

Multi-Objective Evolutionary Algorithm for Sensor Node Placement in Heterogeneous Wireless Sensor Network

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Abstract— Node placement in the target area is one of the most crucial issues in wireless sensor networks and their deployment should be cost-effective. The deployment cost depends upon the number of sensing devices deployed. Thus, optimum number of sensors should be used while optimizing the various network preliminaries like energy consumption, network coverage and connectivity. In this paper, grid based coverage is considered with minimum energy consumption and proposes a novel deployment algorithm for heterogeneous wsn. This algorithm is based on multi-objective genetic algorithm for deterministic deployment of sensors. A simulation study is carried out to compare the performance of proposed algorithm with multi-objective territorial predator scent marking algorithm (MOTPSMA). Result shows that proposed algorithm outperforms the performance of MOTPSMA in terms of network coverage and energy consumption.

Key words: Heterogeneous Wireless Sensor Network, Sensor Node Placement, Coverage, Energy Consumption, Multi-Objective Evolutionary Algorithm

I. INTRODUCTION

A wireless sensor network consists of numerous sensors that are deployed in a monitored area. The nodes have the ability of sensing the events, communicating with other nodes, aggregating the sensed data [10]. Data aggregation reduces the amount of data sent to the base station and hence less energy is consumed [9]. Advancement in technologies makes the area of wireless sensor network as an emerging research area. The sensing devices can sense within their sensing range and can communicate via built-in antenna with each node that is within the communication range [5, 8].

Wsn potential can be shown in wide-range of applications including target monitoring [26], healthcare [27], agriculture [28] and intruder detection [3]. The deploying environment like battlefield, landslide area, forest, agriculture depends upon the application. These environments have different wsn topology so their performance can't be predicted easily [2].

Optimization of sensor node locations in the region of interest (ROI) is one of the main issues during the design of these networks. Optimal placement of sensors results in communication for a longer duration [5] and hence network lifetime increases.

The placement of sensing devices in the target field can be random and deterministic. In random deployment, the sensors are randomly scattered in the field. This leads to uneven distribution of sensor nodes and it partially covers the area. It may lead to high concentration of nodes in some areas. The areas with dense deployment have more energy consumption and hence energy depletion increases [4]. On

the other hand, in deterministic deployment, the position of sensors is known before placement and offers full coverage even with lesser number of nodes. The selection of a particular approach depends on the environment topology. Former is mainly used when the target area is hostile [5] and information about topological structure network isn't known in advance [4]. Thus, the sensing devices are randomly spread through aerially deployed. But as sensing devices are expensive, it is good to use deterministic approach that requires lesser number of nodes.

The network of sensors can be homogeneous or heterogeneous depending upon the characteristics of the nodes. Homogeneous network consists of identical nodes i.e. they have same sensing and communication capabilities. But in heterogeneous network, nodes have different sensing and communication capabilities [4]. In this paper, heterogeneous sensor network is considered that uses three types of nodes. These nodes have different sensing radii, communication radii and energies.

To provide better coverage, more nodes are to be deployed [18] and hence deployment cost is increased. So, it is a good option to deploy nodes with different sensing capacities so that better coverage will be achieved with lesser nodes. Coverage density got increased when different types of nodes are used as compared to homogeneous network [11].

The sensing devices have limited initial energy and aren't rechargeable. Thus, energy consumption in wsn offers many challenges to researchers as the sensor nodes are prone to failure due to energy depletion [4]. So, there is a need of energy efficient deployment of sensors that minimize energy consumption and hence prolong lifetime of the network. But this statement is partial complete. Along with minimum energy consumption, the node placement problem should be solved with multi-objective optimization by taking other network preliminaries as the objective function. In this paper, network coverage is considered along with energy consumption in heterogeneous sensor network.

The sensing coverage and the energy consumption are strongly dependent on the location of the sensor nodes in the monitored area. If the nodes are deployed near the base station, the energy consumption is reduced but has adverse effect on coverage. Thus, an effective planning mechanism should be used to have maximum coverage and minimum energy consumption with connectivity constraints and it is also important to find the optimum number of nodes for cost-effective deployment.

II. RELATED WORK

There are several research work related to the deployment of wireless sensor networks. Some authors worked on

homogeneous nodes [1, 3, 6-7, 13-14, 16-17] and some worked on heterogeneous nodes [8-9, 15, 21, 30-31]. Most of the work in wsn deployment was done on maximizing coverage or/and minimize energy consumption in homogeneous network.

The multi-objective evolutionary algorithm based on decomposition [1, 3, 6, 13, 14] decomposes the multi-objective problem (MOP) into single objective problems. The author in [13] used this concept by considering energy consumption and network coverage as objectives. In [1], the concept of decomposition was used with differential evolution for optimizing various network preliminaries and in [3, 6, 14] for deployment and power assignment problem (DPAP). This work was further extended by designing heuristics specifically for DPAP [6, 14].

Pattern based deployment was also done in some papers [16, 17]. The authors in [1, 7] address the point coverage problem in which a limited number of points with known locations need to be monitored. The MOTPSMA approach in [7] considers energy consumption, coverage as their main objective with connectivity constraint. MOTPSMA showed better results than shown in [1]. But approach in [7] doesn't limit the number of deployed sensor nodes, which consequently would affect the cost and total energy consumption.

The author in [15] worked on minimizing monetary cost that includes hardware cost and battery cost with lifetime and coverage constraint. The model was based on LEACH that includes cluster formation. Three types of nodes are used to optimize coverage and installation cost (node cost and region cost) [18, 29]. A fitness-based crossover was proposed in [18] and scatter mutation in [29]. But this paper didn't consider the energy consumption in the network.

Author in [21] added routers to the network and provide heterogeneity in the network whereas some authors [9, 24] define heterogeneity in the network on the basis of tasks performed by sensor nodes. The tasks can be sensing the environmental changes, communicating with other devices, data aggregation. The concept of cluster formation is used in [9, 30] and cluster heads should be provided with higher energy than sensor nodes because energy consumed at cluster heads is high.

The concept of dynamically adjusting the sensing range of the nodes to optimize network coverage [8] and energy consumption [31] was considered. In [8], after initial random deployment, pruning pre-processing algorithm was used to speed up the optimization speed. Sensors with low sensing range weren't considered in the optimization process but still they are present on the field and increase the cost.

However, above related works don't consider fixed and heterogeneous sensors which are distributed randomly in the interested area to optimize sensing coverage and energy consumption simultaneously whereas we consider them.

III. METHODOLOGY

A. System Model and Assumptions:

Consider a 2-D static WSN formed by three types of sensors that are deployed in a squared sensing area 'A' of side 60m

and a static sink 'BS' with unlimited energy, placed at the center of 'A'. These sensors have different sensing range communication range and energies.

Furthermore, it is assumed that 'A' is divided into uniform consecutive grids to make the coverage problem more computationally manageable.

$$g(x', y') = \begin{cases} 1 & \text{if } \exists j \in \{1, \dots, N\}, d_{(x_j, y_j), (x', y')} \leq R_s, \\ 0 & \text{otherwise,} \end{cases} \quad (3.1)$$

Is the monitoring status of a grid centered at (x', y') with '1' indicating that grid is covered and '0' otherwise.

The problem is based on the assumptions listed in assumption 1, 2 and 3.

- 1) Assumption 1 The area is obstacle free.
- 2) Assumption 2 Number of sensor nodes potential locations is equal to number of monitoring locations.
- 3) Assumption 3 Number of sensor nodes mustn't exceed the number of monitoring locations.

Parameter	Description
t	Node type
N	Number of sensors indexed by j and t
$g(x', y')$	Variable that indicates whether the monitoring point is covered by any sensor or not
$x(p)$	Variable that indicates whether the monitoring point is equipped by a sensor or not
S	Set of sensor nodes
s	Sensor node
m	Monitoring point
M	Set of monitoring point index by p
P	Number of potential locations
BS	Sink node or Base station
MEngy	Sensor node maintenance energy
TransE	Sensor node transmission energy
ReceiveE	Sensor node reception energy
R_s	Sensing Range
R_c	Communication Range
P_{j-BS}	Distance between sensor node j to the sink node
α_j	Number of nodes from which sensor node j receives data and transfer it to the sink node
$Engy_{jt}$	Energy consumed by sensor node j of type t
NCov	Number of uncovered points
G	Total number of grids
C_v	Coverage Ratio

Table 1: Modeling Parameters

B. Problem Formulation:

Definition 1: Coverage is a measure of how well the whole physical space is observed by the sensors [8, 10, 12]. Coverage is categorized into three types:-

- 1) Area Coverage:- Every point in given region of interest (ROI) is covered by at least one sensor.
- 2) Point Coverage:- Specific points in the ROI are to be monitored.
- 3) Barrier Coverage:- Observe the movement of mobile objects that enter the ROI.

The whole monitored area is divided into number of small squared grids called monitoring locations [7]. The sensor can be placed at any monitoring location with a constraint that each monitoring locations can equipped with only one sensor. To model the coverage of wsn, the center

of each grid called monitoring points [1] is considered. So, point coverage is considered here.

Each type of node has different sensing range and is assumed to be circular. Monitoring locations whose distance from sensor node is less than or equal to the sensing range are said to be covered. Each monitoring location can be covered by a number of sensors.

Definition 2: Network Lifetime is defined as the time span of process which starts when node starts sensing and ends when data isn't successfully delivered to sink node [20].

Each node is provided with some initial energy and network lifetime is affected by the amount of energy consumption in the network. Energy consumption is the energy consumed by the sensor during sensing data, transmitting data, receiving data.

Energy consumed by each node consists of three parts [1, 7]:

- 1) Maintenance energy: required for maintain the sensors in active state.
- 2) Reception energy: depends on the number of sensor nodes from which it receives data for transmitting it to sink node.
- 3) Transmission energy: depends on the path in which the energy flows from the sensor node to the sink node.

Each type of node has different maintenance energy, reception energy and transmission energy.

C. Multi-Objective Formulation:

Objectives: Maximize coverage $NCov(X)$ and minimize energy consumption $Engy(X)$ subject to connectivity.

The two objectives are competing with each other. The coverage objective tries to spread the nodes so as to maximize coverage but results in high energy consumption and the objective energy consumption tries to place the nodes near the base station or sink which results in poor coverage [5].

Energy consumed by each sensor node of type t , $Engy_{jt}$ can be determined as follows [1, 7]:

$$Engy_{jt} = MEngy_{jt} + TransE_{jt} * P_{j-BS} + ReceiveE_{jt} * a_j \quad (3.2)$$

The objective function f_1 is the net energy consumed [7], E :

$$f_1 = E = \sum_{j \in S} Engy_{jt} \quad (3.3)$$

The network coverage $NCov(X)$ is expressed as the number of uncovered monitoring points ($NCov$) that are determined as [7]:

$$NCov_p = \begin{cases} 1 & d(s_{jt}, m_p) > R_{st} \\ 0 & \text{otherwise} \end{cases} \quad (3.4)$$

Where $d(s_{jt}, m_p)$ is the Euclidean distance between monitoring point m_p and sensor node j of type t and R_{st} is the sensing range of the node of type t .

The objective function f_2 is total number of uncovered monitoring points [7]:

$$f_2 = NCov = \sum_{p \in M} NCov_p \quad (3.5)$$

The net multi-objective is

$$\min(f_1, f_2) \quad (3.6)$$

Coverage Ratio is defined as the percentage of the covered grids over the total grids of A and is evaluated as follows [6, 18]:

$$Cu(X) = \frac{\left[\sum_{\text{all}(x', y')} g(x', y') \right]}{G} \quad (3.7)$$

Where ' G ' is the total grids of ' A ' and $g(x', y')$ is calculated using Eq. (3.1)

D. Dominance and Pareto Optimal:

The concept of dominance and Pareto optimal explained in this section are based on [18, 19]. Multi-objective optimization involves more than one objective function to be optimized simultaneously. For a nontrivial multi-objective optimization problem, there doesn't exist a single solution that simultaneously optimizes each objective. In that case, the objective functions are said to be conflicting, and there exists many solutions in the feasible regions.

Consider a MOO problem that has two objective functions f_1 and f_2 . The optimization problem is to minimize the two objective functions at the same time, which are represented in an equation as follows:

$$\min(f_1(x), f_2(x)) \quad (3.8)$$

Such that x belongs to X subject to specific constraints. Solutions for f_1 and f_2 for a number of iterations are represented by feasible region shown in Fig. 3.1.

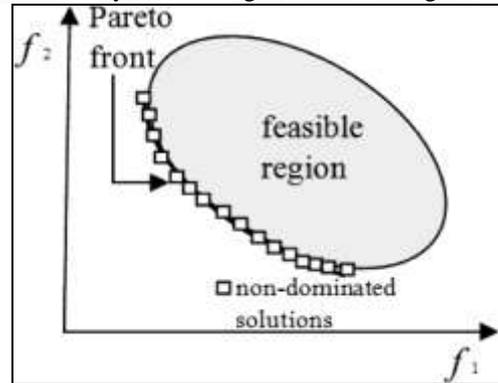


Fig. 3.1: Pareto Front

To determine which individual is superior or inferior to the others, dominance relationship among individuals should be determined.

Individual X_i is said to dominate X_j with respect to objective values if:

- $F_k(X_i) \leq F_k(X_j)$ for all $k = 1, 2, \dots, m$, and
- $F_k(X_i) < F_k(X_j)$ at least one $k = 1, 2, \dots, m$

Where $F_k(X_i)$ denotes the objective value that X_i yields in the k -th objective.

A solution X_i is called Pareto optimal, if there does not exist another solution that dominates it. The set of Pareto

optimal outcomes is often called the Pareto front shown by square. The rest of the solutions are called “dominated” solutions because there is always another solution that has at least one objective that is better.

E. Constraints:

Three constraints are required in this optimization problem. Firstly, to guarantee connectivity, sensed data through any node must reach to the sink node directly or via other node in the network. Secondly, a cut-off constraint is applied on the number of nodes of each type. The cut-off denotes the minimum number of nodes of each type that must be present in the network. Thirdly, a monitoring location can have only one sensor. To indicate whether the monitoring location is occupied by a sensor or not, it is marked with $x(p)$ as follows [7]:

$$x(p) = \begin{cases} 1 & \text{if location } p \text{ has a sensor node} \\ 0 & \text{otherwise} \end{cases} \quad (3.9)$$

F. Algorithm for Heterogeneous Network:

This section presents the algorithm based on multi-objective evolutionary algorithm for heterogeneous network. The term evolutionary algorithm (EA) stands simulate the process of natural evolution [23]. The evolutionary algorithm that is used in study for optimization is genetic algorithm (GA). When a problem is solved by MOEAs, there are some important aspects to tackle: chromosome representation, crossover and mutation strategies and generation of initial population [21].

The flowchart in fig. 3.3-3.4 represents the most relevant steps of the node deployment algorithm.

1) Chromosome Representation:

Each chromosome is of fixed length equal to the number of sensors in the network. Each chromosome consists of ‘N’ segments. Each segment represents three properties of sensors: X-coordinate, Y-coordinate and node type, T. The node type, T can take values 1, 2, 3. The chromosome representation is shown in Fig. 3.2. Each (x,y) represent any potential location where sensor node can be placed. The gene of each chromosome can take any real value.

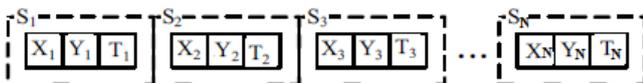


Fig. 3.2: Encoding

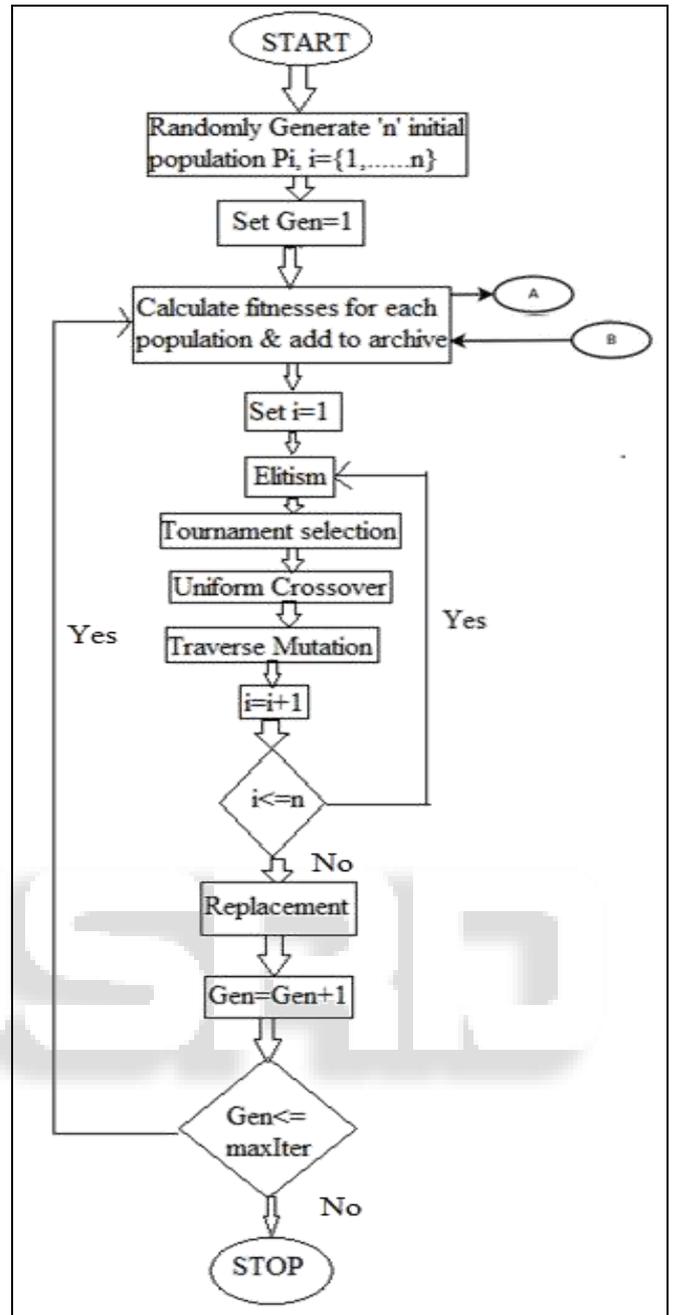


Fig. 3.3: Steps of Proposed Algorithm

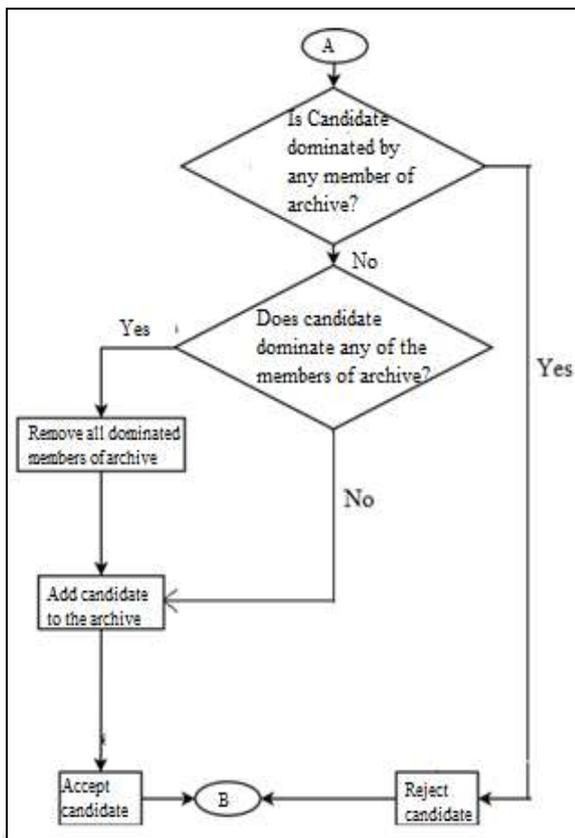


Fig.3.4: Steps of Proposed Algorithm (Archive Concept)

2) *Population Generation:*

For 'n' population, the values of X-coordinate, Y-coordinate and node type T for each sensor node are randomly generated by considering three constraints. The first constraint is that the value of x-coordinate and y-coordinate doesn't go beyond the minimum and maximum area dimension. The second constraint is that within a population, no two sensors get location from the same potential location. The third constraint is that number of nodes of each node type mustn't be less than the cut-off value for that type.

3) *Fitness Evaluation:*

For each population i, the fitness value of each objective are calculated i.e the energy consumption and the number of uncovered monitoring points.

4) *Pareto Archive:*

In any iteration, non-dominated solutions are stored in a set called the Pareto Archive. The solutions obtained in each iteration are compared with the solutions existing in the Pareto Archive set by using non-dominated relations. The selected non-dominated solutions are then considered as a new Pareto Archive [21-22].

5) *Elitism:*

Due to randomness, good solutions can be lost during the optimization process [23]. So, to maintain good solution in the population, elitism is used i.e. the best solution from the current generation is carry over to the next. This strategy is known as elitist selection.

6) *Tournament selection:*

Selection in genetic algorithm is done to select two individuals from a set of individuals. In this study, tournament selection is used. Tournament selection involves running several "tournaments" among a few individuals

chosen at random from the population [25]. The winner of each tournament (the one with the best fitness) is selected for crossover. Parents are selected from the population by using a binary tournament selection.

7) *Uniform Crossover:*

Crossover represents mating between individuals to generate offspring. The uniform operator is used in algorithm. Uniform crossover with crossover probability, pc is used to mix the characteristics of two parents to form child. The uniform crossover algorithm is as follows (M.L denotes monitoring location):

Algorithm 1: Uniform Crossover

Inputs: indv1, indv2

Outputs: indv

for j=1 to number of elements in a input individuals

if rand() ≤ pc then

if jth gene M.L in indv1 isn't occupied in indv then

indv(j)=indv1(j)

Mark M.L as occupied in indv

else

Randomly generate a M.L that isn't occupied in indv

set indv(j) to any point within the generated M.L

Mark generated M.L as occupied in indv

endif

endif

if jth gene M.L in indv2 isn't occupied in indv

indv(j)=indv2(j)

Mark M.L as occupied in indv

else

Randomly generate a M.L that isn't occupied in indv

set indv(j) to any point within the generated M.L

Mark generated M.L as occupied in indv

End if

end if

end for

8) *Traverse Mutation:*

Mutation introduces random modifications in the individual. Modification in the value of gene is done with the mutation probability, pm. The gene is mutated to the monitoring location that isn't covered by any sensor. The traverse mutation algorithm is as follows (M.L denotes monitoring location):

Algorithm 2: Traverse Mutation

Inputs: indv

Outputs: indv

Randomly generate N values for node type Tj

Alter values if cut-off constraint is violated

Traverse to calculate the uncovered monitoring locations

for j=1 to number of elements in input individual

if rand() ≤ pm then

if uncovered M.L are present

Randomly generate a M.L that is uncovered

set indv(j) to any point within the generated M.L

Mark M.L as covered

Traverse to calculate the uncovered M.L

else

Randomly generate a M.L until it isn't occupied in indv

set indv(j) to any point within the generated M.L

Mark generated M.L as occupied in indv

Traverse to calculate the uncovered M.L

endif

endif

endfor

9) *Replacement and Termination Criteria:*

After applying genetic operations, new population is produced. This new population should replace the old population. At the end of each generation, the termination criterion is checked to decide whether it is time to stop the search. The algorithm terminate when maximum iteration is reached.

IV. SIMULATION STUDY

A. *Simulation Network Model:*

An experimental simulation has been carried out using MATLAB 7.10.0 on windows 7 with core-i3 processor specification to compare the performance of the algorithm for the heterogeneous network with MOTPSMA [7]. The monitoring area is of 60m x 60m dimension as shown in fig. 4.1. It consists of 144 equal squared potential locations. Each potential location consists of a monitoring point in the center. The node characteristics are listed in table 4.1. The simulation parameters used for proposed algorithm is listed in Table 4.2.

1	2	3	4	5	6	7	8	9	10	11	12
13	14	15	16	17	18	19	20	21	22	23	24
25	26	27	28	29	30	31	32	33	34	35	36
37	38	39	40	41	42	43	44	45	46	47	48
49	50	51	52	53	54	55	56	57	58	59	60
61	62	63	64	65	66	67	68	69	70	71	72
73	74	75	76	77	78	79	80	81	82	83	84
85	86	87	88	89	90	91	92	93	94	95	96
97	98	99	100	101	102	103	104	105	106	107	108
109	110	111	112	113	114	115	116	117	118	119	120
121	122	123	124	125	126	127	128	129	130	131	132
133	134	135	136	137	138	139	140	141	142	143	144

Fig. 4.1: Simulation Network Model

Parameters	Sensor Node		
	Type 1	Type 2	Type 3
Sensing Range (R_s)	12 m	18 m	15 m
Communication Range (R_c)	12 m	18 m	15 m
Initial Energy	0.5Ah	2Ah	1Ah
MEngy	6mA	26mA	13mA
TransE	10mA/m	40mA/m	20mA/m
ReceiveE	1mA	4mA	2mA
Cut-off	1	1	1

Table 2: Node Characteristics

Parameter	Value
Network Size (A)	60 m x 60 m
Population Size (n)	600
Generations (maxIter)	100
Tournament Size	2
Crossover Probability (P_c)	0.5
Mutation Probability(P_m)	0.5

Table 3: Simulation Parameters

B. *Simulation Results:*

The simulation results are compared with MOTPSMA [7] in terms of coverage ratio, average energy consumption.

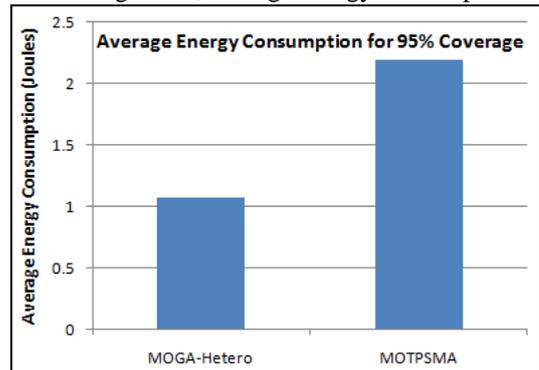


Fig. 4.2: Average Energy Consumption for Minimum of 95% Coverage

Fig.4.2 shows the average energy consumed by sensor network when minimum of 95% coverage is achieved. It can be clearly seen from the bar graph that algorithm for heterogeneous network consumes half of the energy consumed by MOTPSMA. So, the lifetime of the network formed using proposed algorithm is high as compared to that of MOTPSMA.

Fig. 4.3, 4.5 shows the pareto graph for 6 nodes and 8 nodes respectively. The red symbols are solutions that are stored in archive and form the pareto set. It can be seen that the MOGA for heterogeneous network requires 6 nodes but MOTPSMA require 10 nodes for 95% coverage. The proposed algorithm requires only 6 nodes whereas MOTPSMA require 24 nodes for 100% coverage. It's a huge difference. Thus, MOGA for heterogeneous network provides better coverage with lesser number of nodes.

Fig. 4.4, 4.6 illustrates the sample of sensor nodes positions for 6 nodes and 8 nodes respectively. The red dot represents the monitoring point. The green square denotes the sensor. The blue circles show the coverage range of the sensors.

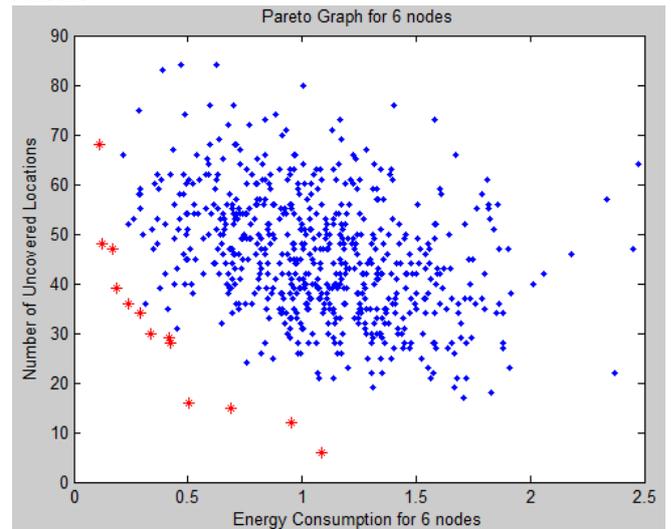


Fig. 4.3: Pareto Graph for 6 Nodes

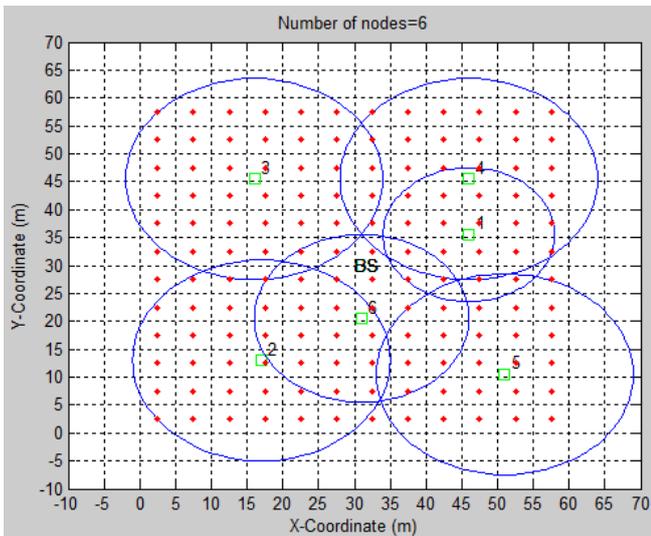


Fig. 4.4: Sensor Node Position for 6 Sensor Nodes

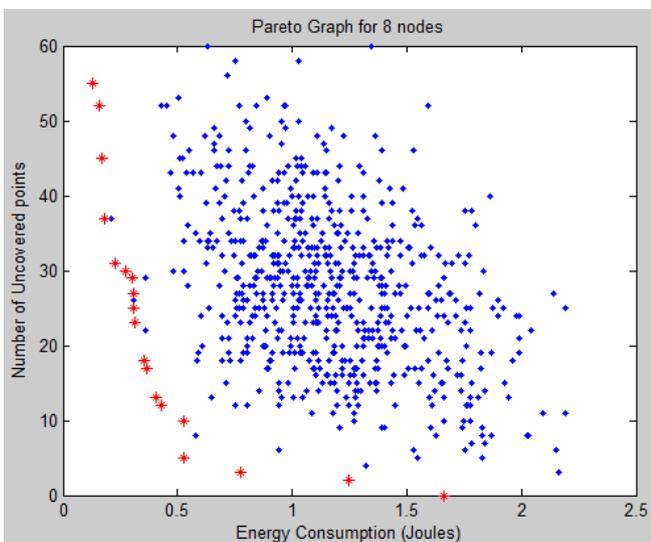


Fig. 4.5: Pareto Graph for 8 Nodes

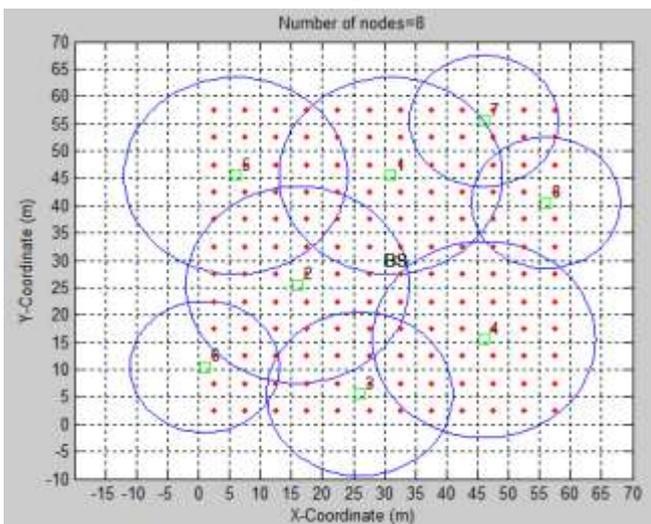


Fig. 4.6: Sensor Node Position for 8 Sensor Nodes

V. CONCLUSION AND FUTURE SCOPE

Heterogeneous wireless sensor network consists of sensor nodes with different energies and capabilities. A multi-objective sensor node positioning algorithm has been developed for heterogeneous network to optimize energy

consumption and network coverage. The simulation results show that MOGA for heterogeneous reduce the energy consumption to half of the energy consumption by MOTPSMA. It requires only 8 nodes to provide 100% coverage as compared to MOTPSMA which require 24 nodes. Due to huge decrease in the number of sensor node, the deployment cost of the got decreased. So, proposed algorithm outperforms MOTPSMA. This work is further extending by considering network deployment in 3-dimensional or by considering obstacles in the monitoring area.

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