Artificial Bee Colony Algorithm for Probabilistic Target Q-coverage in Wireless Sensor Networks

S. Mini[1], Siba K. Udgata[2], and Samrat L. Sabat[3]

[1] Department of Computer Science and Engineering
School of Engineering and Technology
Central University of Rajasthan, Rajasthan, India
mini2min2002@yahoo.co.in

[2] School of Computer and Information Sciences
University of Hyderabad, Hyderabad-500046, India
udgatacs@uohyd.ernet.in

[3] School of Physics
University of Hyderabad, Hyderabad-500046, India
slssp@uohyd.ernet.in

Abstract. The lifetime of a wireless sensor network is dependent on the type of sensor deployment. If the application permits deterministic deployment of nodes and if the sensor nodes are limited, quality of sensing and energy conservation can be enhanced by restricting the sensing range requirement. This paper addresses deterministic deployment of nodes for probabilistic target **Q**-coverage. A probabilistic coverage model considers the effect of distance and medium on the sensing ability of a node. We use Artificial Bee Colony (ABC) algorithm to compute the optimal deployment of sensor nodes such that the required sensing range is minimum for probabilistic target **Q**-coverage.

Keywords: Sensor Deployment, Target Coverage, **Q**-Coverage, ABC Algorithm.

1 Introduction

Maximization of network lifetime is one of the main challenges in wireless sensor networks. Energy can be efficiently used through proper energy utilization schemes, depending on the application. If the application permits deterministic deployment of nodes, energy wastage can be controlled by restricting the sensing range required and the quality of coverage can be improved in case of probabilistic coverage.

Sensor nodes are deployed to achieve either area coverage or target coverage. To achieve area coverage, if the sensors have fixed sensing range, optimal deployment patterns are preferred to minimize the number of sensor nodes required. The coverage requirement of the application also has an impact on the network lifetime. Some applications require that each target has to be monitored by at least one sensor node (simple coverage), whereas some might require a high number of sensor nodes to monitor the targets (k-coverage). In some applications, each target may

B.K. Panigrahi et al. (Eds.): SEMCCO 2013, Part I, LNCS 8297, pp. 446–456, 2013.

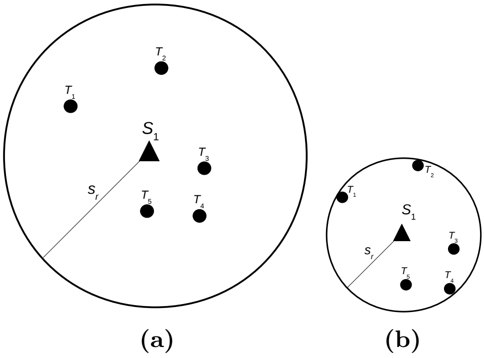

Fig. 1. Comparison (a) Random deployment with fixed sensing range and (b) Deterministic deployment with optimal sensing range

have a different coverage requirement. This is known as **Q**-coverage problem. In this paper, we focus on probabilistic target **Q**-coverage problem. The number of sensor nodes to be deployed are limited and the sensing range has to be minimized to control energy usage and improve quality of coverage.

Figure 1a shows a random deployment of sensor node S_1. Here S_1 has a predefined sensing range s_r. Figure 1b shows a case of deterministic deployment of S_1 where the sensing range is restricted/reduced so that it is optimal for all the targets to be monitored.

1.1 Types of Sensor Deployments

The deployment of sensor networks varies with the application considered. In some environments, it can be predetermined and be placed in the exact locations. For some environments, the nodes can be air-dropped or deployed by other means [1].

Depending on the density of nodes in a network, a sensor network deployment can be categorized as dense deployment or sparse deployment.

- Dense Deployment
  A dense deployment involves relatively large number of sensor nodes. It is used when higher level of coverage has to be satisfied.
- Sparse Deployment
  A sparse deployment includes only a few number of nodes. It is used when dense deployment is not feasible because of cost of deployment or other factors.

Based on the type of deployment, a sensor network deployment can be categorized as random deployment or deterministic deployment.

- Random Deployment
  Random deployment is suitable if no prior knowledge of the region is available. It is mainly used for military applications, inaccessible area, hostile region etc. However, random deployment does not always lead to effective coverage, especially if the sensors are clustered at some parts of the region [2].
- Deterministic Deployment
  Deterministic deployment is suitable for accessible regions. It is also preferred if powerful, sophisticated and expensive nodes are used which require careful planning and placement [3]. Non-sensitive applications usually use deterministic deployment.

1.2 Types of Sensing Models

Most research works assume that the sensing region of a sensor node is a sensing disc, that is, a sensor node has the uniform contribution in all directions of its sensing region. In the basic (binary) model, if a target lies within the sensing region of a sensor node, it is always assumed to be detected with probability 1 otherwise with probability 0. This idealized binary model has been extensively used to analyze the coverage problems of sensor networks. But in real deployment of sensor nodes, the sensing capabilities of sensor nodes have relations with the environment and then it is imperative to have practical considerations at the design stage. Such a sensing model is known as probabilistic sensing model. Thus, in general there are two sensing models: binary sensing model and probabilistic sensing model.

Binary Sensing Model In a binary sensing model, the target is either monitored with full confidence or not monitored. Let $S = \{S_1, S_2, \ldots, S_m\}$ be the set of sensor nodes and $T = \{T_1, T_2, \ldots, T_n\}$ be the set of targets in a given region. A sensor node located at (x_1, y_1, z_1) can cover a target at (x_2, y_2, z_2) if the Euclidean distance between the sensor node and the target is less than or equal to the sensing range s_r.

$$\sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2 + (z_1 - z_2)^2} \leq s_r \tag{1}$$

A binary sensing model is given by,

$$ST_{ij} = \begin{cases} 1 & \text{if } d_{ij} \leq s_r, \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

where $i = 1, 2, \ldots, m$ and $j = 1, 2, \ldots, n$. d_{ij} corresponds to the Euclidean distance between S_i and T_j

Probabilistic Sensing Model. The sensing range is not a disk in probabilistic sensing models [4]. With probabilistic model, the probability that the sensor detects a target depends on the relative position of the target within the sensors' sensing range. Basically the probability of detecting a target is assumed to diminish at an exponential rate with the increase in distance between a sensor and that target. Probabilistic coverage applies with some kinds of sensors e.g. acoustic, seismic etc., where the signal strength decays with distance from the source, and not with sensors that only measure local point values e.g. temperature, humidity, light etc. [5].

As in [6], we use the following exponential function to represent the confidence level in the received sensing signal:

$$ST_{ij} = \begin{cases} e^{-\alpha d_{ij}} & \text{if } d_{ij} \leq s_r, \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

where $0 \leq \alpha \leq 1$ is a parameter representing the physical characteristics of the sensing unit and environment.

The coverage of a target T_j which is monitored by multiple sensor nodes S_j is given by,

$$ST_j(S_j) = 1 - \prod_{S_i \in \mathbf{S}_j} (1 - ST_{ij}) \tag{4}$$

2 Related Work

Network performance metrics such as energy consumption, coverage, delay and throughput etc. are affected by the position of sensor nodes. For example, large distances between nodes weaken the communication links, lower the throughput and increase the energy consumption [6]. It is always a challenging task to make use of the available energy in a fair manner. The coverage requirement varies from application to application. **Q**-coverage is one where each target may have a different coverage requirement. Earlier work on **Q**-coverage problem [7][8][9] is based on random deployment of nodes. The model under consideration is binary. In such cases, sensor scheduling is a solution to maximize the network lifetime. The method proposed by Gu et al. [7] is based on column generation, where each column corresponds to a feasible solution. Chaudhary et al. [8] present a greedy heuristic, High Energy and Small Lifetime (HESL), to generate **Q**-covers by prioritizing sensors in terms of the residual battery life. Liu et al. [9] also propose a heuristic for **Q**-coverage problem with scheduling as a solution.

Du et al. [10] propose to improve sensor network performance by deploying some mobile sensors in addition to a large number of static sensors. Mobile sensors are used to increase sensing coverage, provide better routing and connectivity for sensor networks. The areas that equire better coverage are identified and mobile sensors are moved towards that area. Shen et al. [11] propose Grid Scan which is applied to calculate the basic coverage rate with arbitrary sensing radius of each node. This approach is used to ensure k-coverage of the area and it is used to provide better coverage with less nodes. A re-deployment approach is used to obtain better coverage rate.

Initial work on probabilistic coverage address area coverage problem [5][12]. In [12], the problem is formulated as an optimization problem with the objective to minimize cost while all the points are covered with some required probability. The minimum number of sensors that are to be activated to maintain the required level of coverage is identified in [4].

Artificial Bee Colony (ABC) Algorithm [13] is an optimization algorithm based on the intelligent foraging behavior of honey bee swarm. ABC algorithm has been found to solve optimization problems efficiently. There are other algorithms also based on the behavior of natural bees [14]. Compared to other swarm intelligence based algorithms like GA, Particle Swarm Optimization (PSO), ABC is observed to perform better [13]. ABC algorithm was applied to sensor deployment problem in irregular terrain by Udgata et al. [15]. Mini et al. used ABC algorithm initially to solve simple coverage problem [16] and later to solve k-coverage and **Q**-coverage problems [17]. The sensing model used in these problems is a binary sensing model, where a target is fully monitored or not at all monitored.

The dynamic deployment problem in WSNs with mobile sensors on a binary sensing model was solved using ABC algorithm [18]. Ozturk et al. [19] use ABC algorithm to solve dynamic deployment problem in WSNs within the scenario of mobile and stationary sensors on a probabilistic detection model. Andersen et al. [20] consider sensor deployment in a three dimensional space to achieve a desired degree of coverage and also to minimize the number of sensor placed. Most of the existing works on sensor deployment address area coverage problem in wireless sensor networks.

To the best of our knowledge, this is the first work to address sensor deployment for probabilistic target **Q**-coverage problem. This paper is an extension to our earlier work [21] where we use artificial bee colony algorithm to solve probabilistic target k-coverage problem.

3 Problem Definition

Given a set of n targets $T = \{T_1, T_2, \ldots, T_n\}$ located in $U \times V \times W$ region and m sensor nodes $S = \{S_1, S_2, \ldots, S_m\}$, place the nodes such that $T = \{T_1, T_2, \ldots, T_n\}$ is monitored by $\mathbf{Q} = \{q_1, q_2, \ldots, q_n\}$ number of sensor nodes such that target T_j needs to be monitored by at least q_j number of sensor nodes, where $1 \leq i \leq n$ and with a total probability p such that the required sensing range is minimum. The objective is to cover T_j with at least q_j sensor nodes, probability p and to minimize

$$F = \forall_i((max(distance(S_i, H_g)))) \tag{5}$$

where H is the set of all targets monitored by S_i, $i = 1, 2, \ldots, m$, $g = 1, 2, \ldots, h$, where h is the total number of targets S_i monitors.

Algorithm 1. Proposed Method of sensor deployment for probabilistic sensing model

Initialize the solution population B
Evaluate fitness ((Equation(5)))
Produce new solutions based on probabilistic **Q**-coverage
Choose the fittest bee
$cycle = 1$
repeat
  Search for new solutions in the neighborhood
  if new solution better than old solution **then**
    Memorize new solution and discard old solution
  end if
  Replace the discarded solution with a newly randomly generated solution
  Memorize the best solution
  $cycle = cycle + 1$
until cycle = maximumcycles

4 Proposed Method

Let B be the solution population in a region with stationary targets. Each solution $B_a = \{(x_1, y_1, z_1), (x_2, y_2, z_2), \ldots, (x_m, y_m, z_m)\}$ where $a = 1, 2, \ldots, nb$, nb the total number of bees and m the total number of nodes to be deployed, corresponds to a bee. The initial solution is generated in such a way that all the targets can be probabilistically covered, and no sensor node is left idle without contributing to probabilistic **Q**-coverage. Let R_j be the subset of sensor nodes which can make each target T_j meet the required probability. If R_j satisfies **Q**-coverage requirement of T_j, T_j is assigned to each sensor node in R_j. If it does not satisfy **Q**-coverage, then identify the nearest nodes which do not belong to R_j that can make T_j **Q**-covered, along with R_j. T_j is assigned to these new sensor nodes in addition to R_j. Each sensor node is then placed at the center of all the targets which are assigned to it. If some target will not be probabilistically covered due to this shift of location, this move should not be allowed.

The fitness function used to evaluate the solutions is the euclidean distance between each target and the sensor location to which it is associated. Each sensor node is associated to a cluster, where a cluster corresponds to the set of targets monitored by the sensor node. Let $D_i = (D_{i1}, D_{i2}, D_{i3})$ be the initial position of i^{th} cluster. $F(D_i)$ refers to the nectar amount at food source located at D_i. After watching the waggle dance of employed bees, an onlooker goes to the region of D_i with probability G_i defined as,

$$G_i = \frac{F(D_i)}{\sum_{l=1}^{m} F(D_l)} \tag{6}$$

where m is the total number of food sources. The onlooker finds a neighborhood food source in the vicinity of D_i by using,

$$D_i(t+1) = D_i(t) + \delta_{ij} \times v \tag{7}$$

Table 1. Sensing Range for Probabilistic Target **Q**-Coverage

			Sensing Range		
α	Probability	Q	Best	Mean	Standard Deviation
0.05	0.6	1-2	2.0616	2.0616	0
		1-3	3.9751	4.0235	0.0439
		1-4	3.9427	3.9547	0.0208
	0.7	1-2	2.0616	2.0616	0
		1-3	3.7723	3.8672	0.0836
		1-4	3.9147	3.9761	0.0719
	0.8	1-2	2.0616	2.0616	0
		1-3	3.8876	3.9565	0.0815
		1-4	3.8286	3.9514	0.1233
	0.9	1-2	2.0616	2.0616	0
		1-3	3.943	3.9721	0.0297
		1-4	3.9254	3.9858	0.055
0.1	0.6	1-2	2.0616	2.0616	0
		1-3	3.8579	3.9443	0.1061
		1-4	3.9178	3.9591	0.0611
	0.7	1-2	2.0616	2.0616	0
		1-3	3.8544	3.9946	0.1216
		1-4	3.8623	3.9178	0.1078
	0.8	1-2	2.0616	2.0616	0
		1-3	3.9269	3.9494	0.0264
		1-4	3.9652	4.0359	0.0627
	0.9	1-2	3.6976	3.9003	0.1771
		1-3	4.0306	4.1559	0.1095
		1-4	4.1482	4.3142	0.1648
0.15	0.6	1-2	2.0616	2.0616	0
		1-3	4.0044	4.0378	0.0289
		1-4	3.9331	3.9378	0.004
	0.7	1-2	2.0616	2.0616	0
		1-3	3.9766	3.9827	0.0061
		1-4	3.9273	3.9803	0.0912
	0.8	1-2	3.4953	3.6227	0.1207
		1-3	3.8904	4.0533	0.168
		1-4	3.9161	4.0423	0.1204
0.2	0.6	1-2	2.0616	2.0616	0
		1-3	3.9354	3.9735	0.0449
		1-4	3.8028	3.9391	0.1228
	0.7	1-2	3.4768	3.5369	0.0941
		1-3	3.9114	4.0044	0.1294
		1-4	3.8978	3.9552	0.0516

The onlooker finds a neighborhood food source in the vicinity of D_i by using Equation 7. The solutions are never allowed to move beyond the edge of the region. The new solutions are also evaluated by the fitness function. If any new solution is better than the existing one, that solution is chosen and the old one

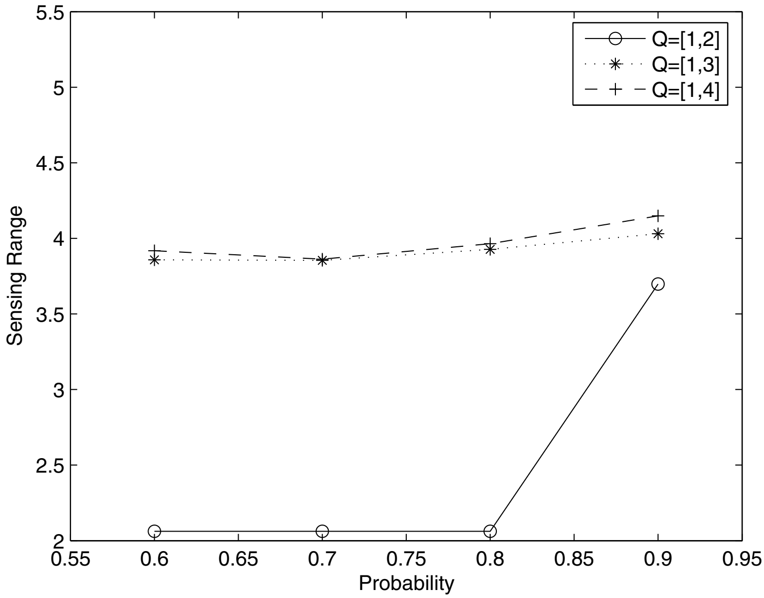

Fig. 2. Sensing range requirement for 10x10x10 grid with α=0.1

is discarded. Scout bees search for a random feasible solution. The solution with the least sensing range and that satisfies probabilistic **Q** coverage is finally chosen as the best solution. The proposed scheme is shown in Algorithm 1.

5 Results and Discussion

The initial experiments are carried out on a 10x10x10 grid. 5 sensor nodes are to be deployed to monitor 10 targets. The total number of bees (colony size) is 10, with half of them being employed bees and half onlookers. The number of cycles is 500, limit for neighborhood search is 20 and the number of runs is 3. MATLAB 2007a is used for implementation.

Since a probabilistic coverage model considers the effect of medium on the sensing ability of a node, we vary the value of α. α is assumed to take values 0.05, 0.1, 0.15 and 0.2. The value of **Q** also affects the sensing range required. We vary Q-values 1 to 2, 1 to 3 and 1 to 4. The required probability is set to 0.6, 0.7, 0.8 and 0.9. The sensing range required depends highly on **Q**. With α at 0.15, the targets cannot be covered with a probability 0.9 and with α = 0.2, the targets cannot be covered with a probability 0.8 or higher (Table 1). Figure 2 shows the sensing range requirement for this set-up with α = 0.1. It can clearly be seen that for the targets to be monitored with **Q**=[1,2], the sensing range required for coverage with probability 0.6, 0.7 and 0.8 are the same. But when a higher probability of 0.9 is required, a noticeable increase in the sensing range is observed. When the

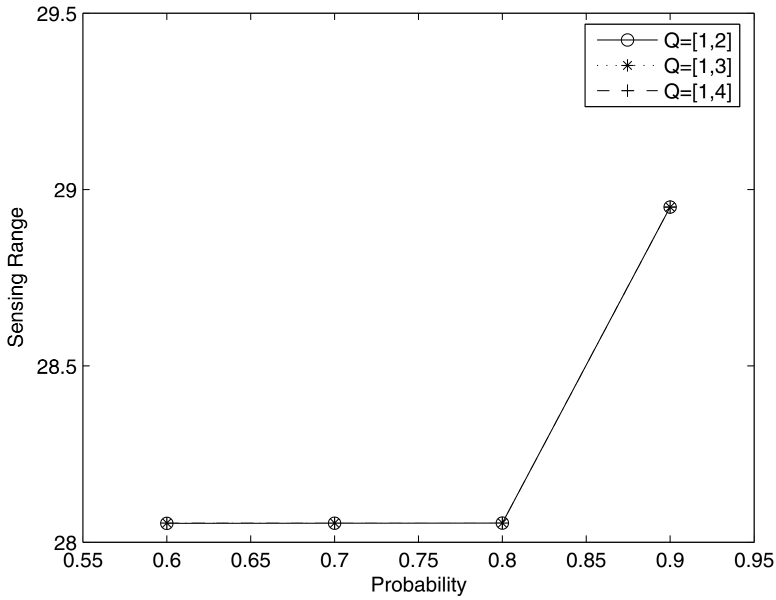

Fig. 3. Sensing range requirement for 100x100x20 grid

Table 2. Sensing Range for Probabilistic Target **Q**-coverage (100×100×20 grid)

		Sensing Range		
Probability	Q	Best	Mean	Standard Deviation
0.6	1-2	28.0531	28.0764	0.0378
	1-3	28.0543	28.0998	0.0517
	1-4	28.0545	28.0560	0.0027
0.7	1-2	28.0538	28.0955	0.0422
	1-3	28.0545	28.1372	0.0737
	1-4	28.0545	28.1345	0.1386
0.8	1-2	28.0545	28.4431	0.3564
	1-3	28.0545	28.4431	0.3564
	1-4	28.0545	28.4431	0.3564
0.9	1-2	28.9500	29.2468	0.2888
	1-3	28.9500	29.2468	0.2888
	1-4	28.9500	29.2468	0.2888

value of **Q** is increased, the sensing range required for coverage with probability 0.6, 0.7 and 0.8 is much higher compared to that for **Q**=[1,2]. But there is no major change in the sensing range requirement even for a higher probability requirement of 0.9. The measured standard deviation shows that the method is a robust one.

We also consider a $100 \times 100 \times 20$ grid for experimentation to see how the algorithm performs on a larger grid. Three instances of 100 targets being monitored by 10 sensor nodes are considered. The results are reported as an average of the sensing range required for these three instances. α is assumed to be 0.01. Figure 3 clearly shows that there is no significant change in the sensing range requirement for different values of $\mathbf{Q}$. The slight variation in the sensing range required can be seen in Table 2. With $\mathbf{Q}$-coverage requirement, for probability 0.8 and 0.9, the sensing range required for $\mathbf{Q}$ values 1 to 2, 1 to 3 and 1 to 4 are the same. These results show that the algorithm is a reliable one even for a larger grid.

6 Conclusion

In this paper, we consider deterministic deployment of sensor nodes for probabilistic sensing model where the deployment locations are computed such that the required sensing range is minimum and probabilistic $\mathbf{Q}$-coverage requirement is satisfied. Here, the number of sensor nodes is assumed to be limited. ABC algorithm is used to computed the optimal deployment locations. We studied the variation in sensing range for a range of detection probabilities (p), coverage requirement ($\mathbf{Q}$) and physical medium characteristics (α). The use of ABC algorithm proves to be a reliable one since no significant change is observed in the standard deviation of obtained sensing range among various runs for a larger region or for higher values of $\mathbf{Q}$. In future, we plan to study connected coverage with probabilistic detection model.

References

1. Poe, W.Y., Schmitt, J.B.: Node Deployment in Large Wireless Sensor Networks: Coverage, Energy Consumption, and Worst-Case Delay. In: Proc. of Asian Internet Engineering Conference, pp. 77–84 (2009)
2. Zou, Y., Chakrabarty, K.: Sensor Deployment and Target Localization Based on Virtual Forces. In: Proc. of INFOCOM, pp. 1293–1303 (2003)
3. Liu, X., Mohapatra, P.: On the Deployment of Wireless Sensor Nodes. In: Proc. of Third International Workshop on Measurement, Modelling, and Performance Analysis of Wireless Sensor Networks, in Conjunction with MobiQuitous (2005)
4. Hefeeda, M., Ahmadi, H.: Energy-Efficient Protocol for Deterministic and Probabilistic Coverage in Sensor Networks. IEEE Transactions on Parallel and Distributed Systems 21, 579–593 (2010)
5. Ahmed, N., Kanhere, S., Jha, S.: Probabilistic Coverage in Wireless Sensor Networks. In: Proc. of IEEE Conference on Local Computer Networks, pp. 672–681 (2005)
6. Zou, Y., Chakrabarty, K.: A Distributed Coverage- and Connectivity-Centric Technique for Selecting Active Nodes in Wireless Sensor Networks. IEEE Transactions on Computers 54, 978–991 (2005)
7. Gu, Y., Liu, H., Zhao, B.: Target Coverage With QoS Requirements in Wireless Sensor Networks. In: Proc. of Intelligent Pervasive Computing, pp. 35–38 (2007)

8. Chaudhary, M., Pujari, A.K.: Q-Coverage Problem in Wireless Sensor Networks. In: Garg, V., Wattenhofer, R., Kothapalli, K. (eds.) ICDCN 2009. LNCS, vol. 5408, pp. 325–330. Springer, Heidelberg (2008)
9. Liu, H., Chen, W., Ma, H., Li, D.: Energy-Efficient Algorithm for the Target Q-coverage Problem in Wireless Sensor Networks. In: Pandurangan, G., Anil Kumar, V.S., Ming, G., Liu, Y., Li, Y. (eds.) WASA 2010. LNCS, vol. 6221, pp. 21–25. Springer, Heidelberg (2010)
10. Du, X., Lin, F.: Improving Sensor Network Performance by Deploying Mobile Sensors. In: Proc. of 24th IEEE International Performance, Computing, and Communications Conference (2005)
11. Shen, X., Chen, J., Sun, Y.: Grid Scan: A Simple and Effective Approach for Coverage Issue in Wireless Sensor Networks. In: Proc. of IEEE International Conference on Communications (2006)
12. Carter, B., Ragade, R.: A Probabilistic Model for the Deployment of Sensors. In: Proc. of IEEE Sensors Applications Symposium, pp. 7–12 (2009)
13. Karaboga, D., Basturk, B.: A powerful and efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm. Journal of Global Optimization 39, 459–471 (2007)
14. Mozaffari, A., Gorji-Bandpy, M., Gorji, T.: Optimal design of constraint engineering systems: application of mutable smart bee algorithm. Int. J. of Bio-Inspired Computation 4(3), 167–180 (2012)
15. Udgata, S.K., Sabat, S.L., Mini, S.: Sensor Deployment in Irregular Terrain using ABC Algorithm. In: Proc. of IEEE BICA 2009, pp. 296–300 (2009)
16. Mini, S., Udgata, S.K., Sabat, S.L.: Sensor Deployment in 3-D Terrain Using Artificial Bee Colony Algorithm. In: Panigrahi, B.K., Das, S., Suganthan, P.N., Dash, S.S. (eds.) SEMCCO 2010. LNCS, vol. 6466, pp. 424–431. Springer, Heidelberg (2010)
17. Mini, S., Udgata, S.K., Sabat, S.L.: Artificial Bee Colony Based Sensor Deployment Algorithm for Target Coverage Problem in 3-D Terrain. In: Natarajan, R., Ojo, A. (eds.) ICDCIT 2011. LNCS, vol. 6536, pp. 313–324. Springer, Heidelberg (2011)
18. Ozturk, C., Karaboga, D., Gorkemli, B.: Artificial Bee Colony Algorithm for Dynamic Deployment of Wireless Sensor Networks. Turkish Journal of Electrical Engineering & Computer Sciences 20, 255–262 (2012)
19. Ozturk, C., Karaboga, D., Gorkemli, B.: Probabilistic Dynamic Deployment of Wireless Sensor Networks by Artificial Bee Colony Algorithm. Sensors 11, 6056–6065 (2011)
20. Andersen, T., Tirthapura, S.: Wireless Sensor Deployment for 3D Coverage with Constraints. In: Proc. of Sixth International Conference on Networked Sensing Systems, INSS (2009)
21. Mini, S., Udgata, S.K., Sabat, S.L.: Sensor Deployment for Probabilistic Target k-Coverage using Artificial Bee Colony Algorithm. In: Panigrahi, B.K., Suganthan, P.N., Das, S., Satapathy, S.C. (eds.) SEMCCO 2011, Part I. LNCS, vol. 7076, pp. 654–661. Springer, Heidelberg (2011)