

To Perform an Optimization of the Novel Security Protocol for Incorporating Maximum Security Strength in WSN

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Abstract

WSN are deployed in 2D or 3D plane and they are omnidirectional in nature. The researchers in WSN are not concentrating on practical situation. The proposed study will concentrate on the deployment problem of heterogeneous DSN in 3D plane. These studies will be more suitable for practical security monitoring system. In this proposed work a novel sensing is introduced which is based on non-probabilistic measure based fusion operator. In this paper three experiments on real world 3D plane data has been conducted. The analysis will be done clearly on the multi objective deployment of the sensor node for high security in directional sensor networks with many applications.

Index terms: HDSN, non-probabilistic measure, 3D plane.

1. Introduction

The deployment problem of WSN in security monitoring system has been discussed by many researchers [1][2]. The range of detection by sensor was in circular shape for traditional sensor but in practical situation due to different geographical region the shape of detection range will be different so with development of advanced sensing technology different types of directional sensors have come to market eg ultrasonic and image sensor nodes [3][4]. Ma et al concentrated on the coverage problem of directional sensor nodes [5]. The study on the directional sensor network is concentrating on the sector shaped models. Some other scholar concentrates on triangle shaped model and irregular polygon model [6][7]. Teng et al worked on sensor sensing model. This model is a 2D model [8]. Some researchers in [9] concentrated sensing model which consider sensing distance, sensing angle and sigmoid function these parameters are important for studying practical deployment. Deterministic sensing models and probabilistic sensing models are two different sensing models.

Deterministic models refer Boolean models are shown fig 1a and sensing probability is found by radius of sensing “Rs” this model is simple and not suitable for practical scenario experimental simulations. Mathematical functions were designed to simulate sensing behavior of sensor. As the sensing distance increases sensing probability will decrease. Elfes model (b)[10] is used to characterize the sensing models. The multi layered model(c)[11]. The shadow fading model(d)[12], and sigmoid model(e)[9]. Are as shown in fig 1. The DSN deployment problem is majorly focused in this research work. The major focusing point this deployment problem is coverage [13][17]. Many researches have concentrated on 2D planar region but 3D planar regions are more suitable for practical deployment requirements. Some studies are based on 3D plane[18]. In this paper mainly coverage range is considered. The connectivity and cost problems are not considered. Temel et al[19] Proposed cat swarm optimization using wavelet transform for deployment technique.

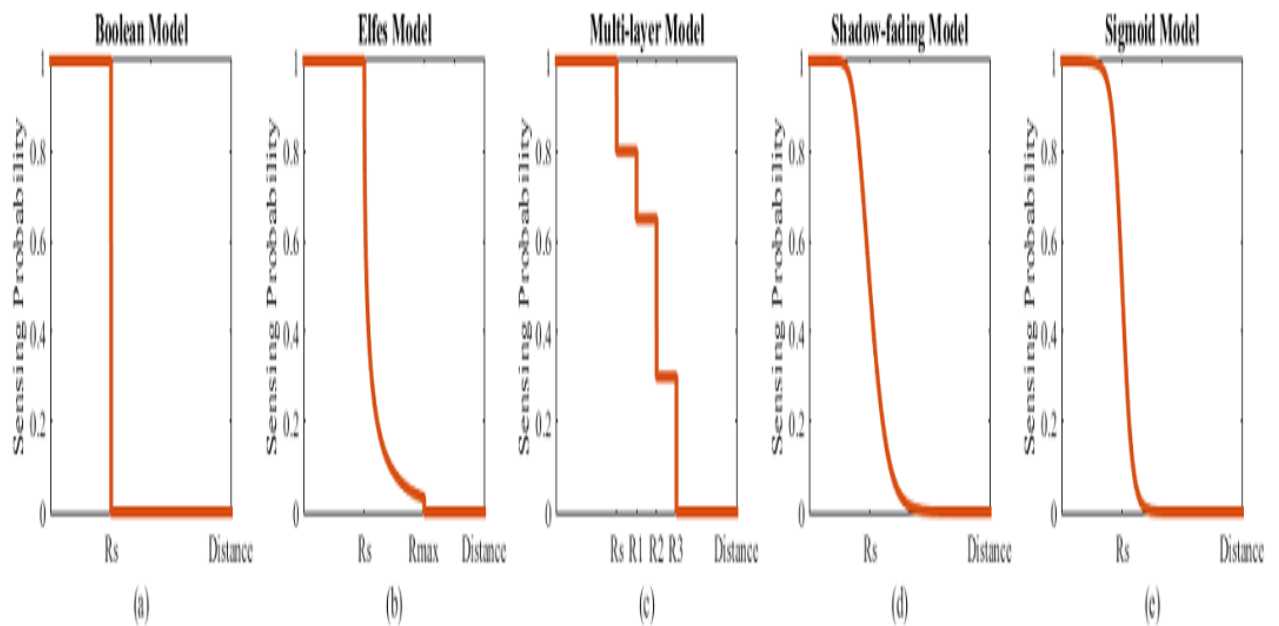


Figure 1: Traditional sensing models. (a) Boolean model; (b) Elfes model; (c) multi-layer model; (d) shadow-fading model; (e) sigmoid model.

In WSN deployment many parameters are considered such as connectivity, life time, uniformity etc[20]. Modified Elitist non deterministic sorting genetic algorithm (NSGA-2)[21] is used to overcome connectivity and coverage problem study on multiobjective optimization algorithm for WSN were discussed in [22]-[24]. A few studies have been taken on 3D plane

optimization. The study on 3D plane optimization technique for sensor deployment technique is the novelty of the proposed work.

The present paper has following conditions:

- 1) A 3D probabilistic sensing model is introduced and fuzzy logic is used.
- 2) Deployment problem is analyzed in 3D plane scenario which is more suitable for practical scenario.
- 3) The directional sensor nodes are heterogeneous in nature and become more complex suitable for biologically inspired optimization algorithms.
- 4) The deployment problem is transformed into multi objective optimization. Section 2 of this paper about novel uncertain comprehensive coverage model. Section 3 deals with objective function of deployment problem of HDSN. Section 4 discuss about terrain data used in experimentation. Section 4 deals with results analysis finally section 4 deals with condition.

2. Literature Survey

During the last few years, WSNs (wireless sensor network) have been widely studied and utilised in many industrial applications, related to forest monitoring [28], agriculture monitoring [29], and healthcare [30-31]. Compared to the practical working environment of above applications, marine environment systems are quite sensitive to the effects of human activities. Traditionally, marine application mostly utilizes oceanographic research vessel methods [1-2] to monitor the environment and human parameters. But these methods are usually expensive and time-consuming, also limited resolution in time and space. For marine environment research, a WSN-based approach can dramatically improve the access to real-time data covering long periods and large geographical areas [32]. According to Tateson et al. [33], a WSN-based approach is at least one order of magnitude cheaper than a conventional oceanographic research vessel.

Typically, a WSN-based marine system needs to measure different physical and chemical parameters. While the development and deployment of an adaptive, scalable and self-healing WSN system need to address a number of critical challenges such as autonomy, scalability, adaptability, self-healing and simplicity [34], the design and deployment of a lasting and scalable WSN for marine environment monitoring should take into account the following

challenges different from those on land [35]: stronger robustness, higher energy consumption, and sensor coverage problem, maintenance of sensor nodes.

There are many concerns relevant to the deployment problem, one of which is coverage [36-37]. The authors of [38] simultaneously considered connectivity, cost and lifetime. Similarly, in the present paper, in addition to the 3D space coverage, we also consider the lifetime of the IWSN. To prolong the lifetime, Kuila et al. [39] utilized a heterogeneous structure that contained both sensor nodes and relay nodes simultaneously. The energy consumptions of different types of nodes were considered simultaneously. The energy consumed by each relay node was comprehensively balanced with respect to the sensor nodes that it was in charge of, data aggregation and extra energy consumption by acting as a hop node for other relay nodes. Consequently, the overall lifetime could be prolonged to a large extent.

Among these studies, the deployment problem of WSNs is a key issue for operational management and security monitoring of Intelligent Maritime Grids (IMGs). Traditional sensing models for 2-D sensor nodes are Omni-directional and include the disk/Boolean sensing model [8], the Elfes sensing model [9] and the Li sensing model [10]. The most common fusion operator is the probabilistic fusion operator [11-12]. The traditional coverage models of WSNs are based on probability measures such as those in the problems of certain coverage discussed in [13-14]. While above studies have demonstrated promising performances on dealing with the coverage optimisation in ideal 2D WSN environment, it is still difficult to achieve practical needs of WSN deployment in real word 3D cases. However, most existing deployment strategies in WSNs focus on ideal 2D WSN environment, which are hardly to be applied in real maritime application environments. The sensing models considered in traditional maritime wireless sensor networks (MWSNs) [15-17] are very simple, mostly with the deployment on a 2D plane.

In light of coverage problem of the 3D space, the most common ways are to extend the 2D solution from 2D ideal plane region of interests (RoI) to 3D full space RoI. Brown et al. [18] provided solutions for the 3D full-space coverage problem for wireless video sensor networks (WVSNs). Yang et al. [19] attempted to minimize the cost for the target coverage problem in a 3D space above a 3D terrain. However, the above studies did not consider network lifetime or energy consumption [20]. In real-world marine environment application, sensor nodes in WSNs have limited battery power. The energy consumption of sensor nodes is important for sensor networks. The lifetime is a result of energy consumption in WSNs. Consequently, so

far there are no existing practically efficient solutions in literature for dealing with coverage and deployment problems in complex 3D surface of WSNs in marine environment application. This paper aims at exploring the possibility of utilising biological inspired optimisation algorithms to efficiently solve the coverage problem in 3D WSNs for maritime application.

In this paper, we study the 3D deployment problem of an IWSN in a 3D engine room space of a very large crude oil carrier (VLCC), in which there are many power devices. To better consider the coverage problem, we propose a 3D directional sensing model by simultaneously considering the sensing distance and horizontal and vertical sensing angles, which is probabilistic to improve precision and practicability. Also, our model has considered supporting heterogeneous directional sensor nodes [21] with improved practicability.

In this paper, we inspired from the idea of particle swarm optimisation [22] and simultaneously deploy sensor nodes and relay nodes. Consequently, the energy consumptions of relay nodes are balanced to maximize the lifetime. For an IWSN, reliability is also crucial. In the work of [23], Wang et al. guaranteed reliability by ensuring the associations of each node to multiple relay nodes.

In this paper, we also consider the reliability of the IWSN. Instead of making the reliability objective a constraint, we transform it into an objective to be optimized. Due to the fact that this model has considered three above objectives simultaneously, the deployment problem can be characterized as a multi-objective optimization problem (MOP). Thus, we use multi-objective evolutionary algorithms (MOEAs) to address the deployment problem. Hacioglu et al. [24] considered multiple aspects of energy consumption, and Non-dominated Sorting Genetic Algorithm II (NSGA-II) [25] was applied. In the work of [24], Jameii et al. simultaneously considered coverage, energy consumption and the number of active sensors, and NSGA-II was also utilized. Sengupta et al. [26] formulated the deployment problem with respect to three aspects: lifetime objective, coverage objective and the connectivity constraint; to solve this MOP, they blended fuzzy Pareto dominance with Multi-objective Evolutionary Algorithm Based on Decomposition (MOEA/D) [27], therein proposing MOEA/DFD, which outperformed popular MOEAs and several single-objective evolutionary algorithms (EAs).

3. Objective Functions and Multiobjective

Optimization algorithms

We can conceptualize HDSN deployment problem into three objectives connectivity, coverage and deployment cost they are denoted as “f” “fs” and “fd”. In these sections we will discuss these points in detail.

A. Coverage

Coverage range is the important parameter to analyse WSN deployment problem. In this work we assume fixed sensor nodes to increase the coverage range. The horizontal sensing angle δp_{AN} and vertical sensing angle δT_{ILT} are adjusted during the optimization where $0 < \delta p_{AN}, \delta T_{ILT} < 2\pi$. We use proposed model to access the coverage ratio of deployment on 3D plane $f_{coverage}$ indicates the coverage fitness which is calculated using below equation

$$f_{coverage} = 1.0 - CQ(11).$$

B. Connectivity uniformity

To exchange information between sensors first we need to confirm the connectivity between them. Every sensor node should communicate with at least one sensor node or two sensors node in WSN set up. The energy of one sensor node is limited if any sensor energy runout the connectivity will be lost. To increase the life time of sensor nodes the communication uniformity should considered. The distance between two sensors should be very less as possible as to achieve uniformity standard deviation is used to measure uniformity [27].

C. Deployment cost

The altitudes and fluctuations degrees of deployment position are considered to reduce deployment cost [28]. Higher altitudes and more rugged local terraines create higher deployment cost.

D. Multi objective optimization algorithm

In this paper we decide the deployment problem into a multi objective phase for this we use 25 fixed sensor nodes. The distance between each nodes is different but fixed for multi objective algorithm the node population is represented as $X_1, Y_1, \delta p_{AN}, \delta T_{ILT}, \dots, x_m, y_m, \delta p_{AN}, \delta T_{ILT}$ where $m=25$, x_i and y_i represent position of sensor

node $\delta \theta$ AN ; I ; is the horizontal sensing angle and δI T ILT is vertical sensing angle and $\delta \theta$ AN , δI T ILT belongs $[0, 2\pi]$.

Number of variables are 100, we used four multi objective optimization algorithm cooperative evolutionary generalized evolution 3 (CCGDE3)[29]. (CMODE)[30], (MOEA/DVA)[31]. CCGDE is proposed large scale optimization problem.

4. 3D Terrain Data

For practical implementation we use terrain data of real-life geographical environment. Digital elevation model initial data will be resourced from internet 1 by dipping we obtain 3 type of terrain data. After sampling we will get matrices of size 32×32 this is used for sensor deployment. The terrain region we used is $160m \times 160m$ which is illustrated in figure 2(a). the sensor deployed region is hilly region area of hill region is $160 \times 10m$ as shown in fig 2(b). the extracted data from sensor in mountain region has large fluctuation area of mountain is $160m \times 160m$ as shown in fig 2(c).

We use 4 multi objective algorithms (CCGDE3, CMODE) to address the multi objective deployment problem. For each type of theorem each algorithm runs 24 time. The function of evaluation (FE) is set to $1e+6$.

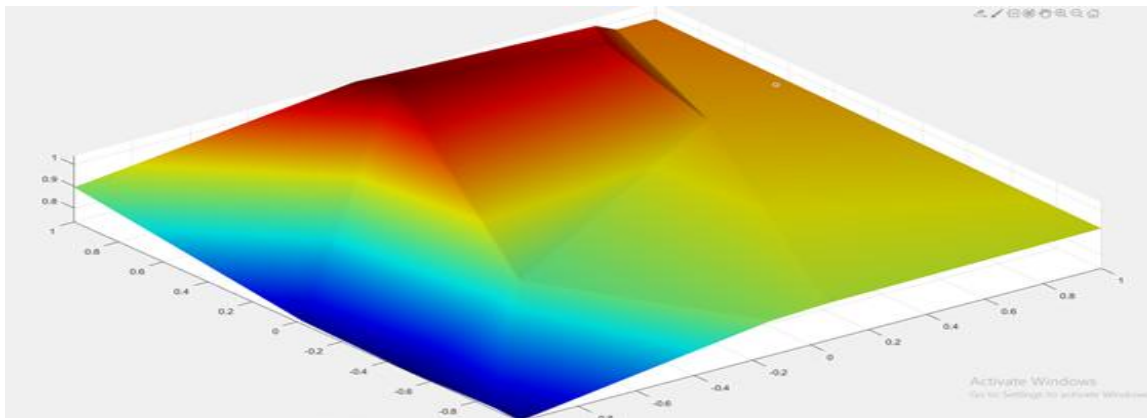


Figure 2(a): plain terrain

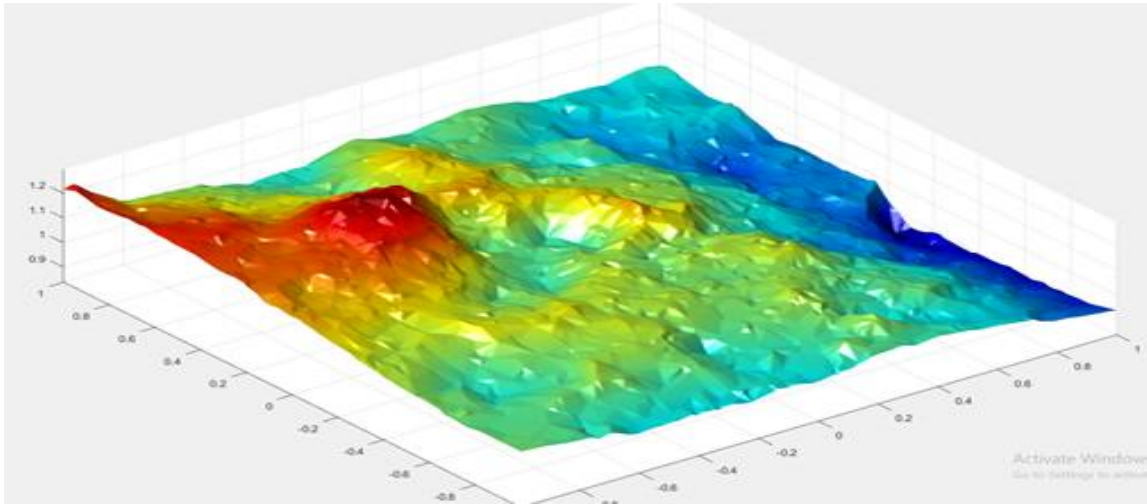


Figure 2 (b): Hilly terrain

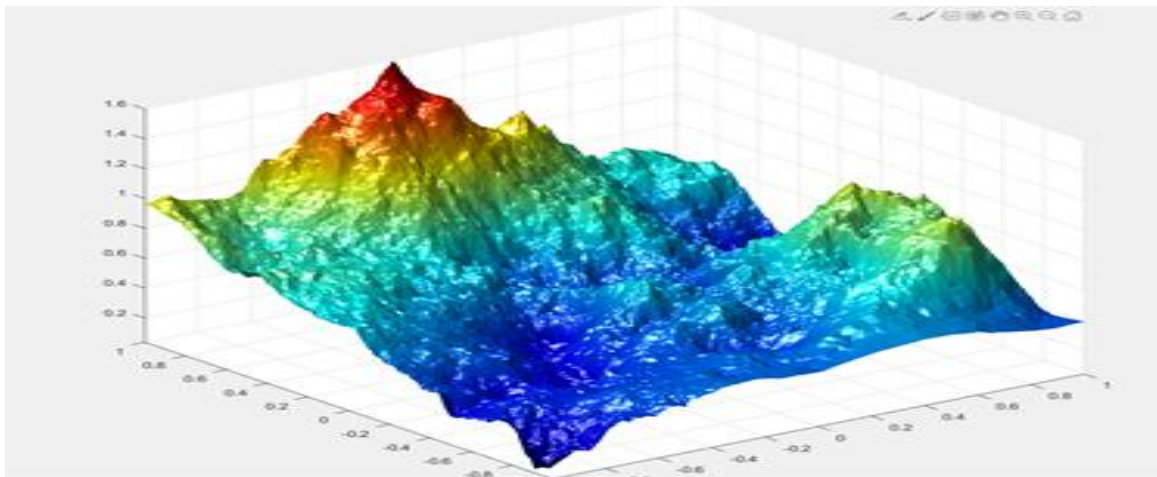


Figure (c): Mountainous terrain

Figure 2: extracted terrain data from all types

4.1 Population Size

The population size of all four algorithms is 120[31]. There are two sun population found in ccGDE3 and 60 individuals for each subpopulation. There are three swarms mentioned in optimization and 3 objectives in multi objective deployment problem, swarm size is 20 and archive size is 120. Population size of MOEA/DVA 120. The population size of NSGA-3 is taken by no of reference points (H), where $NP=H$. H is given by $(p1,P2)$, source set them as $(14,0)$, thus $NP=H=120$.

- 1) For DE in CCDGE and MOEA/DVA, $F=0.5$ and $CR = 1.0$ polynomial notations are used in MOEA/DVA and NSGA-3 are discussed.

4.2 Coverage model parameters

The parameters of proposed coverage model are discussed. we use hypervolume (HV) indicator [33]-[35] to evaluate optimization results. HV calculate convergence and each operation and average the all values of each operation. We also showed the 2D projects which gives the comparison of each pairs of objectives.

5. Experimental Results and Analysis

First, we observe the deployment optimization results on plain terrain and perform the corresponding analysis. For the HV indicator (Fig. 3), MOEA/DVA and CMODE are quite similar; NSGA-III ranks third; and CCGDE3 performs the worst. In detail, MOEA/DVA reaches 0.9821311, For the HV indicator (Fig. 4), CMODE and MOEA/DVA are still quite similar, NSGA-III is worse and CCGDE3 is obviously not as good as the other algorithms. In detail, the HV value of MOEA/DVA reaches 0.9759476, CMODE reaches 0.8620413, NSGA-III reaches 0.9753346 and CCGDE3 only reaches 0.9575401. From the solution set visualization (Fig. 5), the distribution and diversity of CMODE and MOEA/DVA are still the best, and they can more comprehensively cover the objective space, much better than NSGA-III and CCGDE3.

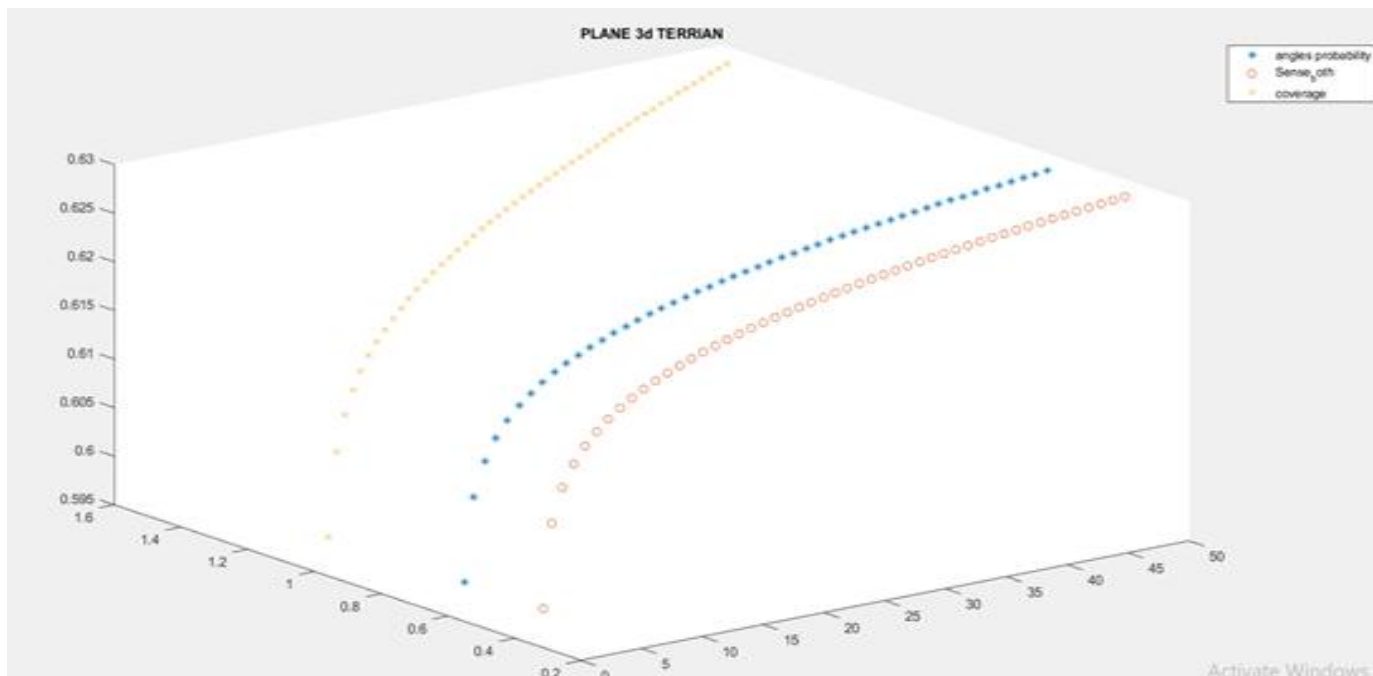


Figure 3(a): plain 3D Terrain

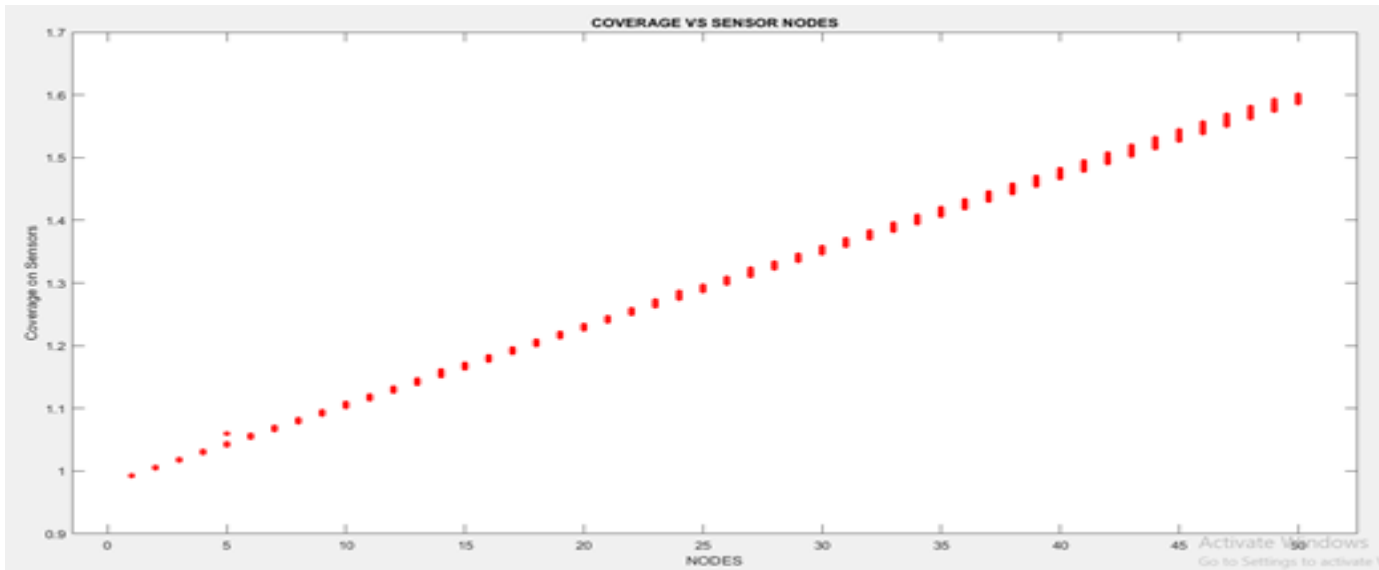


Figure 3(b): coverage vs sensor nodes

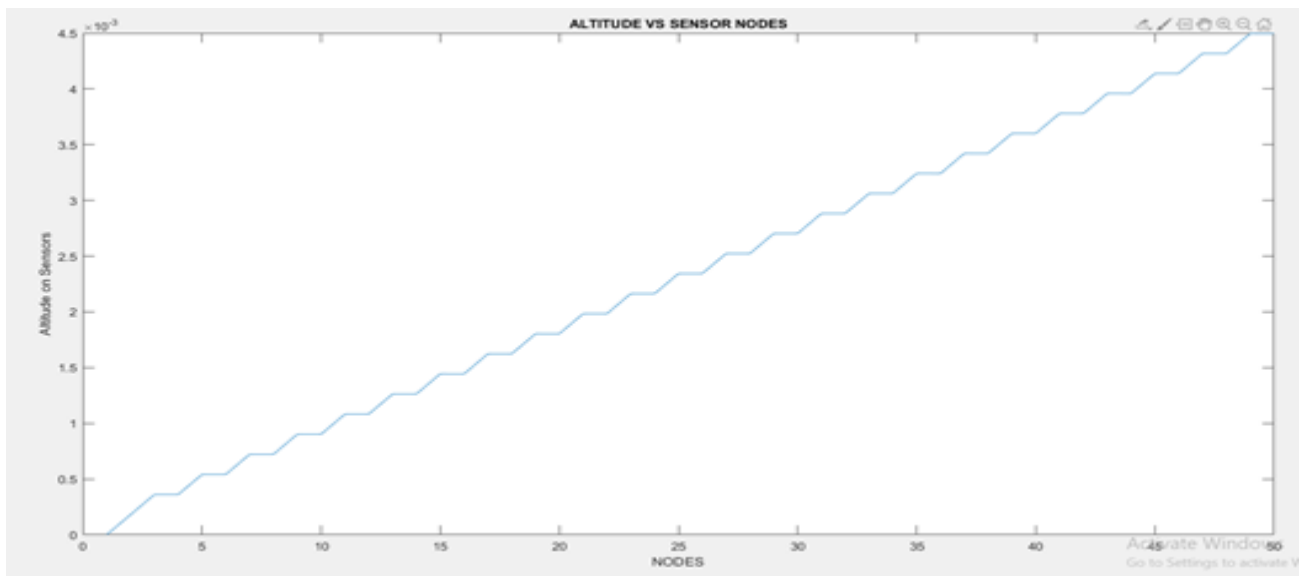


Figure 3(c): altitude vs sensor nodes

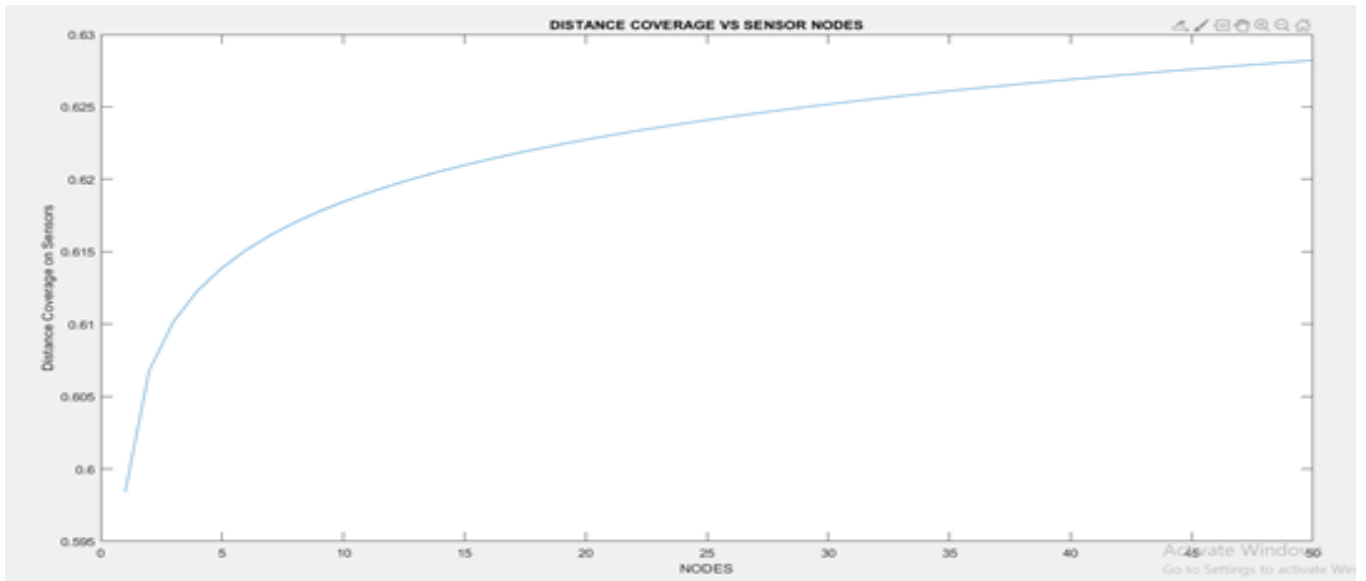


Figure 3(d): distance coverage vs sensor nodes

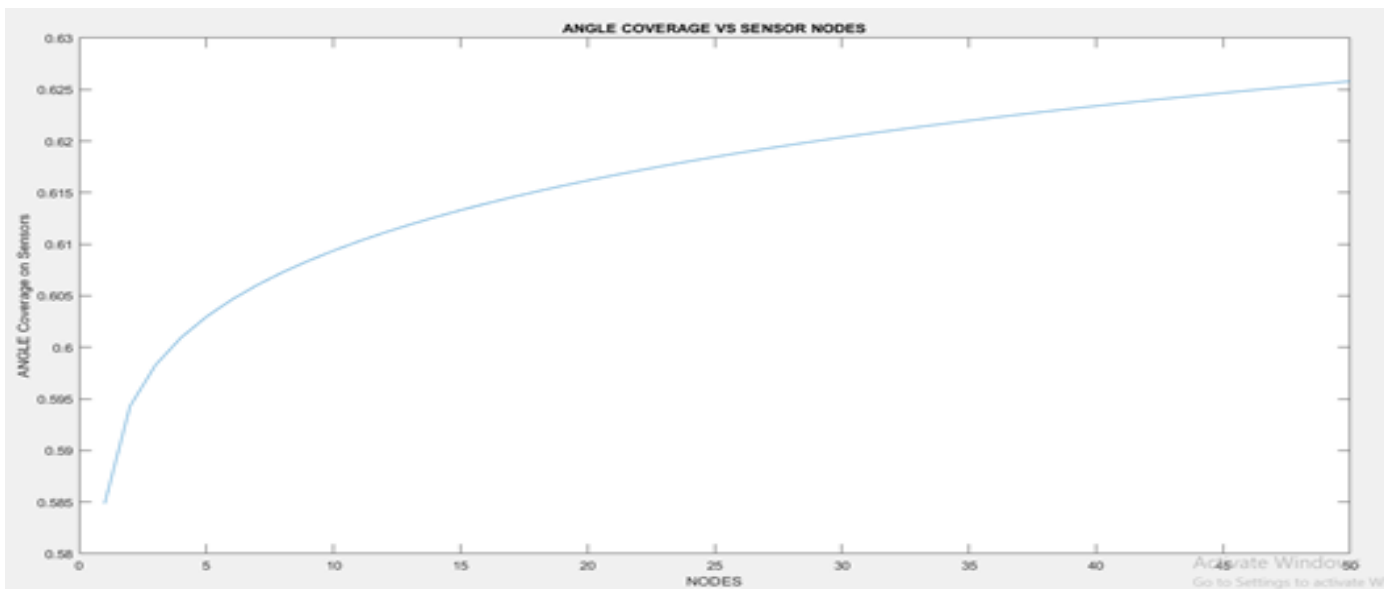


Figure 3(e): angle coverage vs sensor nodes

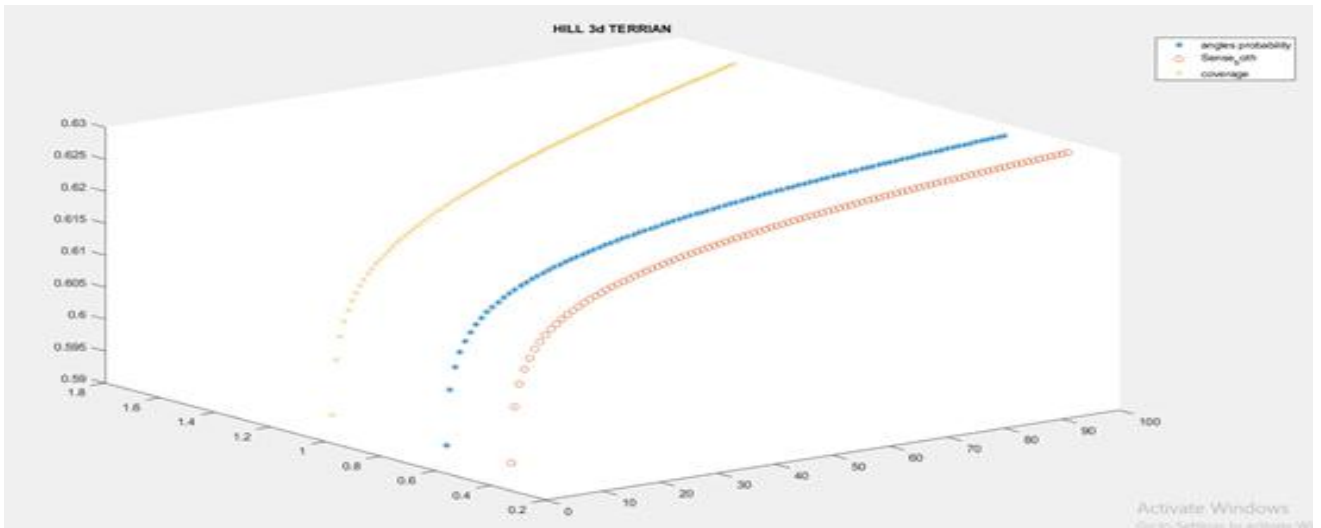


Figure 4(a): Hill 3D Terrain

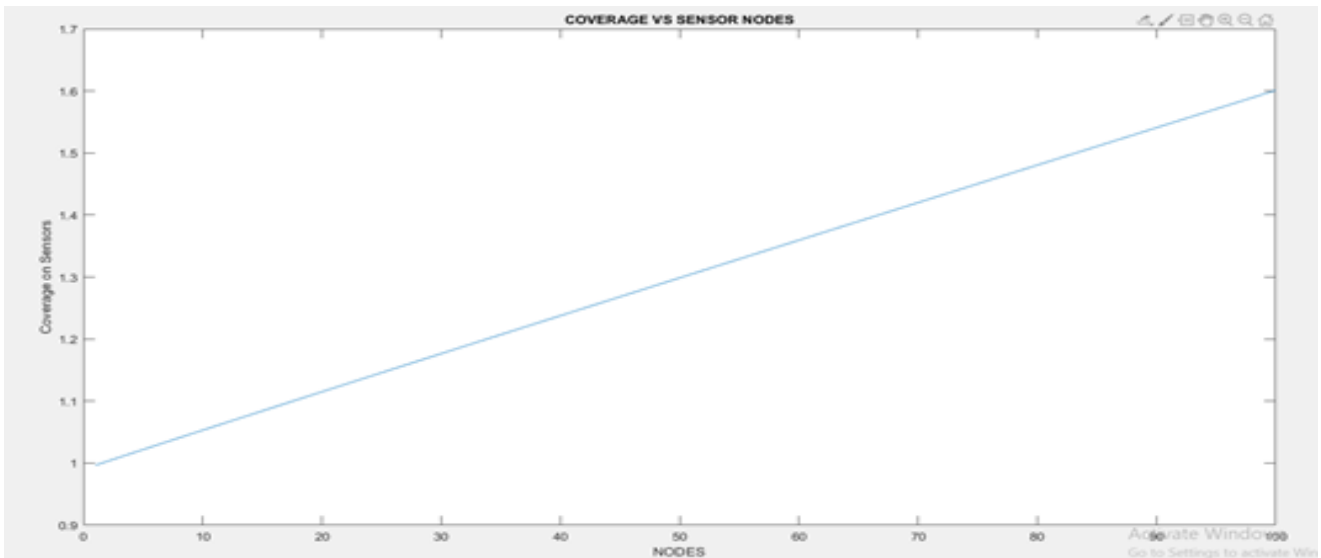


Figure 4(b): coverage vs sensor nodes

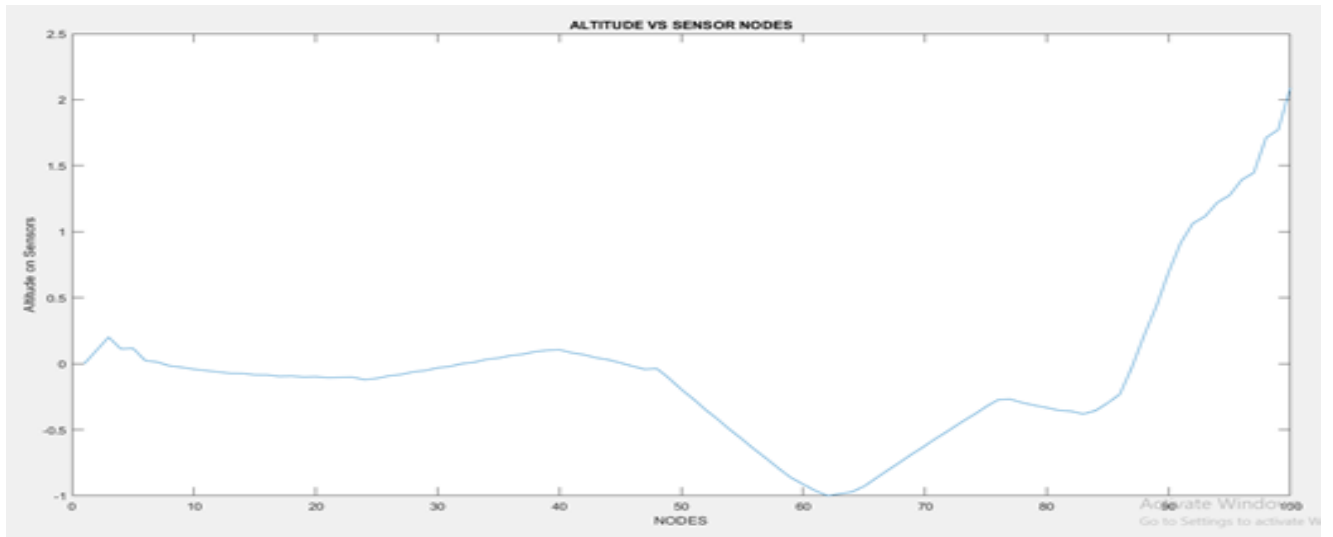


Figure 4(c): altitude vs sensor nodes

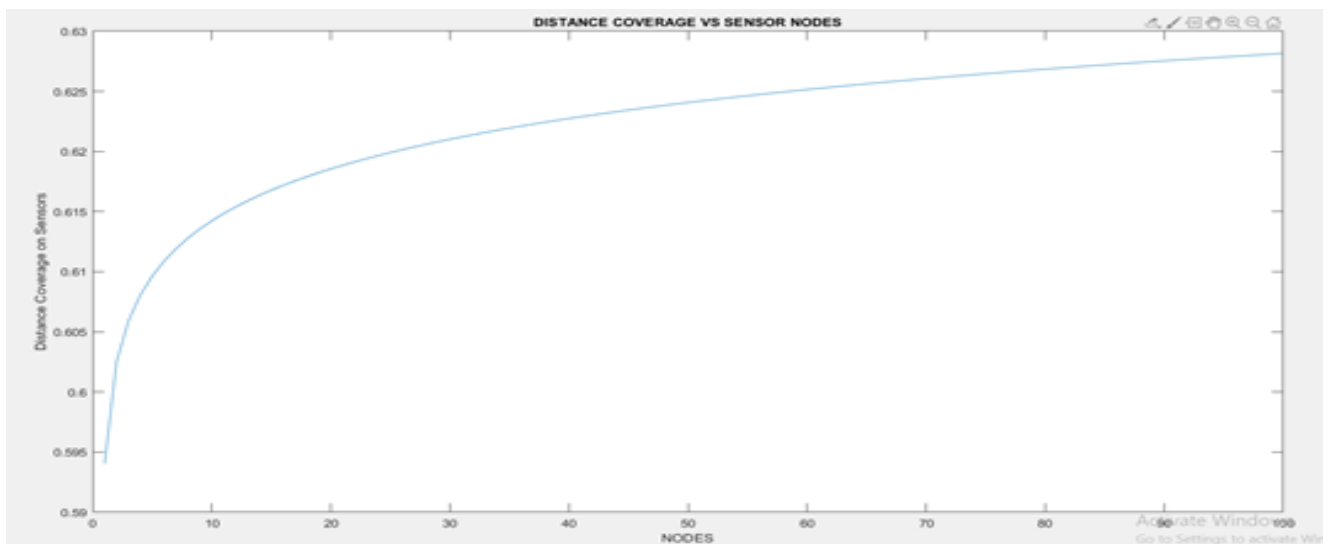


Figure 4(d): distance coverage vs sensor nodes

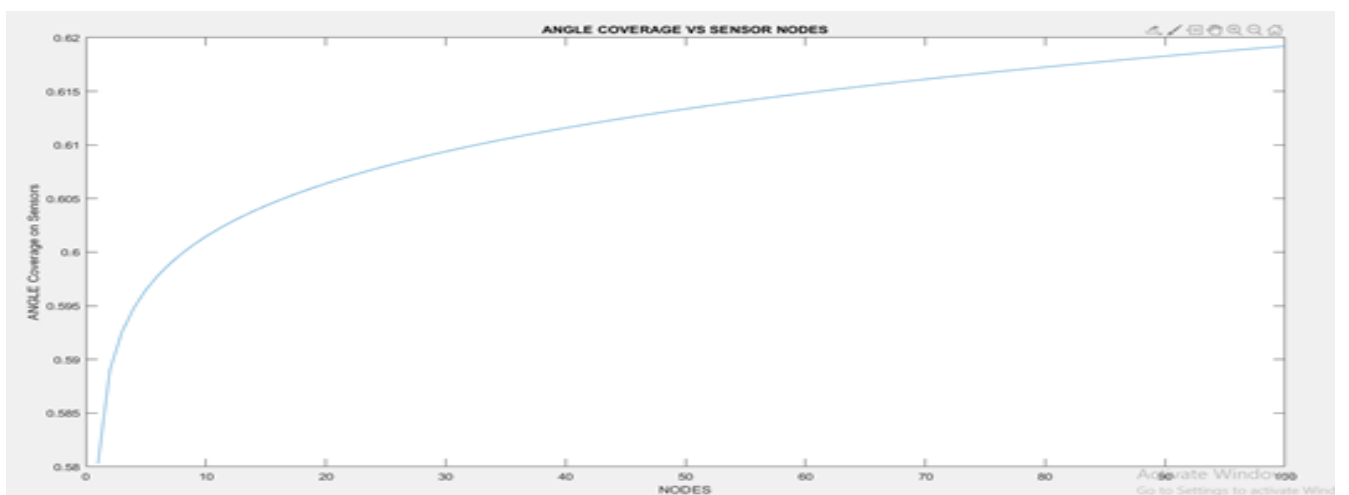


Figure 4(e): angle coverage vs sensor nodes

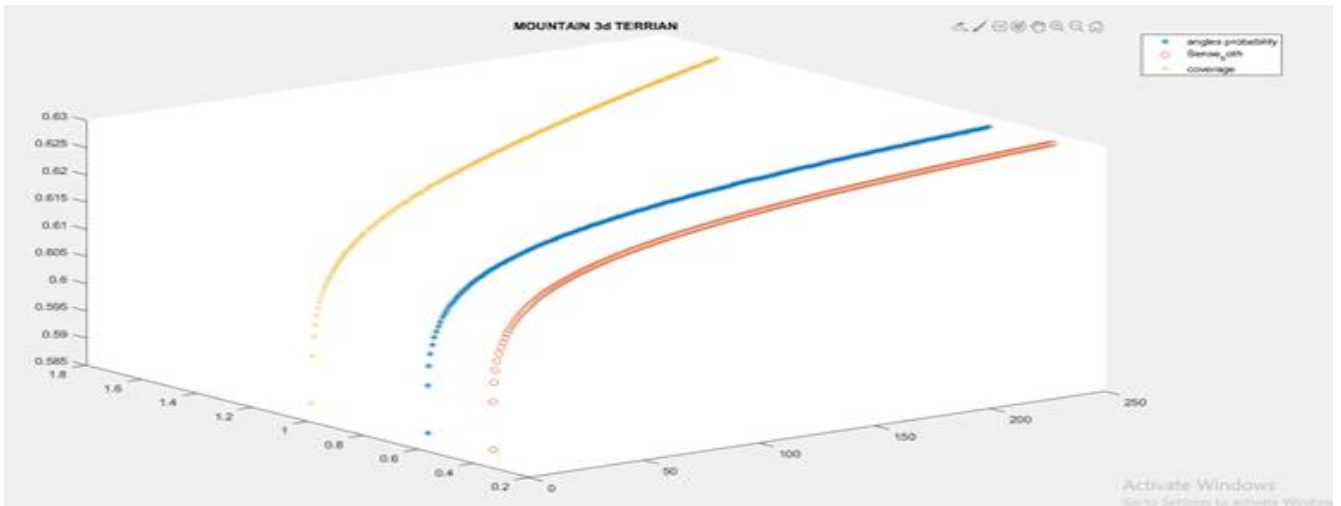


Figure 5(a): Hill 3D Terrain

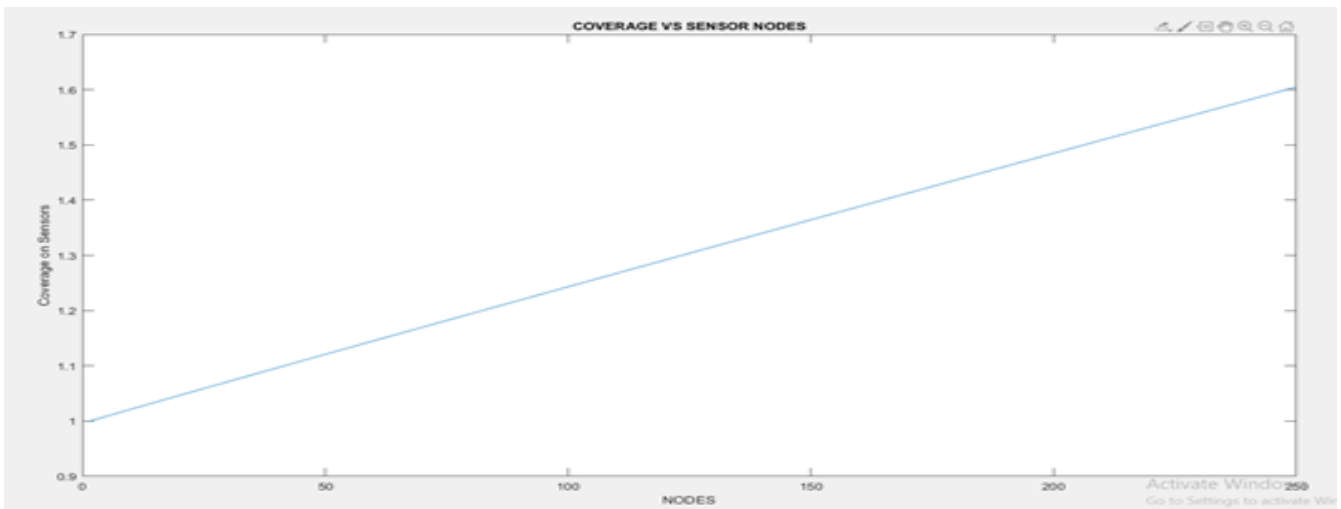


Figure 5(b): coverage vs sensor nodes

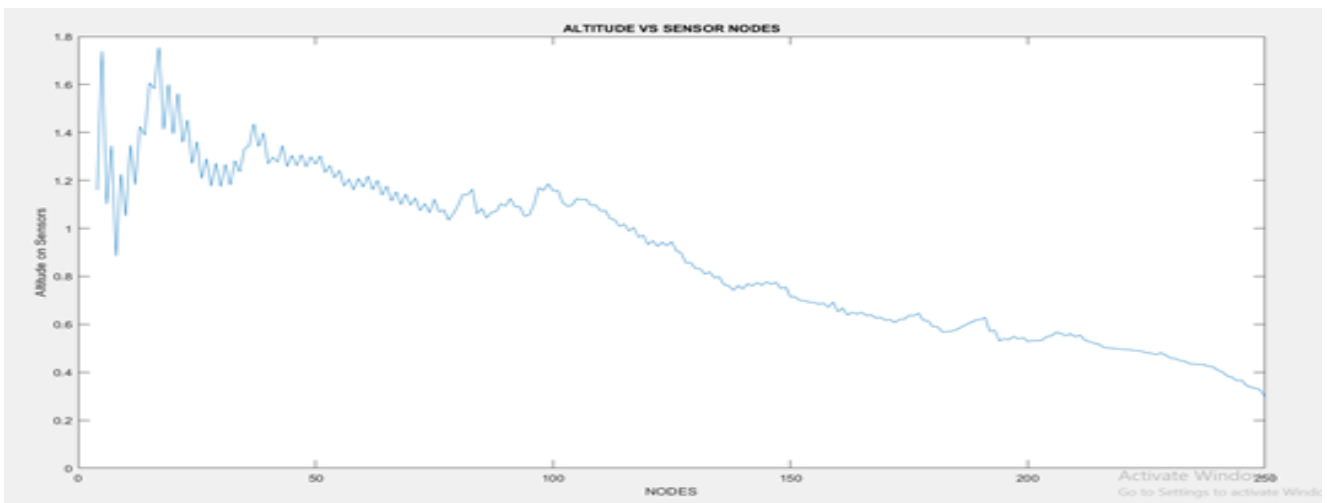


Figure 5(c): altitude vs sensor nodes

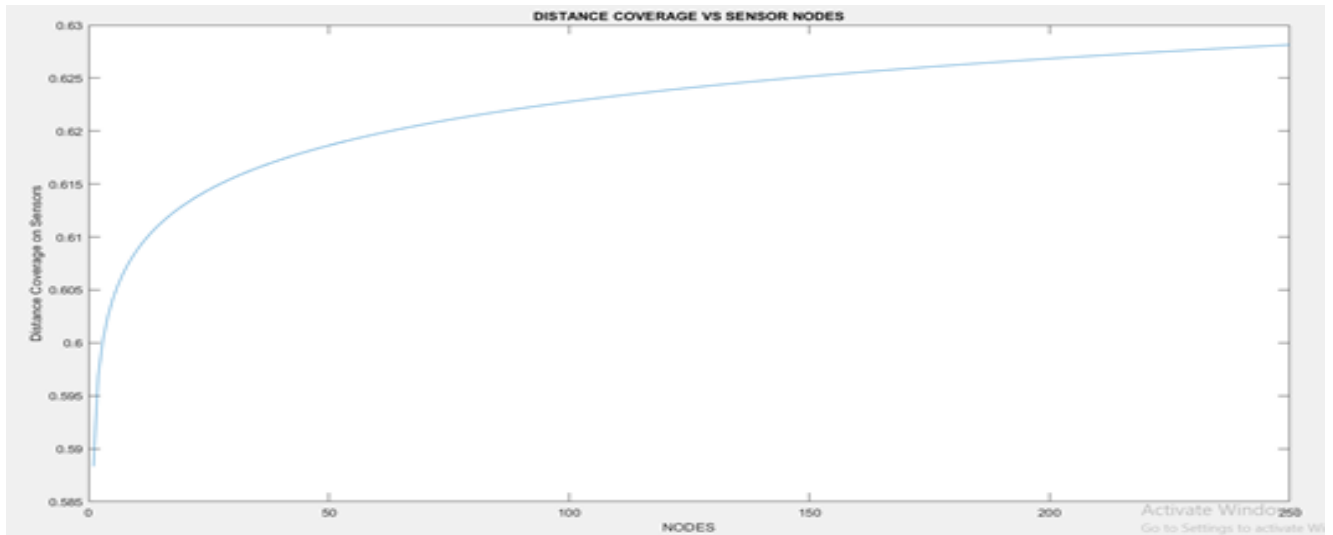


Figure 5(d): distance coverage vs sensor nodes

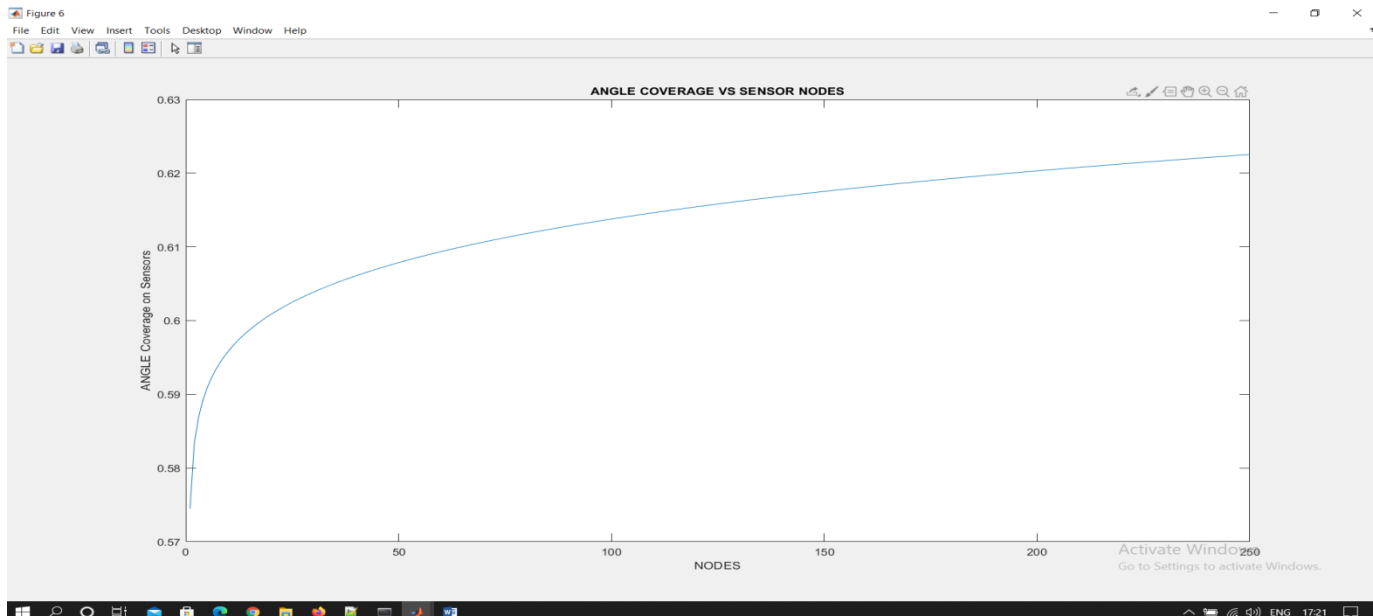


Figure 5(e): angle coverage vs sensor nodes

Contrasted with plain territory (Fig. 3), NSGA-III performs much better, which adds to the way that its appropriation turns out to be better yet at the same time not very great regarding MOEA/DVA and CMODE. For the primary marker, Coverage, MOEA/DVA and CMODE are the awesome, MOEA/DVA appears to be better, NSGA-III is more terrible and CCGDE3 is the most noticeably awful. As a rule, $MOEA/DVA \geq CMODE > NSGA-III > CCGDE3$. Finally, we examine the sensor hub organization results on hilly territory is presented. Working together, CMODE performs great as to both assembly and variety. MOEA/DVA

proposes the choice variable investigation (DVA) system to order the choice factors, in light of which choice.

CCGDE3 utilizes basic irregular gathering and basic DE analyzer (DE/rand/1), so its exhibition is very terrible. Joining the HV metric outcomes, we realize that as the intricacy of the territory expands, MOEA/DVA and CMODE perform very comparable however MOEA/DVA has some benefit over CMODE. For a wide range of landscapes, CCGDE3 can just accomplish a low Coverage rate, and the circulation is poor, so it is more terrible than MOEA/DVA and CMODE. NSGA-III is obviously superior to CCGDE3, yet it is as yet not comparable to CMODE and MOEA/DVA. From the abovementioned, we can say that, generally, the outcomes are as per the HV pointer and CMODE and MOEA/DVA are the awesome, MOEA/DVA appears to be superior to CMODE. NSGA-III is more terrible, and CCGDE3 is the most exceedingly awful for all cases.

6. Conclusion

In this paper, for the sending issue of HDSNs on 3D landscape, we present a 3D detecting demonstrate and receive an on-probabilistic measure-based combination administrator and propose a novel questionable 3D directional inclusion model based on the "fluffy ring". We mimic the sending issue as a multiobjective improvement issue with the accompanying three targets: Coverage, Connectivity Uniformity and Deployment Cost. Four multiobjective streamlining calculations. (MOEA/DVA, CMODE, NSGA-III and CCGDE3) are utilized to address the problem. To study the influence of different types of terrains on the deployment results, we conduct experiments on three types of terrains (plain, hill and mountain). From the experimental analysis, we conclude that MOEA/DVA performs the best, CMODE is a little worse, NSGA-III ranks third and CCGDE3 is the worst. Unlike traditional studies on the deployment problem, we extend the deterministic sensing model to an uncertain sensing model and present a novel coverage model, extending from the 2D plane and 3D full space to complex 3D terrain and also from omni-directional sensors to heterogeneous directional sensors. Therefore, the deployment problem becomes more complex but has more practical significance.

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