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Deployment Strategies for Mobile Wireless Sensor Networks (MWSNs)

Krishna P. Sharma
Department of Computer Science and Engineering
National Institute of Technology
Hamirpur (HP), India-177005

T.P.Sharma
Department of Computer Science and Engineering
National Institute of Technology
Hamirpur (HP), India-177005

***Abstract**:* Wireless Sensor Networks (WSNs) generally are deployed in hostile and remote areas randomly. The major challenge in such ill-disposed areas is to find a tradeoff between desired and contrary requirements for the lifetime, coverage and cost with limited available resources. For utilizing the resources effectively, in recent years the mobile sensor nodes are deployed. Mobile nodes are able to relocate themselves on optimized locations within the region of interest. But in such distributed environment, coordinating the movement of nodes and relocating them on optimized locations by utilizing minimum energy is challenging. In recent years, many techniques have been proposed and evaluated. In this paper, we manly classify the existing approaches in four categories on the basis of mathematical approaches used to solve the deployment problem like Genetic Algorithms (GAs), Computational Geometry, Artificial Potential Field (APF), and Particle Swarm Optimization (PSO). We also explain some models and metrics for evaluating the performance of deployed networks and give an extensive comparison based on such performance matrices.

Keywords: wireless sensor networks, random deployment, virtual force, genetic algorithm, particle swarm optimization

I. INTRODUCTION

Due to advancements in various technologies like wireless communication, system-on-chip (SoC), and Micro-Electro-Mechanical System (MEMS), the development of intelligent sensors (e.g. Tmote Sky from Moteiv, Mica motes from Crossbow, the MKII nodes from UCLA, etc.) have been facilitated. Also the concept of mobile sensors has been spurred by the recent advancements in distributed computing and robotics technology. Sensor nodes are small-sized battery-operated devices with embedded sensing, limited processing, low memory and restricted wireless communication capabilities. These nodes communicate among themselves to create a Wireless Sensor Networks (WSNs) for environmental monitoring and target tracking. When a sensor network has locomotive capability, then it is called Mobile Wireless Sensor Network (MWSN). The locomotive capabilities are achieved by mounting static sensors on mobile vehicles or mobile robots [1]. New technologies facilitate low cost sensor nodes, which are deployed in Region of Interest (ROI) to form a distributed wireless sensor network in order to monitor events within the ROI. Today's sensors can monitor temperature, pressure, humidity, vehicular movement, lighting conditions, pressure, absence and presence of certain kind of objects or substances, mechanical stress level on attached objects and other properties. Due to the cost viability, versatility and flexibility, WSNs have various applications like industrial real-time monitoring and automation, traffic surveillance and control, continuous health monitoring, target tracking in military operations, and environmental monitoring [2-3].

Different applications have its own challenges in terms of coverage, connectivity and quality of data needed which are heavily affected by the deployment strategy used to construct the network. There are many proposed deployment approaches for optimizing coverage, connectivity and lifetime of WSNs. But the optimal node placement in WSNs is a very challenging task which has been proven to be NP-Hard for most of the formulations of sensor deployment [4]. To tackle such complexity, several heuristics have been proposed to find sub-optimal solutions [4]. In case of some applications like home automation, industrial automation, etc. sensing field is approachable, where the best utilization point within the ROI can be calculated for deterministically placing the sensors. This deterministic placement of sensor nodes constructs a high performance network. In [5] author's proposed various schemes to deploy a sensor network deterministically. But for many other applications like military surveillances, habitat monitoring, and target tracking, networks are deployed in unattended and possibly hostile environments where the deterministic deployment of the network is not possible. In such situations nodes are deployed randomly by throwing them from an aircraft which is called the random deployment. In random deployment, it is not necessary that every node occupies an optimized location and thus randomly deployed networks may have an uncertain distribution of nodes. Sensor nodes can have higher density in some locations, resulting in high cost of network and computation overhead and can be more scattered in other areas which may lead to poor data quality, poor connectivity, and network partition. The network density can be controlled by adding some mobile sensors. Some approaches have been proposed to make uniform density of nodes in ROI with some mobile sensors [6-7]. A lot of work exists in [8-10] which consider mobile sensors and propose various approaches to relocate the randomly deployed sensors to achieve high coverage with minimum energy consumption. In such approaches, mobile nodes have to move to best utilizing positions in order to enhance effective coverage with minimum movement and using less number of sensors. The use of mobile nodes in WSNs adds more dimensions and challenges in terms of the energy consumed in movement for relocation and executing the relocation algorithm in a distributed environment. Schemes presented in [11] consider these challenges and propose various relocation algorithms for maximizing the coverage.

The rest of the paper is organized as follows. The next section gives the description of performance metrics and some models to evaluate deployed networks. In section III, we present the different classifications of deployment techniques. Section IV, gives an extensive comparison of classified deployment techniques on the basis of deployment performance metrics and models followed by a conclusion.

II. METRICS AND MODELS

A. *Metrics*

The performance of a sensor network can be measured on the basis of various parameters like coverage, connectivity, lifetime of the network, time to converge, etc. This section gives some evaluation metrics and models to evaluate the performance of deployed networks.

1) Coverage

Coverage area [12] is an area A which is covered by N sensors such that for every point x in A the $d_i(x)<R_s$ (Sensing Range), where the $d_i(x)$ is the Euclidian distance of sensor i from x for $\exists i,(1\leq i\leq N)$. When every point x in A is covered by at least k sensors or there are at least k sensors at a distance less than R_s from x then this is called k-coverage.

2) Uniformity

The uniformity can be defined as the average local standard deviation of the distance between nodes [11]:

$$U=\frac{1}{N}\sum_{i=1}^{N}U_i$$

and

$$U_i=\left(\frac{1}{K_i}\sum_{j=1}^{K_i}(d_{i,j}-M_i)\right)^{\frac{1}{2}} \tag{1}$$

where,

N is the total number of nodes.

K_i is the number of neighbors of the ith node.

$d_{i,j}$ is the distance between ith and jth nodes.

M_i is the mean of inter-modal distances between the i^{th} node and its neighbors.

3) Time

In case of some time-critical applications such as search-and-rescue and disaster recovery operations, time spent in deployment of a network is very important [6]. The convergence time is an important parameter to improve in case of mobile WSNs. The time for deploying a working mobile sensor network depends upon complexity of relocation algorithms. The total time elapsed is defined here as the time elapsed until all the nodes reach their final positions.

4) Energy

Energy utilization is an important issue in WSNs. Energy is a critical factor to consider during the development of relocation algorithms for MWSNs. Mainly the energy is consumed in computation, communication and movement of mobile sensors during the relocation process. The average distance traveled by each node is related to the energy required for its movement [6]. Hence, all mobile node deployment techniques try to relocate node exploiting minimum movement.

5) Obstacle Adaptability

WSNs have a huge list of targeted applications with varying characteristics of ROI. For most of the applications, field cannot be considered always 2D or 3D plane surface as there may be many obstacles in the ROI. During the deployment, it is necessary to consider obstacles in the field and modeling their effect on the performance of deployed networks. Many authors consider the obstacles during deployment and propose various approaches to handle the obstacle in the field.

B. *Models*

1) Sensing Model

On the basis of sensing probability of an event corresponds to the distance of event occurred from sensor nodes, there are two type of sensor nodes [7]. First type of sensors follow the binary sensing model and able to sense all events occurring within the range of R_s (Sensing range of sensor node) with probability 1 and does not able to sense events occurring outer than range R_s. While second type of sensors senses the events with a gradually decreasing probability as the distance between occurred event and sensor increases and follow probability sensing model. The both type of nodes are shown in Fig. 1.

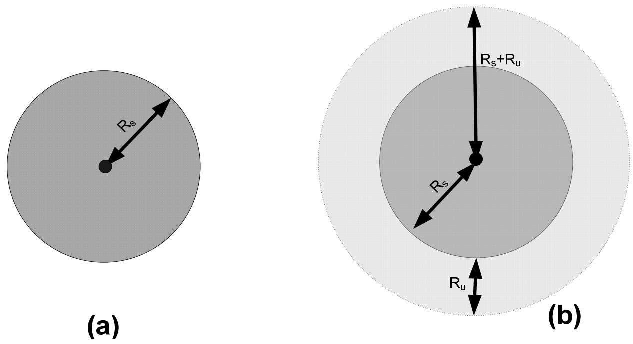

Fig. 1**.** Illustration of binary and probability sensing model

The behavior of both type of sensor nodes for a point $Q(Xq,Yq)$ is modeled in following equations. Where Ps the probability of sensing and D_{qo} is the distance of point Q from the center of the sensing region is denoted by $O(X_o,Y_o)$. The probability of sensing an event in case of binary sensing model is given as:

$$P_s=\begin{cases}1 & D_{qo}\leq R_s\\ 0 & Otherwise,\end{cases} \tag{2}$$

The probability of sensing an event in case of the probability sensing model is given as:

$$P_s = \begin{cases} 1 & D_{qo} \le R_s \\ e^{-\lambda a^{\beta}} & R_s < D_{qo} \le R_s + R_u \\ 0 & R_s + R_u < D_{qo} \end{cases} \tag{3}$$

where $a=R_u-R_s$ and λ and β are the environment dependent coefficients.

2) Coverage Model

There are two types of sensing models (binary and probabilistic) which affects the coverage area achieved from a deployment strategy. As shown in Fig.1, the binary sensing model can be considered as a special case of probability sensing model. Therefore, a single coverage model can be proposed for both sensing models. There exist coverage model [13] which fits with both sensing models. An area is said to be covered if it is completely sensible by at least one or the joint detection of several sensor nodes. To compute the effective coverage achieved by N sensors, the entire sensing field is represented as a 2-D grid containing a finite number of m grid points. The joint detection probability for an event at a particular grid point x_j where $j \in \{1,2,3\ldots\ldots\ldots m\}$ can be calculated as:

$$P_{(x_j)} = 1 - \prod_{S=1}^{S=N} (1 - P_s) \tag{4}$$

where, P_s is the probability of detection of an event.

3) Energy Model

In this section, an energy model is given to calculate the energy consumption require in the relocation process of MWSNs. The given model is based on the model proposed in [14] with some modifications. In the relocation process, a lot of energy is consumed in moving, turning, communicating and executing the relocation algorithm. If the speed and weight of a sensor node are constant, then energy consumed in the movement of sensors represented by E_d is linear with respect to traveled distance. Another consumption of energy is in turning of the sensor is which is represented by E_t. It is also linearly related to the angles turned by the sensor during relocation of its position. The total energy consumed in movement E_m is the energy consumed in successive traveled distances and turning angles to reach at the final position.

$$E_m = E_d + E_t$$

where,

$$E_d = k_d . D_{total}$$
$$Et = k_t . A_{total}$$

Where k_d and k_t are coefficients, representing the energy consumption rate. D_{total} and A_{total} are the total distance travelled and the total angle turned by the sensors respectively.

III. CLASSIFICATION OF DEPLOYMENT TECHNIQUES

Due to the advancement of MIMS and robotics technology, now the mobile sensors are possible. Mobile sensors have the capability to move in some limited region after throwing them randomly from any source. Sensors are battery powered, resource constrained devices which are generally being deployed in an environment where the replacement of their battery and sensor nodes are not possible. Random deployment is a non-uniform deployment where the uniformity is achieved by making some or all nodes mobile. Therefore, some algorithms have developed to rearrange the randomly deployed sensor nodes. The main objective of such algorithms is to optimize the coverage, connectivity and lifetime of deployed networks. The deployed network can be further utilized for a variety of applications to relocate their positions according to the need of different applications. This movement of sensors provides the best utilization of sensor nodes with some drawbacks in terms of energy consumption in movement. The energy consumed in the movement is much higher comparative to the energy consumed in processing. The main goal of relocation algorithm is to minimize the energy consumption in traveling distances and communication to achieve the best suited position for sensors. The relocation algorithms execute in a distributed sensor network where minimizing the communicated messages for relocation process and deciding how to execute the algorithm centrally or in distributed fashion is also big issues. The authors mainly focused on the energy consumption in communication and movement of nodes and presented many solutions. The existing schemes can be categorize differently, but in this paper we categorize the available schemes based of their mathematical background in following four categories.

*A. **Artificial Potential Field (APF)***

Artificial Potential Field (APF) based techniques were first introduced in the field of Robotics [15]. The idea in the scheme is similar to the equilibrium of molecules, which minimizes molecular electronic energy and inter-nuclear repulsion. Each molecule determines its own lowest energy point in a distributed manner and its resulting spacing from the other particles is almost the same. There are various techniques which use the concept of virtual force.

In [8], the mobile nodes and obstacles in the field are considered with some negative and positive virtual forces. The nodes apply the positive force while the field and obstacles apply the negative forces. Every nodes try to moves to the locations where the resultant force on the nodes become zero. It has been proved that equilibrium state can be achieved in a sensing field with boundaries. The result shows that algorithm is able to increase coverage and handle obstacle in ROI. The scheme in [7] is also based on the virtual force where a judicious combination of attractive and repulsive forces is used to determine virtual motion paths and the rate of movement for the randomly-placed sensors. The author also proposes a probabilistic target localization scheme that is executed by the cluster head. The author in [9] proposed an algorithm based on Target Involved Virtual Force Algorithm (TIVFA) for self-deployment in the context of target tracking. The nodes dynamically adjusts sensor network configuration according to the terrains, intelligence and those detected maneuvering targets for improving coverage and detection probability. The approach in [10] is the improvement of the virtual force algorithms by applying a back-off delay time. The sensors relocate themselves one-at-a-time in each round of movement by the use of back-off delay and have the most updated position information of the other sensors, including the movement of previous sensors within the current round. In this way, the sensors can move comparatively less if they use the old location information. In [16], the similar approach to [7] and [9] is proposed based on repulsive and attractive forces by considering both mobile and static sensor nodes. In [8], only repulsive force is used where in [16] both repulsive and attractive forces are acting on sensors. The algorithm simulates in consideration of 2D ROI with single target in the absence of obstacles. A virtual force enhancement scheme is proposed in [17], where the algorithm does not need to have the previous knowledge of deployment field. The schemes presented in [8-9] require nodes to be localized prior to their execution while the scheme in [17] uses a spiral movement policy and does not has no need of prior location information. An algorithm to manage sensor mobility using network dynamics is proposed in [18]. In this approach, every node calculates the virtual force periodically by communicating with its neighbors. In the next interval the nodes determines the movement speed and direction.

B. ***Genetic Algorithms (GAs) Based***

Genetic algorithms (GAs) are a type of evolutionary, optimization algorithms based on the mechanics of natural selection and genetics. Such type of optimization algorithms becomes popular after they introduced by Barricelli in 1957 [19]. GAs have been used for solving optimization problems in various fields such as computer networking, industrial engineering and machine learning. GAs are heuristic search algorithms that come from the idea of natural evolution and use the concept of inheritance, mutation, chromosomes and crossover. GAs are effective in combinatorial and multi-objective optimization problems, in which deterministic optimization methods are not applicable.

In [20], the author proposes a Multi Objective Genetic Algorithm (MOGA) for deploying N static and mobile sensor nodes for achieving maximum coverage and lifetime by using the minimum number of sensors. The author assumes 2D type of region of interest (ROI), homogeneous sensors with the binary sensing model. In [21], the authors extends their work by using the same MOGA of [20], but applied to three specific surveillance scenarios. Each scenario had its own set of objectives according to the surveillance required. The approaches in [20] and [21] are flexible, which can be applied to the scenarios with different set of objectives. However, there are some drawbacks; the approach uses the binary sensing model and 2D plane without any obstacle which is not realistic.

C. ***Computational Geometry (CG) Based***

The computational geometry (CG) is basically used to solve the coverage problem in the sensor network deployment. The sensor nodes are assumed as a point in 2D and 3D Region of Interest. The region is divided generally in two geometric structures one is Voronoi Diagram (VD) and another is Delaunay Triangulation (DT). The VD is a fundamental construct defined by a discrete set of points [22]. In 2D plane, the discrete points (site) partition the plane into various convex polygons called Voronoi cell for each point (site) such that all points inside a polygon are closest to only one site. Another structure is a Delaunay triangulation, which is directly related to Voronoi diagrams. The Delaunay Triangulation is constructed by connecting the sites in the Voronoi diagram whose polygons share a common edge.

In [23], the approach uses both mobile and static sensor nodes, where mobile sensors moves from dense area to sparse area for balancing the coverage overlap and uniformity. The movement and direction of mobile nodes is determined by a distributed bidding protocol which uses Voronoi diagrams (VD) for identifying coverage hole and moves sensor nodes towards them. Similar to [23], the scheme in [24] find the coverage hole by using VD and relocate nodes inorder to fill the coverage holes. The author proposed three distributed movement-assisted sensor deployment protocols, VEC (VECtorbased), VOR (VORonoi-based), and Minimax based on the principle of moving sensors from densely deployed areas to sparsely deployed areas. Some identical mobile sensors of the same communication and sensing range in a 2-D ROI with a flat terrain and well-like boundaries are considered. In [25], two distributed and iterative deployment algorithms namely the Centroid and the Dual-Centroid with the objective of maximizing the area coverage of initially deployed MWSNs are proposed. The algorithm improves the coverage in each iteration, which is computed by locally constructed Voronoi cell of sensors in the same way as in [24] and [23].The results of both algorithms are compared with the approach in [24]. The result shows that both algorithms have better performance than of Minimax presented in [24]. In [11], the author considers the same deployment problem as in [23-24] and [25] but with the objective of minimizing the energy consumption. The author presents a Voronoi Diagram Deployment Algorithm (VDDA) of distributed in nature with the same assumption as in [25]. In VDDA, for sensor movement the multiple points are considered for the next position. While In [26], the author proposed an algorithm for self deployment called restricted Delaunay triangulation graph based algorithm (RDTG). The author discussed the performances of the topology graph by theory analysis. RDTG constructs a logical topology graph without intersection of edges, and tries to make the node’s neighbor equal to 6 by moving the node according the property of maximum the minimum angle of the triangles in TDG. The result shows that the RTDG is effective to reach the ideal deployment with good performance.

D. ***Particle Swarm Optimization (PSO) Based***

Particle Swarm Optimizations (PSOs) are based on Swarm Intelligence, which is a branch of Artificial Intelligence (AI) and first introduced by R. Eberhart *et. al.* in 1995 [27]. In this approach, there are some interacting agents organized in small societies, called swarms, which exhibit traits of intelligence, such as the ability to react to environmental threats and decision making capacities. The individual in the group finds the best solution or particles and keep it into memory as an experience. That experience, then communicates to the part of the swarm to directing the movement towards the search space region where it is more likely finding the optimal solution.

There are various techniques in WSNs, which uses PSOs for network deployment. The PSOs also used in base station positioning, node localization, data aggregation, and energy aware clustering.

In [28], author uses clustering strategy to deploy a finite number of N-sensors of similar type in 2D ROI in order to reduce network cost. Initially, sensor nodes throw randomly in ROI, and then PSO-based relocatable algorithm executes on a powerful base station centrally. The central system then communicates the optimized locations in the network. The algorithm starts by randomly generating a number of solutions or particles and distribute sensor node uniformly in the entire ROI. In [29] sensor nodes are relocated in order to optimize the coverage area. The algorithm runs after the random deployment of the sensor node to maximize the coverage with minimum movement. The proposed algorithm considers two cases, in the first case, the sensor can move to any distance where in the second case the movement is limited to a certain distance. In [30], a hybrid algorithm called VFCPSO which uses the concept of Virtual Force (VF) and co-evolutionary particle swarm optimizations (CPSO) is proposed. The algorithm updates the evolving velocity of each candidate solution and different, cooperating swarms by the use of virtual forces. Compared to the traditional PSO, the VFCPSO can perform better in optimizing the deployment of static and mobile sensors with increasing dimensionality of the optimization problem and decreasing the computation time. The VFCPSO provides 10% coverage increased compared to the traditional PSO. The scheme in [32] scheme is based on PSO with dynamic cloning. The algorithm control variation range of particles and clone number, which represents the positions of all mobile sensor nodes. While in [32] authors' main objective is to maximize the area coverage of WSNs composed by a finite number of homogeneous static sensors in a 2D ROI. In this approach, authors combine PSOs and Voronoi diagram for optimal deployment of sensors. The algorithm uses the same particle encoding in PSO-Grid as in [28] and used a Voronoi diagram to calculate the coverage area.

The table1 shows an extensive comparison of various available techniques on the basis of various parameters discussed.

Table I. Comparison of various mobile wireless sensor networks deployment techniques

Type	*Proposed Algorithm & Ref.*	*Basic Principle*	*Issues handled*	*Sensing Model*	*Sensor Type*	*Main Drawbacks*
Self-Deployment (Distributed)	*Bidding Protocol [23]*	*CG/VD*	*Area coverage, Energy, Cost Convergence time*	*B*	*HTG*	*-No obstacle handling*
	VEC, VOR, MiniMax [24]	*CG/VD*	*Area coverage, Cost*	*B*	*HG*	*-No obstacle handling -More energy consumption*
	Centroid, Dual-Centroid [25]	*CG/VD*	*Area coverage, Cost*	*B*	*HG*	*-No obstacle handling -Computationally slow*
	RDTG [26]	*CG/DT/VF*	*Area coverage, Cost*	*B*	*HG*	*-No obstacle handling*
	Andrew Howard et al. [8]	*VF*	*Area Coverage, Obstacles, Convergence time*	*----*	*HG*	*----*
	VFA [7]	*VF*	*Coverage, Connectivity, Energy, Obstacles*	*BP*	*HG*	*- Use only 2D ROI*
	TIVFA [9]	*VF*	*Coverage, Multiple targets, Obstacles*	*P*	*HG*	*- Use only 2D ROI*
	TheinLai Wong et al. [10]	*VF*	*Coverage, Energy, Obstacles*	*B*	*HG*	*-All sensors need a GPS*
	Dan O. Popa et al. [16]	*VF*	*Network throughput, Obstacle handling*	*B*	*HTG*	*-No coverage - Use only 2D ROI*
	CPVF [17]	*VF*	*Coverage, connectivity, Energy, Obstacles*	*B*	*HG*	*-Slow - Use only 2D ROI*
	PDND [18]	*VF*	*Coverage, Connectivity*	*B*	*HG*	*----*
	X. Bai et al. [629]	*PSO*	*Coverage, Energy*	*B*	*HG*	*-Use only 2D ROI -No Obstacle handling*
	VFCPSO [30]	*PSO/VF*	*Coverage, Energy, Convergence time*	*P*	*HTG*	*Use only 2D ROI -No Obstacle handling*
	Zhaohe Huang et al. [31]	*PSO/GA*	*Coverage, Energy, Convergence time*	*----*	*HTG*	*-No Obstacle handling*
	Zhaohe Huang et al. [31]	*PSO*	*Coverage, Energy*	*----*	*HTG*	*-No Obstacle handling*
Self-Deployment (Centralized)	*DSSA, IDCA, VDDA [11]*	*VF/VD*	*Coverage, Connectivity, Obstacle, Energy*	*BP*	*HG*	*- Use only 2D ROI*
	W. Xiaoling et al. [28]	*PSO*	*Coverage, energy, Convergence time*	*BP*	*HG*	*-Use only 2D ROI -No Obstacle handling*
	PSO-Voronoi [33]	*CG/VD/PSO*	*Coverage, Cost*	*----*	*HG*	*-No obstacle handling*

Abbreviations used in table:

GA-Genetic Algorithm
VD-Voronoi Diagram
DT-Delaunay Triangulation
VF-Virtual Force
CG-Computational Geometry
PSO-Particle Swarm Optimization
P-Probability Sensing
HN-Hopfield network
B-Binary Sensing
HG- Homogeneous
HTG-Heterogeneous
BP-Binary and Probability

IV. CONCLUSION

In the paper, we classified various deployment techniques for Mobile Wireless Sensor Networks on the basis of the mathematical background used by them. The techniques are categorized mainly in four types like Genetic Algorithms (GAs), Computational Geometry, Artificial Potential Field (APF), and Particle Swarm Optimization (PSO). We also presented a brief discussion of some parameters and models to evaluate the performance of deployed networks. The comparative analysis of deployment techniques belongs to each category was presented in table and analyzed extensively.

V. REFERENCES

[1] L. Yua, W. Chen, and Y. Xi, “A review of control and localization for mobile sensor networks,” in Proc. 6th World Congress on Intelligent Control and Automation, (WCICA’06), vol. 2, 2006, pp. 9164–9168.

[2] I. Stoianov, L. Nachman, S. Madden, T. Tokmouline, and M. Csail, “Pipenet: A wireless sensor network for pipeline monitoring,” in Proc. 6th International Symposium on Information Processing in Sensor Networks, (IPSN’06), 2007, pp. 264–273.

[3] V. Jelicic, T. Razov, D. Oletic, M. Kuri, and V. Bilas, “Maslinet: A wireless sensor network based environmental monitoring system,” in Proc. 34th International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO), 2011, pp. 150– 155.

[4] A. Efrat, S. Har-Peled, J.S.B. Mitchell, Approximation algorithms for two optimal location problems in sensor networks, in: Proceedings of the 3rd International Conference on Broadband Communications, Networks and Systems (Broadnets’05), Boston, October 2005.

[5] B. Carter and R. Ragade, “An extensible model for the deployment of non-isotropic sensors,” in Proc. IEEE Sensors Applications Symposium, 2008, pp. 22–25.

[6] A. Howard, M. J. Mataric´, and G. S. Sukhatme, “An incremental self deployment algorithm for mobile sensor networks,” Autonomous Robots, vol. 13, no. 2, pp. 113–126, 2002.

[7] D. O. Popa, H. E. Stephanou, C. Helm, and A. C. Sanderson, “Robotic deployment of sensor networks using potential fields,” in Proc. IEEE International Conference on Robotics and Automation (ICRA ’04), vol. 1, 2004, pp. 642–647.

[8] A. Howard, M. Mataric and G. Sukhatme, "Mobile Sensor Network Deployment using Potential Fields: A Distributed, Scalable Solution to the Area Coverage Problem," in the 6th International Symposium on Distributed Autmomous Robotics System (DARS), Fukuoka, Japan, Jun 25-27, 2002.

[9] S. Li, C. Xu, W. Pan and Y. Pan, "Sensor deployment optimization for detecting maneuvering targets," in 8th International Conference on Information Fusion, PA, USA, July 25-29, 2005.

[10] T. Wong, T. Tsuchiya and T. Kikuno, "A self-organizing technique for sensor placement in wireless micro-sensor networks," in 18th International Conference on Advanced Information Networking and Applications, Fukuoka, Japan, March 26-29, 2004.

[11] Nojeong Heo and Pramod K. Varshney, “Energy-Efficient Deployment of Intelligent Mobile Sensor Networks” IEEE Transaction on System, Man, and cybernetics-Part A: System and Humans, Vol. 35, No. 1, Jan 2005.

[12] Sonali Sen Baidya, C.K.Bhattacharyya “Coverage and Connectivity in Wireless Sensor Networks: Their trade-offs,” Sixth International conference on Sensing Technology (ICST), IEEE 2002.

[13] Dina S. Deif, Yasser Gadallah, Senior Member, IEEE “Classification of Wireless Sensor Networks Deployment Techniques” IEEE Communication Surveys and Tutorials-June 19, 2013.

[14] Qu, Yipeng, "Wireless Sensor Network Deployment" (2013). FIU Electronic Theses and Dissertations. Paper 854.

[15] O. Khatib, “Real-time obstacle avoidance for manipulators and mobile robots,” International J. Robotics Research, vol. 5, no. 1, pp. 90–98, 1986.

[16] D. O. Popa, H. E. Stephanou, C. Helm, and A. C. Sanderson, “Robotic deployment of sensor networks using potential fields,” in Proc. IEEE International Conference on Robotics and Automation , vol. 1, 2004, pp. 642–647.

[17] Guang Tan, Stephen A. Jarvis, Member, and Anne-Marie Kermarrec “Connectivity-Guaranteed and Obstacle-Adaptive Deployment Schemes for Mobile Sensor Networks” IEEE transactions on mobile computing, vol. 8, no. 6, June 2009.

[18] Ma K, Zhang Y, Trappe W, ” Managing the mobility of a mobile sensor network using network dynamics”,. IEEE Trans Parallel DistribSyst 19(1):106–120-2008

[19] Barricell and N. Aall, "Symbiogenetic evolution processes realized by artificial methods," Methods, pp. 143-182, 1957.

[20] D. B. Jourdan and O. L. de Weck, “Layout optimization for a wireless sensor network using a multi-objective genetic algorithm,” in Proc. IEE Semi-annual Vehicular Technology Conference-Spring (VTC’04-Spring), vol. 5, 2004, pp. 2466–2470.

[21] D. B. Jourdan and O. L. de Weck, “Multi-objective genetic algorithm for the automated planning of a wireless sensor network to monitor a critical facility,” in Proc. SPIE Defense and Security Symposium, 2004, pp. 565–575.

[22] F. Aurenhammer, “Voronoi Diagrams—A Survey of a Fundamental Geometric Data Structure,” ACM Computing Surveys 23, pp. 345-405, 1991.

[23] Guiling (Grace) Wang, Guohong Cao, Piotr Berman, and Thomas F. La Porta, Fellow, IEEE, ” Bidding Protocols for Deploying Mobile Sensors”, IEEE Transaction on mobile computing, Vol. 6, No. 5, May 2007.

[24] G. Wang, G. Cao, and T. La Porta, “Movement-assisted sensor deployment,” in Proc. Annual IEEE International Coneference on Computer Communications (INFOCOM’04), 2004, pp. 2469–2479.

[25] H.-J. Lee, Y.-h. Kim, Y.-H. Han, and C. Y. Park, “Centroid-based movement assisted sensor deployment schemes in wireless sensor networks,” in Proc. IEEE 70th Vehicular Technology Conference-Fall, 2009, pp. 1–5.

[26] Jun Li, Baihai Zhang and Lingguo Cui “A Restricted Delaunay Tringulation Graph Based Algorithm for Self-Deployment in Mobile Sensor Networks” Journal of Computational Information Systems 2010.

[27] R. Eberhart and J. Kennedy, “A new optimizer using particle swarm theory,” in Proc. 6th International Symposium on Micro Machine and Human Science, 1995, pp. 39–43.

[28] W. Xiaoling, S. Lei, Y. Jie, X. Hui, J. Cho, and S. Lee, “Swarm based sensor deployment optimization in ad hoc sensor networks,” in Proc. International Conference on Embedded Software and Systems (ICESS’05). Springer, 2005, pp. 533–541.

[29] X. Bai, S. Li, C. Jiang and Z. Gao, "Coverage Optimization in Wireless Mobile Sensor Networks," 5th International Conference on Wireless Communications,

Networking and Mobile Computing, pp. 1-4, Beijing, China, September 24-26, 2009.

[30] X. Wang, S. Wang and a. J.-J. Ma, "An Improved Co-evolutionary Particle Swarm Optimization for Wireless Sensor Networks with Dynamic Deployment," Sensors, vol. 7, p. 354–370, 2007.

[31] Z. Huang and T. Lu, "A particle swarm optimization algorithm for hybrid wireless sensor networks coverage," IEEE Symposium on Electrical & Electronics Engineering, pp. 630-632, Kuala Lumpur, Malaysia, June 24-27, 2012.

[32] Nor Azlina Bt. Ab Aziz ,Ammar W. Mohemmed and Mohammad Yusoff Alias "A Wireless Sensor Network Coverage Optimization Algorithm Based on Particle Swarm Optimization and Voronoi Diagram" Proceedings of the 2009 IEEE International Conference on Networking, Sensing and Control, Okayama, Japan, March 26-29, 2009.