Int J Syst Assur Eng Manag (June 2017) 8(2):493–514
DOI 10.1007/s13198-016-0457-8

ORIGINAL ARTICLE

An approach to solve the target coverage problem by efficient deployment and scheduling of sensor nodes in WSN

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Received: 16 December 2014 / Revised: 4 April 2016 / Published online: 13 April 2016

Abstract Network lifetime play a vital role in setting up an energy efficient wireless sensor network. The lifetime of the network can be improved by efficient deployment and scheduling of the sensor nodes inside the network. In this paper, on the basis of mathematically calculated upper bound lifetime of the network, the sensor nodes are efficiently deployed by using Simulated Annealing and Particle Swarm Optimization with pre-specified sensing range of the sensor nodes and on the second fold the sensor nodes are efficiently scheduled by applying the Simulated Annealing and Dempster Shafer Theory. The overall objective of this paper is to find the optimized location and schedule for sensor nodes. The comparative study shows that the simulated annealing and particle swarm optimization algorithms performs better for sensors deployment. Simulated annealing and Dempster Shafer theory achieves the goal to provide the different schedules with high efficiency.

Keywords Coverage · Simulated annealing · Dempster Shafer theory · WSN

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1 Introduction

Wireless sensor networks are applicable in many fields such as military surveillance, environmental monitoring, structural monitoring, security and traffic control (Chong and Kumar 2003). Network lifetime (The duration between the network starts functioning to the coverage requirement not satisfied.) play a crucial role in development of the wireless sensor network (WSN). Efficient use of energy can be one factor to develop an efficient WSN because the sensors nodes in WSN are battery powered.

Coverage (The region should be monitored by some sensor nodes according to the degree of reliability.) must be guaranteed in WSN to achieve to the data from the whole area. Position of sensor nodes plays a major role in the algorithms which are designed to achieve the required coverage inside the WSN (Wang et al. 2010). The coverage problem can be classified into two types as: Point or target coverage and Area or region coverage. The meaning of k-coverage in target coverage is that each target nodes must be covered by at least k sensor nodes. The sensor nodes in a region can be deployed in two manners one is random and second is deterministic. In random deployment, the sensor nodes are deployed randomly in an area which is inaccessible to human such as military wars. The only way to achieve the efficiency in WSN is the efficient scheduling of sensor nodes in such a ways that some sensor nodes should be active at a time which provide the proper coverage (Huang and Tseng 2003). The second way of deployment is deterministic, in this; the region of deployment is known apriori. There are two ways to design the efficient WSN one is to find the deployment positions of the sensor nodes that achieves maximum coverage and second is scheduling of sensor nodes. Once the optimized positions of sensor nodes are known, we can schedule the sensor nodes to provide the maximum lifetime. In the further text WSN and network are used interchangeably.

The rest of paper is organized as follows: in Sect. 2, we briefly reviews some related literatures. Section 3 formulates the problem. In Sect. 4, we have explored the proposed approach to solve the considered problem. Section 5 presents the simulation results and discussion about results. Concluding remarks are given in Sect. 6.

2 Related works and motivation

Most of the research on deployment problem focuses on the area coverage. Onur et al. (2005) have focused on quality of deployment and quality measures. Quality of deployment specify that the sufficient area is covered or not and quality measures considered that redeployment is required or not. Bai et al. (2006, 2010) worked on the optimal coverage and deployment pattern that provides more than two-connectivity and proposed diamond and double striped pattern. Diamond pattern can be viewed as a series of evolving patterns; they have given voronoi diagram based methodology for sensor deployment also. Chang et al. (2008) proposed some methods for deployment of sensor nodes that improves the lifetime of the network by mitigating the hotspot around the sink. Yun et al. (2010) considered the problems of Bai et al. (2006) and proposed the sensor deployment pattern for 3-, 4-, 5-, 6-connectivity inside the network. Ozturk et al. (2011) give the ABC (Artificial Bee Colony) algorithm based dynamic sensor deployment method that considers the stationary and mobile sensor nodes on a probabilistic detection model. Many researchers have proposed strategies to solve the sensor scheduling for area coverage problem (Liu et al. 2005; Yen and Cheng 2009; Keshavarzian et al. 2006; Makhoul and Pham 2009; Chang and Chang 2008). Udgata et al. (2009) give an ABC algorithm based deployment strategy, but it can be applied if the numbers of target nodes are more as compared to the number of sensor nodes. They are able to get the energy efficiency by reducing the sensing range of the sensor nodes. Mini et al. (2011) proposes a heuristic algorithm to schedule the sensor nodes inside the network that can increase the lifetime of the network. The heuristic is able to achieve the upper bound for all experimental cases.

In the literature, the deployment and scheduling are considered as independent problems. In this paper, we have considered deployment and scheduling of sensor nodes as one problem. The coverage must be considered as a crucial factor to evaluate the sensor network. The coverage inside the network can depend upon the applications such as for habitat and environmental monitoring the lower level of coverage can be efficient but for tracking a target, we need a higher level of coverage (Li and Gao 2008). The level of coverage can vary for the same application which depends upon the situation, for example, the detection of fire in a forest required less coverage in rainy season as compared to summer season. Sensor deployment and scheduling must be considered as one to increase the lifetime of the network and to provide balanced performance which is crucial for most applications.

3 Problem formulation

Let, a region $(x \times y)$ contains n targets as $\{T_1, T_2, T_3 \ldots T_n\}$ and m sensor nodes $\{S_1, S_2, S_3 \ldots S_m\}$ should be placed in such a manner that can fulfill the coverage requirements. The objectives that are covered in this paper are:

- To deploy the sensor nodes in a particular region to achieve the coverage requirement and maximum lifetime.
- To provide the different schedule of sensor nodes to maximize the optimal network lifetime with optimum coverage.

3.1 Maximum lifetime of the network

Let m sensors nodes $\{S_1, S_2, S_3 \ldots S_m\}$ covers n target nodes $\{T_1, T_2, T_3 \ldots T_n\}$ placed in a region $(x \times y)$. The sensing range of each sensor node is r and the initial energy of the sensor node is E. The measure by which the sensor S_i, $1 \leq i \leq m$, covers the target T_j, $1 \leq j \leq n$ is given by the coverage matrix (M_{ij}) as:

Let the target node T_j is placed at (a,b) and sensor node S_i is placed at (x_i,y_i) then.

$$M_{ij} = (x_i - a)^2 + (y_i - b)^2 - r^2 \quad \text{for i} = 1,2,3\ldots\text{m and j} = 1,2,3\ldots\text{n}. \tag{1}$$

Coverage lifetime factor is given as stated in Onur et al. (2005), Bai et al. (2006).

$$\text{Coverage lifetime factor(f)} = \min_j \left[\frac{\sum_i M_{ij} \times b'_i}{q_j} \right] \tag{2}$$

where $b'_i = \frac{E_i}{e_i}$, e_i represents the power consumption rate of S_i and E_i shows the initial energy of the sensor node. For k-coverage $q_j = k$. As the Coverage lifetime factor decreased the coverage lifetime increased because negative value of M_{ij} depicts that the target is inside the sensing range of the sensor node.

3.2 Sensor deployment

1. *1-Coverage deployment*: Given a set of m sensor nodes $\{S_1, S_2, S_3 \ldots S_m\}$ and n target nodes $\{T_1, T_2, T_3 \ldots T_n\}$, to satisfy the requirement of 1-coverage the sensor nodes should be deployed in such a manner so that each target is covered by at least one target node and to minimize f.
2. *k-Coverage deployment*: Given a set of m sensor nodes $\{S_1, S_2, S_3 \ldots S_m\}$ and n target nodes $\{T_1, T_2, T_3 \ldots T_n\}$. For k-coverage deployment each target node must be monitored by k sensor nodes and to minimize f.

3.3 Sensor scheduling

1. *1-Coverage scheduling*: Suppose m sensor nodes $\{S_1, S_2, S_3 \ldots S_m\}$ are given that can monitor n target nodes $\{T_1, T_2, T_3 \ldots T_n\}$. then 1-coverage schedule $\{H_1, H_2, H_3 \ldots H_c\}$ for times $\{t_1, t_2, t_3 \ldots t_c\}$ means each target node is monitored by at least one sensor node and maximize the network lifetime $\sum_{v=1}^{c} t_v$.
2. *k-Coverage scheduling*: Assume m sensor nodes $\{S_1, S_2, S_3 \ldots S_m\}$ and n target nodes $\{T_1, T_2, T_3 \ldots T_n\}$. k-coverage schedule $\{H_1, H_2, H_3 \ldots H_c\}$ for times $\{t_1, t_2, t_3 \ldots t_c\}$ means each target node is monitored by k sensor node and maximize the network lifetime $\sum_{v=1}^{c} t_v$.

4 Proposed method

The Senor nodes can be deployed randomly or deterministically, for deterministic deployment of sensor nodes, it's possible at sink to determine the best position of the sensor node before actual deployment. The proposed algorithm 1 considers two cases:

- Case 1: The given n target nodes $\{T_1, T_2, T_3 \ldots T_n\}$ and m sensor nodes $\{S_1, S_2, S_3 \ldots S_m\}$ are not mobile.
- Case 2: The given n target nodes $\{T_1, T_2, T_3 \ldots T_n\}$ and m sensor nodes $\{S_1, S_2, S_3 \ldots S_m\}$ are mobile with some initial velocities.

Our method is twofold: First fold consists of two cases, for case 1 Simulated Annealing algorithm is used to find the optimal location of the sensor nodes that achieves maximum coverage and lifetime of the network. For case 2 particle swarm optimization algorithm is applied to get the optimal locations of sensor nodes with required velocities, and provides maximum coverage and lifetime of the network. In the other fold it provides the scheduling algorithm that can provide the different schedule for different time slots and maximize the network lifetime.

Algorithm 1:

Step 1: Randomly deploy sensor nodes in the region.
Step 2: Compute coverage lifetime factor by using equation (2)
Step 2: Check for mobility of sensor nodes and target nodes
Step 3: if both are not mobile then apply Simulated Annealing algorithm to find the optimized location of the sensor nodes
Step 4: if both are mobile then apply Particle swarm optimization algorithm to compute the optimized location of sensor nodes.
Step 5: Find the schedules of sensor nodes by applying simulated annealing algorithm such that network lifetime maximized.

4.1 Sensor deployment

Deterministically, the maximum lifetime or minimum coverage lifetime factor of the network can be computed (Onur et al. 2005; Bai et al. 2006). One of these factors can be used as fitness function to find the optimized location of sensor nodes according to the required k-coverage. For getting the optimized location, simulated Annealing (SA) (Kirkpatrick et al. 1983) and Particle swarm optimization (PSO) (Kennedy and Eberhart 1995;

Eberhart and Kennedy 1995) can be applied on the basis of mobility of the nodes.

1. *SA based sensor deployment*: Simulated Annealing is a probabilistic method used in Bai et al. (2010) for achieving the global minima of a cost function that contain many local minima. It depends on a physical process where a solid is slowly cooled so that it eventually gets frozen this occurs at minimum energy configuration.

Suppose the solution population is $Y = \{(x_1, y_1), (x_2, y_2), (x_3, y_3) \ldots, (x_m, y_m)\}$. Initially the sensor nodes $\{S_1, S_2, S_3 \ldots S_m\}$are randomly deployed inside the region. The target nodes $\{T_1, T_2, T_3 \ldots T_n\}$ are located inside the region. Algorithm 2 elaborates the steps of SA.

Algorithm 2:

Create random Population $Y = \{(x_1, y_1), (x_2, y_2) \ldots \ldots (x_m, y_m)\}$
Calculate $f_{old} = min_j \left[\frac{\sum_i M_{ij} \times b_i'}{q_j}\right]$
T ← temperature
for(cycle=1; cycle>-1; cycle=cycle-.0025) // cycle represent the number of epochs
{
Randomly select the element of Y
$f_{new} = min_j \left[\frac{\sum_i M_{ij} \times b_i'}{q_j}\right]$
$\Delta f = f_{new} - f_{old}$ //Deviation from the initial value
if (Δf >0) then
if $(random() \geq e^{-\frac{\Delta f}{k \times T}})$ // random() generates any value between 0 and 1
Reselect the elements of Y
otherwise
$f_{old} = f_{new}$
Otherwise
$f_{old} = f_{new}$
}

Here k represents Boltzman Constant.

2. *PSO based Sensor Deployment*: Particle swarm optimization method consists of many swarm particles moving in a search space to provide the optimized solution of a problem. Every particle has a position vector and a velocity vector. Position vector is an actual candidate of the solution. These particles have a small amount of memory that can store its global best position and local best position which are obtained by communicating with neighboring particles (Cheng et al. 2008; Yun et al. 2010).

A particle p occupies position x_{pd} and velocity v_{pd} in the dth dimension of the hyperspace, $1 \leq p \leq m$ and $1 \leq d \leq nd$. We have taken two dimension (d_1,d_2) of hyperspace.

Let the target node T_j is placed at (a,b) and sensor node S_i is placed at (x_{id1},x_{id2}) and, if the sensing range of the sensor node is r then

$$M_{ij} = (x_{id_1} - a)^2 + (x_{id_2} - b)^2 - r^2 \quad (3)$$

For $i = 1, 2, 3, \ldots m$ and $j = 1, 2, 3, 4 \ldots n$.

Algorithm 3 shows the steps that are used to provide PSO based sensor deployment.

Algorithm 3:

Create random population as sensors are placed at Y= ($x_{1d}(0), x_{2d}(0)\ldots\ldots x_{md}(0)$) and target are placed at X=(($y_{1d}(0), y_{2d}(0)\ldots\ldots y_{nd}(0)$))

Set the initial velocities of Target node (T) and Sensor node(S) as

$$v_{Td}^{j}(0) = 0 \; and v_{Sd}^{i}(0) = 0, where \;\; i \le m, j \le n \; and \; d = 1,2$$

for(cycle=1; cycle<100; cycle=cycle+1)

{

Calculate $f_i = min_j \left[\frac{\sum_i M_{ij} \times b_i'}{q_j}\right]$

$g_{best}^{T} = LOC_T^i$ // g_{best} is the local best in the target set X

$f_j = min_i \left[\frac{\sum_j M_{ij} \times b_i'}{q_j}\right]$

$g_{best}^{S} = LOC_S^j$ // g_{best} is the local best in the sensor set Y

$P_{best}^{Tj} = LOC_T^j$ //P_{best} is the local best in the target set X

$P_{best}^{Si} = LOC_S^i$ // P_{best} is the local best in the sensor set Y

Find the velocities of the particle as (by assuming r1,r2 in the random range (0,1)) as:

here j=1,2,3…..n and i=1,2,3…m

$v_{Td}^{j}(cycle) = v_{Td}^{j}(cycle-1) + r_1(P_{bestd}^{Tj} - y_{jd}(cycle-1)) + r_2(g_{bestd}^{Tj} - y_{jd}(cycle-1))$ // provides the velocity of //target for d= 1,2

$v_T^j = \sqrt{\sum_1^d \{v_{Td}^j(cycle)\}^2}$ // Resultant vector of two vectors at 90^0 for d=1,2

$v_{Sd}^{i}(cycle) = v_{Sd}^{i}(cycle-1) + r_1(P_{bestd}^{Si} - x_{id}(cycle-1)) + r_2(g_{bestd}^{Si} - x_{id}(cycle-1))$ //provides the velocity of //sensor for d= 1,2

$v_S^i = \sqrt{\sum_1^d \{v_{Sd}^j(cycle)\}^2}$ // Resultant vector of two vectors at 90^0 for d=1, 2

Now Update the value of Y and X as:

$y_{jd}(cycle) = y_{jd}(cycle-1) + v_T^j \;\; where \; j \le n \; and \;\; d = 1,2$

$x_{id}(cycle) = x_{id}(cycle-1) + v_S^i \;\; where \; i \le m \; and \; d = 1,2$

}

4.2 Sensor scheduling

As mentioned earlier, second objective of this paper is to schedule the sensor nodes such that it improves the lifetime of the network. The given algorithm 4 is used to find the different set of schedules that monitored the targets according to k-coverage and maximize lifetime of the network.

1. *Optimized Cover by SA*: There are three methods that all together used to find the optimized cover:

(a) *SA cover method*: SA cover method is used to provide the different covers that provide the required k-coverage and maximize the lifetime of the network. The optimized solution which has provided less Δf value is the right choice. The value of b_i' is decreased by random factor between [0,1]. Algorithm 5 explores the steps of SA cover method.

(b) *Coverage method*: This method maintains the coverage matrix as given in Eq. (1). The method,

Algorithm 4:

Step 1: Apply SA to get the optimized solution for cover (Call Algorithm 5). Cover is a set of sensor nodes that can provide coverage to a particular target node.

Step 2: On this cover apply Dempster Shafer Theory (Dempster 1968; Shafer 1976) to find the different schedules that fulfil the k-coverage and maximize the lifetime of the network.

Algorithm 5:

```
T← temperature
for(cycle=1;cycle>-1;cycle=cycle-.0025)
{
Call Algorithm 6                                   // Find the Initial Coverage Matrix
```

$f_{new} = min_j \left[\frac{\sum_i M_{ij} \times b_i'}{q_j}\right]$

$\Delta f = f_{new} - f_{old}$

if (Δf >0) then

  if $(random() \geq e^{-\frac{\Delta f}{k \times T}})$

      Decrease b_i'

      Call Algorithm 6 // Update the Coverage Matrix

  otherwise

      Decrease b_i'

      $f_{old} = f_{new}$

otherwise

      Decrease b_i'

      $f_{old} = f_{new}$

}

initially applies cover assignment method to find the cover for each target node then applies the coverage method to evaluate the elements of coverage matrix. Algorithm 6 gives the details of coverage method.

(c) Cover Assignment method: This method is used to provide the maximum number of sensor nodes that cover a particular target node. The information that is provided by cover assignment method is used to find the different covers by using the Dempster Shafer theory.

Algorithm 6:

// Output: Coverage matrix

Call Algorithm 7 // Find the initial set of sensor nodes that cover a target

for i=1 to n // for each target node

  for j=1 to m // for each sensor node

    $if(Sensornode(S_i) \in cover) then$

      $M_{ij} = (x_{id_1} - a)^2 + (x_{id_2} - b)^2 - r^2$ // calculate the coverage matrix for the sensor S_i //placed at the position (x_{id_1}, x_{id_2}) by using the equation (1)

    otherwise

      $M_{ij} = 0$

Algorithm 7:

// Output: cover matrix

Cover=Ø

for j=1 to n // for each target node

  for i=1 to m // for each sensor node

    $d_{S_i} = distance\ between\ sensor\ node(S_i)\ and\ Target\ node\ (T_j)$

      $if(d_{S_i} \leq r\ and\ b_i' \geq E_{min})then$ // E_{min} is the threshold energy //required for working of a sensor node.

      $cover = cover \cup S_i$

2. *Schedules by dempster shafer theory*: Dempster Shafer Theory (DST) is a mathematical theory of evidence. DST combines the independent items of evidence from different sources and arrives at a degree of belief (Ozturk et al. 2011; Liu et al. 2005). It is applied to find the different schedules of sensor nodes. The DST calculates three terms:

    - Mass
    - Belief
    - Plausibility

In the following sections, these terms are calculated by using three algorithms as Mass Assignment Algorithm, Belief Assignment Algorithm and Plausibility Assignment respectively.

(a) Mass assignment algorithm:

Mass (B) refers to the proportion of all relevant and evidences that supports the reason that actual state belongs to B, where B is a member of the power set of a given hypotheses. If a sensor node (i) covers a target node(j) then the value of cover[j][i] is 1. The algorithm calculates the cover value of each element in the power set of sensor nodes and then evaluates the mass value for each element in the power set. Details are given in Algorithm 8 for assigning the masses to different hypotheses.

Algorithm 8:

```
// m and n represent total number of sensor nodes and target nodes respectively.
// Mass[] and sum_cover[] are 1-dimentional arrays.
//Cover[][] is a 2-dimentional array.
Output: Mass matrix
C=0;
total=0;
   power_set= power set of the set {S1, S2, S3 ... ... Sm}          // the elements of the power set of the set {S1,S2,S3....Sm}
                                                                    //are stored in the variable power_set.
for i=1 to 2^m{
        for j=1 to n{
                for each element(Sp,Sq) in power_set{
                        if (cover[j][p] or cover[j][q]==1) then{
                                Cover[j][i]=1
                        }
                }
                C=C+Cover[j][i]
        }
        Sum_cover[i]=C;
}
for i=1 to 2^m{
        total=total+sum_cover[i]
}
for i=1 to 2^m{
        Mass[i]=sum_cover[i]/total;
}
```

(b) Belief assignment algorithm:

Belief (B) is the sum of masses of all subsets of B (including B), where B is a member of hypotheses. Algorithm 9 gives the details of assigning the Belief to each element in the power set of sensor nodes.

Algorithm 9:

```
// Output: Belief matrix
   Power_set= power set of the set {S1,S2,S3 … … .Sm}      // the elements of the power set of the set {S1,S2,S3….Sm}
                                                           //are stored in the variable power_set.
B=0;
for i=1 to 2^m{
        Calculate the power set (PS) of each element in Power_set
        for each item(k) in PS{
                B=B+Mass[k]
        }
        Belief[i]=B
}
```

(c) Plausibility assignment:

Plausibility (P) is the sum of all members of hypotheses that intersect with B. Algorithm 10 shows the steps of Plausibility Assignment algorithm.

Algorithm 10:

```
// Output: Plausibility matrix
   Power_set= power set of the set {S1,S2,S3 … … .Sm}      // the elements of the power set of the set {S1,S2,S3….Sm}
                                                           //are stored in the variable power_set.
for j=1 to 2^m{
        for i=1 to 2^m{
                if (Power_set[j] intersection Power_set[i] != φ) {
                        p=p+Mass[i]
                 }
        }
        Plausibility[j] = p
}
```

The Belief interval [Belief (B), Plausibility (B)] is used to find the certainty of the belief. A small difference between Belief and Plausibility shows, we are certain about our belief and a large value depicts, we are uncertain about our belief.

5 Results and discussion

For evaluating the performance of deployment methods, we have used MATLAB 2007b. We have taken 10 and 20 sensor nodes to check the performance of proposed methods. Coverage, we have considered in the evaluation is k-coverage where k = 1, 2, 3, 4, 5. Two scenarios are developed for simulating the deployment algorithm by using simulated annealing. Scenario 1 contains 10 sensor nodes and 10 target nodes; scenario 2 contains 20 sensor nodes and 10 target nodes. The initial position of sensor nodes for scenario 1 is {(4,5), (10,12), (15,10), (2,3), (4,6), (6,10), (1,2), (3,2), (4,3), (20,10)} respectively. Target nodes position for scenario1 and scenario2 is {(2,3), (1, 11), (12,8), (2,3), (2,6), (10,10), (8,4), (4,6), (4,10), (17,12)}. The Battery power (in nJ) for each sensor of scenario 1 is given as {12, 5, 9, 5, 7, 9, 10, 11, 17, 18} respectively. Minimum battery requirement for a sensor node is more than 1 nJ to work as active sensor node inside the sensor network. The sensing range of the sensor nodes is 5 m. Figures 1, 2, 3, 4 and 5 shows the optimized location of sensor nodes after the application of SA based sensor deployment method for different k-coverage in scenario 1.

For scenario 2 the sensor nodes are initially positions at {(14, 11), (12, 2), (5, 23), (5, 6), (8, 1), (15, 7), (3, 7),

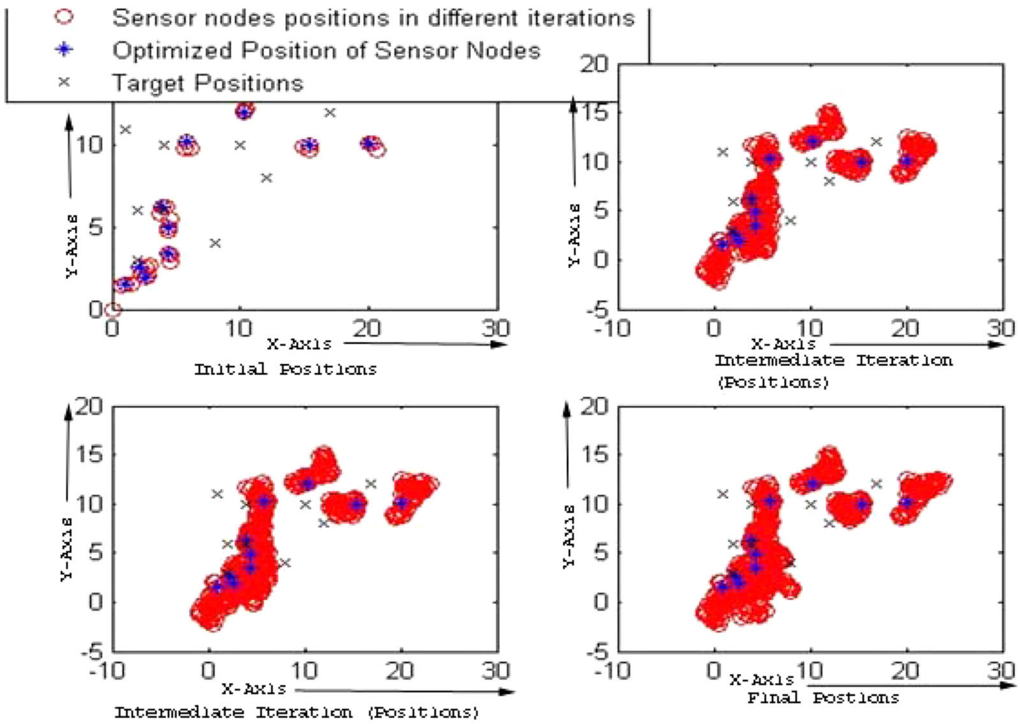

Fig. 1 Optimized location of sensor nodes (1-coverage)

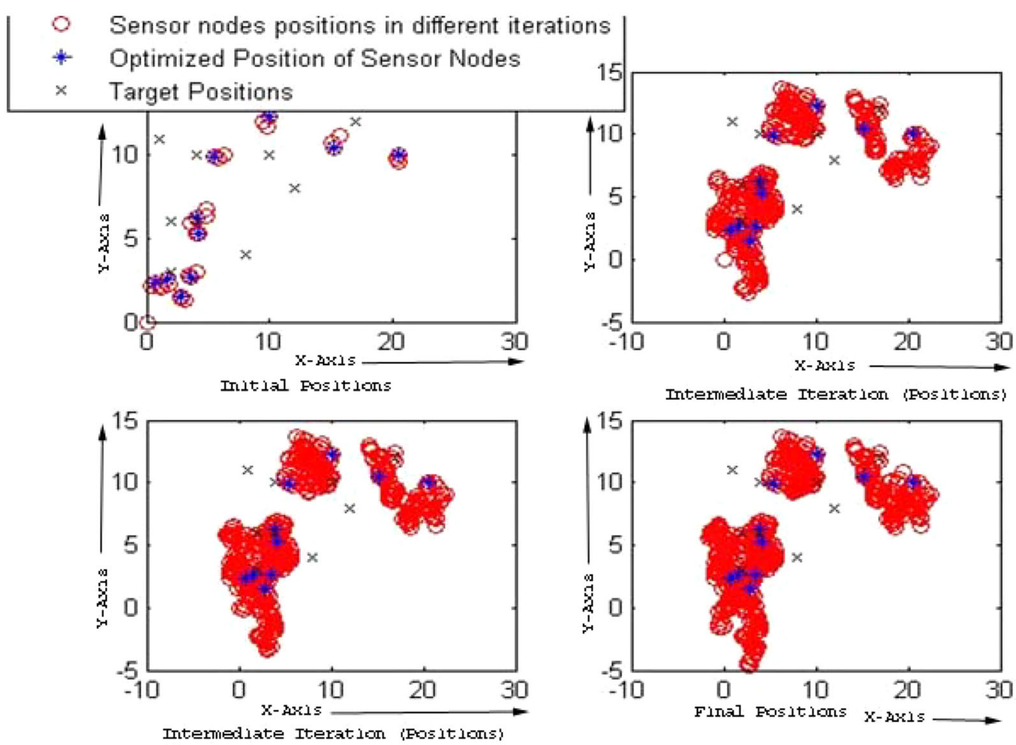

Fig. 2 Optimized location of sensor nodes (2-coverage)

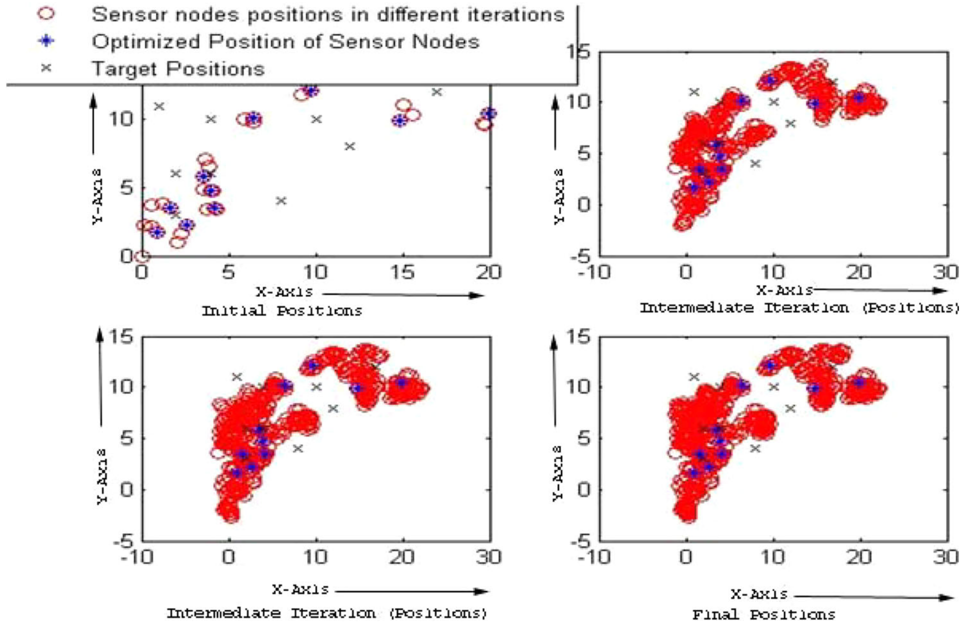

Fig. 3 Optimized location of sensor nodes (3-coverage)

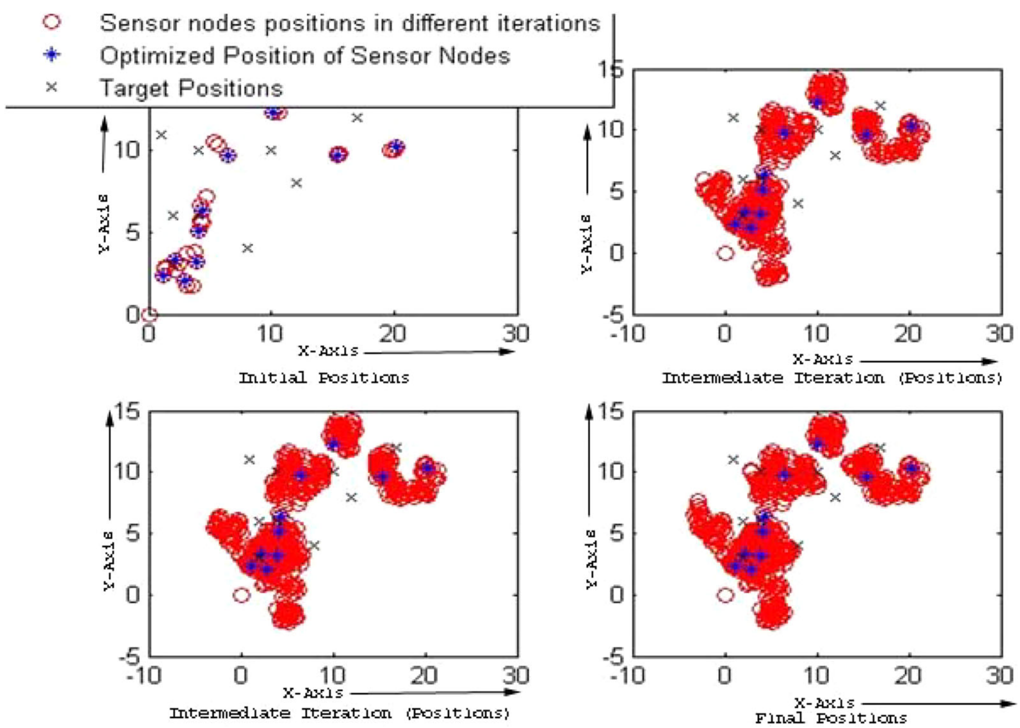

Fig. 4 Optimized location of sensor nodes (4-coverage)

(1, 4), (14, 8), (13, 6), (10, 20), (23, 12), (6, 5), (7, 9), (11, 23), (5, 4), (7, 4), (3, 8), (3, 1), (12, 1)}. The Battery power (in nJ) for these sensor nodes is {12.3, 5, 9, 5, 7, 9, 10, 11, 17.6,18, 23, 43, 7.1, 8, 12, 23, 11, 10.4, 9, 20} respectively. Minimum battery requirement for a sensor node is more than 1 nJ to work as active sensor node

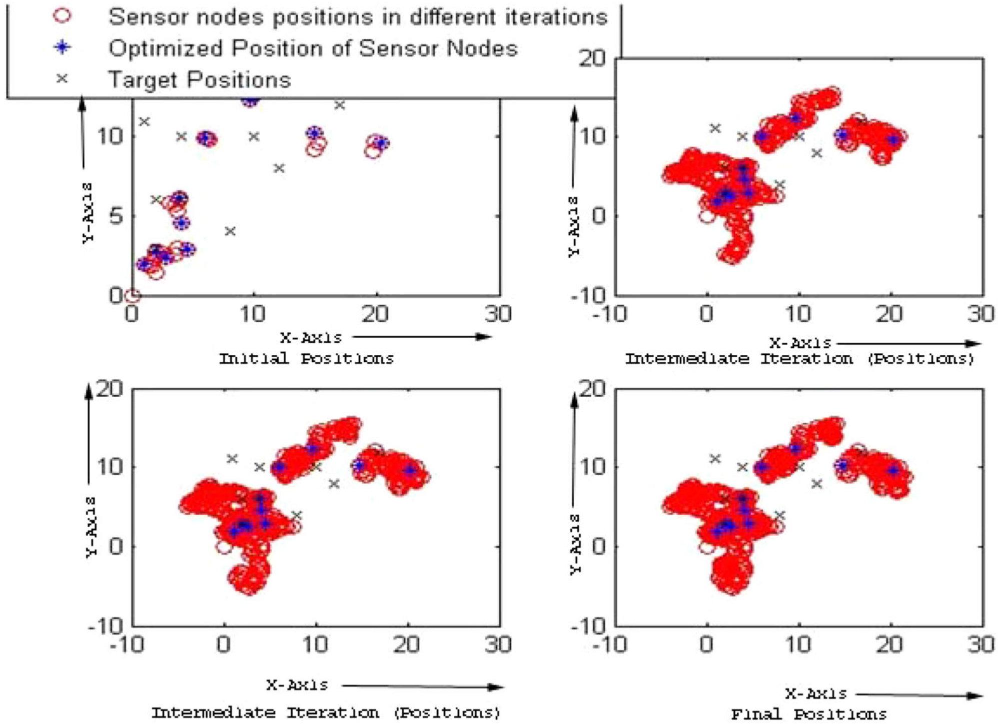

Fig. 5 Optimized location of sensor nodes (5-coverage)

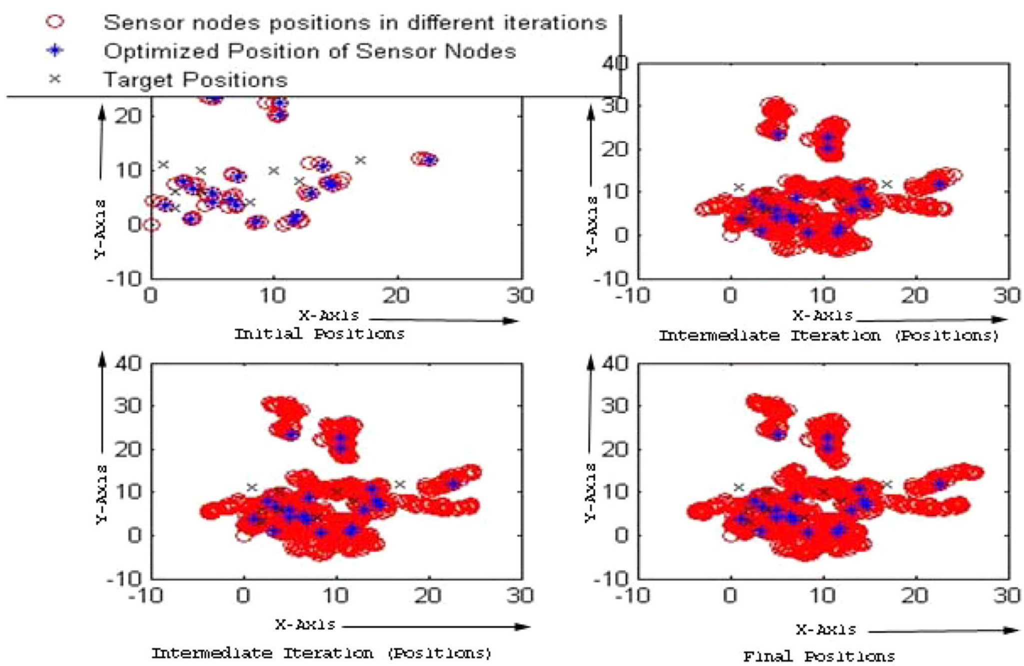

Fig. 6 Optimized location of sensor nodes (1-coverage)

inside the sensor network. The sensing range of the sensor nodes is 5 m. Figures 6, 7, 8, 9 and 10 shows the optimized location of sensor nodes for scenario 2 with different k-coverage.

For evaluating the performance of PSO based sensor nodes deployment algorithm, we have designed two scenarios. Scenario 1 consists of 10 sensor nodes and 10 target nodes which are placed at {(4, 5), (10, 12), (15, 10), (2, 3),

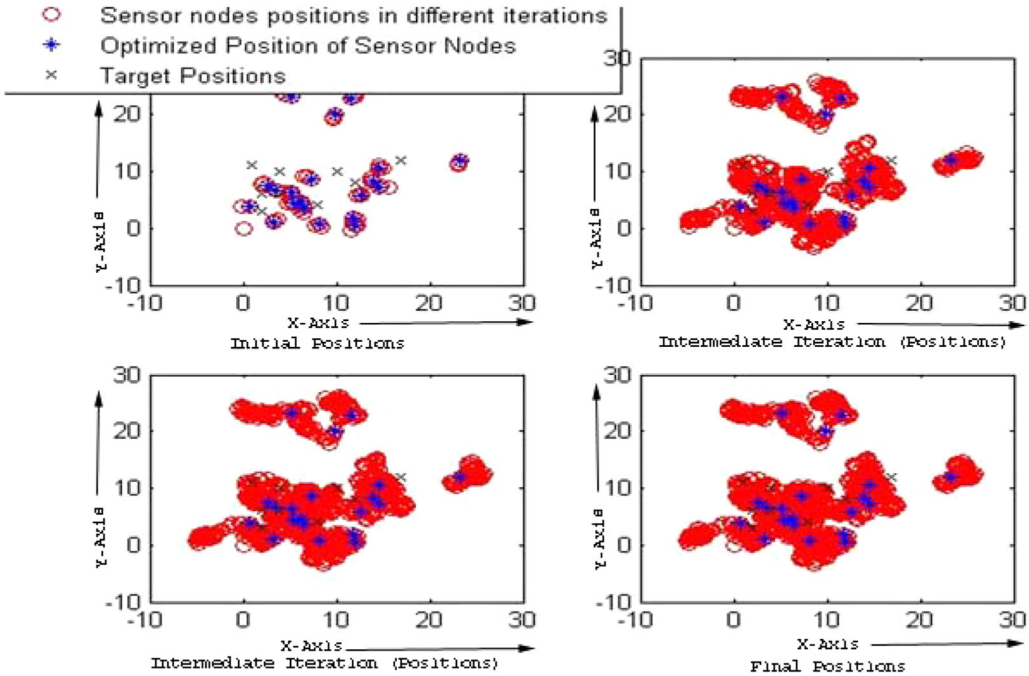

Fig. 7 Optimized location of sensor nodes (2-coverage)

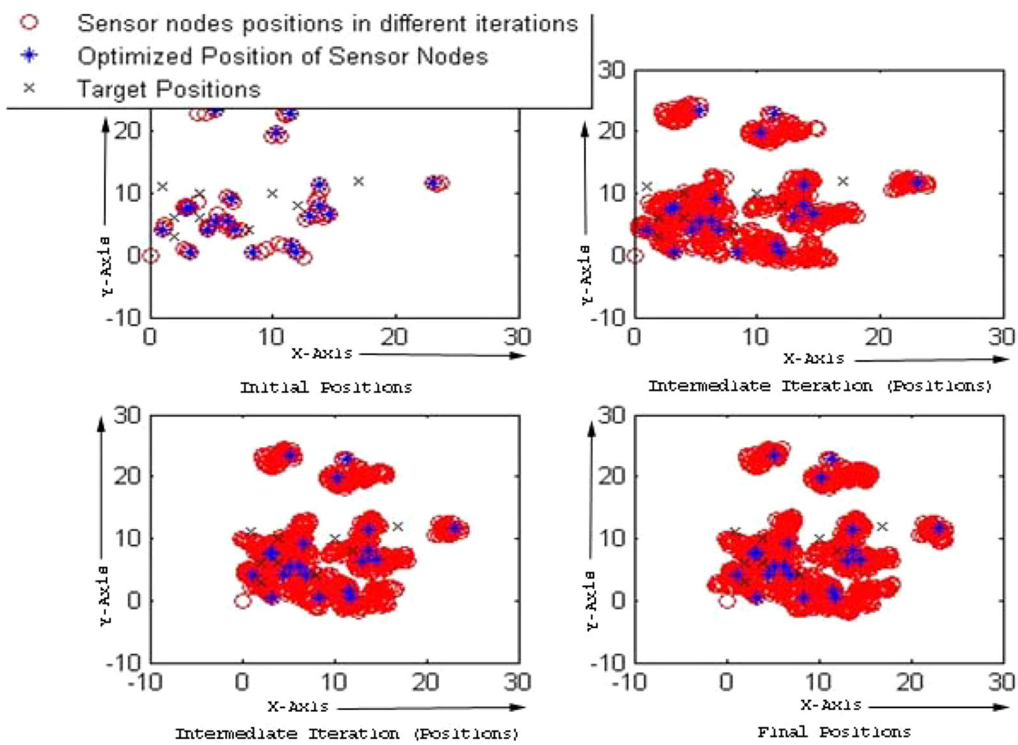

Fig. 8 Optimized location of sensor nodes (3-coverage)

(4, 6), (6, 10), (1, 2), (3, 2), (4, 3), (20, 10)} and {(2, 3), (1, 11), (12, 8), (2, 3), (2, 6), (10, 10), (8, 4), (4, 6), (4, 10), (17, 12)} respectively. The sensor nodes contain the battery power (nJ) as {12, 5, 9, 5, 7, 9, 10, 11, 17, 18}. The coverage is k-coverage where $k = 1, 2, 3, 4, 5$ and the minimum power required by a sensor node to work in

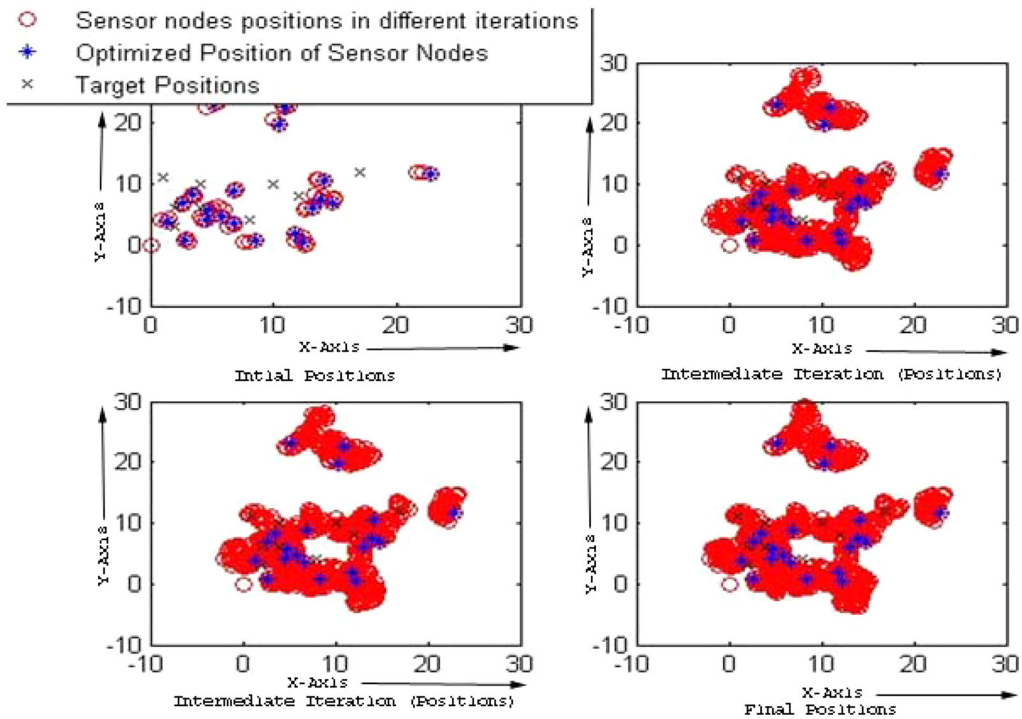

Fig. 9 Optimized location of sensor nodes (4-coverage)

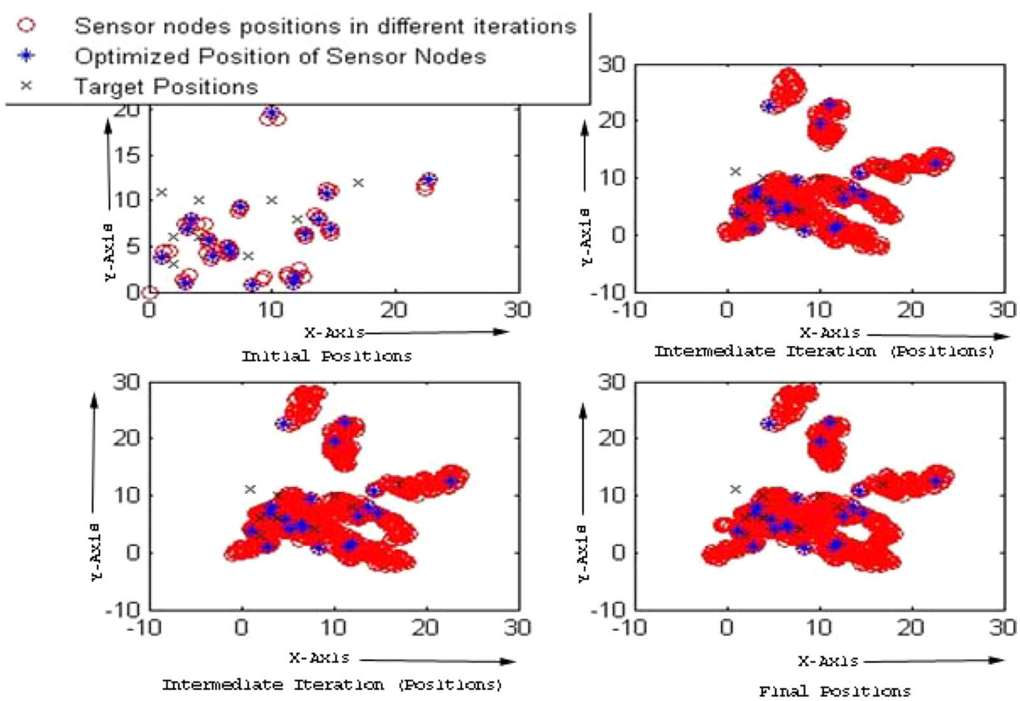

Fig. 10 Optimized location of sensor nodes (5-coverage)

active mode is 1 nJ. Figure 11 shows the optimized position of sensor nodes and target nodes. Figure 11 shows the optimized location of sensor nodes in first iteration, middle iterations and last iteration in left to right order. In the same manner Figs. 12, 13, 14 and 15 shows the optimized positions of sensor nodes and target nodes.

In the second scenario for evaluating the PSO based sensor deployment algorithm, we have considered 20

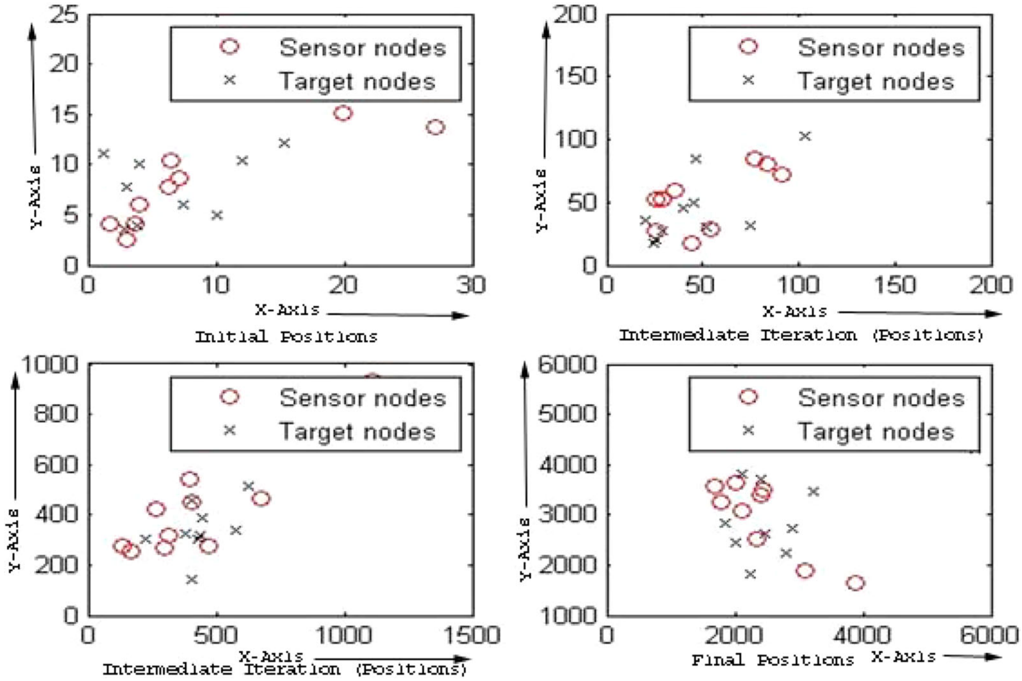

Fig. 11 Optimized location of sensor nodes and target nodes (1-coverage)

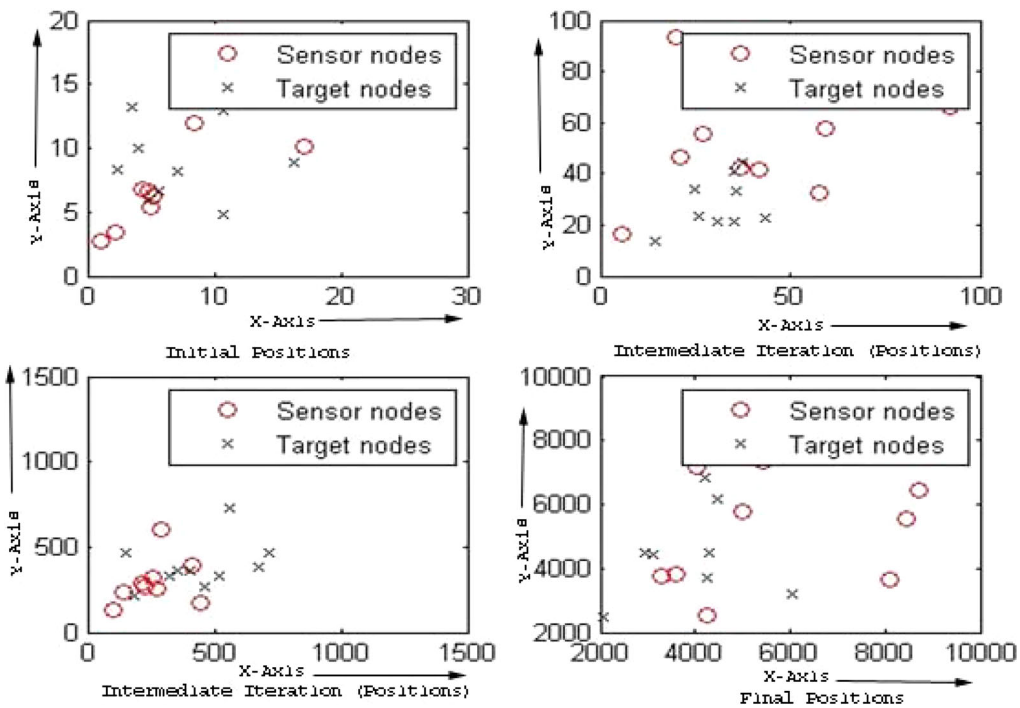

Fig. 12 Optimized location of sensor nodes and target nodes (2-coverage)

sensor nodes and 20 target nodes which are positioned at {(14, 11), (12, 2), (5, 23), (5, 6), (8, 1), (15, 7), (3, 7), (1, 4), (14, 8), (13, 6), (10, 20), (23, 12), (6, 5), (7, 9), (11, 23), (5, 4), (7, 4), (3, 8), (3, 1), (12, 1)} and {(2, 3), (15, 7), (9, 2), (10, 7), (2, 8), (10, 12), (12, 22), (14, 11), (23, 2), (8, 5), (14, 9), (12, 10), (11, 8), (7, 13), (18, 10), (20,

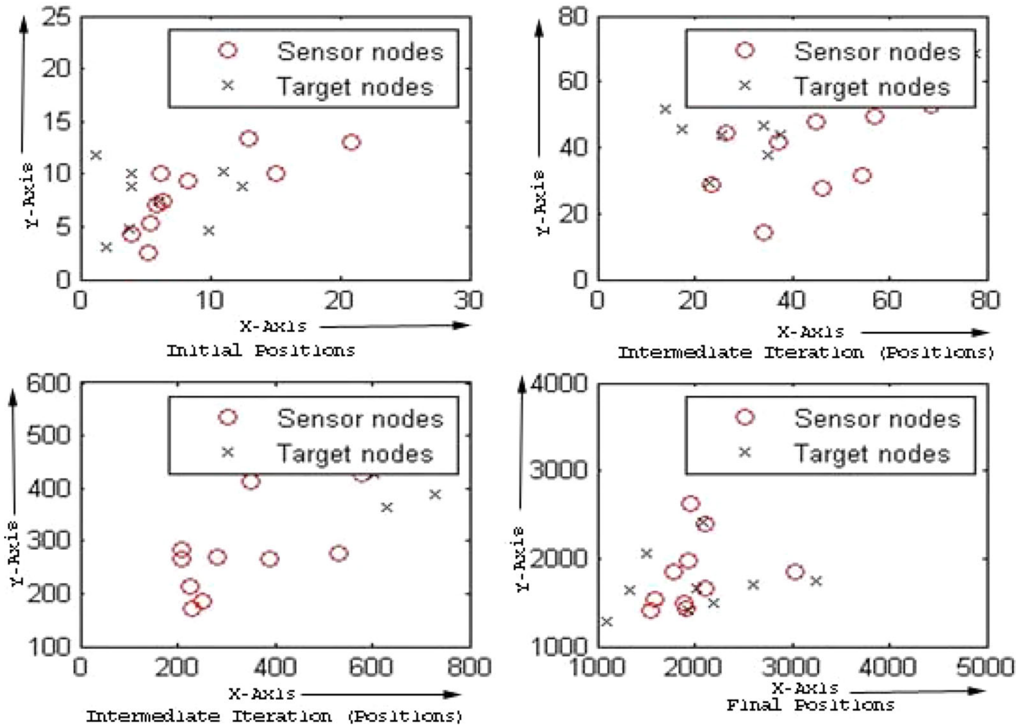

Fig. 13 Optimized location of sensor nodes and target nodes (3-coverage)

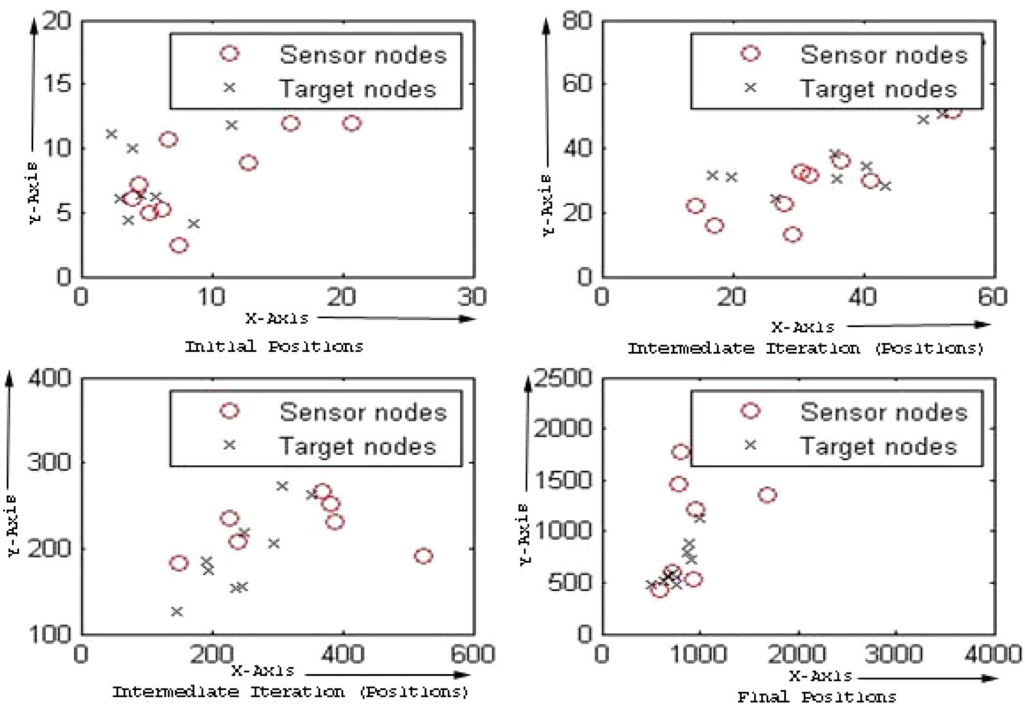

Fig. 14 Optimized location of sensor nodes and target nodes (4-coverage)

12), (21, 9), (15, 8), (17, 8), (9, 12)} respectively. The battery power (in nJ) of sensor nodes is as {12, 4, 9, 12, 13, 17.1, 21, 22, 56, 43, 7, 8, 11, 10.2, 14, 17, 19, 21, 16.3, 22}. The sensing range of each sensor nodes is as 5 m. Minimum battery required by a sensor node to work as active is 1 nJ. Figure 16 shows the position of sensor

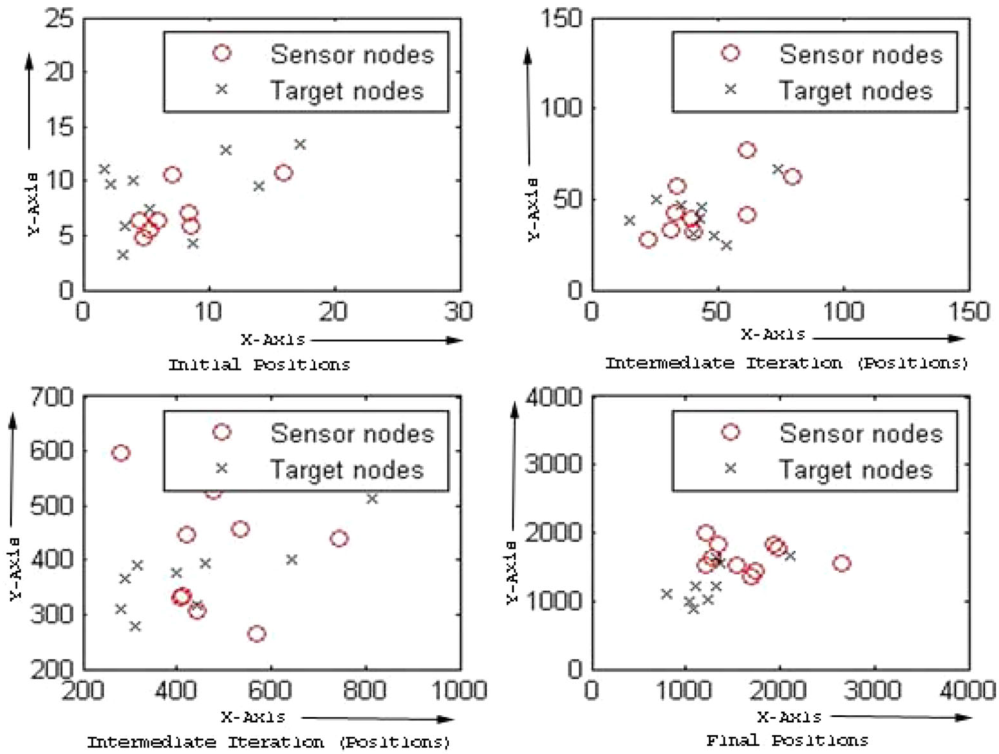

Fig. 15 Optimized location of sensor nodes and target nodes (5-coverage)

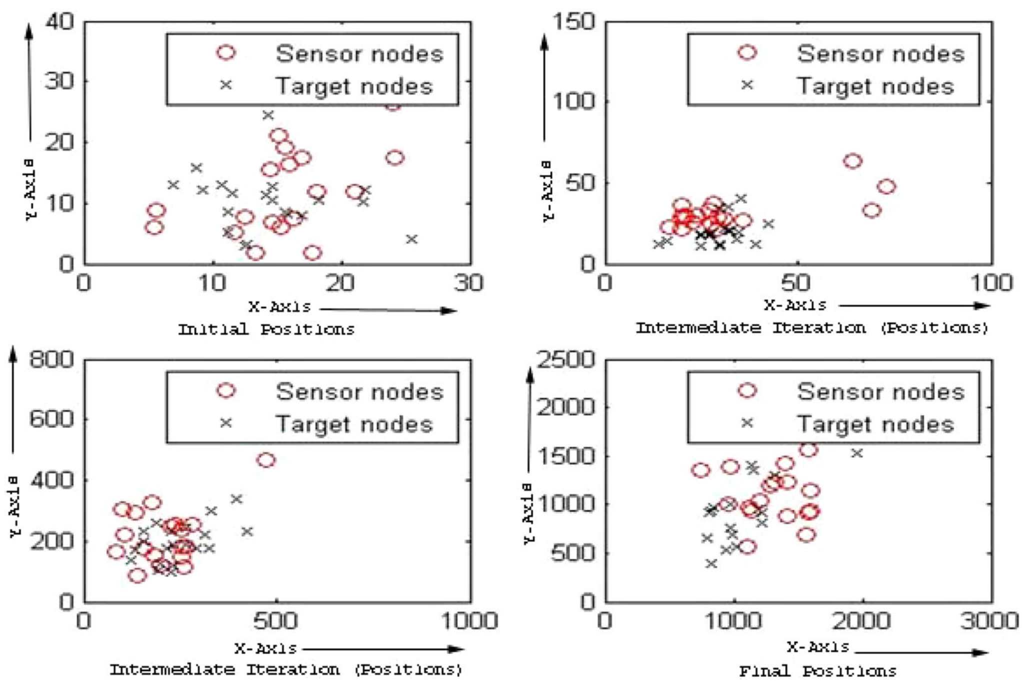

Fig. 16 Optimized location of sensor nodes and target nodes (1-coverage)

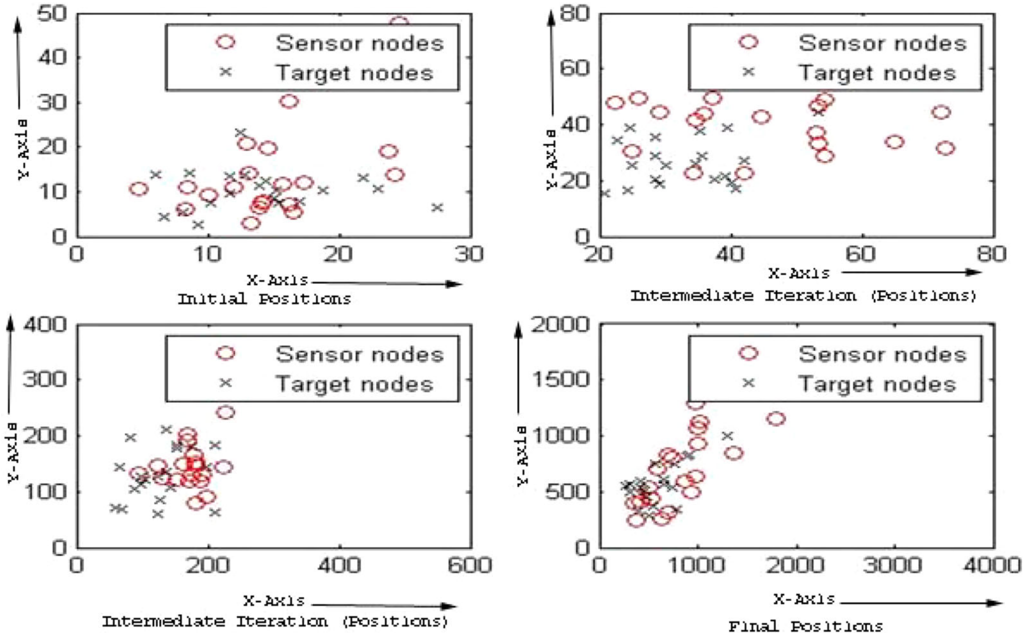

Fig. 17 Optimized location of sensor nodes and target nodes (2-coverage)

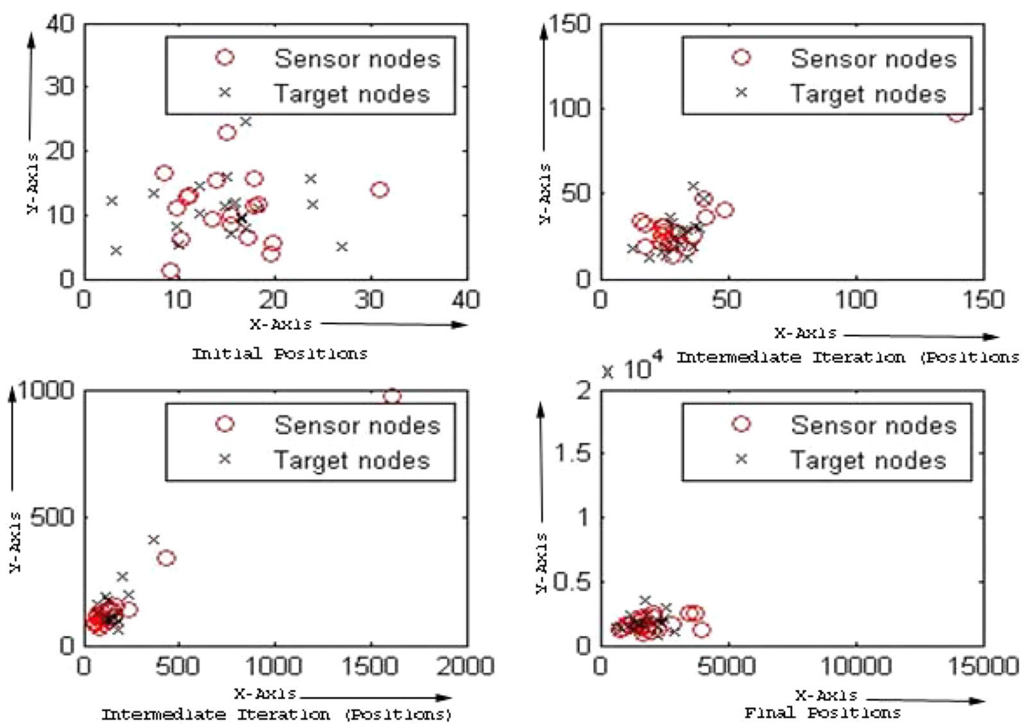

Fig. 18 Optimized location of sensor nodes and target nodes (3-coverage)

nodes and target nodes in first iteration, mid-iterations and last iteration from left to right order. In the same way Figs. 17, 18, 19 and 20 show the optimized location of sensor nodes and target nodes.

As mentioned in the above text, we have applied the Dempster Shafer Theory to get the schedules of sensor nodes. The group of sensor nodes that provides minimum difference between belief and plausibility are good

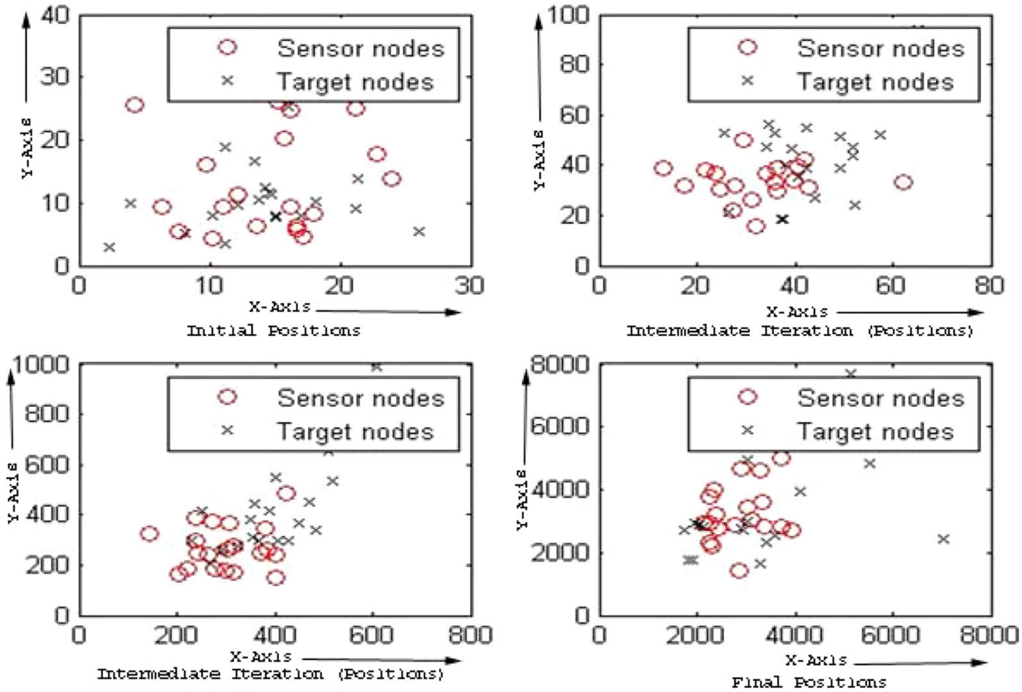

Fig. 19 Optimized location of sensor nodes and target nodes (4-coverage)

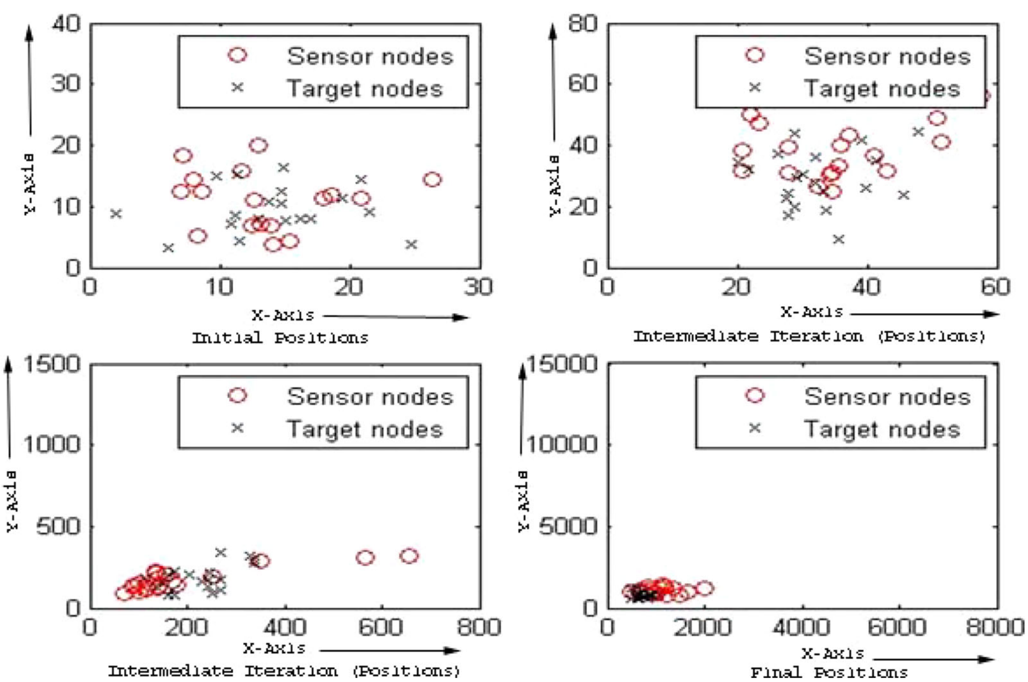

Fig. 20 Optimized location of sensor nodes and target nodes (5-coverage)

candidate for selection. On the basis of this selection, we have achieved the lifetime of the sensor network. We have compared the lifetime of the WSN after application of Dempster Shafer Theory with the lifetime of the WSN with random deployment of the senor nodes. Two scenarios are considered, scenario1 contains 10 sensor nodes and 10 target nodes and scenario 2 has 14 sensor nodes and 10 target nodes, with the sensing range of senor nodes as 5 m and k-coverage where k = 1, 2, 3, 4, 5 for both scenarios. Figures 21, 22, 23, 24, 25 shows the belief- plausibility

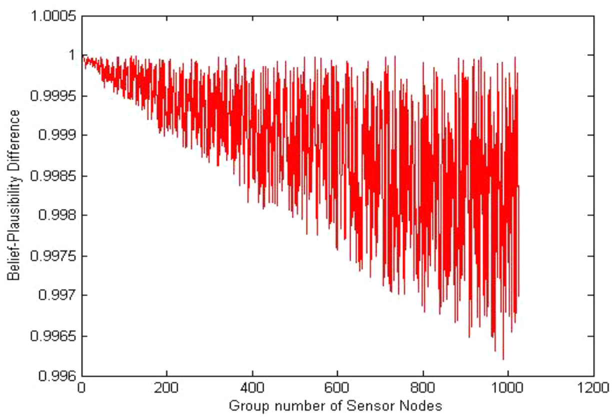

Fig. 21 Belief-Plausibility difference for different group of sensor nodes (1-coverage)

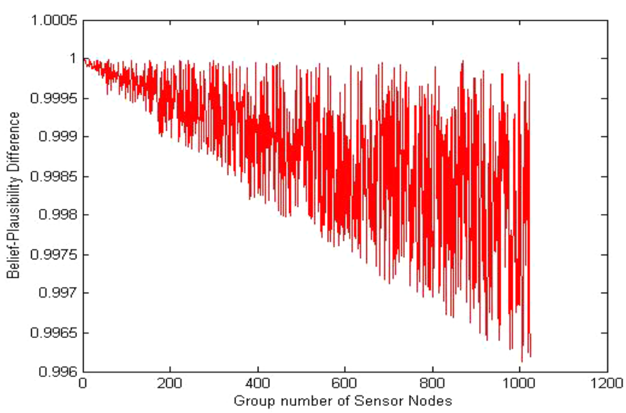

Fig. 22 Belief-Plausibility difference for different group of sensor nodes (2-coverage)

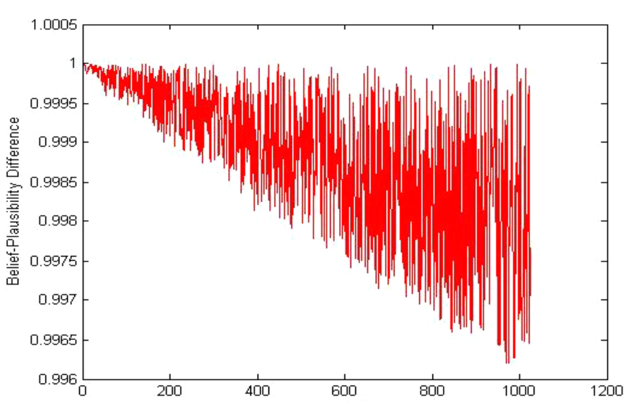

Fig. 23 Belief-Plausibility difference for different group of sensor nodes (3-coverage)

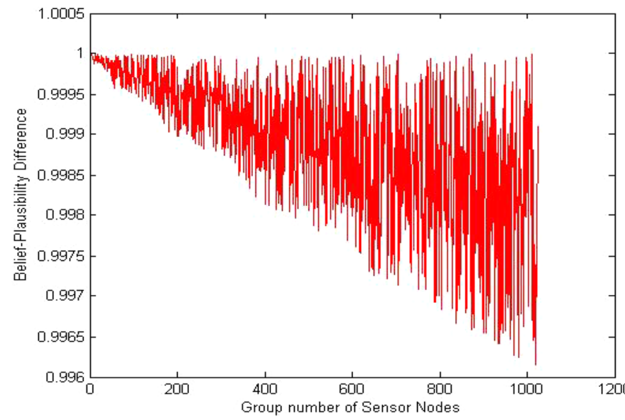

Fig. 24 Belief-Plausibility difference for different group of sensor nodes (4-coverage)

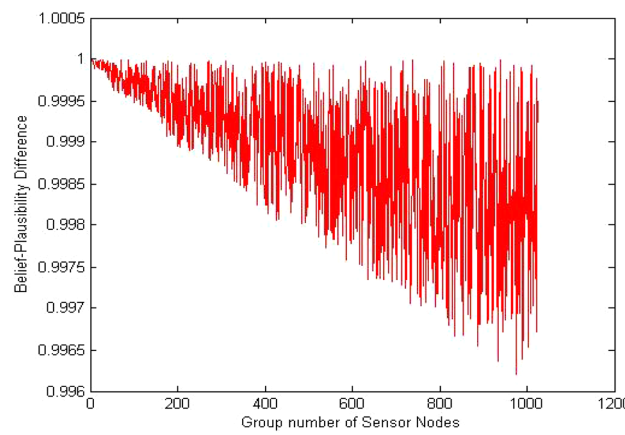

Fig. 25 Belief-Plausibility difference for different group of sensor nodes (5-coverage)

difference for different groups of sensor nodes with different k-coverage where k = 1, 2, 3, 4, 5 for scenario 1. The result of comparison for scenario 1 is shown in Fig. 26. The belief- plausibility difference for different groups of sensor nodes with different k-coverage where k = 1, 2, 3, 4, 5 for scenario 2 is given in Figs. 27, 28, 29, 30, 31 and the figure for comparison of lifetime is shown in Fig. 32.

5.1 Key findings

We have simulated the proposed methods and found the following important results (shown in Tables 1, 2)

From the data given in Tables 1 and 2, we can conclude that for 10 sensor nodes in average the increment in the lifetime for k-coverage is 27.795 % and for 14 sensor nodes in average the improvement in the lifetime of the sensor network is 33.4266 %.

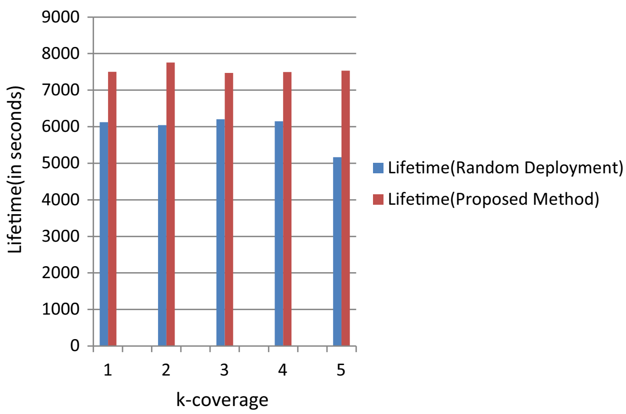

Fig. 26 Lifetime of the network for 10 sensor nodes (comparison between random deployment and after application of proposed method)

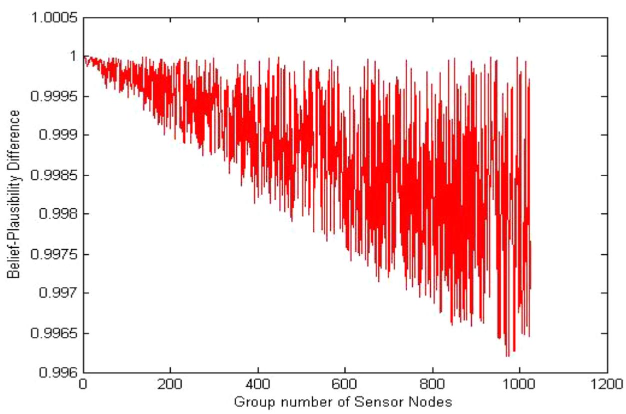

Fig. 27 Belief-Plausibility difference for different group of sensor nodes (1-coverage)

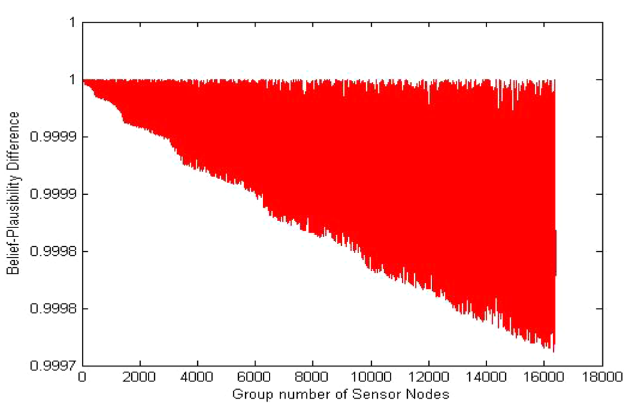

Fig. 28 Belief-Plausibility difference for different group of sensor nodes (2-coverage)

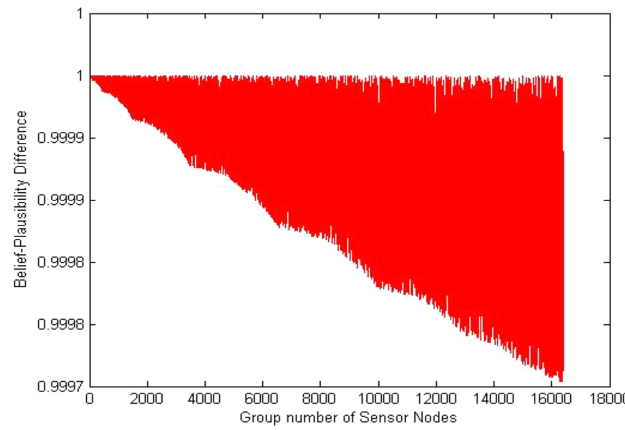

Fig. 29 Belief-Plausibility difference for different group of sensor nodes (3-coverage)

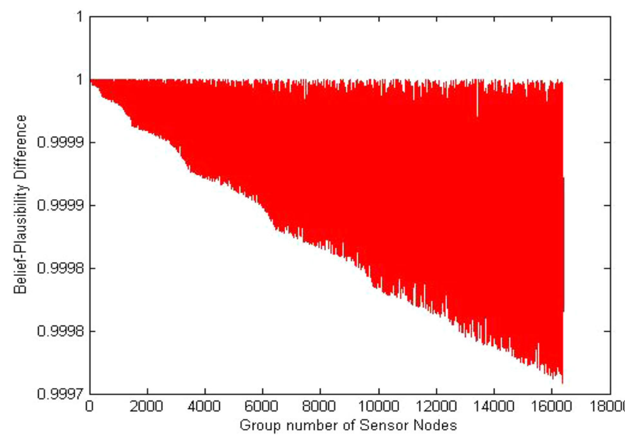

Fig. 30 Belief-Plausibility difference for different group of sensor nodes (4-coverage)

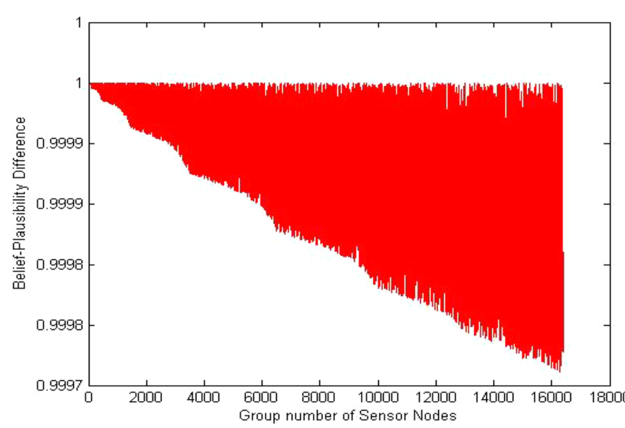

Fig. 31 Belief-Plausibility difference for different group of sensor nodes (5-coverage)

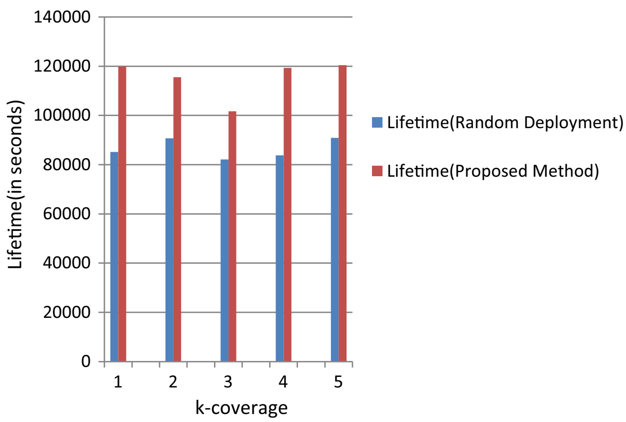

Fig. 32 Lifetime of the Network for 14 sensor nodes (Comparison between random deployment and after application of proposed method)

Table 1 Increase in lifetime

k-Coverage	Increase in lifetime (%)
Number of sensor nodes 10	
1-Coverage	22.445
2-Coverage	28.335
3-Coverage	20.474
4-Coverage	21.893
5-Coverage	45.829

Table 2 Increase in lifetime

k-coverage	Increase in lifetime (%)
Number of sensor nodes 14	
1-Coverage	40.813
2-Coverage	27.469
3-Coverage	23.857
4-Coverage	42.513
5-Coverage	32.481

6 Conclusion

In this paper, Simulated Annealing and Particle Swarm Optimization approaches are used to calculate the optimized location of sensor nodes for deployment in a region which have some target nodes. These approaches depend on the mobility of sensor and target nodes. In order to increase the lifetime of the wireless sensor network, the approach of scheduling the sensor nodes is applied, for this purpose Simulated Annealing and Dempster Shafer Theory is used. The Dempster Shafer Theory provides the different schedules for sensor nodes that cover the target nodes according to k-coverage requirement. The schedule that contains minimum sensor nodes and fulfills the coverage needs has higher priority than the schedule that has more sensor nodes.

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