

# Artificial bee colony algorithm for dynamic deployment of wireless sensor networks

Celal ÖZTÜRK\*, Derviş KARABOĞA, Beyza GÖRKEMLİ

*Department of Computer Engineering, Faculty of Engineering, Erciyes University,  
Kayseri-TURKEY*

e-mails: {celal, karaboga, bgorkemli}@erciyes.edu.tr

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## Abstract

*As the usage and development of wireless sensor networks increases, problems related to these networks are being discovered. Dynamic deployment is one of the main issues that directly affect the performance of wireless sensor networks. In this paper, an artificial bee colony algorithm is applied to the dynamic deployment of mobile sensor networks to gain better performance by trying to increase the coverage area of the network. The good performance of the algorithm shows that it can be utilized in the dynamic deployment of wireless sensor networks.*

**Key Words:** *Artificial bee colony, wireless sensor networks, dynamic deployment*

## 1. Introduction

Wireless sensor networks (WSNs) are used for target tracking, environmental monitoring, surveillance, and data collection for factors such as humidity, temperature, light, and pressure or the weight, velocity, and movement direction of an object in the area of the interest [1]. However, while these networks are widely used in many applications, their success highly depends on the sensors' positions, known as the deployment of the network.

Determining the positions of the sensors is the main subject of sensor network deployment, which depends on the coverage of the interest area. In some types of networks, like global positioning systems (GPS), the sensors know their positions and may also learn their neighbors' positions. In the dynamic deployment problem, sensors are initially located in the area with random positions. If the sensors are mobile, they can change their positions by using their knowledge of other positions. With these movements, they try to increase the coverage rate. On the other hand, if the sensors are stationary, they do not have the ability to change their positions.

The use of optimization techniques in the dynamic deployment of WSNs is a very hot topic for researchers, and some dynamic deployment algorithms have been developed for the dynamic deployment problem in WSNs [2-5]. For improving the coverage of the network, one of the important approaches among this research is the virtual force (VF) algorithm [6]. The VF algorithm works well for WSNs that consist of mobile sensors

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\*Corresponding author: Department of Computer Engineering, Faculty of Engineering, Erciyes University, Kayseri-TURKEY

[6-8]. In [9], a blackboard mechanism-based ant colony theory was proposed for the dynamic deployment of mobile sensor networks. None of these approaches consider stationary sensors that could not change their initial position. In real-life problems, to save energy and reduce costs, stationary sensors are widely used in networks. Wang et al. considered both stationary and mobile sensors together in WSNs and proposed a new approach based on parallel particle swarm optimization (PPSO) in [10]. They then combined the VF algorithm and coevolutionary particle swarm optimization (CPSO), calling the product the VF-CPSO algorithm, in [11]. The VF-CPSO algorithm was tested on networks of mobile and stationary sensors. Li and Lei proposed a method of improved particle swarm optimization (PSO) to solve the deployment problem of WSNs consisting of stationary and mobile sensor nodes [12]. Soleimanzadeh et al. considered mobile and stationary sensors together as a hybrid network and proposed 3 dynamic PSO-based deployment algorithms: PSO-learning automata (PSO-LA), improved PSO-LA, and improved PSO-LA with logical movement. In the PSO-LA algorithm, a hybrid of the PSO algorithm and learning automata, the speed of the particles is corrected by using the existing knowledge and the feedback from the actual implementation of the algorithm. To improve the performance of the PSO-LA, the improved PSO-LA algorithm was introduced, regulating movement without impact from the movement of other mobile nodes and based on the result gained from previous movements. In the third version, improved PSO-LA with logical movement, sensors virtually move new positions by calculating their target locations with the same procedure used in improved PSO-LA. The real movement only happens in the last round, after the final destinations are determined [13].

In this study, a new approach to the dynamic deployment problem for WSNs is proposed. This approach is based on the artificial bee colony (ABC) algorithm, which was developed by considering the foraging behavior of honey bee swarms [14]. It is known that the ABC algorithm works well for numerical optimization problems and clustering techniques [15]. Using the ABC algorithm is a proper approach for the sensors in the network to obtain good coverage in a 2-dimensional space.

The paper is organized as follows: we describe the dynamic deployment problem of WSNs and our sensor detection model in Section 2. The ABC algorithm is introduced in Section 3. Experiments and results are presented and discussed in Section 4. We conclude the paper in Section 5 with summarizing observations and remarks on future work.

## 2. WSN dynamic deployment problem and sensor detection model

The performance of a sensor network depends on the positions of the sensors in the area of interest. Therefore, in responding to all system objectives, deployment of the sensors in the mission space is a problem that is called the coverage control or active sensing problem [16-19]. Sensors must deploy by maximizing the information that they can get in the area of interest. In the static version of the problem, after the sensors' first positioning, there will not be any further mobility in the network. Optimal locations can be found by using an offline scheme as a facility location optimization problem. On the other hand, in the dynamic version of the networks, sensors can move coordinately in the mission space [20].

In WSNs, sensors can collect information about the area within their detection ranges. They share their information with their neighbor sensors. Therefore, to have effective detection in a network that includes sensors communicating with each other, the covered area should be expanded. In order to increase the ratio of covered area, the changeability of the mobile sensors' positions can be used.

There is no a priori information about the area of the interest, so initial deployments of the WSNs are

chosen randomly. Each sensor knows its position. The mobile sensors can communicate with others and can change their positions by using information from the others. The coverage ratio of the WSN is calculated by Eq. (1):

$$CR = \frac{\cup c_i}{A}, \quad i \in S, \quad (1)$$

where  $c_i$  is the coverage of sensor  $i$ ,  $S$  is the set of nodes, and  $A$  is the total size of the area of interest.

There are 2 sensor detection models for finding the effective coverage of WSNs: the binary detection model and the probabilistic detection model [6]. In this study, we used the binary detection model, which assumes that there is no uncertainty. We further assume that there are  $k$  sensors in the random deployment stage, each sensor has the same detection range  $r$ , and sensor  $s_i$  is positioned at point  $(x_i, y_i)$ . For any point  $P$  at  $(x, y)$ , the Euclidean distance between  $s_i$  and  $P$  is  $d(s_i, P)$ . The binary sensor model [21,22] is shown in Eq. (2).

$$c_{xy}(s_i) = \left\{ \begin{array}{ll} 1, & \text{if } d(s_i, P) < r \\ 0, & \text{otherwise} \end{array} \right\}, \quad (2)$$

where  $c_{xy}(s_i)$  is the coverage of a grid point  $P$  by sensor  $s_i$ .

### 3. Dynamic deployment of wireless sensor networks with artificial bee colony algorithm

The ABC algorithm, a new swarm intelligence method inspired by the intelligent foraging behavior of honey bees, is used for the dynamic deployment problem of WSNs. The aim of the optimization technique is to maximize the coverage rate of the network, as given in Eq. (1). In the network's scenario, it is assumed that:

- The detection radii of the sensors are all the same ( $r$ ).
- All of the sensors have the ability to communicate with the other sensors.
- All sensors are mobile.

In the ABC algorithm, the position of a food source represents a possible solution to the optimization problem and the nectar amount of a food source corresponds to the quality (fitness) of the associated solution. Therefore, the deployment of the sensors in the sensed area (each solution of the deployment problem) refers to a food source in the algorithm. The coverage rate of the network, i.e. the total coverage area, corresponds to the fitness value (nectar) of the solution. In the ABC model, artificial bee colonies, in which the goal of the bees is to find the best solution [23], comprise 3 groups of bees: employed bees, onlookers, and scouts. A bee waiting in the dance area to determine the choice of a food source is an onlooker, and when a bee goes to a previously visited food source, it is an employed bee. A bee that carries out random searches is called a scout.

The steps of the algorithm are as follows.

1. Initialize the parameters: detection radius  $r$ , size of area of interest  $A$ , number of mobile sensors  $m$ , colony size  $cs$ , maximum number of iterations  $MaxCycle$ , and limit for scout  $l$ .
2. Deploy  $m$  sensors randomly for each food source  $x_i$  of employed bees using Eq. (3).

$$x_{ij} = min_j + rand(0, 1)(max_j - min_j) \quad (3)$$

3. Evaluate the population.
4.  $c = 0$ .
5. Repeat.
6. Produce new solutions  $v_i$  in the neighborhood of  $x_i$  for the employed bees using Eq. (4).

$$v_{ij} = x_{ij} + \phi_{ij}(x_{ij} - x_{kj}) \tag{4}$$

Here,  $k$  is a solution in the neighborhood of  $i$ ,  $\phi$  is a random number in the range  $[-1,1]$ , and  $j$  is the randomly selected mobile sensor's position.

7. Check  $v_{ij}$  for staying in the bounds of the area.
8. Apply the greedy selection process between  $x_i$  and  $v_i$ .
9. Calculate probability values  $P_i$  for solutions  $x_i$  by means of their fitness values using Eq. (5).

$$P_i = \frac{0.9 \times fit_i}{fit_{best}} + 0.1 \tag{5}$$

10. Produce the new solutions,  $v_i$ , for the onlooker bees from solutions  $x_i$ , selected depending on  $P_i$ , and evaluate them.
11. Apply the greedy selection process for the onlookers between  $x_i$  and  $v_i$ .
12. Memorize the best solution achieved thus far.
13. Determine the abandoned solution; if it exists, replace it with a new randomly produced solution using Eq. (3).
14.  $c = c + 1$ .
15. Until  $c = MaxCycle$ .

Each solution represents an array that has  $m$  items. Figure 1 shows the solution array. Items of the solution array are  $(x, y)$  positions of the mobile sensors in the network.

1	2	3	4	5	6	...	$m$
$(x_1, y_1)$	$(x_2, y_2)$	$(x_3, y_3)$	$(x_4, y_4)$	$(x_5, y_5)$	$(x_6, y_6)$	...	$(x_m, y_m)$

Figure 1. Solution array.

## 4. Simulation results

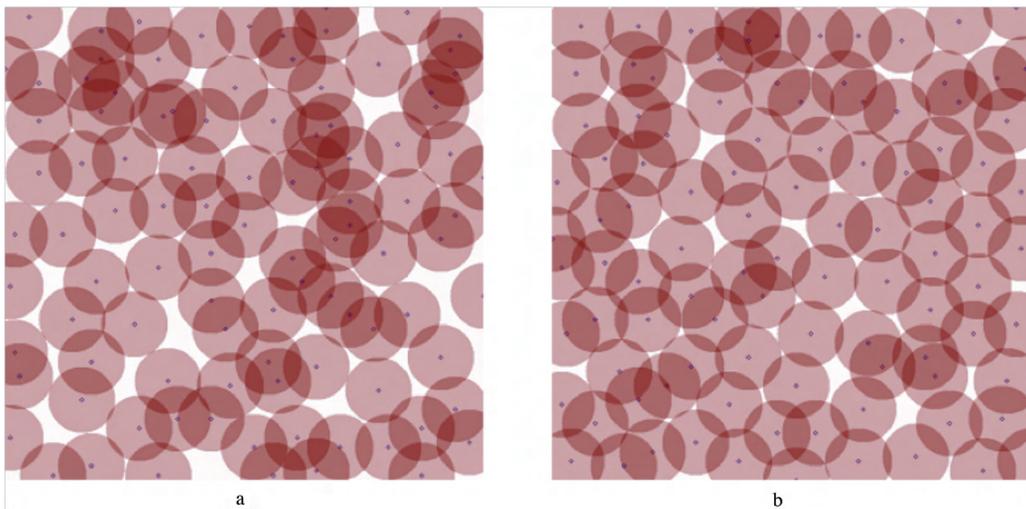
A wireless sensor network including 100 mobile sensors was simulated. The detection radius of each sensor  $r$  was 7 m, the size of area  $A$  was 10,000 m<sup>2</sup>, the colony size  $cs$  was 20, and the limit parameter  $l$  for the scout was 100.

The ABC algorithm was run with different numbers of iterations: 100, 500, 1000, and 10,000 iterations. To observe the performance of the algorithm, each scenario was run 20 times, starting with random seeds. The average coverage rates with different iteration numbers are given in Table 1. The mean values of 20 runs, along with the standard deviation (SD) of those runs and the best and worst values, are shown.

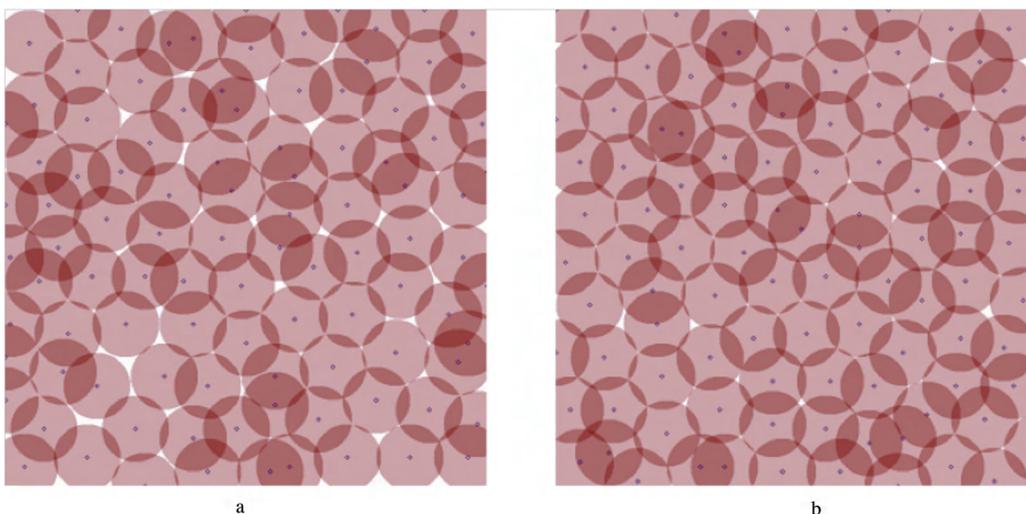
**Table 1.** Dynamic deployment results.

Number of iterations	100	500	1000	10,000
Mean	0.8962	0.9666	0.9833	0.9934
SD	0.0109	0.0028	0.0022	0.0010
Best	0.9267	0.9714	0.9862	0.9953
Worst	0.8767	0.9624	0.9774	0.9919

As seen in Table 1, the effective coverage area was improved considerably while the iteration number increased: the mean coverage rates were 89.62%, 96.66%, 98.33%, and 99.34% for 100, 500, 1000, and 10,000 iterations, respectively. By looking at the decrease in the standard deviation values, it can be easily said that the stability of the algorithm also increased with larger numbers of iterations. To highlight this improvement, the best dynamic deployments obtained by the ABC algorithm for each number of iterations are shown in Figures 2 and 3, respectively, where the colored areas represent detected coverage areas.

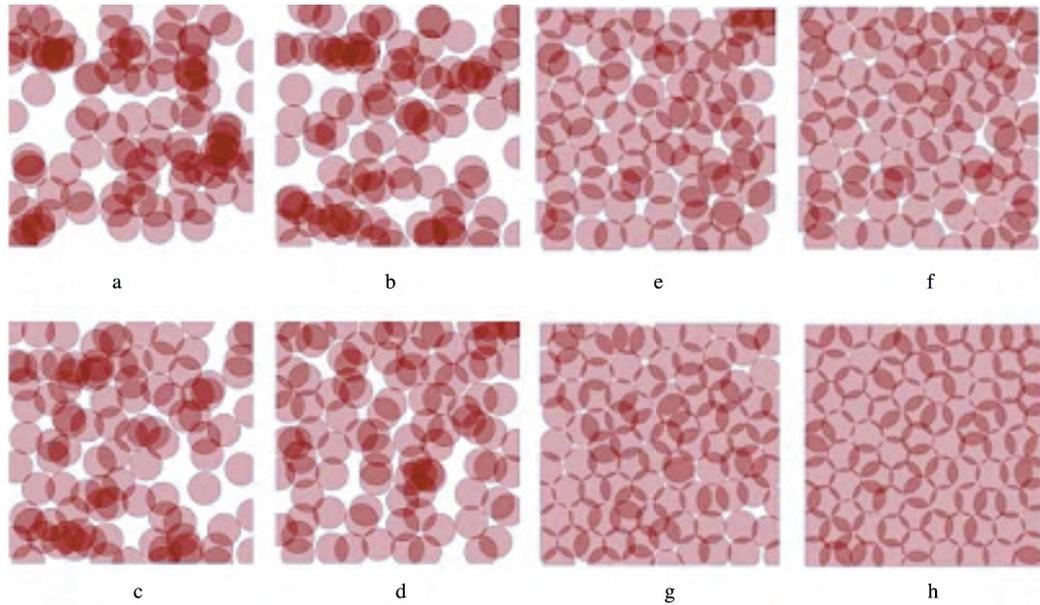


**Figure 2.** Best deployment for a) 100 iterations and b) 500 iterations.

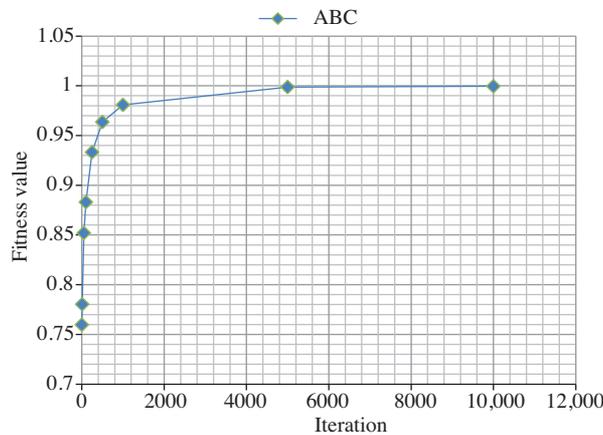


**Figure 3.** Best deployment for a) 1000 iterations and b) 10,000 iterations.

Figures 4 and 5 demonstrate the development of the best solution through the iterations. The convergence of the algorithm is shown from the first iteration to iteration 10,000. In Figure 4, the coverage area of iteration 1, iteration 10, iteration 50, iteration 100, iteration 250, iteration 500, iteration 1000, and iteration 10,000 are presented. It should be noted in Figure 5 that the largest coverage ratio was obtained in about 6000 iterations.



**Figure 4.** Best solutions of a) iteration 1, b) iteration 10, c) iteration 50, d) iteration 100, e) iteration 250, f) iteration 500, g) iteration 1000, h) iteration 10,000.



**Figure 5.** Development of the best of the population through the iterations.

## 5. Conclusion

In this study, the ABC algorithm was applied to the dynamic deployment problem in WSNs with mobile sensors. Simulation results showed that the ABC algorithm gives good deployment for WSNs. In future work, we plan to apply the ABC algorithm for dynamic deployment of WSNs including not only mobile sensors but also stationary ones. A probabilistic sensor detection model will be used to decide the effectively covered area.

In these networks, we plan to compare the performance of the algorithm with other well-known optimization techniques.

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