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Coverage and Lifetime Maximization of Wireless Sensor Network with Multi-Objective Evolutionary Algorithm

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Abstract- Coverage and lifetime maximization of wireless sensor networks is an area of interest for the researchers in recent years. Activating minimum number of sensor nodes while maintaining the coverage saves energy and extends the lifetime of wireless sensor network. In this paper we have presented a model for coverage and lifetime maximization using multi-objective optimization. The goal of the proposed work is to cover the maximum area of the target region by at least k- sensor nodes to make the network fault tolerant and to extend the lifetime of wireless sensor network by dividing the set of sensors into maximum number of cover sets. In addition, we have also proposed an order based chromosome representation in NSGA-II which always gives disjoint cover sets and also has an advantage of not to specify the upper bound on the cover sets. A series of simulations are conducted and results obtained for the proposed model are better than for the other strategies found in the literature.

Keywords- Coverage, Cover sets, EECGA, Fault Tolerant, Lifetime, NSGA-II, Wireless Sensor Network.

1 INTRODUCTION

Wireless Sensor Networks (WSNs) have wide range of applications such as disaster management, environment monitoring, military surveillance, habitat monitoring, etc. In these applications sensor nodes are randomly and densely scattered without any human involvement in vast unapproachable geographical area. These nodes operate independently in unattended and hostile environment. Each Sensor node has four main components, Power source to provide adequate amount of energy, transceiver for communication, external memory for storing application or programming related data, and sensors to measure physical environments. Sensor nodes are powered by batteries with limited capacity and it is very difficult to recharge or replace these small sized batteries (Akyildiz et al., 2002). Therefore energy conservation is crucial and important for extending lifetime of wireless sensor network. Since sensors may be spread in an arbitrary manner, the coverage becomes a challenging research issue which directly affects the capability and effectiveness of WSN. Generally Coverage reflects how well the deployed sensors monitor the area of interest. Therefore it can be considered as the measure of Quality of service (QoS) in a sensor network (Meguerdichian et al., 2001). A sensor network should be deployed with density of up to 20 nodes/m3 (Shih et al., 2001) in order to prolong the network lifetime. In a hostile environment, as sensors are dropped randomly, the node density may not be uniform in the whole deployment area. If the number of sensor nodes deployed, are small, some target area may be uncovered and some nodes may get isolated. To maintain QoS, sensor nodes are deployed with high density and some area may be covered by redundant sensor nodes. These redundant sensors improve coverage but increases network cost, energy consumption and decreases network lifetime. Some applications of WSN desired to cover each and every point by only one sensor node while in many applications it is required to cover each target area by more than one sensor for better accuracy and to make the network fault tolerant. The rest of the paper is organized as follows. In section 2 work existing in the literature related to coverage and lifetime of wireless sensor is discussed. Section 3 explains our proposed model and assumptions that we have made in the designing of the model. In section 4 we have discussed multi-objective optimization problem and the methodology used. Performance

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evaluation of the proposed model is discussed in section 5. Finally the conclusion of the work is presented in section 6.

2 Related Work

(Slijepcevic and Potkonjak, 2001) used heuristic technique to find the maximal number of covers from the deployed sensors. Each cover has a set of nodes that can completely cover the target area. Only one set is active at a time. After some specified time another set becomes active while the first one is deactivated. All sets are used in each round and the process continues until the power of sensor node drains. In this way the lifetime of the network is extended. With the help of simulation authors compared most constrained and –minimally constrained heuristics with simulated annealing and found that heuristics perform better than simulated annealing. (Paul et al., 2008) proposed an energy efficient dynamic sleep scheduling scheme for heterogeneous wireless sensor network. This scheme is based on multiple criteria such as distance of sensor node from Cluster head, remaining energy of sensor nodes, and buffer queue for optimization of sleep scheduling process. This optimization problem is solved using the Analytical Hierarchy Process (AHP) mechanism. In AHP mechanism best solution can be found by assigning weights and decomposing the complex problem into smaller sub problems. (Tian and Georganas, 2002) proposed a node scheduling scheme to reduce energy consumption and extends the network lifetime. This scheme is based on off duty eligibility rule and back-off based self-scheduling approach to turn off redundant nodes and to minimize the number of working nodes. A node scheduling scheme is proposed based on the local neighbor information. A node decides to go into sleep mode when it discovers that its neighbors can monitor its whole sensing area. With the help of simulations authors showed that these schemes save more energy as compared to LEACH which is a data communication protocol in WSN. (Martins et al., 2011) proposed a Multi-objective optimization approach for improving the performance of WSN. A Multi objective Online Hybrid Algorithms (MultiOnHa) which combines multi-objective Global on Demand Algorithm (MGoDA) and Local online Algorithm (LoA). This algorithm is proposed to solve the problem of Dynamic Coverage and Connectivity. In this approach Coverage is maximized by keeping the energy consumption minimum and whole network connected. With the help of simulations authors compared it with Integer Linear Programming and similar mono-objective approaches and found that MultiOnHa performs better taking lesser computational time. (Sengupta et al., 2012) presented a Multi-objective Optimization based scheduling algorithm for density control to achieve the maximum coverage and lifetime of a WSN. This algorithm schedules the randomly deployed active nodes. Whenever there is a node failure the optimization algorithm runs again to rearrange the network unless all nodes have lost their energy or connectivity. (Habib M. Ammari, 2013) studied the tradeoff between energy, battery power depletion and delay. They solve the problem by using multi-objective optimization approach. To obtain better solution between three conflicting objectives i.e minimum energy depletion, minimum delay and uniform power exhaustion from battery, communication range of a sensor is divided into concentric circular bands (CCBs) based on the minimum transmission distance. (Zhang and Jennifer, 2005) proposed a decentralized density control algorithm known as Optimal Geography Density Control (OGDC). This algorithm retains coverage as well as connectivity by activating minimum number of sensor nodes. Authors also proved that when the communication range is at least twice of sensing range, the whole network is fully connected.

3 Coverage Model & Assumption

3.1 Sensor Detection Model

We assume that in the monitoring area of square region A_s, set S of N homogeneous sensors $(S=\{s_1, s_2, \dots s_N\})$ are randomly deployed. Each sensor monitors an event of interest and reports it to the base station with either single or multi hop communication. Sensing range of a node $n_i (i = 1.....N)$ is assumed to be circular with radius r. Each sensor initially has the same amount of energy available. The number of sensors deployed randomly is more than the required number to achieve maximum coverage of the monitoring area. Scheduling of sensor nodes should be considered for wake up and sleep to minimize energy consumption and to extend lifetime of the sensor network. Practically, detection of an event by a sensor is inexact and the overlap among sensing range of different sensors is indefinite. Therefore for activating the minimum number of sensor nodes for maximum coverage, we use probabilistic coverage model. Let us assume that the network is divided in $m \times n$ sensor field and N sensors are randomly deployed. A sensor S_k is positioned at point (x_k, y_k). For any point p at (x, y) the Euclidean distance between s_k and p is denoted as:

$$d(s_k, p) = \sqrt{(x_k - x)^2 + (y_k - y)^2} \qquad (1)$$

There are two types of detection model -Binary detection model and probabilistic detection model. In binary detection model sensing coverage is assumed to be circular in all directions. An event of interest that falls within the sensing radius of a sensor node is assumed to be detected with probability 1, otherwise 0. This model is easy to design and analyze the coverage protocol. The detection probability of a point $p(x, y)$ by a sensor s_k with binary detection model is expressed as:

$$P_{\mathrm{cov}}(S_k) = \begin{cases} 1, d(S_k, P) \le r \\ 0, otherwise \end{cases} \qquad (2)$$

In reality the probability of detection of an event decays with distance between a sensor and the target event. Therefore to study the real behavior of a sensor node, probabilistic coverage model is more appropriate. In this model the detection probability varies exponentially as the distance between sensor node and the target increases. The probabilistic coverage of a point $p(x, y)$ by a sensor node s_k is expressed by (Ghosh et al. 2008).

$$P_{\mathrm{cov}}(s_k) = \begin{cases} 0, & r + r_u \le d(s_k, p) \\ e^{-\gamma a^\beta}, & r - r_u < d(s_k, p) < r + r_u \\ 1, & r - r_u \ge d(s_k, p) \end{cases}$$

(3)

Where, r_u is an error in detection of a target and measures the uncertainty in detection by a sensor, and $\gamma, \beta\, and\, a = d((s_k, p) - (r - r_u))$ are decay factors. When an object is within the distance of $(r - r_u)$ from the sensor node it is said to be detected with probability 1. If all the event of interest lies within the range $((r - r_u), (r + r_u))$, the coverage value decreases exponentially as the distance between sensor and target increases. If the distance between target point and sensor is greater than $(r + r_u)$, the probability of coverage is zero.

3.2 K-Coverage

Coverage means that every point in the target region is observed by at least one sensor. To improve the accuracy and to cope up with sensor failure, some applications, such as forest fire detection, intruder detection, military surveillance, require more than one sensor to cover a target. A coverage is called K-coverage (K> 1), when every point in the region is monitored by at least k distinct sensor nodes. Let a set of S, $(S = s_1, s_2, ...s_N)$ sensor nodes scattered in a 2-D dimensional area A_s. The area A_s is divided into $m \times n$ grid points (Jia et al., 2012). Probability that a grid point $\{(x_i, y_j), i = 1.....m, j = 1.....n\}$, covered by a sensor node s_k is given by

$$P(g_{ij}) = P((x_i, y_j), s_k) \qquad (4)$$

Probability that a sensor node s_k does not cover the grid point is given by

$$P(\overline{g_{ij}}) = 1 - P((x_i, y_j), s_k) \quad (5)$$

Now, since the probability of coverage of a point by a sensor node is independent other nodes, the cooperative probability that the grid point is not covered by any of the N sensor nodes is given by

$$\prod_{S_k \in S} (1 - P(x_i, y_j), s_k) \quad (6)$$

Now, the cumulative detection probability that the grid point g_{ij} is covered by each sensor node in the set S is given by the following equation:

$$P(g_{ij}, S) = 1 - \prod_{S_k \in S} (1 - P(x_i, y_i), s_k) \quad (7)$$

A monitoring point covered by more than one sensor enhances the reliability of the coverage and makes the network fault tolerant. Let (θ_k) is the threshold required for k-coverage. Every grid point is covered by at least k-sensors if $P(g_{ij}, S)$ is not less than the threshold value required for k-coverage.

$$P(g_{ij}, S) \geq \theta_k, \forall g_{ij} \in m \times n \quad (8)$$

Now, the coverage rate of the sensor set S can be calculated as segment of area having threshold above θ_k

$$C_r(S) = \sum_{x_i=1}^{m} \sum_{y_j=1}^{n} P(g_{ij}, S) / m \times n \quad (9)$$

Here, the objective is to maximize coverage and can be expressed as

$$C_r(S) = \max imize \sum_{x_i=1}^{m} \sum_{y_j=1}^{n} P(g_{ij}, S) / m \times n$$

(10)

Subject to

$$P(g_{ij}, S) \geq \theta_k, \forall g_{ij} \in m \times n \quad (11)$$

3.3 Maximum Disjoint Set Covers Problem

To maximize the lifetime of network, sensor nodes are partitioned into disjoint set covers. More number of disjoint set covers results in longer the network life time. Therefore, the maximal network lifetime problem is to find the maximum-disjoint set covers that are activated successively. Sensor nodes are activity scheduled to alternate between sleep and active mode such that the desired area is continuously monitored by a set of active sensors. Let N sensor nodes $(S = s_1, s_2, \ldots s_N)$ are deployed in a square area A, where each sensor node monitors the grid point g_{ij}. We have to generate maximum number of cover sets, and each cover set must have disjoint sensors that can monitors the entire target area. The decision variables of the above problem are:

$$C_k = \begin{cases} 1, & if\ set\ cover\ k\ is\ selected \\ 0, & otherwise \end{cases}$$

$$x_{kj} = \begin{cases} 1, & if\ sensor\ j\ is\ in\ the\ set\ cover\ k \\ 0, & otherwise \end{cases}$$

To maximize the disjoint set covers, the problem can be mathematically formulated as follows:

$$DSC = \max imize \sum_{k=1}^{M} C_k, \quad (12)$$

S.t the following constraint $\sum_{k=1}^{M} C_k \subseteq S$

(13)

$$E_i \leq e_i, \forall i \in N \quad (14)$$

$$S_i \cap S_j = \phi \ where\ i \neq j \quad (15)$$

Where M is the number of disjoint set covers, C_k (k=1…..M) is the k[th] set cover. e_i is the initial energy of a sensor node and E_i is the energy consumed by i[th] sensor node when it is in active mode. Constraint (13) guarantees that every sensor in cover set belongs to the available sensor set. Constraint (14) assures that the

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energy consumed by each sensor node must be less than or equal to the initial energy. S_i and S_j represent i^{th} and j^{th} cover sets respectively, therefore constraint (15) guarantees that no sensor can be assigned in more than one cover set.

3.4 Energy Consumption Model

A sensor node consists of sensing unit, processing unit, transceiver unit, and power unit. Each unit consumes different amount of energy in performing the task assigned to it. Transceiver unit consumes most of the energy of a sensor node in transmitting and receiving of data frequently. In this paper, we have used first order radio model (Heinzelman et al., 2000) to calculate the energy dissipation in transmitting and receiving of data. Therefore, energy consumption $E_{tx}(m,d)$ in transmitting m-bit packet to a distance d is given by

$$E_{tx}(m,d) = E_{\text{int}} * m + \varepsilon_{amp} * m * d^{\eta} \quad (16)$$

Where E_{int} is the energy required to activate the transceiver circuitry and ε_{amp} is the energy required by the transmit amplifier to transmit the data consistently. η is path loss exponent and it takes a value between 2 and 6. Its value for free space is 2 and for multipath fading is 4. Due to short range communication we have used free space communication model and thus the value of path loss exponent η is taken as 2.The energy $E_{rx}(m)$ required to receive the same m-bit packet is calculated as

$$E_{rx}(m) = E_{\text{int}} * m \quad (17)$$

The total energy required in transmitting and receiving of data should be minimum and is given by

$$E_i = \min \sum_{j=1}^{N-1} (E_{\text{int}} * m + \varepsilon_{amp} * m * d_j^{\,2}) + E_{\text{int}} * m \quad (18)$$

Subject to: $E_i \le e_i, \forall i \in N$ (19)

$$d_j \le r_t, \forall j \in N \quad (20)$$

Equation (18) shows the sum of traffic transmitted and received by sensor node i to/from all other sensor nodes in the network. E_i is the total energy consumed by sensor node i, e_i is the initial energy of node i and d_j is the Euclidean distance between the node i and j $(i \ne j)$. Constraint (19) guarantees that the total energy E_i consumed by the node i should not be greater than its initial energy e_i. Equation (20) represents that the Euclidean distance d_j between node i and j, and this distance is less than or equal to the transmission range r_t, so that data can be transferred between node i and j.

4 Multi-Objective Optimization Problem

Multi-objective optimization problem (MOOP) deals with more than one objective function that has to be minimized or maximized. In MOOP, the goal is to find optimal solutions satisfying objective functions. These set of optimal solutions known as Pareto optimal solutions. In general Multi-objective optimization can be formulated as:

$$\begin{aligned} &\textit{Minimize / Maximize} && F(x) = (f_1(x), f_2(x) \cdots f_M(x)) \\ &\textit{subject to} && g_i(x) \le 0, \quad i = \{1,2\cdots\cdots,k\} \\ & && h_j(x) = 0, \quad j = \{1,2\cdots\cdots,p\} \\ & && x_i^{[L]} \le x_i \le x_i^{[u]} \quad i = \{1,2\cdots\cdots n\} \end{aligned}$$

Where, x is an n-dimensional decision variable vector $x = (x_1,.....x_n)$.

In our problem, first objective that should be met is the maximum coverage given in equation (10), second objective function is maximum number of cover set given in equation (12), and third objective is minimum consumption of energy given in equation (18).

Pareto optimal solution: let x ⊆X be a subset of solutions, if x1 is non-dominated by any element of x, then x1 is called non-dominated solutions with respect to x. The solution x1 is called Pareto optimal. In multi-criteria decision making optimization problem, when there are many conflicting objectives, no unique solution exists. But a set of solutions called non dominant solutions exist and none of these solutions are said to be the best with respect to all conflicting objectives.

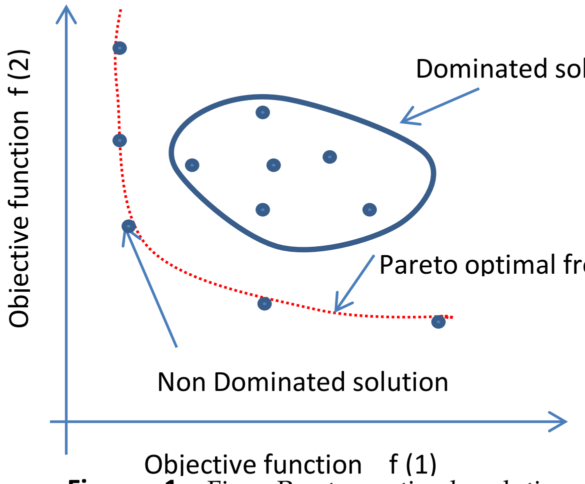

Figure 1. Five Pareto optimal solutions with two conflicting objectives

Pareto optimal set: set of Pareto optimal solutions are called Pareto optimal set. Figure 1 shows the set of Pareto optimal solutions. **Dominance:** A vector $u=(u_{1,}\cdots u_k)$ is said to dominate another vector $v=(v_1\cdots v_k)$ iff u is partially less than v, mathematically this can be expressed as $\forall i \in \{1,\ldots k\}, u_i \le v_i \wedge \exists i \in \{1,..k\}, u_i < v_i$

4.1 Energy Efficient Coverage with NSGA-II (EECGA)

Non-dominated Sorting Genetic Algorithm-II (NSGA-II) is a popular multi-objective evolutionary algorithm but criticized for its computational complexity, lack of elitism and sharing of parameter required. A modified version NSGA–II algorithm was developed by (K deb et al., 2002). This algorithm provides better sorting algorithm incorporates elitism and does not sharing of parameters. It is a population-based genetic algorithm, and gives number of Pareto optimal solutions within a single generation. The objective of Genetic Algorithm (GA) is to schedule the minimum number of sensor nodes so that coverage and lifetime of the network is maximum and energy consumption is minimum. In this paper we use n bit binary string of chromosomes to represent sleep or wakeup state of sensor nodes as shown in figure 2.

1	2	3	4	....	n-2	n-1	n
1	1	0	1	......	0	1	1

Figure 2. Binary representation of chromosomes

The value of 1 indicates that the sensor node is in active mode and 0 shows it is in sleep mode. A chromosome $c_j = \{g_{1j}, g_{2j}, ...g_{kj}\}$ consist of a series of genes where j=1, 2 … size of population. Length of a chromosome is equal to the number of sensors deployed and a population has several chromosomes. In our algorithm cover sets formed on the basis of order based representation. In this approach a chromosome can be represented as a sequence of sensors, and according to this given sequence the sensor nodes forms the cover sets. The advantage of order based representation is that a sensor node is assigned to only one cover set and there is no need to specify the upper bound on the cover sets. These chromosomes represent the possible solution of a given problem. Every single chromosome is evaluated according to the fitness function given for maximum coverage, maximum cover set and minimum energy. Each chromosome is compared with every other chromosome to find non dominated solutions. The non-dominated individuals are sorted according rank and crowding distance. Solutions are selected according to binary tournament selection for comparison, if they belong to different ranks, the one which has highest rank is selected for crossover, and if they belong to same front, the solution which has larger crowded distance is selected. Best individuals are inserted into the mating pool for crossover to produce new off-springs. In this paper we have used two point crossovers where two points are selected randomly, and the contents between two points are swapped between parents. In the newly generated population mutation operation is applied by complimenting a randomly chosen bit i.e. from 1 to 0 or from 0 to 1 to maintain diversity in the population and to increase the speed of convergence. Parent population and current offspring are combined together and sorted again based on non-dominated sorting. From the sorted population only N best off-springs are selected, where N is the population size. The algorithm terminates when the maximum number of iteration is achieved.

5 Result Analysis and Performance Evaluation

The results obtained in this section are simulated in Matlab to examine the coverage and lifetime of WSN. Parameters used in simulation are listed in table 1. In the simulation 2-D area of size 100×100 is divided in the grid, each of size 1×1. 400 homogeneous sensor nodes are deployed randomly in the target region for monitoring the target. The sensing range of each sensor node is assumed to be 10 m. The energy model used in our simulation is first order radio model. Initially, 3 Joules of energy is assigned to each sensor node. EECGA algorithm which is based on NSGA-II is a multi-optimization approach implemented in Matlab to find the optimal solutions. This algorithm runs for 250 generations with population size of 100, mutation probability 0.01 and crossover rate 0.9.The fitness function for coverage, cover sets and energy is calculated in each generation and best result is calculated from the set of solutions. Fig.3 shows the Pareto optimal front obtained from the simple Genetic Algorithm (GA) and EECGA at the end of 250 generations. EECGA produces 12 non dominated solutions for the network lifetime and coverage objective. As shown in figure when the probability of coverage increases, it requires more number of nodes to cover the target region. Further, it generates lesser number of cover sets and thus results in decreased lifetime of the network. It is also revealed from fig 3 that EECGA has more superior quality solution than GA.

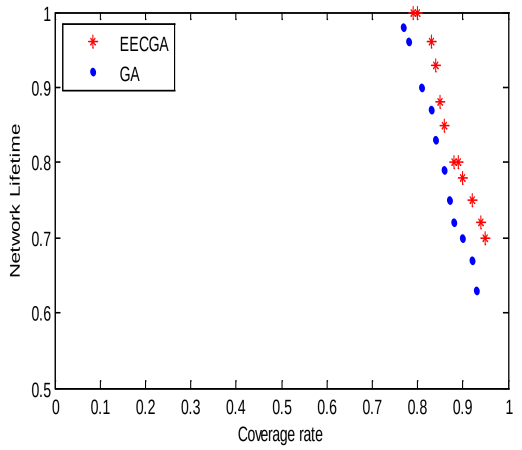

Figure 3. Pareto Optimal front for network lifetime Vs. Coverage

As we have already discussed that to extend the lifetime of wireless sensor network, number of disjoint set cover should be maximized. To make the system fault tolerant every point in the target area must be monitored by k-sensors (k>1). Figure 4 shows that the average number of cover sets obtained for different values of k when the number of sensor nodes varies from 200 to 400. As shown in figure as the value of k increases the number of cover set decreases because for higher value of k each cover set requires large number of sensor nodes.

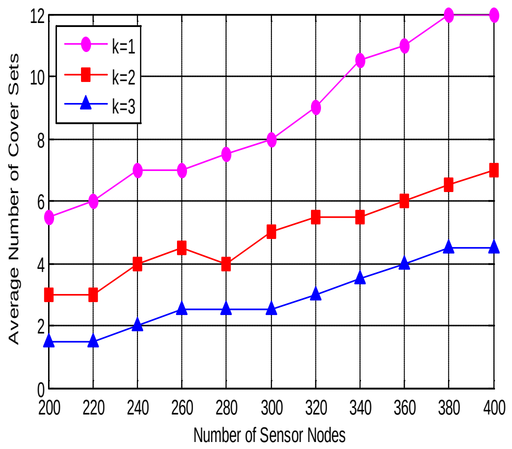

Figure 4. Average number of Cover Sets obtained for different Coverage level

Figure 5 shows the results of the probability of coverage for the varying number of sensor nodes for two different algorithms. In order to provide Coverage with probability > 90%, EECGA requires approximately 210 sensor nodes in the area of 100×100 m2. For similar case OGDC requires 327 sensor nodes for the sensing range of 10m. To achieve the desired threshold for coverage only 300 sensor nodes are required. Therefore, the proposed algorithm (EECGA) performs better and provides high coverage rate with low sensor density as compared with OGDC.

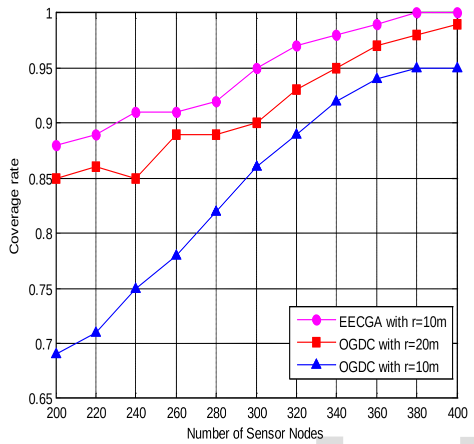

Figure 5. Coverage rate vs. Number of Sensor nodes

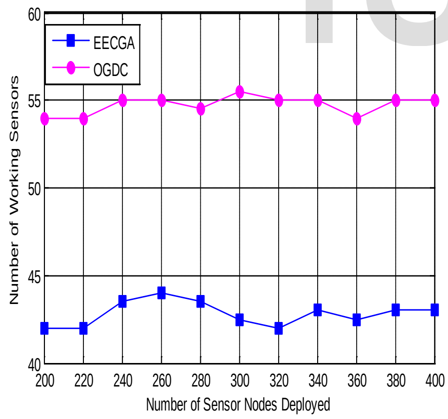

Figure 6. Number of working nodes vs Number of deployed nodes

In Figure 6 shows the number of active sensor nodes to achieve the desired coverage. EECGA requires lesser number of sensor nodes as compared to OGDC with sensing radius 10m. Moreover as revealed from the figure that in both OGDC and EECGA, number of working nodes does not increases in the ratio of deployed sensor nodes.

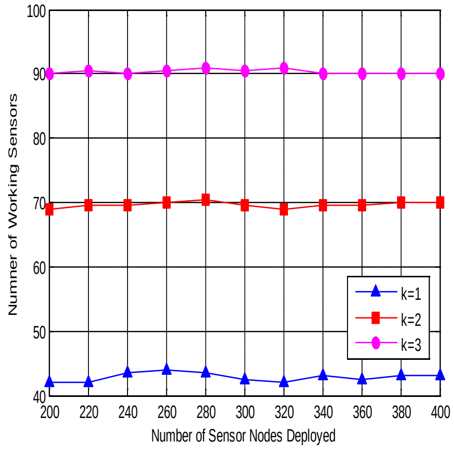

Figure 7. Number of working nodes for different level of Coverage

Figure 7 illustrates the active nodes in each subset for a different value of k-Coverage. It also clear from the figure that the number of working nodes is almost constant in each set. As the value of k increases the number of working nodes also increases in their respective cover sets. But the number of sensor nodes remains almost constant in each set for individual value of k. For k=1, 2, and 3 the number of sensor nodes required are approximately 40, 70 and 90, respectively.

6 Conclusion

In this paper, we have proposed a lifetime maximization scheme with coverage constraint by using multi-objective evolutionary approach. This solution is suitable for high density networks where it is difficult to obtain optimal solutions between conflicting objectives. An EECGA algorithm which is based on NSGA-II has advantage against Genetic Algorithm in terms of quality of solutions. Our proposed algorithm provides maximum k-coverage and consumes minimum energy by schedule the sleep and wakeup period of a sensor node. This algorithm also converges faster than OGDC algorithm.

Table 1

Parameter	**Value**
A	100×100 m2

Number of sensors	400
Sensing range	10m
Population size	400
Selection type	Binary tournament
Crossover	Two point crossover
Crossover rate	0.9
Mutation rate	0.002
Maximum iteration	250
Initial energy of sensor	3J
E_{int}	50 nJ/bit
Data size	2000 bits
$\in_{amp}$	10 PJ/bit/m2

Table 2

EECGA Algorithm

Step1. Initialize population P_{int} . **Step2.** Generate random population of size N . **Step3.** Evaluate population based on objective function in equation (10), (12), and (18) . **Step4.** Assign rank, based on Pareto dominance. **Step5.** Apply selection, crossover and mutation on P_{int} . **Step6.** Generate new offspring Q_{int} **Step7.** Combine initial population Pint and new generated offspring Q_{int}

$R_{int}=P_{int}+Q_{int}$ **Step8.** Calculate objective function for every solution in R_{int} **Step9.** Assign rank based on Pareto dominance to R_{int} **Step10.** Assign crowding distance to R_{int} **Step11.** Check stopping criteria, if criteria are met go to 13. **Step12.** Create new population Pint based on rank and crowding distance, and go to step 3 **Step13.** Select N individual population from R_{int}

Step14. Terminate algorithm.

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