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A ROBUST HARMONY SEARCH ALGORITHM BASED MARKOV MODEL FOR NODE DEPLOYMENT IN HYBRID WIRELESS SENSOR NETWORKS

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ABSTRACT: The performance of the wireless sensor networks, composed of static sensor nodes, is significantly influenced by the random deployment. Often, the sensors are scattered incorrectly and hence positioned inaccurately. A frequent criticism of the random deployment of stationary nodes is that it might cause coverage holes in the field being monitored. In this paper, we propose adding mobile sensor nodes after the initial deployment of the stationary nodes to overcome the coverage holes problem. To achieve optimal coverage, we first described the network dynamics using Markov chain model, and then harmony algorithm is employed to find the optimal solution for the added mobile nodes intended for covering of the holes. The proposed algorithm determines the best locations of the mobile nodes that need to be added after the initial deployment of the stationary nodes. The performance of the proposed algorithm was evaluated using several metrics, and the simulation results demonstrated that, compared to similar state-of-the-art algorithms, the proposed algorithm can optimize the network coverage in terms of the overall coverage ratio, coverage degree and the number of additional mobile nodes.

Keywords: *Target Coverage; Mobile Sensor Nodes; Meta Heuristic Algorithms; Coverage Maximization; Stationary Sensor Nodes.*

1. INTRODUCTION

A Wireless Sensor Network (WSN) is a spatially distributed system consists of collection of autonomous, tiny, low-cost, battery operated sensor nodes that cooperate with each other to monitor and record physical or environmental conditions such as remote environmental monitoring and target tracking [1]. Based on the needed purpose, the sensor nodes achieve the sensing, communication and computation tasks. Usually, each node in WSNs is configured to accomplish sensing task, and thus the sensing attribute is considered as an essential factor in designing the network. Moreover, the coverage of the sensing field and the motion of sensor nodes are the important aspects related to the sensing attribute. Many researchers have studied the coverage problem in WSNs either as target coverage or area coverage [2]. The main objective of the area coverage protocols is to maximize the covered area of the whole sensing field while the main objective of target coverage protocols is to split the sensing field into targets and then maximize the number of targets that could be covered in the sensing field.

The coverage performance is affected by many different factors such as sensing model, sensor mobility, network topology, and deployment strategy and so on. One of the most important factors is the deployment strategy in which the sensor nodes are distributed or dispersed in the field being monitored [3]. Based on the application, the sensor nodes can be scattered either deterministically or randomly. The deterministic deployment is based on a pre-determined design of the sensor locations such as grid deployment. On the other hand, in random deployment the sensor nodes are deployed within the sensing field stochastically and independently such as scattering the nodes from an aircraft randomly. In a hostile environment or remote large scale WSNs, the sensor nodes positions cannot be predetermined and thus the random deployment might be the unique choice. Nevertheless, random deployment of the sensor nodes causes some holes in the field under monitoring; therefore, in most cases, random deployment is not guaranteed to be effective for achieving the required objective in terms of the area coverage [2].

Nevertheless, random deployment of the sensor nodes, in most cases, does not guarantee full coverage, leading to holes formulation problem [23]. Therefore, to overcome this problem and maximizing the covered area or targets, an efficient algorithm should be developed.

According to the application requirements, the nodes might be stationary, mobile, or hybrid [23]. In small-scale WSNs where all nodes are stationary, the coverage can be determined by the initial network configuration and the coverage can be maximized by manually deploying additional nodes to the initially deployed ones. On the other hand, in large scale WSNs applications, the sensing filed may be hostile or human intervention is not possible and hence, the sensor nodes can deployed only randomly [1].

Typically, two methods can be used to reduce or remove the holes in random deployment after initial deployment based on the motion of the sensor nodes. In the first method, in case all sensor nodes are mobile, an efficient algorithm should be developed to maximize the coverage area and simultaneously minimize the moving cost of the mobile nodes. In this situation, the coverage area is maximized by utilizing the mobility property of the sensor nodes. Therefore an efficient deployment algorithm, such as virtual force algorithm or potential field algorithm can be used to relocate the mobile sensor nodes after the initial deployment these nodes [4], [5].

In the second method, in case the nodes are hybrid in which some of the nodes are stationary and the other are mobile, an efficient algorithm should be employed to get the number and locations of the mobile nodes that should be added after the initial deployment of the stationary nodes. The most efficient optimization algorithms that can be used are the meta-heuristic algorithms, such as genetic algorithm, ant colony optimization, particle swarm optimization, and harmony search algorithm. These algorithms can be used to find an optimal or close to optimal solution for optimization problems in reasonable time [6]. A few researchers in the field of WSNs have proposed heuristic algorithms to find the optimal number of sensor nodes that should be added after the initial deployment to maximize the coverage [15], [18], [19], [22], and [23].

In this paper, we propose a meta-heuristic approach that utilizes the movements of some nodes to remove the holes which would be formulated after the initial deployment. Our approach employed a harmony search algorithm (HSA) to determine the minimum number of mobile nodes that should be used in addition to the previously deployed stationary nodes such that the coverage of the monitored area is maximized. The reason behind usage of HSA is its stochastic components that can explore more regions where the holes could not be covered by the state-of-the-arts solutions such as GA, in an efficient and effective manner.

The rest of this paper is organized as follows. Section II reviews the related work. Section III views the assumptions and the coverage model. Section IV presents the steps of the HSA based coverage optimization. Section V shows simulation experiments and discussion, and Section VI is the conclusion of the paper.

2. RELATED WORK

An important research problem in WSN is the coverage problem. Many researchers have studied the node deployment problem to attain maximum coverage in WSN extensively. Some researchers have addressed WSNs with mobile sensor nodes [4],[5],[7],[8] where others have addressed WSNs with both static and mobile nodes [9-12].

For mobile sensor networks, several approaches have been proposed. Firstly, Howard proposed a potential field-based approach for deployment. It formed the fields in such a way that allows each node to be repelled by both obstacles and by other nodes, thus forcing the network to distribute the nodes in the field evenly [4]. After that, Zou and Chakrabarty proposed a virtual force algorithm [5] to enhance the coverage by both pulling and pushing force among the nodes. Then, Wang, Cao and Porta used Voronoi diagrams to find the uncovered areas and determine the positions where the nodes can move [7]. Later, Tahiri et al. employed simulated annealing algorithm for nodes placement that maximize the coverage of the area of interest [8]. According to the authors, the algorithm is able to find the near-optimal solution.

In contrast, several works have considered both static and mobile nodes in WSN. Wang et al. designed two bidding protocols to increase the coverage by the movement of mobile sensors. The protocols used Voronoi diagrams with static sensors to discover coverage holes and bid mobile sensors which convene the largest holes by accepting the highest bids [9]. After that, Ahmed, Kanhere and Jha proposed a distributed protocol used the geometric right-hand rule to determine the boundary nodes. Then, the static nodes used a probabilistic coverage algorithm with realistic sensing coverage model to calculate the area coverage and determine coverage holes. Finally, the mobile nodes used the virtual force algorithm to move [10]. In ref [11], Wang and Wang proposed several variants based on particle swarm optimization and virtual force algorithm. These variants used multi-objective function to strike a balance between the coverage and the energy consumption. Their obtained solutions were analyzed to select the variant with best performance for better deployment [11]. Recently, Wang et al. proposed a biogeography-based optimization algorithm to maximize the coverage area of the network with dynamic deployment of static and mobile sensor [12].

In addition to the previous studies, different meta-heuristic algorithms have been proposed to address the problem of node deployment as it is an optimization problem. It is worthy to note that the genetic algorithms is the most popular meta-heuristic used to solve this problem. Most of the proposed genetic algorithms have focused on solving the deterministic node deployment [13-18]. In turn, few researches have addressed the random node deployment [19-22]. In random deployment, genetic algorithms are applied to maximize the coverage by find the near optimal positions for additional mobile. Sahin et al. in [19] proposed a force-based genetic algorithm in which the mobile nodes utilize the sum of the forces used to choose their direction by the neighbours. After that, Qu and Georgakopoulos developed a multi-objective genetic algorithm which running on a base station to provide maximum sensing coverage area. They claimed that the algorithm can strike a balance between the travelled distance and coverage area by maximizing the coverage and minimizing the travelled distance [20]. Nematy, Rahmani and Yagouti proposed a genetic algorithm to be used in cluster based WSN. The results showed that the algorithm able to increase coverage by finding the best places for the cluster heads with more density of sensor nodes [21]. Rahmani et al. proposed new approach, based on Voronoi diagrams and genetic algorithm, to maximizing coverage. Voronoi diagrams were used to divide the field into cells and then a genetic algorithm was used to determine the best positions for additional mobile nodes maximizing the coverage in every cell [22].

Recently In [23], GA was employed to find the best positions of extra mobile nodes to be added to the network for enhancing the coverage after the initial deployment of stationary nodes.

The harmony search algorithm has not been investigated well to solve the coverage holes problem, especially in hybrid wireless sensor networks. In [24], a simple schema of HSA was employed to find the assignment of sensor nodes in a wireless sensor network that enhance the network coverage. However, it has not considered the coverage degree (i.e., k-coverage), and has not even declared a method for holes removal.

3. PRELIMINARIES

3.1 Network Assumptions

In this paper we assume that the deployment of the sensor nodes is randomly and each node equipped with GPS. Furthermore, the base station node position is stationary and the number of sensor nodes that are initially deployed equals to those that are required to reach the full coverage in case these nodes were deterministically deployed. In addition, extra few mobile nodes are available to be used for repairing the coverage holes after initial deployment of the stationary nodes.

3.2 Coverage Model

For the coverage model, it was assumed that every sensor node with a sensing radius r can cover an area of circular shape. Also, sensor S_i can detect a target object O_j if it is inside the sensing range of S_j. Equation (1) shows the binary model of sensor detection:

$$\textbf{Coverage}\ (\mathbf{S}) \leftarrow \begin{cases} \mathbf{1}, & \mathbf{D}(\boldsymbol{S_i}, \boldsymbol{O_j}) \le \boldsymbol{r} \\ \mathbf{0}, & \mathbf{D}(\boldsymbol{S_i}, \boldsymbol{O_j}) > \boldsymbol{r} \end{cases} \tag{1}$$

where D is the distance between the sensor node S_i and the target object being sensed O_j. When the target object can be covered or sensed, the coverage function (S) equals 1, otherwise 0.

4. MARKOV-BASED COVERAGE MODELING

The system dynamics of the networks can simply be modelled using Markov Decision Process (MDP) mathematical framework. Markov chains are used to model the evolution of states in probabilistic systems. System states are usually chosen to be *0, 1, 2, ..* in which the MDP predication of the future state X_n depends on the history only via the most recent state information X_{n-1}. Formally,

$$\boldsymbol{P}\{\boldsymbol{X_{n+1}} = \boldsymbol{j}\,|\boldsymbol{X_n} = \boldsymbol{i}, \boldsymbol{X_{n-1}} = \boldsymbol{i_{n-1}}, \dots, \boldsymbol{X_0} = \boldsymbol{i_0}\} = \boldsymbol{P}\{\boldsymbol{X_{n+1}} = \boldsymbol{j}\,|\boldsymbol{X_n} = \boldsymbol{i}\} = \boldsymbol{P_{ij}} \tag{2}$$

The process is said to be in state i at time n if $X_n = i$, and P_{ij} is the transition probability from state i to j. MDP can be used to describe a stochastic decision process of the coverage of grid of points inside WSN field. Consider a network with M points in which the state of the network in a given time is observed. A given point in the grid at time n has probability p to be a hole before the next observation at time $n + 1$. A point that was in a hole state at time n has a probability r of being covered by time $n + 1$, independent of how long this point has been in a hole state. The transition from hole state to coverage state is according to specific technique (For example, HSA in our case). The hole and coverage states are mutually independent events. Let X_n be the number of points in operation at time n. The process {X_n, n = 0, 1, . . .} is a discrete time homogeneous Markov chain with state space I = 0 (hole state), 1(HSA running state), 2(fully covering state).

The state transition diagram for these three possible states 0,1, 2, with their transition probabilities can be described using the following transition probability matrix:

$$\boldsymbol{P} = \begin{bmatrix} \mathbf{1}-\boldsymbol{r} & \boldsymbol{r} & \mathbf{0} \\ \boldsymbol{p}(\mathbf{1}-\boldsymbol{r}) & \mathbf{0} & \boldsymbol{r}(\mathbf{1}-\boldsymbol{p}) \\ \boldsymbol{p} & \mathbf{0} & \mathbf{1}-\boldsymbol{p} \end{bmatrix} \tag{3}$$

Assuming that percentage of time the network has a given hole is π_0, under repairing using HSA is π_1, or in a fully coverage state is π_2. These statistics can be derived according to the solution of the following linear equations, under Markov process limiting probability property.

$$\boldsymbol{\pi_0} + \boldsymbol{\pi_1} + \boldsymbol{\pi_2} = (\boldsymbol{\pi_0} + \boldsymbol{\pi_1} + \boldsymbol{\pi_2})\boldsymbol{P} \tag{4}$$

$$\boldsymbol{\pi_0} + \boldsymbol{\pi_1} + \boldsymbol{\pi_2} = \mathbf{1} \tag{5}$$

5. HSA-BASED APPROACH

Harmony search algorithm (HSA) had been very effective in a wide variety of optimization problems, presenting numerous advantages compared to traditional optimization technique [26-28]. The simplicity of implementation and high quality solution of HSA highlight the potential of its usage for the systems that require improvement such as WSN. HSA is a music-based meta-heuristic optimization algorithm. It requires fewer mathematical requirements and does not require initial value settings of the decision variables [28].

HSA has stimulated by the observation that musician intends to create a piece of music with a suitable state of harmony. This harmony in music is equivalent to find the optimal solution (i.e. global optimum) for a problem under the optimization process. HSA attains the best solution using a determined objective function that is also limited by specific constraints.

The main objective of employing the HSA in this paper is to maximize the coverage by reducing the holes that are formulated as consequence of initial deployment of the stationary nodes.

It is assumed that the base station will run the HSA after gathering the locations of the stationary sensor nodes in order to determine the number and locations of the mobile nodes as follow:

Step 1: *Define the optimization problem and initialize algorithm parameters.*

For the current problem, we have to maximize the coverage ratio of the network and minimize the number of added mobile nodes to the network, which is defined by the objective function as given in (6).

The function is used to estimate the fitness of each solution. The formulation of the fitness depends on the problem determinants. The fitness function is defined to select the best harmony for the purpose of enhancement of the next generated solutions by the HSA. The fitness function in the present problem defines the mutually exclusive coverage ratio of each mobile node. That is, the maximum number of covered targets by each mobile node that have not been uncovered by other mobile or static nodes. Such constraint to the fitness function prevents the overlapping among the coverage regions of the deployed mobile nodes and forces each mobile node to cover only a distinct region. The fitness function of the mobile sensor node $\boldsymbol{M_{Si}}$ is $\boldsymbol{F(M_{Si})}$, that is given by:

$$\boldsymbol{F(M_{Si})} = \begin{cases} \boldsymbol{F(M_{Si}) + 1,\ D(M_{S_i}, O_j) \le r} \\ \quad \textbf{and } \boldsymbol{O_j} \not\in \{\boldsymbol{S_C}, \boldsymbol{F(M_{S/i})}\} \\ \boldsymbol{F(M_{Si})}, \qquad\qquad \boldsymbol{Otherwise} \end{cases} \tag{6}$$

$$FR = \left(\frac{\boldsymbol{F(M_{Si})}}{\sum \boldsymbol{O_j}}\right)\% \tag{7}$$

$$\text{Coverage} = \boldsymbol{S_C} + \sum_{i=1}^{m} \boldsymbol{F(M_{Si})} \tag{8}$$

This function calculates the coverage of the $\boldsymbol{M_{Si}}$ as function of the number of covered target locations $\boldsymbol{O_j}$, provided that $\boldsymbol{O_j}$ does not belong to the coverage of any stationary node $\boldsymbol{S_C}$ or mobile node $\boldsymbol{F(M_{S/i})}$. $\boldsymbol{S_C}$ is the coverage of deployed previously stationary sensor nodes , $\boldsymbol{F(M_{S/i})}$ means the coverage of any mobile node except mobile node $\boldsymbol{i}$. In equation (3), the fitness ratio (FR) for each mobile node estimates the percentage coverage of the mobile nodes with respects to other nodes in the network, which is defined as function of its coverage $\boldsymbol{F(M_{Si})}$ and the total number of targets in the network. Furthermore, the whole coverage of the network can be estimated as an accumulation for the coverage of static nodes ($\boldsymbol{S_C}$) and the selected mobile nodes($\boldsymbol{m}$) coverage, as in (4). The solution of the formulated problem is the (x,y) location of a potential mobile sensor node in the sensing field.

Likewise the population in GA, HSA uses a Harmony Memory Size (HMS) that contains the number of solution vectors in Harmony Memory Matrix. In our case, we initialize the HMS to 50.

In order to use this memory effectively, HSA depends on three variables to improve the solution vector, which are Harmony memory considering rate (HMCR), Pitch Adjusting Rate (PAR), and the maximum number of searches (stopping criterion) [28]. The value of HMCR is assumed to be 0.95. If HMCR rate is too low, only few elite harmonies are selected and it may converge too slowly. Otherwise, the pitches stored in the harmony memory are mostly used, and newer pitches are not explored well. The second variable, PAR, is assumed to be 0.8, which controls the pitch adjustment. Lastly, the maximum number of iterations is considered as 3000.

Step 2: *Initialize the harmony memory (HM)*

The solution of the formulated problem is the (x,y) locations of potential mobile sensor nodes. For the first time, this solution is randomly generated to initialize HM. HM with the size of HMS can be represented by (5).

$$\boldsymbol{HM} = \begin{bmatrix} \boldsymbol{I_1^1} & \boldsymbol{I_2^1} & \cdots & \boldsymbol{I_k^1} \\ \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{I_1^{HMS}} & \boldsymbol{I_2^{HMS}} & \cdots & \boldsymbol{I_k^{HMS}} \end{bmatrix} \rightarrow \begin{bmatrix} \boldsymbol{F^1} \\ \vdots \\ \boldsymbol{F^{HMS}} \end{bmatrix} \tag{5}$$

Each row vector of the first matrix represents a random solution for the optimization problem under consideration, while the value of the objective function given by (4) is computed for each harmony row vector and represented by $\boldsymbol{F^j}$ in the second matrix, respectively.

Step 3: *Improvise a new harmony from the HM*

In this step, the improvisation of randomly generated solutions stored in HM shown in (5) is ensued by generating a new harmony vector $[\grave{I}_1 \ \ \grave{I}_2 \ \cdots \ \grave{I}_k]$. Each part of a new harmony vector $\grave{I}_j$ is generated based on the value of HMCR defined in step 1 and according to (6)

$$\grave{I}_j \leftarrow \begin{cases} \grave{I}_j \in \ \ \boldsymbol{HM} \textbf{ with probability HMCR} \\ \grave{I}_j \in \grave{I}_j \textbf{ with probability } (\mathbf{1-HMCR}) \end{cases} \quad (6)$$

As in (6), the components of the new harmony vector $\grave{I}_j$ consist of components selected from the HM members with probability of HMCR, and others generated randomly with probability of (1-HMCR). If $\grave{I}_j$ is generated from the HM, then it is further amended according to PAR. The PAR determines the probability of a candidate from the HM to be modified and (1-PAR) is the probability of remaining unchanged. The Pitch adjustment for the selected is $\grave{I}_j$ given by (7)

$$\grave{I}_j \leftarrow \begin{cases} \mathbf{I}_j^{\mathbf{n}} \in \ \ \textbf{HM with probability PAR} \\ \grave{\mathbf{I}}_j \quad \textbf{with probability } (\mathbf{1-PAR}) \end{cases} \quad (7)$$

Step 4: *Update the HM*

The generated vector from step3 and 4 is evaluated based on the objective function value, and compared to the worst harmony vector in the HM. If the objective function value for the new harmony vector is better than the objective function value for the worst harmony in the HM then new Harmony is placed in the HM and the existing worst harmony is excluded from the HM. Otherwise, no changes would happen to the content of HM.

Step 5: *Go to step 3 until termination criterion is reached.*

After the termination criterion is reached, the current best solution is chosen from the HM to represent the solution for the articulated optimization problem.

6. SIMULATION RESULT AND DISCUSSION

In this section, the performance of the proposed algorithm is evaluated and compared against genetic algorithm (GA) in [23], in terms of coverage ratio, degree of coverage (k-coverage), and number of additional mobile nodes. Moreover, the effect of the number of randomly deployed static nodes and the sensing ranges on coverage and number of additional mobile nodes were investigated.

In the simulation environment, it was assumed that the sensor nodes were randomly deployed and the targets were uniformly located in a 200 m x 200 m sensor field. Two simulation experiments were conducted for performance evaluation. In the first experiment, the number of deployed static nodes ranged from 100 to 200 to cover 625 targets, whereas the sensing ranges of all nodes are fixed to 12 m. In the second experiment, the number of deployed static nodes is fixed to 100, while the sensing ranges ranged from 10 m to 20 m. In each experiment, the coverage ratio, k-coverage, and number of extra mobile nodes were measured before and after applying both the HSA and the GA in [23].

6.1 Effect of Number of Static Nodes

It is most likely that the coverage ratio of the network increases as the number of deployed nodes increases, either these nodes static or mobile nodes. Both GA and HSA schemas propose deploying additional mobile nodes alongside the static nodes to improve the network's coverage. The figure compares the coverage ratio of GA and HSA schemas. Both schemas enhance network coverage as the additional mobile nodes are located into regions where targets are not covered by the static nodes.

However, the achieved coverage ratio of HSA schema outperforms the case of GA schema. For instance, if the number of statically deployed nodes is 160, then the coverage of the network is 79.5%. In such case, GA increases the coverage ratio to 91.8%, whereas HSA schema causes 96.2%, as shown in Fig. 1. According to the numerical results, the percentage improvements on the coverage ratio of HSA schema compared to GA schema reach up to 4.57%. The reason behind that is due to trapping the evolving solutions in GA biased local optima. On the other hand, the stochastic components of HSA lead to tactical exploration for many locations and regions where targets are not covered by the static nodes, as possible in an efficient and effective manner.

Figure 2 shows the number of additional mobile nodes for both schemas. As shown, the number of mobile nodes drops as the number of statically deployed nodes goes up. This is because more targets would be covered as the number of static nodes increases and hence less mobile nodes would be added to increase the coverage ratio.

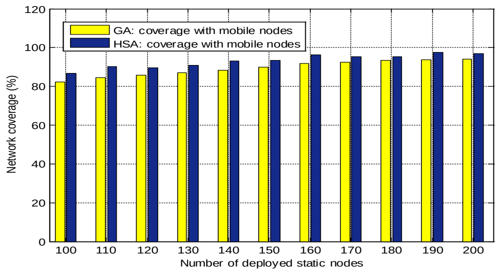

Fig. 1: Comparison of coverage ratio for different number of deployed nodes.

Despite the fact that both GA and HSA schemas ensure to find the minimum number of mobile nodes to be added to the network for improving the coverage, there is a slight increasing in the number of mobile nodes in HSA schema. The petty increasing in the mobile nodes is beneficial for enhancing the part of the coverage that could not be obtained through GA schema. For instance, if the number of statically deployed nodes is 160, the number of added mobile nodes in GA is 28, whereas it is about 30 nodes in HSA schema. The disjoint coverage of the part of increasing is about 1.15%, (i.e., the coverage of surplus two nodes added in HSA), whereas the real percentage of improvement for HSA compared to GA is 4.57%, which means that HSA is more robust and efficient than GA.

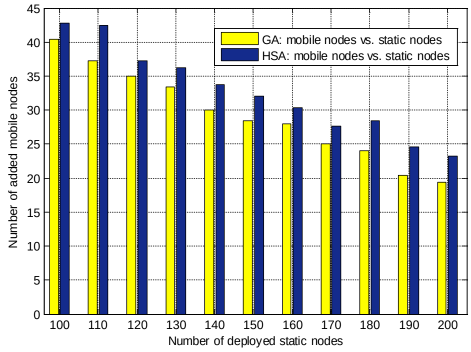

Fig. 2: Number of additional mobile nodes versus number of static nodes

Figure 3 shows the k-coverage after adding the mobile nodes to the randomly deployed static nodes in the network. For both cases, it is shown that as the number of nodes increases, the k-coverage increases. This is because the static nodes in both cases are randomly deployed and it is very likely that the coverage among these nodes is overlapped, hence the targets would be covered by more sensor nodes as the number of static nodes increases. What is more, the k-coverage for both schemas is close to each other, despite the increasing in mobile nodes for HSA. For instance, if the number of statically deployed nodes is 160, the k-coverage in GA is 2.19, whereas it is about 2.17 in HSA schema. That is a proof that few and extra mobile nodes added by HSA is not arbitrary, but it is intended for covering the holes in the network.

6.2 Effect of Sensing Range

Figure 4 compares the coverage ratio for GA and HSA schemas in terms of sensing range. Both GA and HSA schemas propose deploying additional mobile nodes alongside the static nodes to improve the network's coverage. The evaluation HSA conducted when the static nodes are randomly deployed and after adding the mobile nodes to the network.

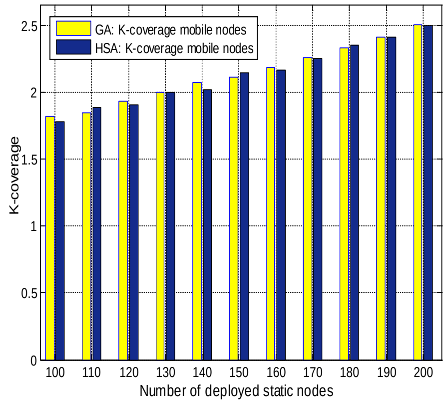

Fig. 3: Comparison of k-coverage for different number of deployed nodes.

It is shown that the coverage ratio increases as the sensing radii of the deployed nodes increase, since sensor nodes with larger sensing range can cover more targets than that with smaller range. The coverage of the static nodes along with the additional mobile nodes clearly outperforms the case of random deployment of the static nodes as the additional mobile nodes are located into regions where targets are not covered by the static nodes.

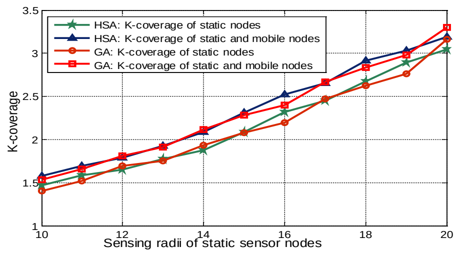

Fig 4: Comparison of k-coverage for different sensing ranges

However, the achieved coverage ratio of HSA schema outperforms the case of GA schema. For instance, if the sensing radius of the deployed nodes is 15m, then the overall coverage ratio of statically deployed nodes is about 80%. In such case and after adding the mobile nodes, GA increases the coverage ratio to 93.22%, whereas HSA schema causes 97.12%. According to the numerical results, the percentage improvements on the coverage ratio of HSA schema compared to GA schema reach up to 4 %.

Figure 5 shows the number of additional mobile nodes for both schemas as a function of the sensing range. It is shown that the number of mobile nodes drops as the sensing radii of the nodes rise. This is because more targets would be covered as the sensing range of the static nodes goes up and hence less mobile nodes would be added to increase the coverage ratio.

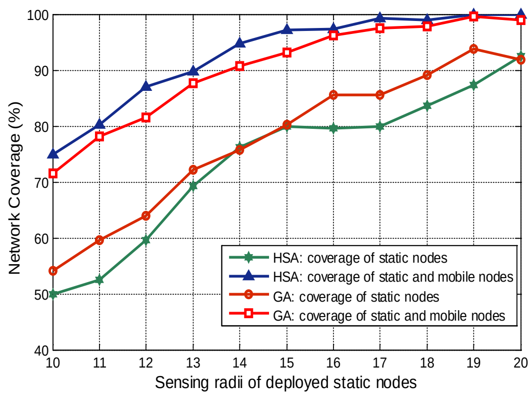

Fig. 5: Comparison of coverage ratio for different sensing ranges.

As stated before in the discussion of Fig. 2, in spite of the slight increasing in the number of mobile nodes in HSA schema, both GA and HSA schemas ensure to find the minimum number of mobile nodes to be added to the network for improving the coverage. However, the minor increasing of the mobile nodes in HSA is advantageous for enhancing the part of the coverage that could not be achieved via GA schema.

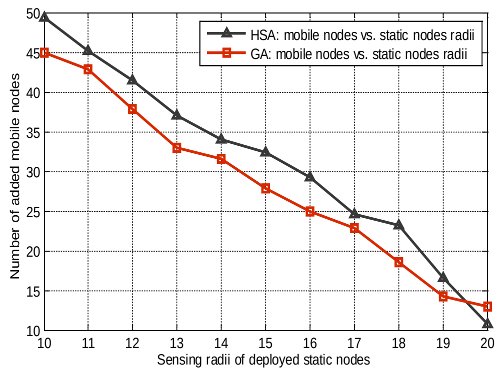

Fig. 6: Number of Additional mobile nodes versus sensing ranges.

Figure 6 shows the k-coverage for GA and HSA when the static nodes are randomly deployed and after adding the mobile nodes as a function of the sensing ranges. As shown, the k-coverage increases as the sensing radii of the deployed nodes increase. This is because the coverage among sensor nodes with large sensing range is very likely to overlap, and hence more targets would be covered by multiple nodes. Furthermore, the k-coverage for both schemas overlaps to each other, despite the increasing in mobile nodes for HSA. For example, if the sensing radius of the deployed nodes is 15m, the k-coverage in GA is 2.31, whereas it is about 2.28 in HSA schema. The closeness between them is a proof that extra mobile nodes added via HSA is absolutely not arbitrary, but it is intended for covering more holes in the network.

7. Conclusion

In this paper, we present a method that tackles the coverage holes problem in hybrid WSN. This method employs HSA to find an optimal solution to the coverage holes problem caused by random deployment of stationary sensor nodes.
The results of employing HSA based Markov chain model have proofed that it explores more regions in an efficient and effective manner where the holes could not be discovered by other solutions. Our simulation results have shown that node deployments based HSA maximize the overall coverage by finding the lowest number of further mobile nodes and their best positions in the sensing field when compared with the state-of-the-art algorithms like GA. Generally, it can be concluded that the HSA simplicity of implementation and high quality solution make it proper for solving complex engineering optimization problems.

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