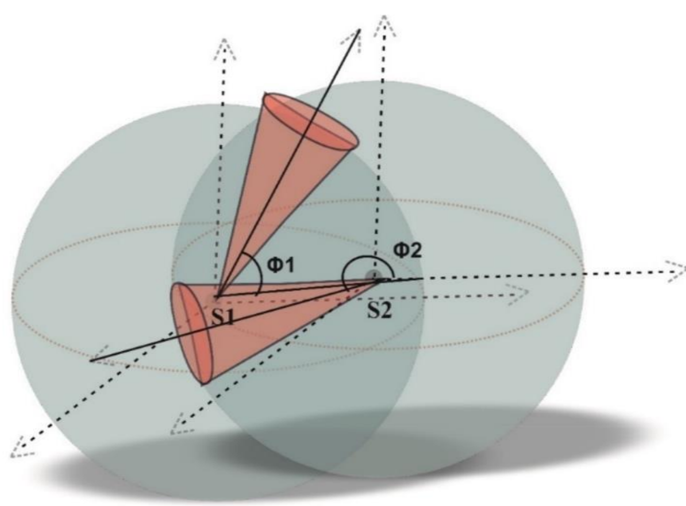


Fig. 9 Overlapping in the case where sensor S_1 is in S_2's sensing area

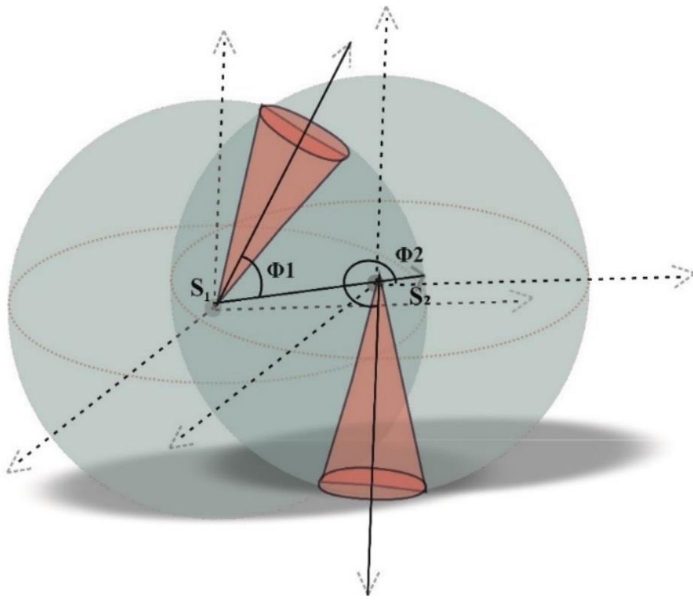


Fig. 10 Overlapping removed after rotation of node S2.

Lemma 4: When sensor S1 falls within the sensing range of sensor S2, an overlap may occur.

Proof: Assume that sensor S1 lies within the sensing range of sensor S2; there is an overlap as shown in Figure 9.

Overlapping is determined by verifying two conditions:

1) $\phi2+\theta>180$ and $\phi2-\theta<180$
2) $ds<=r$

Using the Genetic Algorithm approach, overlapping can be reduced as shown in Figure 10.

Lemma 5: If both sensors are within the sensing range of each other, then there is an overlap.

Proof: Assume that sensor S1 lies within the sensing range of sensor S2, and sensor S_2 lies within the sensing area of sensor S1; there is an overlap as shown in Figure 11. In this case, two rotations are required to remove the overlap, as shown in Figures 12 and 13.

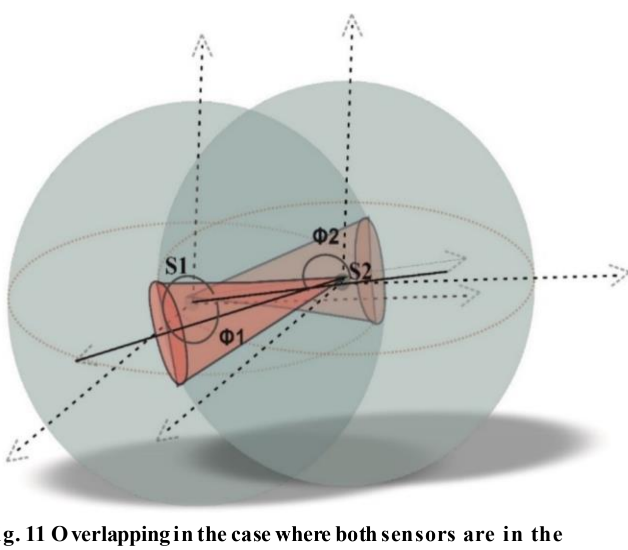


Fig. 11 Overlapping in the case where both sensors are in the sensing range of one another.

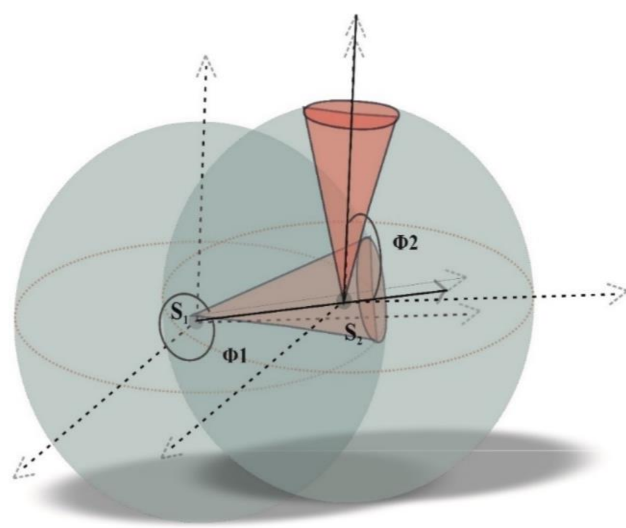


Fig. 12 Rotation of node S2 to remove partial overlapping

4. Overlapping Detection Algorithm

The first algorithm, Overlapping Detection using Computational Geometry Technique, identifies overlapping sensor nodes. A node S_i is considered the reference node, followed by the identification of its neighboring node set. Based on Euclidean distance (ds) between two sensor nodes, if ds< 2r, there may or may not be overlapping in case of directional sensors, and if ds ≥ 2r, then there is no overlapping.

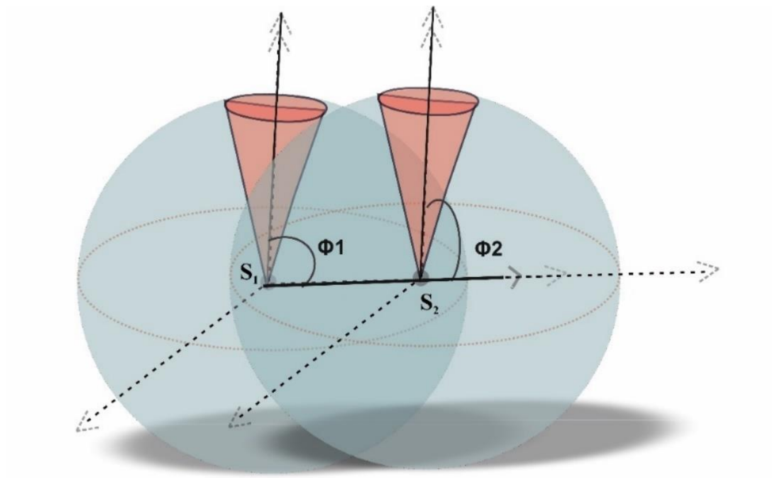


Fig. 13 Rotation of node S1 to remove overlapping

To determine the overlap between two sensor nodes, five distinct lemmas are applied as presented in Algorithm 1. After identifying the set of overlapping nodes, the Genetic Algorithm is employed to identify the minimum angle of rotation. Our primary goal is to eliminate the overlap by minimally rotating the sensing direction of the overlapping node.

5. Proposed Genetic Algorithm for Coverage Optimization Problem

The current section specifies the design of the Genetic Algorithm (GA) based coverage optimization algorithm. The proposed algorithm's design encompasses population initialization, fitness functions, selection operations and crossover. The GA identifies optimal solutions to minimize the coverage overlapping issue. This process is repeated until the desired solution is achieved. Several components of the GA will be elaborated in the following sections:

5.1. Minimum Coverage Overlapping Problem (MCP)

A total of N sensors is randomly distributed in a three-dimensional sensing environment, each initialized with identical energy levels and a uniform transmission range R. Coordinates of each sensor are presumed to be available. Two nodes v_i and v_j establish a link iff $d_{i,j} \leq r$, where $d_{i,j}$ is the distance between two nodes v_i *and* v_j. In order to achieve the required objective, a systematic and efficient method is needed to identify an optimal cover set. C_{opt} such that $C_{opt} = \{C_k \mid O_k = min(O_1, O_2, \ldots O_n)\}$

Where, C_k ε C and O_k represents the degree of overlapping of n sensors. The set of chromosomes $C = \{C_1, C_2, \ldots C_n\}$, n is the number of chromosomes, where $C_1 = \{\phi_1, \phi_2, \ldots \phi_m\}$, ϕ_i are the gene sequence holding angle value of overlapping nodes. The degree of overlapping of n sensors can be computed by using the ratio of the total overlapping area produced by sensors to the total sensing area of the network.

Algorithm 1: Overlapping Detection using Computational Geometry Technique

Input: N number of directional sensor nodes with radius r and view angle 2θ

Phase I (Find neighboring nodes)

1. For each i, do
2. For each j ($j \neq i$)
3. Calculating the distance $d_{i,j}$ with neighboring nodes

$$d_{i,j} = \sqrt{(x_j - x_i)^2 + (y_j - y_i)^2 + (z_j - z_i)^2}$$

4. M_i is the set of neighboring nodes whose distance $d_{i,j} < 2r$
5. Find overlapping (i, j)
6. End

Phase II (Find Overlapping)

Find overlapping (i, j)

1. If $r < d_{i,j} < 2r$
2. If ϕ1-θ>180-ϕ2-θ then,
3. λ= ϕ1-θ otherwise λ=180-ϕ2-θ
4. $S_1 S_1'$=2rcosλ

5. S2 S2'=2rcosλ
6. Overlapping sensing nodes //explained in Lemma 1
7. Add to the set of overlapping nodes
8. Else
9. There is no overlapping
10. Go to step 35
11. End if
12. Else If d<r
13. If ϕ1-θ<0 and ϕ1+θ>0
14. Overlapping sensing nodes //explained in Lemma 3
15. Add to the set of overlapping nodes
16. Else
17. There is no overlapping
18. Go to step 35
19. End if
20. Else If ϕ2+θ> π and ϕ2-θ< π
21. Overlapping sensing nodes // explained in Lemma 4
22. Add to the set of overlapping nodes
23. Else
24. There is no overlapping
25. Go to step 35
26. End if
27. Else If ϕ1-θ<0 and ϕ1+θ>0 && ϕ2+θ> π and ϕ2-θ< π
28. Overlapping sensing nodes // explained in Lemma 5
29. Add to the set of overlapping nodes
30. Else
31. There is no overlapping //explained in Lemma 2
32. End if
33. End if
34. End if
35. End

Output: Set of Overlapped Nodes

5.2. Formulating MCP as an Optimization Problem

The current section presents the issue of determining an optimal overlapping cover set to minimize the degree of overlap. Note that, depending on the requirements of WSN applications, the degree of overlapping is bound to a threshold. O_{TH} . According to the proposed optimization algorithm, the degree of overlapping of a cover set is computed by $O_i = \sum_{i=1}^{n} O_i(S_i, S_j)$ where $O_i(S_i, S_j)$ denotes the overlapping area between the sensor S_i, S_j. To simplify the calculation of the overlapping area, we consider the coverage area of each sensor to be approximately an isosceles triangle.

To find the common area of two overlapping triangles, the Sutherland - Hodgman polygon clipping algorithm [25] is used. This algorithm is applied to clip a triangle against another triangle, where one triangle is the clipping window. After clipping, the area of the polygon is found using the Shoelace method. This mathematical process calculates the area of a basic polygon by cross-multiplying its vertices' coordinates [26].

$$A(O) = \frac{1}{2}[\, x_1y_2 - x_2y_1 + x_2y_3 - x_3y_2 + x_3y_4 - x_4y_3 + \ldots\ldots\ldots + x_{n-1}y_n - x_ny_{n-1} + x_ny_1 - x_1y_n \,] \quad (1)$$

Thus, the problem of finding an optimal overlapping cover set to minimize the degree of overlapping can be formulated as -

$$min\ O_k \quad (2)$$

Subject to

$$O_k = \sum_{i=1}^{n} O_i(S_i, S_j) \geq O_{TH} \quad (3)$$

5.3. Overlapping Cover Set Formulation using Genetic Algorithm

To find the optimal solution of our problem using Genetic Algorithm, we will follow these steps: initializing the population, evaluating the fitness function, performing selection, applying crossover and executing mutation.

5.4. Population Initialization

In the given approach, chromosomes, which are thought to represent potential solutions, are the gene sequence where each gene represents the angle of overlapping nodes. Chromosomes' length may be of variable size, i.e., it depends on the quantity of overlapping nodes. A chromosome's maximum length is N, where N represents the total number of sensing nodes. As shown in Figure 14, there are some overlapping nodes. Initially, several chromosomes are generated randomly after changing the angle values of overlapping nodes. After iterating the chromosome formation progression numerous times, the initial population $IP = [C_1,\ C_2, C_3 \dots \dots C_v]$ can be found.

5.5. Fitness Functions

In the genetic algorithm, finding the fitness value is essential. The core objective of the fitness function is to effectively evaluate how well a proposed solution meets the desired criteria. In this approach, fitness functions are designed to find the degree of overlapping to enhance coverage. The fitness function assesses the performance of each chromosome in a solution pool, favoring those with the least overlap. The fitness function values in the population define whether a chromosome reduces the degree of overlapping or not. So, the fitness function is explained as follows:

$$O(F_j) = \sum_{j=1}^{v_j - 1} O(S_j(i),\ \ S_j(i+1)) \qquad (4)$$

Where and $S_j(i)$ denotes a node of i^{th} index number in j^{th} chromosome, F_j symbolizes the fitness value of j^{th} chromosome and v_j is the size of j^{th} chromosome.

5.6. Selection

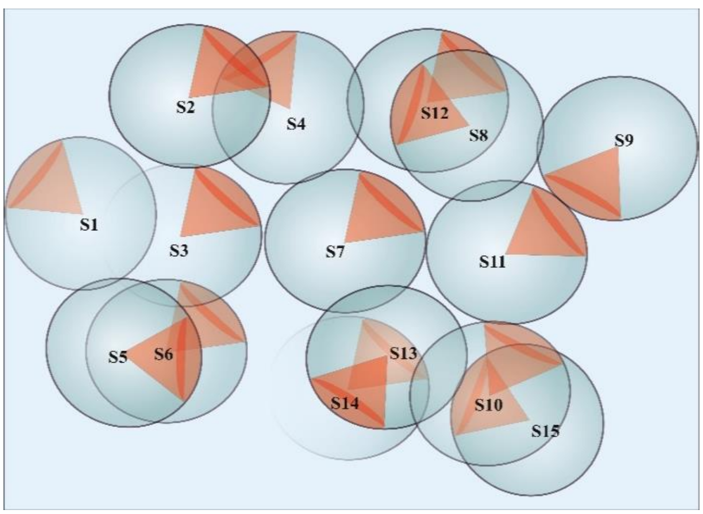
The selection operation aims to increase population quality. It should be highlighted that the selection operator plays an important part in producing high-quality solutions. Hence, an efficient selection operator is essential for rapid convergence to the optimal solution. Selection methods are generally categorized into two types: proportionate selection, which selects chromosomes based on their relative fitness value, while ordinal-based selection chooses chromosomes as per their rank rather than their fitness value, as discussed in [27]. In our algorithm, the proportionate selection method [20] is adopted. Chromosomes with lower fitness values in the current population can still be selected for the next generation.

5.7. Crossover and Mutation

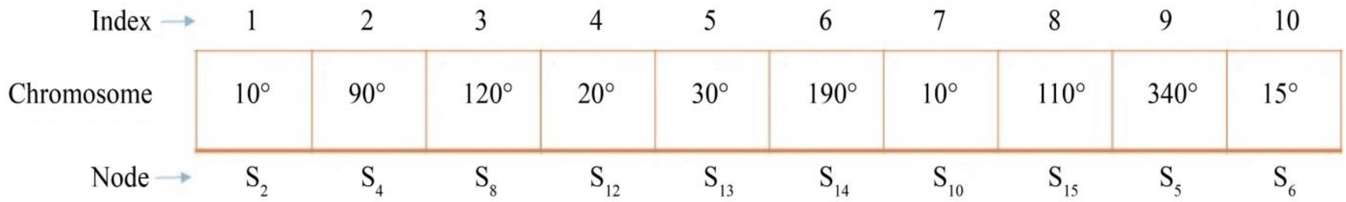
Crossover plays a crucial role in the functioning of Genetic Algorithms. During the crossover procedure, two chromosomes, C_A and C_B, are picked from the selected population to create more effective chromosomes. In the given algorithm, one-point crossover in [28] is used to exchange partial chromosomes. In one-point crossover, two parents are selected for crossover and then randomly choose any one crossover point P_i (i = 1 to n-1) where n is the length of the smaller chromosome from the selected chromosomes for crossover operation. At the crossover moment, the parents combine to produce two offspring. A basic example, as shown in Figure 15, is presented below, which executes one-point crossover between C_A and C_B and produces two new offspring, Off1 and Off2. Mutation is a crucial mechanism in Genetic Algorithms to ensure genetic diversity and prevent early convergence to suboptimal solutions. Introducing minor random modifications to chromosomes enables the algorithm to broaden its search space, thereby increasing the likelihood of discovering an optimal solution [29].

5.8. Termination

One feature that controls the creation of chromosomes/population is the termination. After every generation, this criterion is evaluated. In our approach, the termination condition is based on the fitness function value, i.e. threshold value (O_{TH}).



(a)



(b)

Fig. 14 Example of chromosome formation and encoding

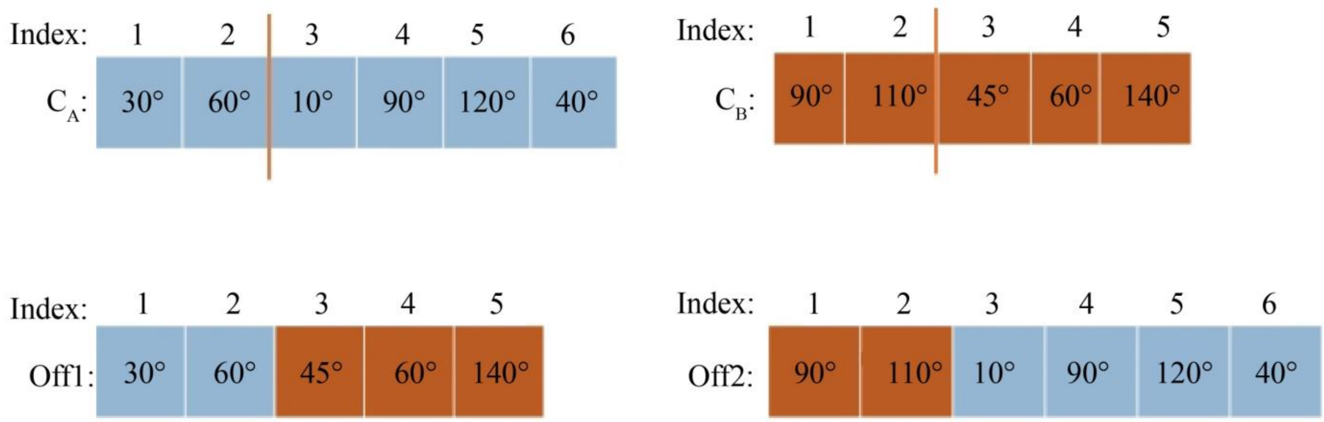


Fig. 15 Example of one-point crossover operation

5.9. Proposed Algorithm

Algorithm 2: Coverage Maximization by Reducing Overlap Using Genetic Algorithm

Input:
- N_o: Set of overlapping Nodes
- r: Sensing range
- ϕ_i : a set of angles of overlapping nodes

Steps:
1. Find N_o: set of overlapping nodes with the help of Algorithm 1
2. Chromosomes creation with the help of overlapping nodes' angles
3. $C = \{C_1, C_2, \dots C_n\}$ //C is the set of chromosomes
4. $C_1 = \{\phi_1, \phi_2, \dots \phi_m\}$ //ϕ_i are the gene sequence holding angle values of overlapping nodes
5. Fitness function to find the minimum degree of overlapping
   $$O(F_j) = \sum_{j=1}^{v_j-1} O(S_j(i),\ S_j(i+1))$$
6. Select two parents with a minimum overlapping area for single-point crossover.
7. Perform a mutation on offspring generated by the crossover operation
8. Termination condition O_{TH} tested after every generation

Output: Set of nodes with minimum overlapping

6. Analytically based Study

This section of the paper derives the mathematical expression for connectivity of the network, coverage probability with directional sensing and energy consumption in a 3D sensor network.

6.1. Connectivity Probability

Let the area of a cube sensing field be A. Let the number of sensors present in the sensing field be N, and the density of nodes φ can be given by $\varphi = \frac{N}{A}\ sensors/m^2$. Let $P_{con}(l)$ is the probability of connectivity of all sensors in the network.

Let a link l_i falls within each other's transmission ranges in all directions established between any two consecutive sensors if they are forming a sphere. The probability $P_{con}(l_i)$ of links present between any two sensors present in a spherical range in the network can be computed as

$$P_{con}(l_i) = 1 - e^{-\frac{4\varphi\pi R^3}{3}} \tag{5}$$

Where R is the transmission range of the sensors and $\frac{4\varphi\pi R^3}{3}$ is the volume of a sphere. We know that the connectivity of a sensor with α arbitrary sensors follows a binomial distribution. Therefore, the probability of the sensors being connected with α sensors is given by

$$P(D = \alpha) = C(N-1, \alpha)\, P_{con}(l_i)^{\alpha}\left(1 - P_{con}(l_i)\right)^{N-\alpha-1} \tag{6}$$

The expected connectivity is computed as,

$$E(D) = (N-1)(1 - e^{-\frac{4\varphi\pi R^3}{3}}) \tag{7}$$

By using the equality approximation $[1-x]^n \approx e^{-nx}$, it can be showcased as

$$E(D) = (N-1)e^{\frac{4\varphi\pi R^3}{3}} \tag{8}$$

6.2. Coverage Probability

Let the sensing region of a sensor be a cone of volume $a = {}^{1}/_{3}\,\pi r^3 (tan\ \theta)^2$, where r is the sensing radius and θ is the angle of view.

The probability of a sensor coverage can be expressed as a/A, where A is the area of a 3D network field in which N sensors are placed randomly. The coverage probability (P_c) of the network can be expressed as

$$P_c = 1 - (1 - a/A)^N \tag{9}$$

By using the equality approximation $[1-x]^n \approx e^{-nx}$, it can be expressed as

$$P_c = 1 - e^{-N({}^{1}/_{3}\pi r^3 (tan\ \theta)^2/A} \tag{10}$$

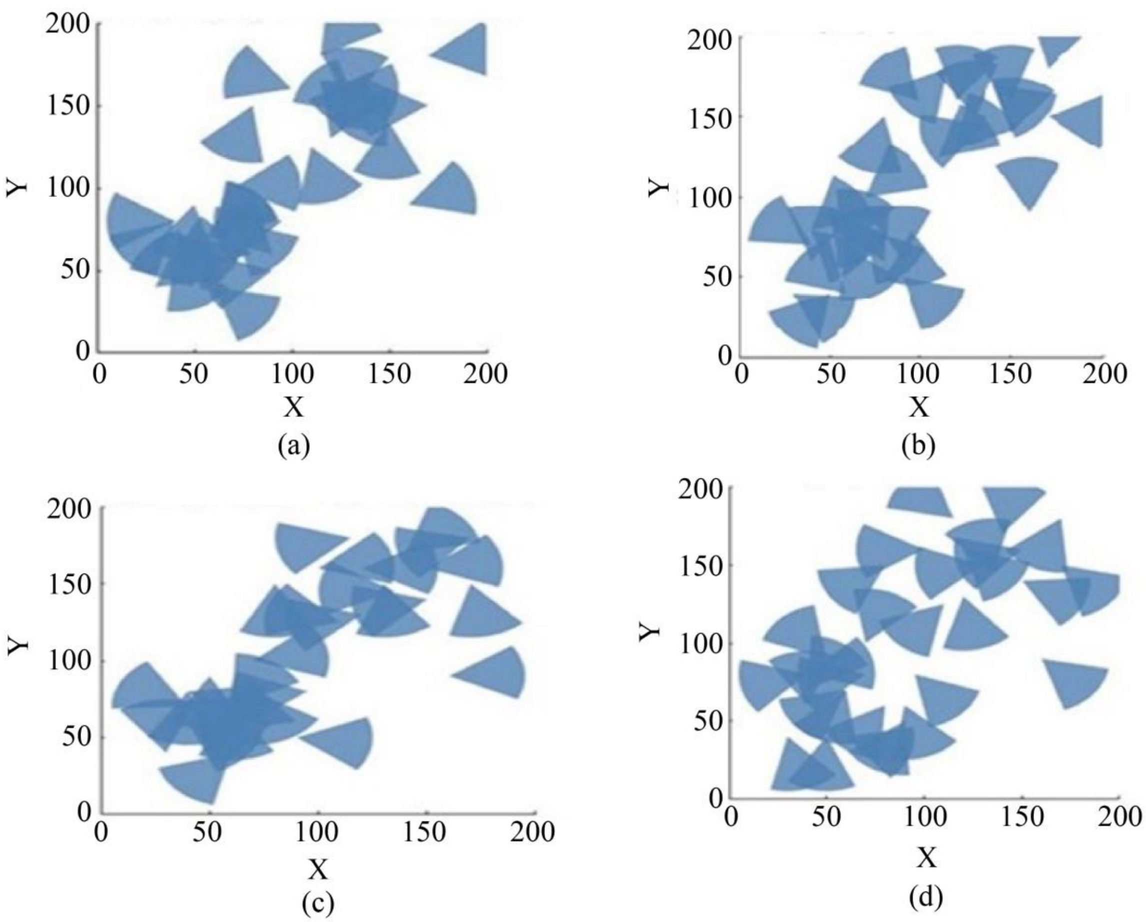
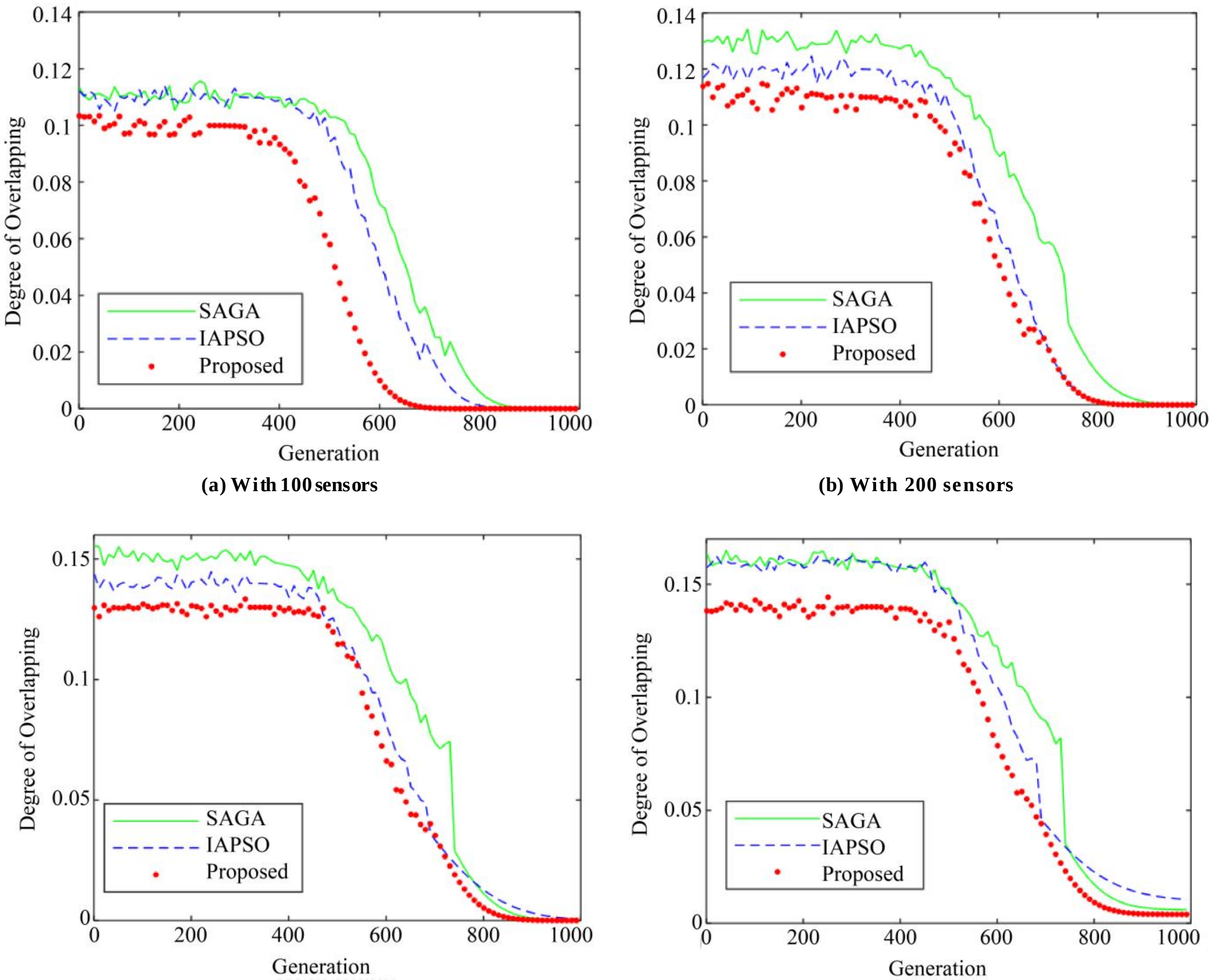


Fig. 16 Scenarios of a GA-based coverage optimization algorithm for coverage enhancement



(a) With 100 sensors (b) With 200 sensors

(c) With 300 sensors (d) With 400 sensors

Fig. 17 Degree of overlapping minimization versus generations

6.3. Energy Consumption

The total energy used up (e_t) in transmitting, receiving and sensing k-bit of data is expressed by

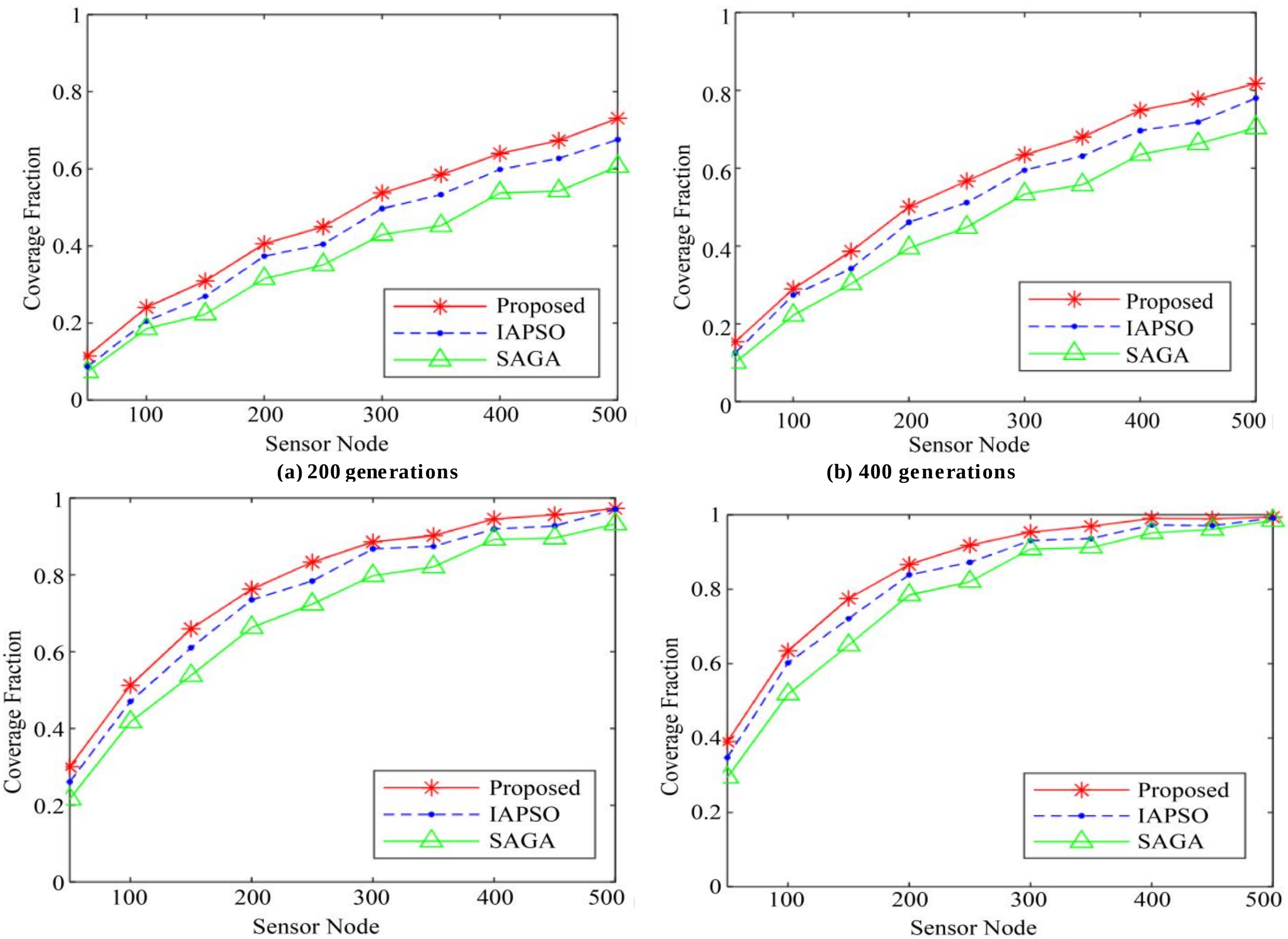
$$\left.\begin{aligned} e_t(k) &= e_{tx}(k) + e_{rx}(k) + e_s \\ e_{tx}(k) &= e_{el}k + e_{am}kd^{\eta} \\ e_{rx}(k) &= e_{el}k \end{aligned}\right\} \tag{11}$$

Where e_{tx} and e_{rx} denoting the energy used for 1-bit data transmission and receiving from two neighboring sensors, respectively, where d is the distance between them. The energy consumed for sensing is denoted by e_s. The e_{el} and e_{am} represent the energy consumed by the electrical circuit and the energy used per bit of amplifier, respectively.

7. Simulation Results and Analysis

The proposed GA based coverage optimization algorithm is simulated, and results are obtained to measure its performance against state-of-the-art coverage optimization algorithms, IAPSO [22], and SAGA [30]. A custom MATLAB script is developed for the Genetic Algorithm-based coverage algorithm. A square of 500m x 500m is taken for simulation, in which 500 sensors are randomly distributed and follow a Poisson point process. The sensing range of each sensor is 20 meters, and the transmission range is considered to be 40 meters. Each simulation is executed 10 times, and the average is computed to get the results. It is considered that the location of each sensor is known by any localization technique. In a randomly generated topology, the coverage angle (direction) of each sensor is taken in a random manner at the beginning. The connectivity of sensors can be ensured either by deploying more sensors or by extending their transmission range. Figure 16 shows the scenarios of GA based coverage optimization algorithm to minimize overlapping and improve coverage. We considered two performance matrices defined as follows:

- The degree of overlapping is the ratio of the total overlapping area produced by sensors to the total sensing area of the network.
- Coverage fraction is a ratio of the area covered by sensors to the total sensing area of the network.



(a) 200 generations

(b) 400 generations

(c) 600 generations

(d)800 generations

Fig. 18 Coverage fraction versus sensors

7.1. Converge Overlapping Minimization

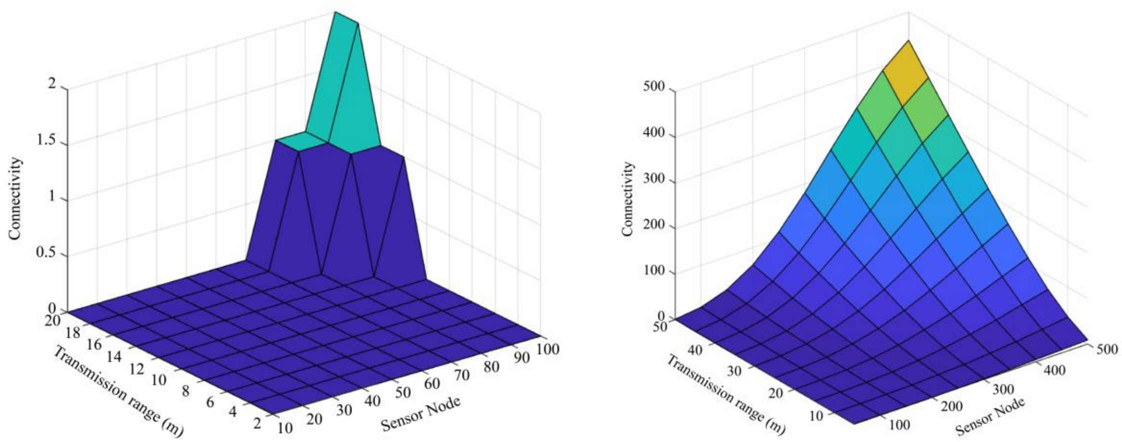
Figure 17 (a) shows the degree of overlapping for 100 sensors deployed in an area of 500 meters by 500 meters while running the proposed GA based coverage optimization algorithm for 100 generations. Initially, around 1%, 1.11% and 1.11% overlapping are detected for the proposed GA based coverage optimization algorithm, IAPSO and SAGA algorithms. The same overlapping is continued for 200 generations. As algorithms proceed, the degree of overlapping for all the algorithms considered in this simulation slowly reduces between 200 and 400 generations. For example, about 0.9% overlapping occurred with the proposed GA based coverage optimization algorithm, while it is about 1.10% for both IAPSO and SAGA algorithms. After 400 generations, the overlap in the proposed GA-based coverage optimization algorithm drops significantly. By 600 generations, the algorithm converges, and the overlap is nearly eliminated. Both the IAPSO and SAGA algorithms converge after 700 generations, and they removed overlapping 800 and 900 generations, respectively. It is clearly seen that the proposed GA based coverage optimization algorithm outperformed both IAPSO and SAGA algorithms. Similarly, Figures 17 (b), 17 (c) and 17 (d) show that the degree of overlapping for 200, 300 and 400 sensors is deployed in an area of 500 by 500 for running the proposed GA based coverage optimization algorithm for 1000 generations. Initially, around 1.1%, 1.2% and 1.3% overlapping are detected for the proposed GA based coverage optimization algorithm, IAPSO and SAGA algorithms with 200 sensors. For 300 sensors, 1.3%, 1.4% and 1.5% overlapping are detected for the proposed GA based coverage optimization algorithm, IAPSO and SAGA algorithms, respectively and for 400 sensors, 1.4%, 1.6% and 1.6% overlapping exist for the proposed GA based coverage optimization algorithm, IAPSO and SAGA algorithms, respectively. As algorithms run for an increasing number of generations, all three algorithms converge, but the proposed

GA based coverage optimization algorithm converges faster and removes overlapping earlier than both IAPSO and SAGA algorithms. It is clearly seen that the proposed GA based coverage optimization algorithm outperformed both IAPSO and SAGA algorithms.

7.2. Coverage Fraction Maximization

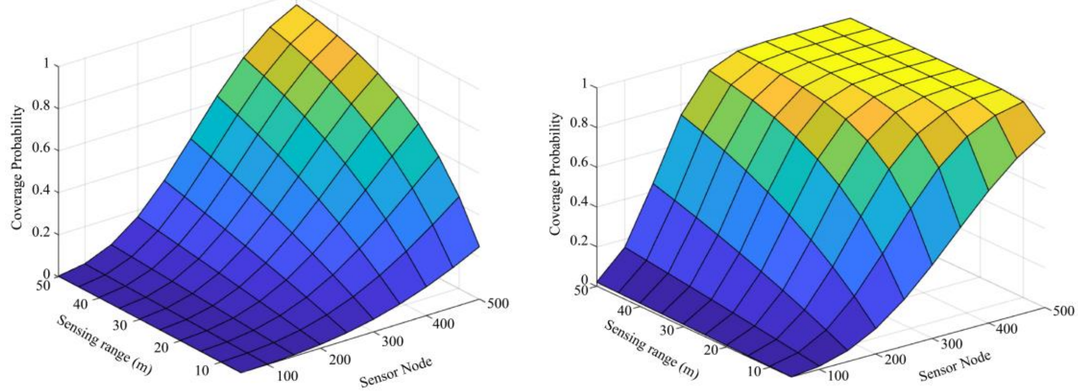
Figure 18(a) shows the coverage fraction for different numbers of sensors deployed in the sensing area. At 200 generations, it is observed that for 100 sensors, 22% of the sensing area is covered using the proposed GA based coverage optimization algorithm while 20% and 21% area is covered by both IAPSO and SAGA algorithms, respectively. As the number of sensors increases, the coverage fraction also increases for all three algorithms. For example, for 300 sensors, the coverage for the proposed algorithm is about 50% area, while IAPSO covers 45% and SAGA covers 40% area with the same sensors. When sensors increase to 500, SAGA gives 55% coverage, and IAPSO gives 65% coverage, whereas the proposed GA based coverage optimization algorithm covers 72% of the sensing area. It is clearly seen that the proposed GA based coverage optimization algorithm outperformed both IAPSO and SAGA algorithms. Similarly,

Figures 18 (b), 18 (c) and 18 (d) show the coverage fraction for 400, 600 and 800 generations for different numbers of sensors that are deployed in the sensing area for the proposed GA based coverage optimization algorithm and two state-of-the-art algorithms. It is clearly observed that when the number of generations increases from 200 to 400, the coverage fraction is improved for 500 sensors. It is about 100%, 98% and 96% with 500 sensors for the proposed GA based coverage optimization algorithm, IAPSO and SAGA algorithms, respectively. It is seen from Figure 18 (a), 18 (b), 18 (c) and Figure 18 (d), that as the quantity of generations increases, coverage fraction also surges. But the proposed GA based coverage optimization algorithm achieves a higher coverage fraction as compared with both IAPSO and SAGA algorithms.



(a)With sensors up to 100 **(b) Sensors between 500**

Fig. 19 Connectivity of 3D Directional Sensor Network



(a) With an angle of view of 30 degrees **(b) With an angle of view of 60 degrees**

Fig. 20 Coverage probability of 3D directional sensor

7.3. Connectivity Analysis in 3D Directional Sensor Network

Figure 19 (a) depicts the connectivity degree of the entire 3D DWSN with 100 sensors using different transmission ranges. It is derived from Equation (8). It is observed that at least 70 sensors are needed to maintain 1-connectivity among all the sensors using a 20 m transmission range for each sensor.

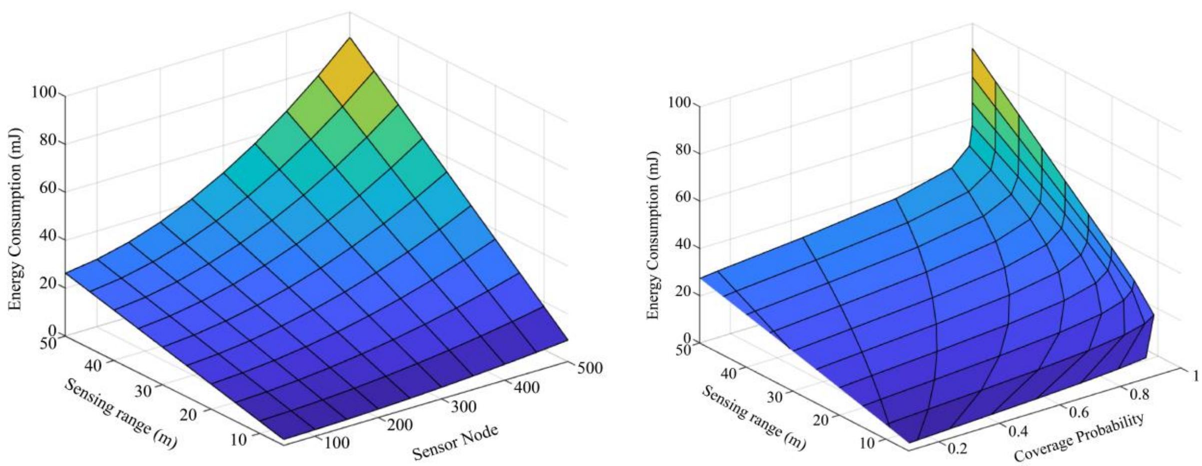
More than 90 sensors are required to maintain 2-connectivity among sensors using a 20 m transmission range for each sensor. From Figure 19 (b), it is observed that if we take a 20 m transmission range for each sensor and a number of sensors of about 500, 29-connectivity can be achieved. As the transmission range increases, the connectivity of the network also increases for any given number of sensors.

7.4. Coverage Analysis in 3D Directional Sensor Network

Figure 20 (a) and Figure 20 (b) depict coverage probability with an angle of view of 30 degrees and 60 degrees, respectively. It is derived from Equation (10). It is noticed that as the number of sensors increases, coverage probability also increases. For a sensing radius of 50 m, when an angle of view of 30 degree is considered, about 80% of the DSN can be covered with 400 sensors. When an angle of view of 60 degree is considered, about 100% of the DSN can be covered with less than 400 sensors. If we compare the results of Figure 19 with the simulation results of Figure 17, both show a similar nature and progress as the number of sensors increases, using a sensing radius of 20 m. It validates the analytical results of Figure 20.

7.5. Energy Consumption Analysis

Figure 21 shows energy consumption for coverage obtained from different numbers of sensors. The values of constants used in Equation (11) of the energy model are $e_{am} = 100$ (pJ/ (bit m-2)) and $= 50\ (\mathrm{nJ/bit})$. Path loss components are assumed to $\eta = 2$, d between 5m to 50m and k=1. Figure 21 (a) shows that as either the sensing radius or number of sensors increases, energy consumption for coverage also increases. Figure 21 (b) shows the energy consumption to obtain a satisfactory coverage level. For example, if we wish to obtain 80% coverage, about 60 mJ of energy is consumed using a 50m transmission range.



(a) Energy consumption with sensors **(b) Energy consumption for % coverage**

Fig. 21 Energy consumption for coverage

8. Conclusion

This paper proposes a GA-based area coverage optimization algorithm using Computational Geometry that takes directional sensing into account, aiming to determine the optimal cover set from multiple cover sets with minimal overlapping requirements. Improved when the algorithm runs for a higher number of generations. The proposed GA based area coverage optimization algorithm outperformed state-of-the-art algorithms. To reduce the coverage overlapping and maximize the coverage area, a fitness function for the degree of overlapping is constructed. It has been observed the degree of overlapping is minimized and the coverage fraction is Further.

An analytical study of coverage is conducted, and the results of the coverage are validated using simulation results. In the future, two objective functions, one for coverage and another for connectivity, can be used, and the formulated optimization problem can be solved using NSGA-II.

Author Contributions

Sharmila Devi: Conceptualization, Investigation, Formal analysis, Visualization, Methodology, Software, Writing – original draft.

Anju Sangwan: Conceptualization, Investigation, Supervision, Formal analysis, Validation.

References

[1] Jian Wang, Changyong Niu, and Ruimin Shen, "Priority-Based Target Coverage in Directional Sensor Networks using a Genetic Algorithm," *Computers & Mathematics with Applications*, vol. 57, no. 11-12, pp. 1915-1922, 2009. [CrossRef] [Google Scholar] [Publisher Link]

[2] Ting-Yu Lin et al., "Enhanced Deployment Algorithms for Heterogeneous Directional Mobile Sensors in a Bounded Monitoring Area," *IEEE Transactions on Mobile Computing*, vol. 16, no. 3, pp. 744-758, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[3] M.A. Guvensan, and A.G. Yavuz, "On Coverage Issues in Directional Sensor Networks: A Survey," *Ad Hoc Networks*, vol. 9, no. 7, pp. 1238-1255, 2011. [CrossRef] [Google Scholar] [Publisher Link]

[4] Yong-hwan Kim et al., "Lifetime Maximization Considering Target Coverage and Connectivity in Directional Image/Video Sensor Networks," *The Journal of Supercomputing*, vol. 65, pp. 365-382, 2013. [CrossRef] [Google Scholar] [Publisher Link]

[5] Zahra Zarei, and Mozafar Bag-Mohammadi, "Coverage Improvement Using Voronoi Diagrams in Directional Sensor Networks," *IET Wireless Sensor System*, vol. 11, no. 3, pp. 111-119, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[6] Tien-Wen Sung, and Chu-Sing Yang, "Voronoi-Based Coverage Improvement Approach for Wireless Directional Sensor Networks," *Journal of Network and Computer Applications*, vol. 39, pp. 202-213, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[7] Tien-Wen Sung, and Chu-Sing Yang, "Distributed Voronoi-Based Self-Redeployment for Coverage Enhancement in a Mobile Directional Sensor Network," *International Journal of Distributed Sensor Networks*, vol. 9, no. 11, pp. 1-15, 2013. [CrossRef] [Google Scholar] [Publisher Link]

[8] Chiu-Kuo Liang, Chih-Hung Tsai, and Ting-Hao Chu, "Coverage Enhancing Algorithms in Directional Sensor Networks with Rotatable Sensors," *2011 IEEE Asia-Pacific Services Computing Conference*, Jeju, Korea (South), pp. 377-383, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[9] Priyanka Sharma, and Rishi Pal Singh, "Energy-Efficient Deterministic Approach for Coverage Hole Detection in Wireless Underground Sensor Network: Mathematical Model and Simulation," *Computers*, vol. 11, no. 6, pp. 1-21, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[10] Dan Tao, Huadong Ma, and Liang Liu, "Coverage-Enhancing Algorithm for Directional Sensor Networks," *Mobile Ad-hoc and Sensor Networks, Second International Conference, (MSN 2006)*, Hong Kong, China, pp. 256-267, 2006. [CrossRef] [Google Scholar] [Publisher Link]

[11] S. Dobrev et al., "Connectivity with Directional Antennas in the Symmetric Communication Model," *Computational Geometry*, vol. 55, pp. 1-25, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[12] You-Chiun Wang, Yung-Fu Chen, and Yu-Chee Tseng, "Using Rotatable and Directional (R&D) Sensors to Achieve Temporal Coverage of Objects and Its Surveillance Application," *IEEE Transactions on Mobile Computing*, vol. 11, no. 8, pp. 1358-1371, 2011. [CrossRef] [Google Scholar] [Publisher Link]

[13] Peng Wang, and Yonghua Xiong, "A Method to Optimize Deployment of Directional Sensors for Coverage Enhancement in the Sensing Layer of IoT," *Future Internet*, vol. 16, no. 8, pp. 1-22, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[14] Jiahui Zhu, and Xianyang Xu, "A Coverage-Enhancing Scheme for Heterogeneous Directional Wireless Sensor Networks," *Proceedings of the 2025 3rd International Conference on Communication Networks and Machine Learning*, Nanjing China, pp. 533-537, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[15] Nguyen Thi My Binh, and Ho Viet Duc Luong, "Solving of the Maximal Exposure Path Problem in Heterogeneous Directional Wireless Sensor Networks using an Improved Genetic Algorithm," *Journal of Computer Science and Cybernetics*, vol. 41, no. 2, pp. 163-180, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[16] Xiaochao Dang, Chenguang Shao, and Zhanjun Hao, "Dynamic Adjustment Optimisation Algorithm in 3D Directional Sensor Networks Based on Spherical Sector Coverage Models," *Journal of Sensors*, vol. 2019, pp. 1-14, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[17] H. Ma, X. Zhang, and A. Ming, "A Coverage-Enhancing Method for 3D Directional Sensor Networks," *IEEE INFOCOM 2009*, Rio de Janeiro, Brazil, pp. 2791-2795, 2009. [CrossRef] [Google Scholar] [Publisher Link]

[18] Junjie Huang et al., "Improved Virtual Potential Field Algorithm Based on Probability Model in Three-Dimensional Directional Sensor Networks," *International Journal of Distributed Sensor Networks*, vol. 8, no. 5, pp. 1-9, 2012. [CrossRef] [Google Scholar] [Publisher Link]

[19] Bin Cao et al., "3-D Deployment Optimization for Heterogeneous Wireless Directional Sensor Networks on Smart City," *IEEE Transactions on Industrial Informatics*, vol. 15, no. 3, pp. 1798-1808, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[20] Bin Cao et al., "Differential Evolution-Based 3-D Directional Wireless Sensor Network Deployment Optimization," *IEEE Internet of Things Journal*, vol. 5, no. 5, pp. 3594-3605, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[21] Zibo Huang et al., "Reinforcement Learning-Driven Hunter-Prey Algorithm Applied to 3D Underwater Sensor Network Coverage Optimization," *IEEE Access*, vol. 13, pp. 78161-78181, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[22] Yu-An Fan, and Chiu-Kuo Liang, "Hybrid Discrete Particle Swarm Optimization Algorithm with Genetic Operators for Target Coverage Problem in Directional Wireless Sensor Networks," *Applied Sciences*, vol. 12, no. 17, pp. 1-19, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[23] Yanli Cai et al., "Energy Efficient Target-Oriented Scheduling in Directional Sensor Networks," *IEEE Transactions on Computers*, vol. 58, no. 9, pp. 1259-1274, 2009. [CrossRef] [Google Scholar] [Publisher Link]

[24] Song Peng, and Yonghua Xiong, "An Area Coverage and Energy Consumption Optimization Approach based on Improved Adaptive Particle Swarm Optimization for Directional Sensor Networks," *Sensors*, vol. 19, no. 5, pp. 1-21, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[25] Rohan Guptae et al., "An Innovative and Easy Approach for Clipping Curves along a Circular Window," *2016 Second International Conference on Computational Intelligence & Communication Technology (CICT)*, IGhaziabad, India, pp. 638-643, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[26] Husameddin Badarin, "*The Geometry of Planar Polygons in the Euclidean Space*," Master of Science Thesis, Palestine Polytechnic University, pp. 1-103, 2024. [Google Scholar] [Publisher Link]

[27] Chang Wook Ahn, and R.S. Ramakrishna, "A Genetic Algorithm for Shortest Path Routing Problem and the Sizing of Populations," *IEEE Transactions on Evolutionary Computation*, vol. 6, no. 6, pp. 566-579, 2002. [CrossRef] [Google Scholar] [Publisher Link]

[28] Sushil Kumar et al., "Towards Green Communication in Wireless Sensor Network: GA Enabled Distributed Zone Approach," *Ad Hoc Networks*, vol. 93, pp. 1-25, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[29] Abolghasem Alibeiki, Homayun Motameni, and Hosein Mohamadi, "A New Genetic-based Approach for Maximizing Network Lifetime in Directional Sensor Networks with Adjustable Sensing Ranges," *Pervasive and Mobile Computing*, vol. 52, pp. 1-12, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[30] Shengxiang Yang, Hui Cheng, and Fang Wang, "Genetic Algorithms with Immigrants and Memory Schemes for Dynamic Shortest Path Routing Problems in Mobile Ad Hoc Networks," *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, vol. 40, no. 1, pp. 52-63, 2009. [CrossRef] [Google Scholar] [Publisher Link]