Adaptive PSO based Algorithm for Optimal WSN Deployment in 3 Dimensional Terrains

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ABSTRACT
Wireless Sensor Networks (WSN) are randomly deployed in the sensor field which brings the coverage problem . To maximize coverage, the sensors need to be placed in a position such that the sensing capability of the network is fully utilized to ensure high quality of service. This can be achieved with minimum number of sensor nodes having maximum coverage in the network and the nodes are within the communication range.

In this paper we propose to use Particle swarm algorithm and adaptive particle swarm optimization to cover the maximum volume possible for 3 – dimensional terrain with limited number of sensors . Particle swarm algorithm determine the best coverage. PSO has been successfully used in numerous engineering applications like in training of neural networks to identify Parkinson's disease, extraction of rules from fuzzy networks, image identification, Thus taking inspiration from earlier researches and success of PSO in various field we intend to use this algorithm for our problem solution . Thus, with the help of this study we finally propose an efficient way of deployment of nodes in WSN to cover the maximum volume possible for 3- dimensional terrain. And also show the comparison between the result of PSO and APSO.

General Terms
Your general terms must be any term which can be used for general classification of the submitted material such as Pattern Recognition, Security, Algorithms et. al.

Keywords
Particle Swarm Optimization, Evolutionary computation techniques, NP-complete, WSN, Volume coverage, 3 D Terrain

1. INTRODUCTION
In WSN systems coverage of area or volume in consideration is required, for detecting any change in environment like temperature , movement , vibration etc. .The task of optimaly deployment of Wireless sensors, radars etc having spherical volume coverage is very significant under various resource constraints such as limited sensor detection range, their numbers and other environment conditions.Prior to this various coverage algorithm for wireless sensors as well as radars (since radar deployment have been extensively researched by various organization including military organization , hence study of these provide a lot of insight for WSN as both technology are analogous to each other varying majorly in areas and type of surveillance) have been proposed. In general , deployment of system having spherical volume coverage is carried out using manually based on the geometry of the surface i.e 2D analysis.

There have been many previous efforts to provide optimal solution for deployment of sensors over a terrain and many evolutionary algorithm have been used to arrive at the solution.

Genetic algorithm base search were proposed by Kai Xie[1]. to find optimal deployment of radar in the two dimension terrain in the low earth orbit space based radar constellation design problem. Yulai [2] also gave a GA based real time mobile sensor network online deployment for maximal coverage of the environment. Multi objective Genetic algorithm is (DamienB . Jourdine) [3] used for sensor optimal placement , where two computing objectives considered are the total sensor coverage and the lifetime of the network. Jae Huan seo proposed a novel and efficient genetic based algorithm to the optimal sensor deployment of nodes for a wireless network designed to monitor enemy vehicles in a hostile region using genetic algorithm based on stable marriage crossover in which heterogeneity between genes is removed by pairing nearest two dimensional genes. Nikitha Kukunuru , Babu Rao Thella and Rajya Lakshmi Davuluri proposed sensor deployment using PSO . Damein B.Jourdan and Olivier L.de Weck [3] explained cluster based deployment of sensor nodes using PSO . Xue Wang[4] used particle swarm optimization algorithm & simulated annealing based optimal deployment of sensors in 2 Dimension terrain to accurately detect the target in such a way that power consumption of the entire network is minimized. The Hybrid algorithm optimizes the energy consumption, in which particle swarm optimization and simulated annealing are combined to find the optimal deployment solution in a distributed manner. But, most of these methods use in above mentioned papers are not addressing the effect of complex terrain (3 Dimension) conditions in the sensor deployment problem
These studies motivated us to formulate a particle swarm optimization (PSO) based efficient solution for optimal deployment of nodes WSN in a realistic 3 dimensional terrain. Static sensor placement was studied with several latest heuristic algorithms. Like Random deployment of WSN , "Greedy" placement which pts each successive sensors at the place improving coverage the most. , "Greedy paths" is similar to greedy except it considers only points on the current least - detectable path. ,Genetic algorithm(GA)[5,6,7,8] ,. Simulated Annealing (SA) .Both GA & SA based heuristic suffer problem of local optima because of pre mature convergence.

Particle Swarm Optimization is an optimization technique which uses an evolutionary based search. This search algorithm was introduced by Dr Russ Eberhart and Dr James kennedy in 1995. The term PSO refers to a relatively new family of algorithms that may be used to find optimal or near to optimal solutions to numerical and qualitative problems. It is implemented easily in most of the programming languages and has proven both very effective as well as quick when applied to a diverse set of optimization problems. PSO algorithms are especially useful for parameter optimization in continuous, multi-dimensional search spaces. PSO is mainly inspired by social behavior patterns of organisms that live and interact within large groups. In particular, PSO incorporates swarming behaviors observed in flocks of birds, schools of fish, or swarms of bees.

Since PSO[9] has a better convergence than other evolutionary algorithms thus we have used it in our study to find the optimal solution . PSO algorithm & its application to the problem is explained in detail in the succeeding paragraph

2. MODELLING

It is assumed that all sensor nodes are homogeneous having same range .Sensors are stationery. Sensing coverage and communication coverage of each node are assumed to have a spherical shape without any irregularity.

The design variables are 3D coordinates of the sensor nodes, $\{(x1, y1,z1), (x2, y2,z2)\ldots\ldots\}$.

A 3 dimensional particle i represents x and y and z coordinates of all n sensors:

Such that Xi = {x1,y1,z1,x2,y2,z2,x3,y3,z3,x4,y4,z4,……xn,yn,zn}

n= number of sensors

f(Xi,Ri) = Volume coverage in 3D terrain by i th particle represented by Xi

2.1 Maximizing Coverage

Maximize f(Xi,Ri) - to miximize the area covered by n no of sensors ,Where

Xi = {x1,y1,z1,x2,y2,z2,x3,y3,z3,x4,y4,z4,……xn,yn,zn}

Ri= range of the i th sensor , f(Xi,Ri)= Coverage(Xi,Ri)

$C = (U_{i=1\ldots.N}\ V_i)/V$

where

Vi is the volume covered by the *ith* node;

N is the total number of nodes;

V stands for the volume of the Region of interest (ROI)

Coverage Calculation

1 In order to prevent recalculating the overlapped area, the coverage here is calculated using Monte Carlo method by creating a uniform grid in the Region of interest.
2 All the grid points being located in the sensing area are labeled 1 otherwise 0, depending on the Euclidean distance between each grid point and the sensor node and also the terrian height is less then the height of grid point (for this Line of sight function from sensor center to grid point is used).
3 Then the coverage can be approximated by the ratio of the summation of ones to the total number of the grid points.

We have considered a rectangular surface of dimension (M,L,B), where L,B & M are length , breadth and height of the Surface.

This rectangular surface is assumed to be completely covering the given terrain or region of interest . The rectangular surface represented by matrix data structure GridCoveredStausMatrix is having M slices of dimension (L,B). This rectangular surface is assumed to be divide into total (M*L*B) small grids. Here any cell of GridCoveredStausMatrix(m,i,j) matrix , stores the coverage status of (i,j) th point of m th Height Slice of this rectangular surface . GridCoveredStausMatrix is made of M slice. Height of any (i,j) th point of m th slice is assumed to be same. If the value of GridCoveredStausMatrix(m,i,j) is 1, then the (i,j) th grid region of the m th slice (Height) will be assumed to be covered by any of the sensors.

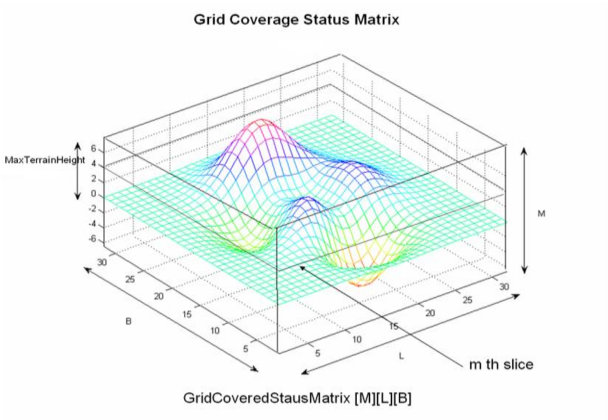


Figure 1.illustrates the 3-D terrain divided in grid as taken into consideration.

Initially no all Grids of GridCoveredStausMatrix cells / grids are covered therefore Initialize (m,i,j) with zero.

GridCoveredStausMatrix (m,i,j)=0

for m =1.. M,

i = 1.. L

j = 1.. B

Where M = 2*MaxTerrainHeight +1

Total Volume to be Covered

Vol = M*L*B

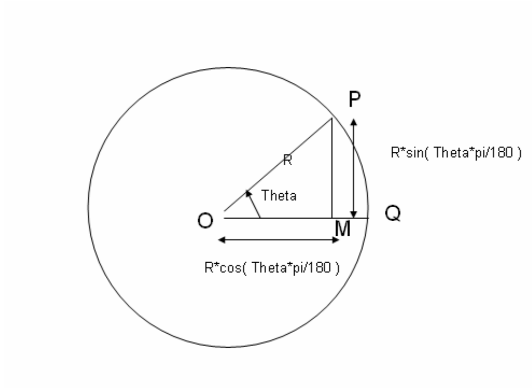


Figure 2.Shows the azimuthal calculation of terrain area coverage

For calculation PSO particles were randomly deployed and over iteration optimal position were found and best particle was output.

The calculations also take into consideration the relay structure wherein any node should be within distance 2r (r is the radius of sensor) to atleast 1 node of all the nodes. Thus creating paths from every node to every other node(direct or indirect) forming a connected graph. (since if any node is farther away , communication between nodes would not be possible.)

Basic Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a relatively newer addition to a class of population based search technique for solving numerical optimization problems. The particles or members of the swarm fly through a multidimensional search space looking for a potential solution. Each particle adjusts its position in the search space from time to time according to the flying experience of its own and of its neighbors.

For a D-dimensional search space the position and velocity of the ith particle are represented as

$X_i = (X_{i1}, \ldots\ldots, X_{id}, \ldots\ldots, X_{iD})$

& $V_i = (V_{i1}, \ldots\ldots, V_{i2}, \ldots\ldots, V_{iD})$ respectively.

These D – dimensions are the parameters on which particles are judged for suitability like amunt of heat , area covered , energy efficiency etc.

Each particle maintains a memory of its previous best position

$p_i^{best} = (p_{i1}, \ldots\ldots, p_{id}, \ldots\ldots, p_{iD})$ .The best one among all the particles in the population is represented as

$p_g^{best} = (p_{g1}, \ldots\ldots, p_{gd}, \ldots\ldots, p_{gD})$

In each iteration, p_g^{best} of the particle with best fitness in the local neighborhood and p_i^{best} of the current particle are combined to adjust the velocity along each dimension and a new position of the particle is determined using that velocity.

The two basic equations which govern the working of PSO are that of velocity vector and position vector given by:

$$V_{id}^{k+1} = w\, V_{id}^{k} + c_1 r_1 (p_{id} - x_{id}^{k}) + c_2 r_2 (p_{gd} - x_{id}^{k}) \quad \textbf{(1)}$$

$$x_{id}^{k+1} = x_{id}^{k} + V_{id} \quad \textbf{(2)}$$

for all d = 1…D

The first part of equation (1) represents the inertia of the previous velocity, the second part is the cognition part and it tells us about the personal thinking of the particle, the third part represents the cooperation among particles and is therefore named as the social component. Acceleration constants c1, c2 and inertia weight w are the predefined by the user and r1, r2 are the uniformly generated random numbers in the range of [0, 1].

To improve the performance of PSO , APSO was introduced.

Adaptive Particle Swarm Optimization

Adaptive PSO[10] is modification of PSO which at each stage eliminates the invaluable or less valuable particles , which on evolution have have undergone undesired process and have lost both local as well as global search capability and will not be able to provide optimal solution in later stages

The fitness of each particle is measured based on a Fitness function Fi.

Where

Fi is the fitness of ith particle , F_{gbest} is the fitness of gbest ,.Δ Fi = f(F_i, F_{gbest}),where f(x) is a error function is calculated.

A ϵ is a predefined critical constant according to the precision requirement, T_c is the count constant.

A replace function replaces all those particles in each iteration which fall below this constant $|\Delta Fi| < \epsilon$ thus eliminating all the inactive particles.

Coverage calculation with PSO

We have used APSO to generate the optimal solution over few iteration to cover maximum area with limited no of sensors

Procedure :

- The random approach is utilized to initialize the first generation of particles.
- The inertia weight is initially set and decreased linearly over the iterations .
- The acceleration constants c1 and c2 are set
- Population size of 30 is taken for 32 iterations.

For APSO,

- ΔF_i ,is set .
- The critical constant is set as $^{10\text{-}4}$, and the count constant T_c is set as 3.

Using the above area calculation technique the optimal solutions over the Specified iterations are produced.

2.2 Use Of repair Algorithm

While randomizing and then updating the velocity and direction of each particle in PSO , some dimension in solution of a particle may violate minimum 2r constraint .In order to keep the solution given by each particle conferring to

the constraint of maximum distance of 2r to maintain relay , a repair algorithm is used which works as follows.
Algorithm : (For reference see fig 3)

1) If the solution is found to be not suitable according to the constraints by applying relay check algorithm over each particle to check whether there there exist a relay in solution or not

2) A repair algorithm is applied over the solution to modify and adjust the solution. The disjkatra based repair algorithm takes each candidate Particle configuration (node location) and gives output as relay feasible / Not relay feasible. If the particle configuration is not relay feasible, the repair algorithm also returns the node index from where the relay need to be repaired

3) In repair algorithm the node violating the constraint are randomly moved over space a little and relay check algorithm is applied over each new configuration till valid configuration is found.

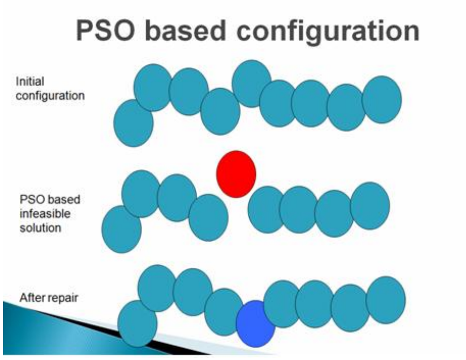


Figure 3. Figure shows the use of repair algorithm

3. SIMULATION RESULTS

3.1 Scenario description

In a particular scenario we have considered a terrain of 32 * 32 meter. Maximum Terrain Height considered was 4 .In this terrain taken 32 number of sensors are to be deployed optimally . sensor range has been taken as 4 meter. PSO was run for 32 iteration . In each iteration PSO particle size was taken as 30. The total dimension of PSO is 32*2=64 (for each x, y coordinates) . The following graph shows generation wise improvement in coverage of the terrain. Figure 2 displays the actual coverage for different generation. For 32 sensor of 4 meter communication range the maximum coverage achieved by **APSO** was 35.5 % and (32.7 %) by **PSO** . **To improve the performance of PSO , APSO was introduced.**

Table 1. Fundamental parameters of WSN

Parameter	Value
Sensing field dimension *LxL*	*32 meter * 32 meter*
Stationary node number *n*	*32*
Sink node coordinates	(4,4)
Sensing radius *Ra*	4 m
Sensor communication range *CR*	4 m

PSO parameters

1. The random approach is utilized to initialize the first generation of particles. The inertia weight is initially set as 1.0 and decreasing to 0.0 linearly over the iterations .
2. The acceleration constants are set as c1=1.6; c2=1.4. Vmin and Vmax are taken as -5 & 5 respectively. Population size of 20 is taken for 32 iterations.

For **APSO,** ΔF_i is set as a relative error function,which is $(F_{gbest}- F_i)$/MAX(ABS(F_i), ABS(F_{gbest})), where ABS(x) gets the absolute value of x, MAX(x_1, x_2) gets the minimum value between x_1 and x_2. The critical constant ϵ is set as 10^{-4}, and the count constant T_c is set as 3.

Computation result

PSO solution (see fig4) started from 15 % to 32 % volume coverage of the terrain.

Coverage (%) of Best PSO Particle (32 Nodes * 2 dimension= 64 dimension)

GBestplot = 15.5792 19.2671 21.9385 23.2151 24.5390 24.8936 25.7447 27.3995 27.3995 27.3995 27.3995 27.3995 27.6123 27.6123 27.6123 27.6123 28.3452 28.3452 28.3452 28.3452 30.9929 31.7730 31.7730 31.7730 31.7730 32.1749 32.1749 32.2459 32.2459 32.5059 32.5050 32.7187

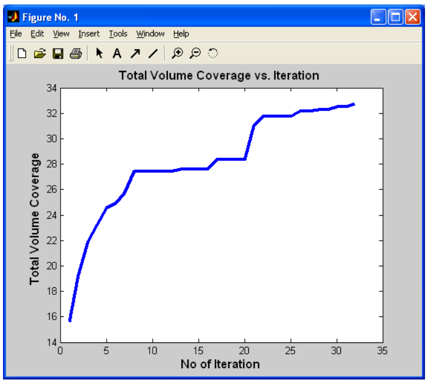


Figure 4.Shows the total volume coverage of an area over iterations given by PSO algorithm

Volume Coverage (%) by APSO in each Iteration

APSO (see fig 5) solution started from 15 % to 35.5 % volume coverage of the terrain.

Coverage (%) of Best APSO Particle (32 Nodes * 2 dimension= 64 dimension)

GBestplot = 15.5792 19.2671 21.9385 23.2151 24.5154 28.2506 28.2506 28.8652 30.1182 30.1182 30.1182 30.1182 31.7967 32.1749 32.1749 32.1749 32.1749 32.1749 32.1749 32.1749 32.1749 32.1749 32.1749 32.1749 32.6478 32.6478 32.6478 32.9551 33.4279 33.4279 33.5697
35.5556

For the same scenario, the maximum expected coverage value of the Terrain is 35.5 % , which indicates that APSO performs better than simple PSO methods by 3%.

Improvement in Volume coverage of the Terrain in each iteration by A- PSO is shown below

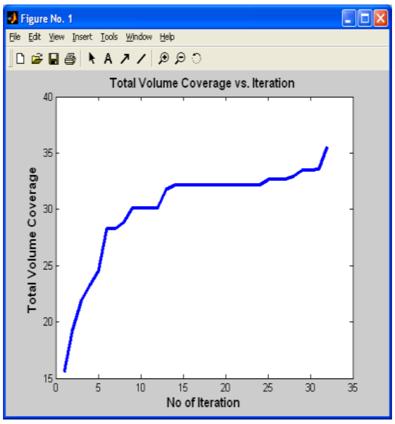


Figure 5. Shows the total volume coverage of an area over iterations given by PSO algorithm

Variation of Volume Coverage (%) by Adaptive PSO in each Iteration each Iteration

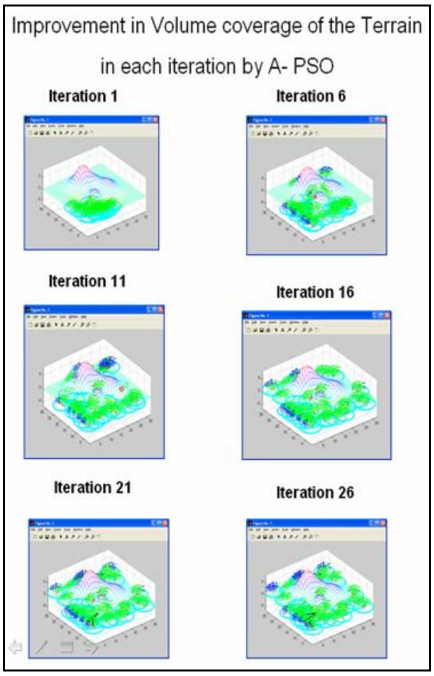


Figure 6. Shows Graphical representation of the area coverage and deployment of sensors in of 3-D terrain over iterations .

Coverage given by last Iteration Number (32)

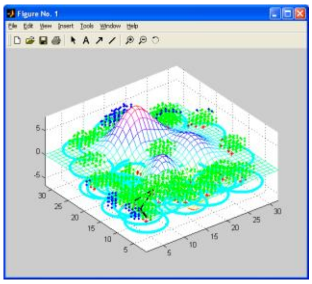
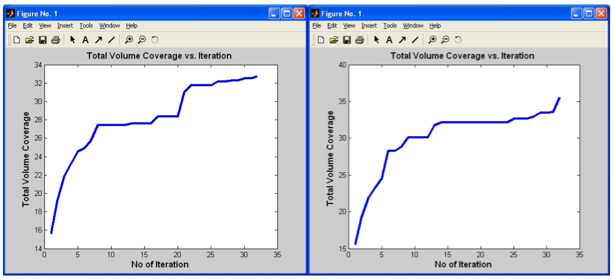


Figure 7. Shows Graphical representation of the area coverage and deployment of sensors in of 3-D terrain after last iterations .

Comparison PSO vs APSO (see figure8)

The simulation results illustrate that the performance of adaptive PSO was 3 % more volume coverage then simple PSO



PSO **APSO**

Figure 8.Shows the comparison between area coverage over iteration produced by PSO and APSO

4. CONCLUSION

In this study, an adaptive particle swarm optimizer was introduced to improve the performance. The adaptive criterion is appended on individual level. Since the critical constant ϵ is decided by the precision requirement to fitness, it is more easily to be decided for different problems. The simulation results illustrate the performance of adaptive PSO can improve the performance. This adaptive method may be also used for other evolutionary computation technologies, such as genetic algorithms.

1 In this study, particle swarm optimizer was introduced to optimally deploy the sensor nodes in the mountainous terrain so that not only the coverage is maximum but the sensor placement is energy efficient.
2 The simulation results illustrate the PSO can improve the Solution quality & give faster convergence.
3 An adaptive particle swarm optimizer was introduced to improve the performance. The adaptive criterion is appended on individual level. Since the critical constant ϵ is decided by the precision requirement to fitness, it is more easily to be decided for different problems. The simulation results illustrate that the performance of adaptive PSO was 3 % more ten simple PSO.

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