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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 heterogenous 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 came to market eg ultrasonic and image sensor nodes [3][4]. Ma et all 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 scholarconcentrates on triangle shaped model and irregular polygon model [6][7]. Teng et all 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 decreases. Elfes model (b)[10] is used characterize the sensing models. The multi layered model(c)[11]. The shadow funding model(d)[12], and sigmoide 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 all[19] Proposed cat swarm optimization using wavelet transform for deployment technique.

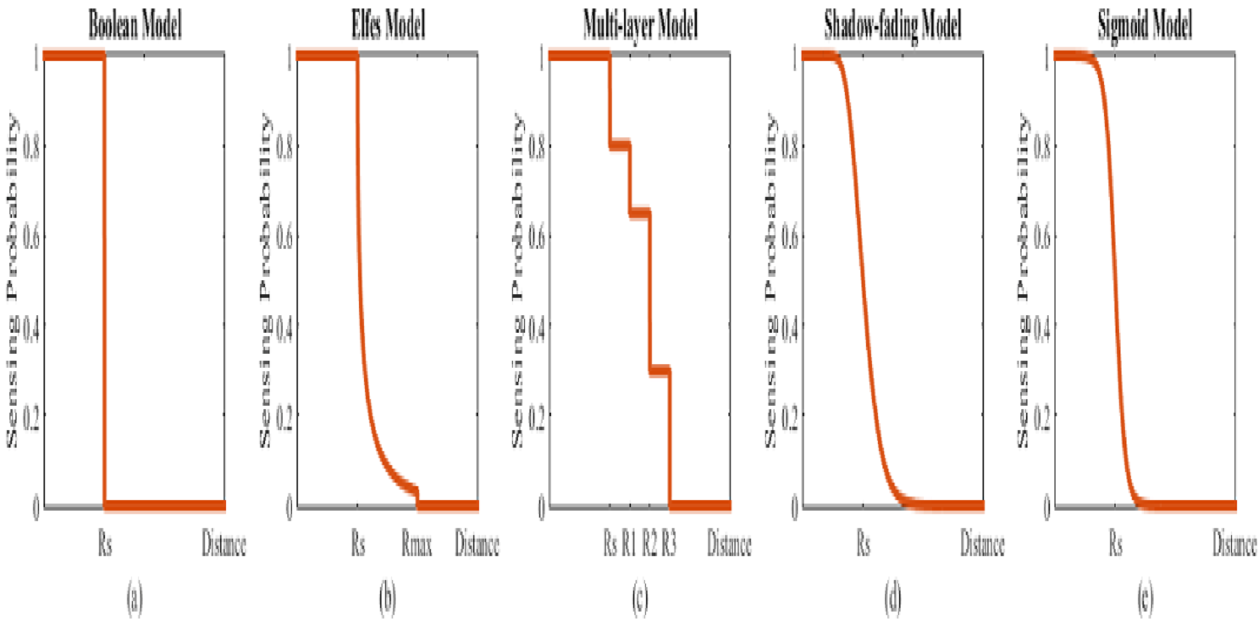

Figure 1: Traditional sensing models. (a) Boolean model; (b) Elfes model; (c) multi-layer model; (d) shadow-fading model; (e) sigmoid model.

In WSN deployment many parameters are considered such as connectivity, life time, uniformity etc[20]. Modified Elisit 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 delta p AN and vertical sensing angle delta T ILT are adjusted during the optimization where 0<dlta p AN , delta T ILT <2*pi. We use proposed modle 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 slandered 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 terranes 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 senor nodes. The distance between each nodes is different but fixed for multi objective algorithm the node population is represented as X1,Y1, delta 1 P AN, delta 1, T ILT….xmym delta MP AN, delta MT ILT where m=25, xi and yi represent position of sensor node dlta p AN ;I; is the horizontal sensing angle and delta I T ILT is vertical sensing angle and delta p AN ,delta I 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 evolution 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*160m which is illustrated in figure 2(a). the sensor deployed region is hilly region area of hill region is 160*10m as shown in fig 2(b). the extracted data from sensor in mountain region has large fluctuation area of mountain is 160m*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).

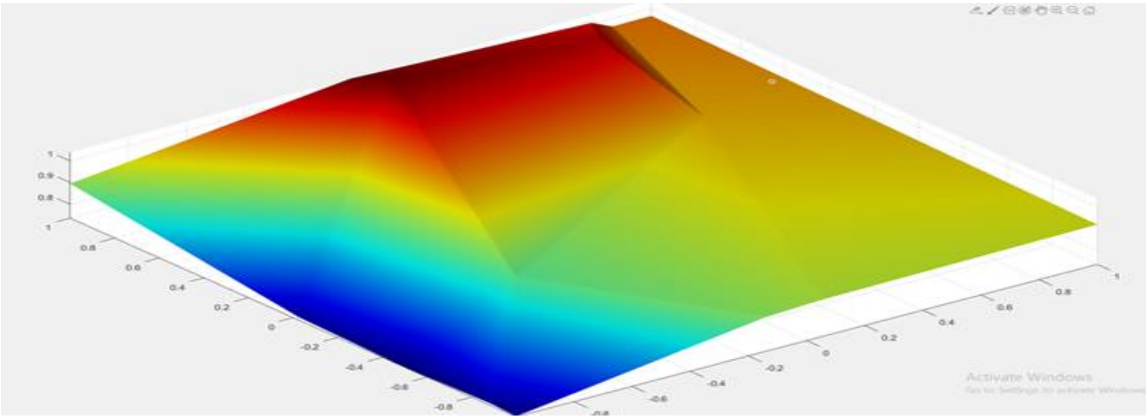

Figure 2(a): plain terrain

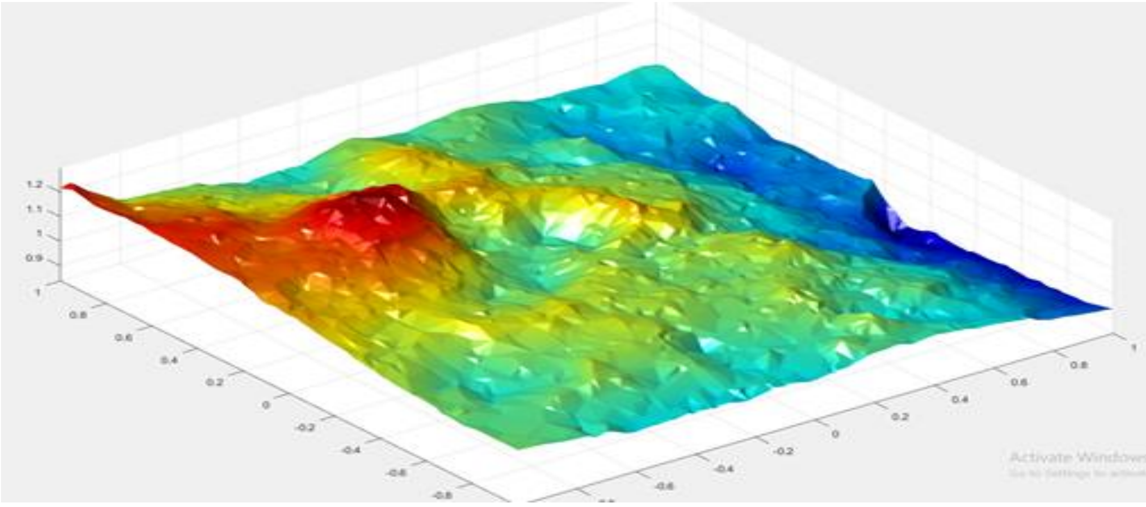

Figure 2 (b): Hilly terrain

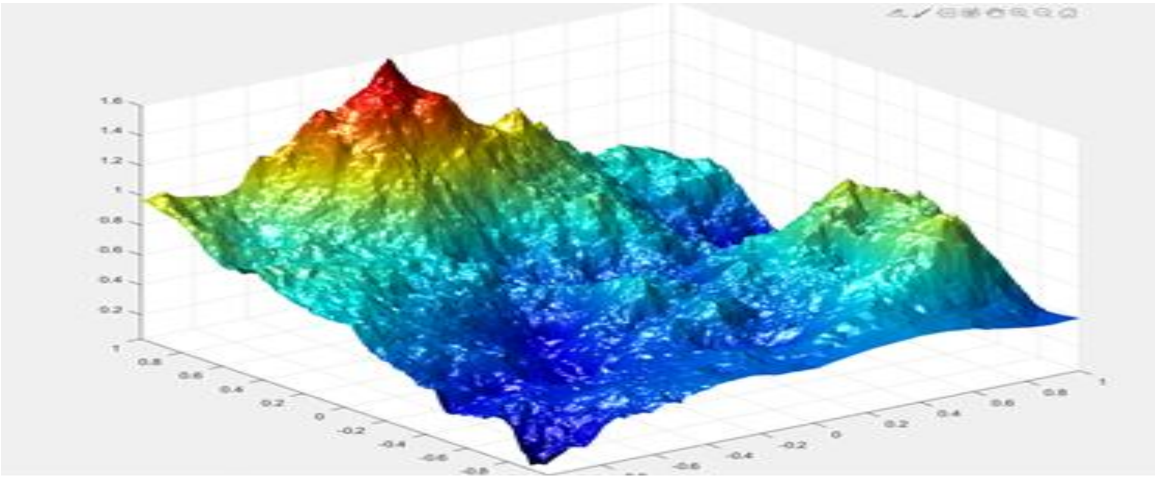

Figure (c): Mountainous terrain

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.

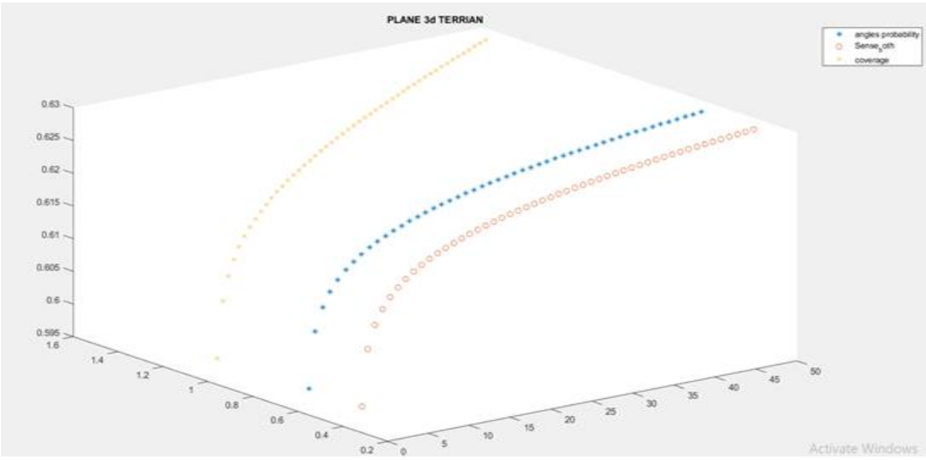

Figure 3(a): plain 3D Terrain

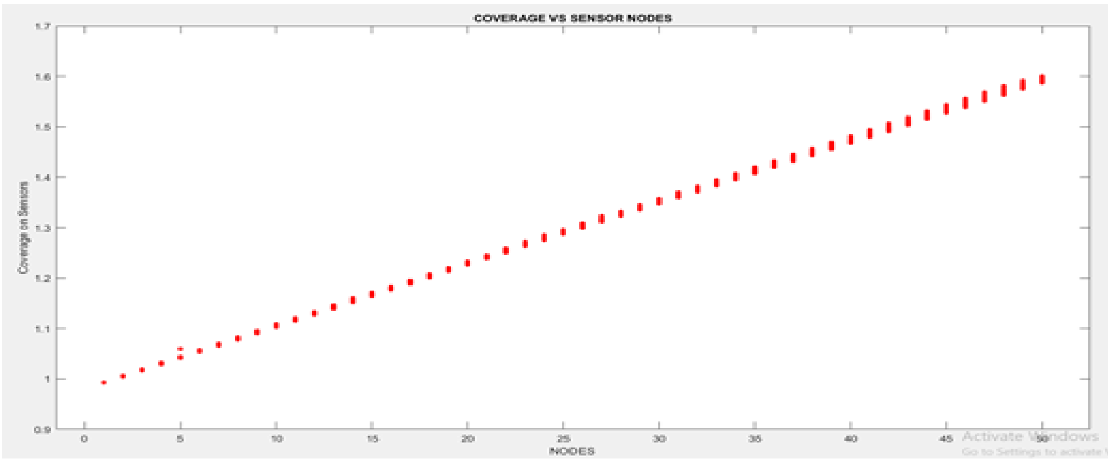

Figure 3(b): coverage vs sensor nodes

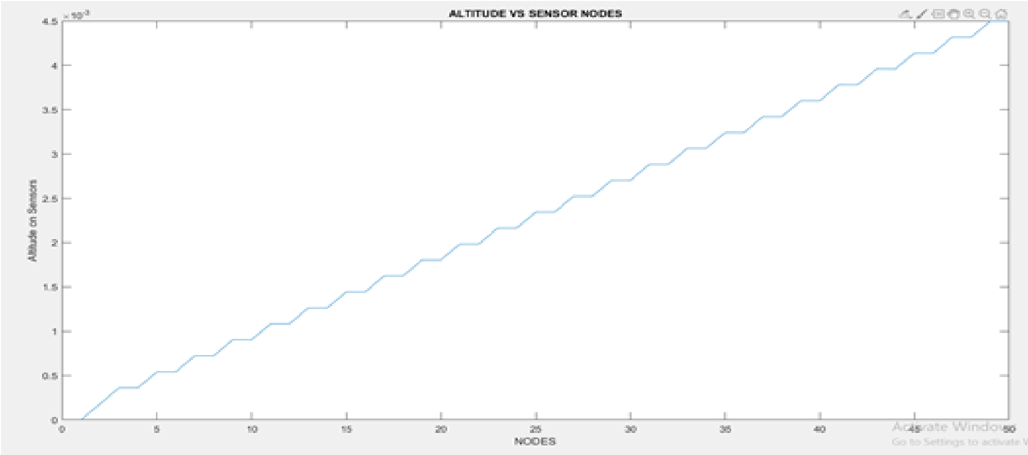

Figure 3(c): altitude vs sensor nodes

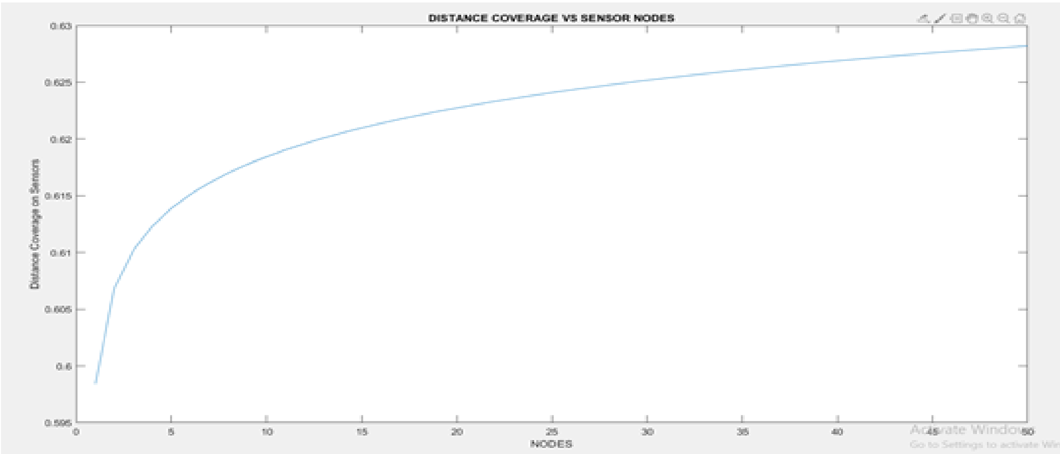

Figure 3(d): distance coverage vs sensor nodes

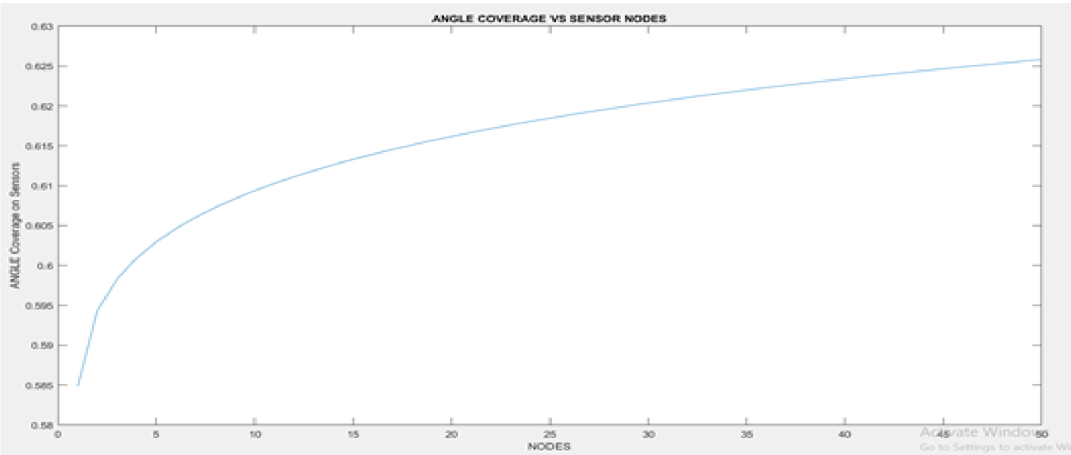

Figure 3(e): angle coverage vs sensor nodes

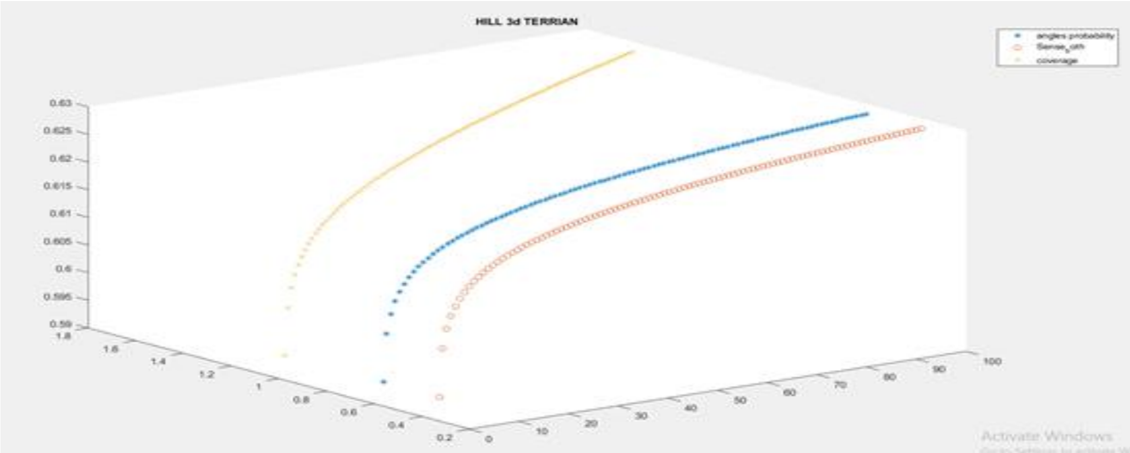

Figure 4(a): Hill 3D Terrain

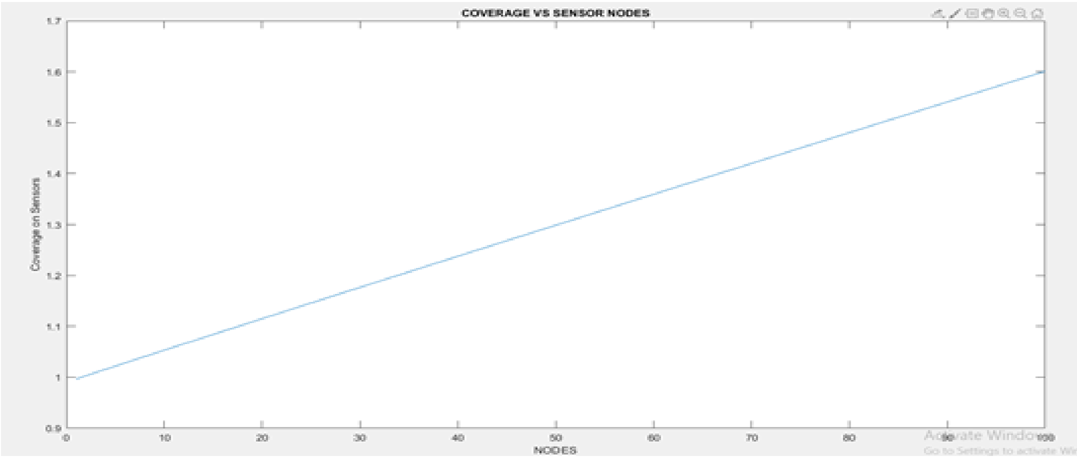

Figure 4(b): coverage vs sensor nodes

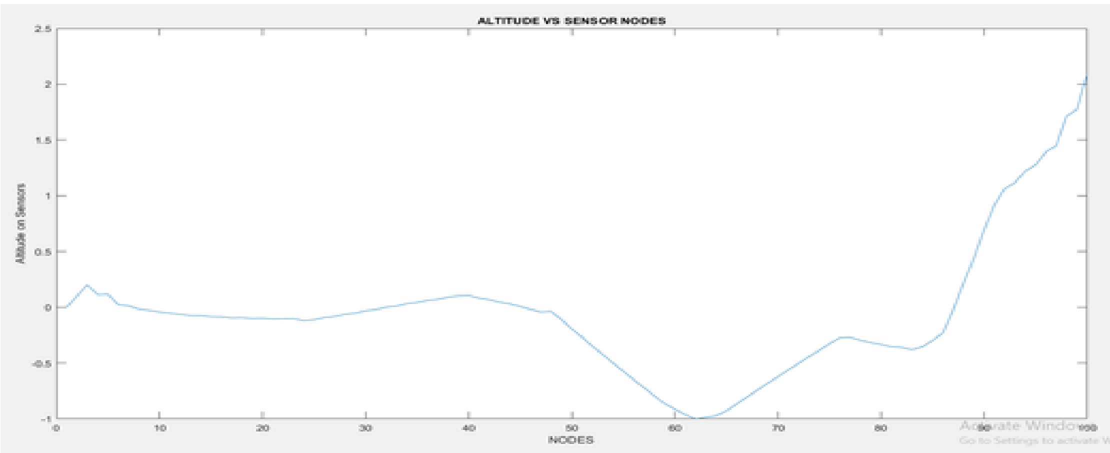

Figure 4(c): altitude vs sensor nodes

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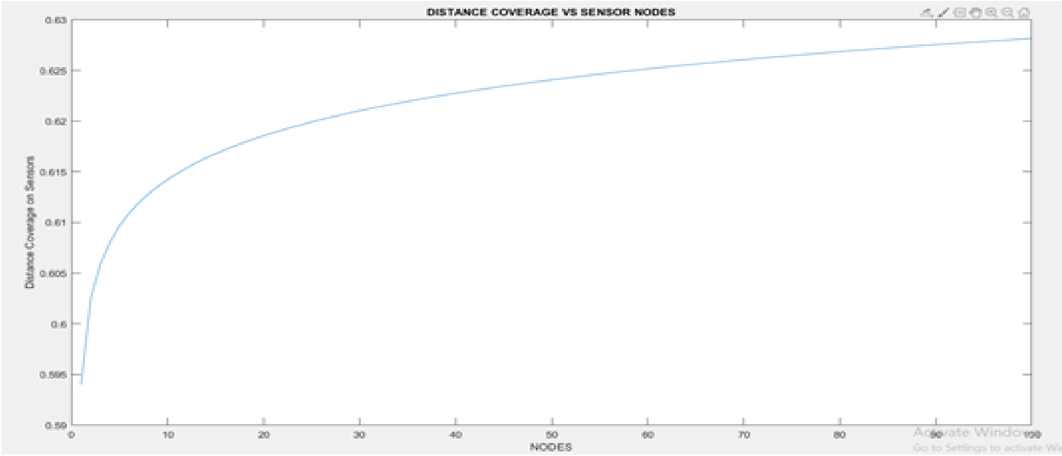

Figure 4(d): distance coverage vs sensor nodes

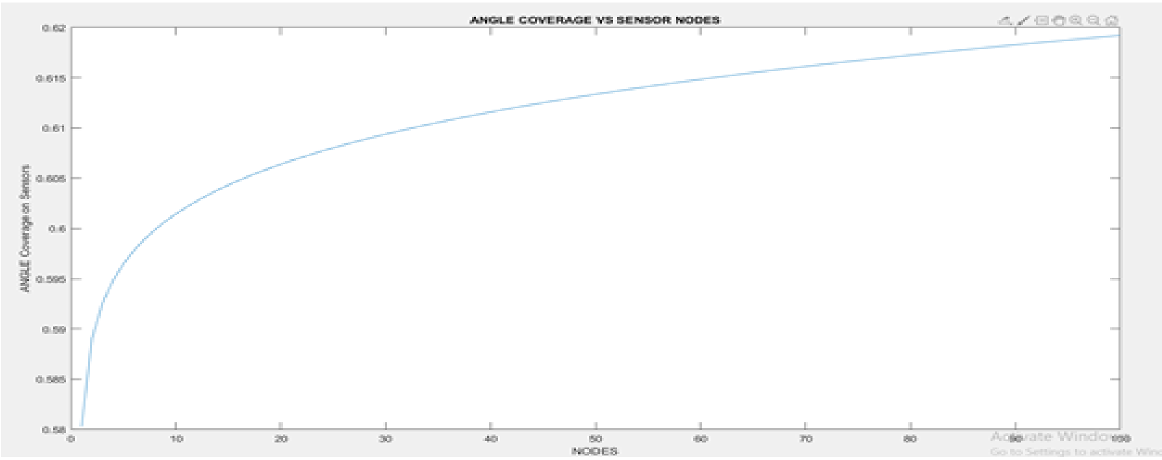

Figure 4(e): angle coverage vs sensor nodes

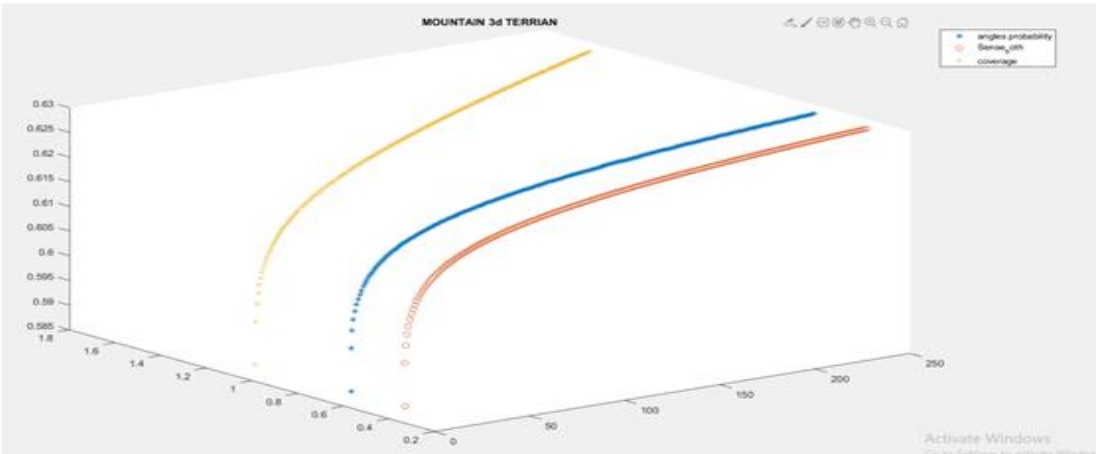

Figure 5(a): Hill 3D Terrain

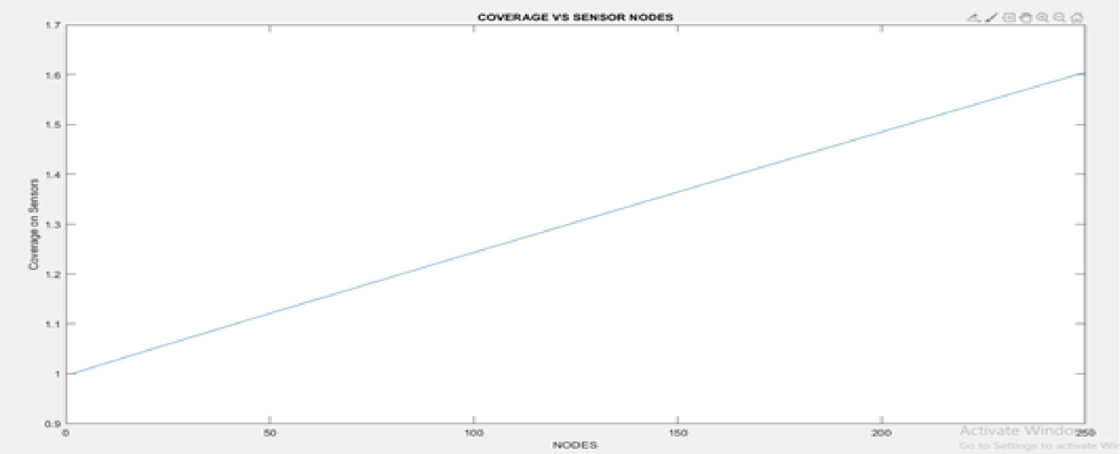

Figure 5(b): coverage vs sensor nodes

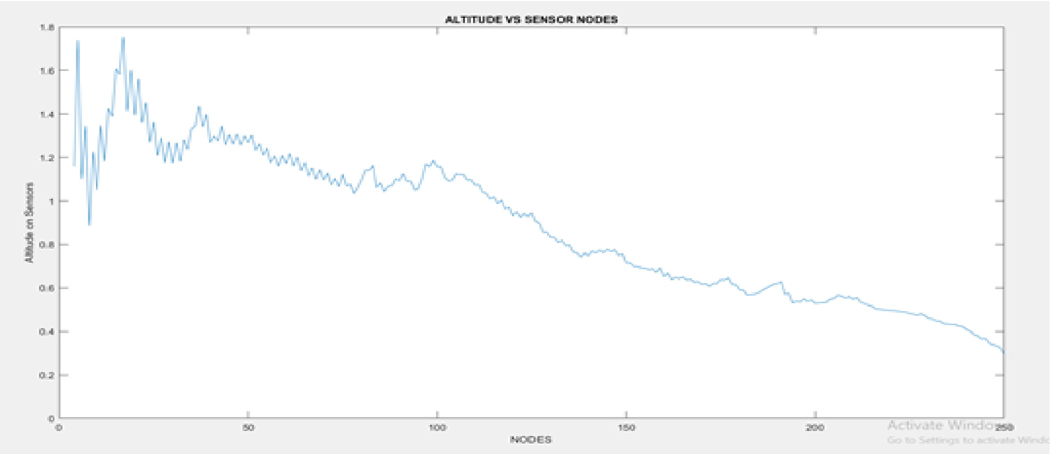

Figure 5(c): altitude vs sensor nodes

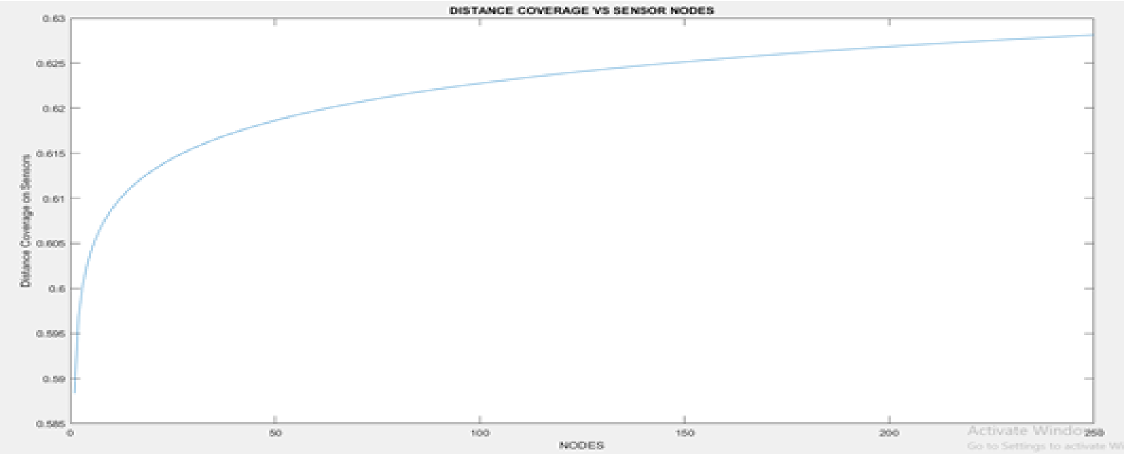

Figure 5(d): distance coverage vs sensor nodes

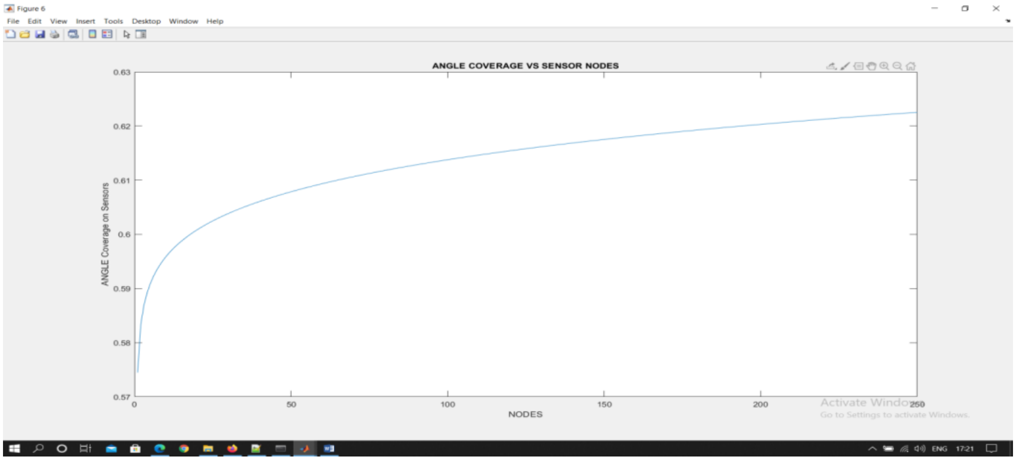

Figure 5(e): angle coverage vs sensor nodes

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 ≥ 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 onthe "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.

References

[1] J. Yick, B. Mukherjee, and D. Ghosal, "Wireless sensor network survey,"*Computer Networks*, vol. 52, no. 12, pp. 2292–2330, August 2008.

[2] M. Younis and K. Akkaya, "Strategies and techniques for node placement in wireless sensor networks: A survey," *Ad Hoc Networks*, vol. 6,no. 4, pp. 621–655, June 2008.

[3] I. F. Akyildiz, T. Melodia, and K. R. Chowdhury, "A survey on wirelessmultimedia sensor networks," *Computer Networks*, vol. 51, no. 4, pp.921–960, March 2007.

[4] M. A. Guvensan and A. G. Yavuz, "On coverage issues in directionalsensor networks: A survey," *Ad Hoc Networks*, vol. 9, no. 7, pp. 1238–1255, September 2011.

[5] H. D. Ma and Y. H. Liu, "On coverage problems of directional sensornetworks," in *First International Conference on Mobile Ad-hoc andSensor Networks*, vol. 3794, January 2005, pp. 721–731.

[6] C. H. Wu and Y. C. Chung, "A tiling-based approach for directionalsensor network deployment," in *IEEE Sensors Conference*, January2010, pp. 1358–1363.

[7] G. Fusco and H. Gupta, "Placement and orientation of rotating directional sensors," in *2010 7th Annual IEEE Communications SocietyConference on Sensor Mesh and Ad Hoc Communications and Networks*,June 2010, pp. 1–9.

[8] H. Teng, C. D. Wu, Y. Z. Zhang, and N. Hu, "Design of probabilisticsensing model for directional sensor node," *Journal of Jiangnan University (Natural Science Edition)*, vol. 11, no. 4, pp. 391–395, 2012.

[9] V. Akbarzadeh, C. Gagne, M. Parizeau, M. Argany, and M. A. Mostafavi,"Probabilistic sensing model for sensor placement optimization basedon line-of-sight coverage," *IEEE Transactions on Instrumentation andMeasurement*, vol. 62, no. 2, pp. 293–303, February 2013.

[10] A. Elfes, "Occupancy grids: a stochastic spatial representation for activerobotperception," *Autonomous Mobile Robots: Perception, Mapping andNavigation*, pp. 136–146, 1991.

[11] N. Ahmed, S. Kanhere, and S. Jha, "Probabilistic coverage in wirelesssensor networks," in *Proc. IEEE Conf. Local Computer Networks (LCN'05)*, November 2005, pp. 672–681.

[12] Y. R. Tsai, "Sensing coverage for randomly distributed wireless sensornetworks in shadowed environments," *IEEE Trans. Veh. Tech.*, vol. 57,no. 1, pp. 556–564, January 2008.

[13] C. K. Liang, C. Y. Chung, and C. F. Li, "A virtual force based movementscheme for area coverage in directional sensor networks," in *2014Tenth International Conference on Intelligent Information Hiding andMultimedia Signal Processing*, Aug 2014, pp. 718–722.

[14] J. Li, R. c. Wang, H. p. Huang, and L. j. Sun, "Voronoi based areacoverage optimization for directional sensor networks," in *2009 SecondInternational Symposium on Electronic Commerce and Security*, vol. 1,May 2009, pp. 488–493.

[15] T.-W. Sung and C.-S.Yang, "Voronoi-based coverage improvementapproach for wireless directional sensor networks," *Journal ofNetwork and Computer Applications*, vol. 39, pp. 202 – 213,2014. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1084804513001501

[16] Y. C. Wang, Y. F. Chen, and Y. C. Tseng, "Using rotatable anddirectional (ramp;d) sensors to achieve temporal coverage of objects andits surveillance application," *IEEE Transactions on Mobile Computing*,vol. 11, no. 8, pp. 1358–1371, Aug 2012.

[17] T. Y. Lin, H. Santoso, K. R. Wu, and G. L. Wang, "Enhanced deploymentalgorithms for heterogeneous directional mobile sensors in a boundedmonitoring area," *IEEE Transactions on Mobile Computing*, vol. PP,no. 99, pp. 1–1, 2016.

[18] H. Ma, X. Zhang, and A. Ming, "A coverage-enhancing method for 3Ddirectional sensor networks," in *IEEE INFOCOM 2009*, April 2009, pp.2791–2795.

[19] S. Temel, N. Unaldi, and O. Kaynak, "On deployment of wirelesssensors on 3-D terrains to maximize sensing coverage by utilizing catswarm optimization with wavelet transform," *IEEE Transactions onSystems, Man, and Cybernetics: Systems*, vol. 44, no. 1, pp. 111–120,Jan 2014.

ISSN: 2233-7857 IJFGCN

[20] A. Syarif, I. Benyahia, A. Abouaissa, L. Idoumghar, R. F. Sari, andP. Lorenz, "Evolutionary multi-objective based approach for wirelesssensor network deployment," in *2014 IEEE International Conferenceon Communications (ICC)*, June 2014, pp. 1831–1836.

[21] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, "A fast and elitistmultiobjective genetic algorithm: NSGA-II," *IEEE Transactions onEvolutionary Computation*, vol. 6, no. 2, pp. 182–197, Apr 2002.

[22] S. C. Oh, C. H. Tan, F. W. Kong, Y. S. Tan, K. H. Ng, G. W. Ng,and K. Tai, "Multiobjective optimization of sensor network deploymentby a genetic algorithm," in *2007 IEEE Congress on EvolutionaryComputation*, Sept 2007, pp. 3917–3921.

[23] D. He, J. Portilla, and T. Riesgo, "A 3d multi-objective optimizationplanning algorithm for wireless sensor networks," in *IECON 2013-39thAnnual Conference of the IEEE Industrial Electronics Society*. IEEE,

2013, pp. 5428–5433. [24] Z.-L. Yang, A. Wu, and H.-Q.Min, "Deployment of wireless sensor networks for oilfield monitoring by multiobjective discrete binary particleswarm optimization," *Journal of Sensors*, vol. 2016, pp. 1–15, 2016.

[25] M. Grabisch, T. Murofushi, and M. Sugeno, *Fuzzy Measures andIntegrals: Theory and Application*. New York: Springer-Verlag, 2000.[26] W. M. Cao, *Fuzzy Information Processing Methods of Sensor NetworkCoverage and Positioning*. Publishing house of electronics industry,2010, ch. 4, pp. 84–93.

[27] L. Wang, X. Fu, J. Fang, H. Wang, and M. Fei, "Optimal node placement in industrial wireless sensor networks using adaptive mutation probability binary particle swarm optimization algorithm," in *2011 SeventhInternational Conference on Natural Computation*, vol. 4, July 2011,pp. 2199–2203.

[28] H. R. Topcuoglu, M. Ermis, and M. Sifyan, "Positioning and utilizingsensors on a 3-D terrain part I — theory and modeling," *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications andReviews)*, vol. 41, no. 3, pp. 376–382, May 2011.

[29] L. M. Antonio and C. A. C. Coello, "Use of cooperative coevolution forsolving large scale multiobjective optimization problems," in *2013 IEEECongress on Evolutionary Computation*, June 2013, pp. 2758–2765.

[30] J. Wang, W. Zhang, and J. Zhang, "Cooperative differential evolutionwith multiple populations for multiobjective optimization," *IEEE Transactions on Cybernetics*, vol. 46, no. 12, pp. 2848–2861, Dec 2016.

[31] X. Ma, F. Liu, Y. Qi, X. Wang, L. Li, L. Jiao, M. Yin, and M. Gong, "Amultiobjective evolutionary algorithm based on decision variable analyses for multiobjective optimization problems with large-scale variables,"*IEEE Transactions on Evolutionary Computation*, vol. 20, no. 2, pp.275–298, April 2016.

[32] K. Deb and H. Jain, "An evolutionary many-objective optimizationalgorithm using reference-point-based nondominated sorting approach,part I: Solving problems with box constraints," *IEEE Transactions onEvolutionary Computation*, vol. 18, no. 4, pp. 577–601, Aug 2014.

[33] E. Zitzler, L. Thiele, M. Laumanns, C. M. Fonseca, and V. G. da Fonseca, "Performance assessment of multiobjective optimizers: an analysisand review," *IEEE Transactions on Evolutionary Computation*, vol. 7,no. 2, pp. 117–132, April 2003.

[34] S. Cheng, Y. Shi, and Q. Qin, "On the performance metrics ofmultiobjective optimization," in *Proceedings of the Third InternationalConference on Advances in Swarm Intelligence - Volume Part I*, ser.ICSI'12. Berlin, Heidelberg: Springer-Verlag, 2012, pp. 504–512.[Online]. Available: http://dx.doi.org/10.1007/978-3-642-30976-2 61

[35] E. Zitzler, "Evolutionary algorithms for multiobjective optimization:Methods and applications," Ph.D. dissertation, Swiss Federal Instituteof Technology Zurich (ETH), November 1999.

[36] J. Zhang and A. C. Sanderson, "JADE: Adaptive differential evolutionwith optional external archive," *IEEE Transactions on EvolutionaryComputation*, vol. 13, no. 5, pp. 945–958, Oct 2009.

[37] J. Brest, S. Greiner, B. Boskovic, M. Mernik, and V. Zumer, "Selfadapting control parameters in differential evolution: A comparativestudy on numerical benchmark problems," *IEEE Transactions on Evolutionary Computation*, vol. 10, no. 6, pp. 646–657, Dec 2006.

[38] M. Li, S. Yang, and X. Liu, "Shift-based density estimation for Paretobased algorithms in many-objective optimization," *IEEE Transactionson Evolutionary Computation*, vol. 18, no. 3, pp. 348–365, June 2014.