PSO Based Node Placement Optimization for Wireless Sensor Networks

Samaneh Hojjatoleslami
Science and Research Branch,
Islamic Azad University
Tehran, Iran
s.hojjatoleslami@srbiau.ac.ir

Vahe Aghazarian
Islamic Azad University,
Central Tehran Branch
Tehran, Iran
v_aghazarian@iauctb.ac.ir

Mehdi Dehghan
Amirkabir University of Technology
Tehran, Iran
dehghan@aut.ac.ir

Nima Ghazanfari Motlagh
Islamic Azad University,
Central Tehran Branch,
Tehran, Iran
ghazanfari_nima@yahoo.com

***Abstract*-This paper presents a multi-objective optimization methodology for sensor network design. A PSO-based approach used as a tool for optimization of most important parameters of wireless sensor networks. Optimal operational modes of the nodes in order to minimize the energy consumption and meet application-specific requirements have been investigated. Also other optimizations have been done on clustering and communication range of sensors.**

Keywords-Wireless sensor networks; Node placement; Optimal design; Particle Swarm Optimization

I. Introduction

Wireless sensor networks (WSNs) consist of numerous small, inexpensive, low-power sensor nodes working together for gathering some necessary information from an environment [1,2]. A WSN has some design and resource constraints. Their major resource constraints include energy consumption, coverage and connectivity. Energy consumption is the most important factor to determine the lifetime. Since sensor nodes have a finite source of energy, and replacing or recharging them is infeasible due to the fact that they are left unattended once they are deployed over a geographical area. Another significant objective in WSNs is obtaining maximum coverage of the monitored area. High degree of coverage leads to more accuracy in data gathering. Network connectivity is also an issue mentioned in WSN design. Grouping sensors into clusters leads to achieve many design goals. Recently, different approaches have been presented for clustering WSNs in the literature [6]. Number of sensors in a cluster depends on capability of clusterheads for handling nodes and ability of nodes for communicating with their clusterheads is issued in network connectivity.

In past few decades, the applications of WSNs have increased considerably. The most important applications of these kinds of networks are agriculture, industrial automation, environmental control, military target tracking and surveillance, habitat monitoring [3], biomedical health monitoring and so on.

Depending upon the application and types of sensors in WSNs, nodes may be deployed either randomly or deterministically. In some applications random deployment is the only feasible method for node placement such as disaster recovery and forest fire detection. Deterministic node placement is usually used for expensive nodes or in scenarios with the need of high precision. Seismic nodes, underwater WSN, video and imaging are such applications. In this case fewer nodes are used in order to perform the same task in random situation.

Due to the limitations and broad applications of WSNs, designing an optimal network to increase the performance, is essential. Designing such a network is an NP-hard problem. Various solutions have been found for an NP-hard problem in its search space. Several algorithms have been proposed as methods for such kind of problems, which take their inspiration from natural selection and survival of the fittest in the biological world.

In this paper, we have tried to optimize the most important parameters of the WSN to increase its performance. Optimal operational modes of the nodes in order to minimize the energy consumption and meet some application-specific requirements have been determined. Also some other optimizations have been done on clustering and communication range of sensors.

In the following section, we review the related works; Section III states the problem, optimization parameters and the PSO approach which is used in our algorithm, followed by the proposed methodology and the simulation results. Finally, in Section V, some overall conclusions are stated.

II. Related Work

The position of nodes affects different parameters of the WSNs. The most important parameters which have been investigated in literature are power consumption, network coverage, and connectivity. Several algorithms have been proposed for optimizing these parameters. Although they have tried to improve one of those issues, many of them fail to optimize them simultaneously. Some of the published work, such as [5], has focused on network lifetime by reducing the energy consumption. In [7], a grid region has been considered, while a greedy heuristic is proposed to achieve maximum coverage through minimum sensors.

Different metaheuristic optimization methods such as Genetic Algorithms, Swarm Optimization, Neural Networks, and Simulated Annealing are presented to provide solutions to multi-objective problems. Several proposed methods for such a problem are based on Genetic Algorithms (GAs). In [9,10], they have used GA for optimization of network lifetime by clustering. In [11], an optimization technique based on multi objective genetic algorithm is proposed for optimizing coverage and network lifetime.

Another powerful heuristics is Particle Swarm Optimization (PSO). Both GA and PSO are population based algorithms. Compared to GA, the advantages of PSO are that PSO is easy to implement and there are few parameters to adjust. PSO has been successfully applied in many areas: function optimization, artificial neural network training, fuzzy system control, and other areas where GA can be applied [4].

In [8], deployment problem has been solved by PSO for optimizing the coverage as a primary objective and energy consumption for reducing cost as a secondary one.

III. Problem Statement

An $i*j$ grid area for a WSN is considered here for problem assumption and statement. Nodes are placed at each intersection of grid. All the sensors have the same communication and computation capabilities, so there is a homogenous network. Sensors may be either active or inactive. An active sensor may operate as a clusterhead (CH sensor), which provides the communication between sensors and the base station or as a regular sensor used for sensing the field of interest. A regular sensor node has two operation modes: low-signal range (LSR) and high signal range (HSR). Simple cluster-based network architecture is assumed for the network. The operation of each sensor relates to its cluster membership. Each sensor should be a member of at least one cluster. A clusterhead is responsible for aggregating data from all the sensors inside its cluster, and sends them to the base station. Sending data to the base station can be done either directly or by multi-hop path. Clusterheads sense nothing from the environment. Energy consumption of nodes is related to their functional modes in the network. It is clear that CHs will consume more power than two other modes, and HSRs will consume more than LSRs as well.

An algorithm is proposed to design optimal network topologies by optimizing some of the most important parameters of the WSN. Multiple objectives of our optimization problem are combined in a single objective function. In [12], design and performance parameters for a WSN are divided into three sets. The first set consists of some *application-specific* parameters. These parameters are specified exactly based on the application of the WSN. Here, two parameters are considered, uniformity of sensing points and some desired spatial density of measuring points. The second set refers to the *connectivity parameters*. One metric is used for assurance on connectivity of each sensor to at least one clusterhead. Considering restricted resources of clusterheads leads to set out another metric for confining the number of sensors communicating with clusterheads. Each clusterhead can communicate just with predefined amount of sensors. The third set is *energy-related parameters* consists of major energy consumption parts in WSNs. The operational energy consumption which depends on the types of active nodes, and the communication energy consumption being dependent on distances between sensors are parameters within this class which are investigated.

Generally, an optimal network topology is achieved by maximizing the uniformity and connectivity and also by minimizing the energy consumption.

The optimization problem is defined by the minimization of energy related parameters and maximization of the spatial density parameter. A weighted sum approach is used for combining these parameters in a single function, and all of them are optimized in their minimization form.

$$f = w_1.MRD + w_2.SDE + w_3.SCE + w_4.SORE + w_5.OE + w_6.CE \qquad (1)$$

The values of weighted coefficients $w_i : i = 1,2,...,6$ are presented in Table (1).

TABLE I. Weighting coefficients of fitness function

Weighting coefficient	Values
w_1	5
w_2	10
w_3	1
w_4	5
w_5	10
w_6	2

A. Optimization Parameters

1) *Application-specific parameters* – Besides some known parameters for WSNs, there are some other parameters related to the specific application of these networks. Each application has its own requirements; by oversighting these requirements, designing an optimal network is impossible. Different application-specific parameters can be considered. In some applications such as agriculture an overall picture of the conditions of the entire area is needed. Therefore uniformity and spatial density are two metrics taken into account in this paper. The goal of uniformity is to cover the whole sensing points as far as possible.

- Mean Relative Deviation (MRD) – This metric is defined to measure the uniformity of the sensing points of the entire area. The area is subdivided into some overlapping sub areas, $i = 1,2,..., N$. It is noteworthy that the larger overlapping ratio leads to higher precise data but a slower algorithm. In order to define the MRD, some notions are used. MRD is defined as follows:

$$MRD = \frac{\sum_{i=1}^{N} \left| \rho_{S_i} - \rho_s \right|}{N \cdot \rho_s} \qquad (2)$$

Where, ρ is the spatial density of the area of the interest. ρ_{s_i} is the spatial density of measurements in sub-area S_i and is defined as the number of measurements over the area of *i*th sub-area. ρ_s is the spatial density of the entire area of interest S which is the total number of measurements of the network over the total area of interest. High uniformity is represented by low values of MRD.

- Spatial Density Error (SDE) – This metric is used for investigation on minimum required spatial density of network. The notion of desired spatial density ρ_d which is set equal to 0.2 measurement points per square length unit and is evaluated as follows:

$$SDE = \begin{cases} \dfrac{\rho_d - \rho_s}{\rho_d} & \text{if } \rho_d < \rho_s \\ 0 & \text{otherwise.} \end{cases} \quad (3)$$

2) *Connectivity parameters* – One of the crucial issues in WSN is connectivity, which it has a main role on performance of the network. Here, the most two important parameters are considered.

- Sensors-per-Clusterhead Error (SCE) – This metric defines an upper bound for each clusterhead to ensure that each one did not have more than the specified number of sensors. The maximum number is assumed to 15. This value can be variable due to the physical communication and data management capabilities of the sensors.

$$SCE = \begin{cases} \dfrac{\sum_{i=1}^{nfull} n_i}{nfull} & \text{If } nfull > 0 \\ o & \text{otherwise.} \end{cases} \quad (4)$$

Where, *nfull* is the number of clusterheads (or clusters) that have more than 15 active sensors in their clusters. n_i, is the number of sensors in *i*th of those clusters.

- Sensors-Out-of-Range Error (SORE) – It is assured that each sensor becomes a member of at least one cluster. It is assumed that the radii of HSR and LSR sensors are 3.6 and 1.8, respectively. This metric directly depends on communication signal range of nodes.

$$SORE = \frac{nout}{n} \quad (5)$$

nout is the number of active sensors that cannot communicate with their CH.

3) Energy-related parameters – Energy consumption is another crucial issue in WSNs. It affects all performance parameters such as network life time, coverage, connectivity and so on of these networks. Sensors mostly consume energy in their operational mode while communicating with their clustersheads. These parameters are considered as follow:

- Operational Energy (OE) – Refers to the amount of energy each sensor consumes during its activity which is clearly related to their operational mode. Energy consumption of different operational modes of sensors, CH, HSR, LSR are assumed proportional to 20:2:1, respectively. OE for inactive sensors is equal to 0.

$$OE = 20.\frac{nch}{n} + 2.\frac{nhs}{n} + \frac{nls}{n} \quad (6)$$

Where, *nch*, *nsh* and *nls* are the numbers of CH, HSR and LSR sensors, respectively.

- Communication Energy (CE) – Some amount of energy is consumed by sensors for communication with each other and their clusterheads. It is related to the distances between them where, larger distances need more energy. It is evaluated by

$$CE = \sum_{i=1}^{c} \sum_{j=1}^{n_i} \mu . d_{ji}^{k}, \quad (7)$$

Where, c is the number of clusters, n_i is the number of sensors in the i th cluster, and d_{ij}, is the eclidean distance from sensor j to its CH. μ and k are constants. The values of μ and k are assumed to be equal to 1 and 3, respectively.

B. Particle Swarm Optimization

In PSO, a number of simple entities—the particles—are placed in the search space of some problem or function. Each particle represents a possible solution to the problem. The problem is stated as one or more objective function(s), which evaluates all the particles' fitness value. Each particle has a position and a velocity which directs the movement of the particle. The objective function is evaluated at the current location of each particle. Each one determines its movement through the search space by combining some aspect of the history of its own current and best (best-fitness) locations with those of one or more members of the swarm, with some random perturbations. The next iteration takes place after all particles have been moved. Eventually, the swarm as a whole, like a flock of birds collectively foraging for food, and is likely to move close to an optimum of the fitness function [13,14]. PSO is a population based algorithm and initializes with some random solutions. The optimal solution will be found by upgrading generations to the optimal or near optimal solution.

Each particle is considered as a point in the D-dimensional search space. The *i*th particle and its best previous position are represented as $X_i = (x_{i1}, x_{i2}, \ldots, x_{iD})$ and $P_i = (p_{i1}, p_{i2}, \ldots, p_{iD})$, respectively. The index of the best particle among all the particles in the population is represented by the symbol g. The rate of the position change (velocity) for particle *i* is represented as $V_i = (v_{i1}, v_{i2}, \ldots, v_{iD})$. The particles are manipulated according to the following equation [15]:

$$v_{id} = w*v_{id} + c_1*rand()*(p_{id} - x_{id}) + c_2*Rand()*(p_{gd} - x_{id}) \quad (8)$$

$$x_{id} = x_{id} + v_{id} \quad (9)$$

Where w is the inertia weight, and c_1 and c_2 are two positive constants as the acceleration coefficients, and rand() and Rand() are two random functions in the range [0,1]. Inertia weight has an important role in search results. A large inertia weight is used for global search while a small one is used for local exploration.

PSO and GA have many similarities in different aspects but there are some issues which make them different from each other. Both of them are initialized with a random group of population. By evaluating and updating the population, the optimum solution will be found. However, PSO does not have the crossover and mutation operators. Unlike GA whose members of population have no relation with each other, in PSO they have memory and make decision using the information of all the population.

In contrast with GA, the implementation of PSO is easier and has fewer parameters to adjust. In different problems, PSO has faster convergence rates than GA. Hence, PSO is selected as an optimization algorithm in this paper.

IV. The Proposed Method

In this section the proposed method is presented as well as the simulation results which were implemented in MATLAB.

The stated problem is optimized by PSO approach. Original version of particle swarm optimization has been introduced for use in real-number spaces. Our problem is discrete although a real-coded PSO is used for simplicity. In our simulation a variable $0 \le x_i < 1$ is assumed. n_s, is the number of possible stated for each node. It can be shown that:

$$1 \le n_s x_i + 1 < n_s + 1 \quad (10)$$

Hence, $\lfloor n_s x_i + 1 \rfloor$[1] is an integer in the set $\{1,2,3,\ldots,n_s\}$, and represents the state of node i. Using this coding scheme, real-coded PSO has been utilized to deal with a discrete optimization problem. The range $[0,1)$ for real-coded variables, are independent of number of states. Even if node i, has its specific number of states, say n_s, then the decoding process will not change.

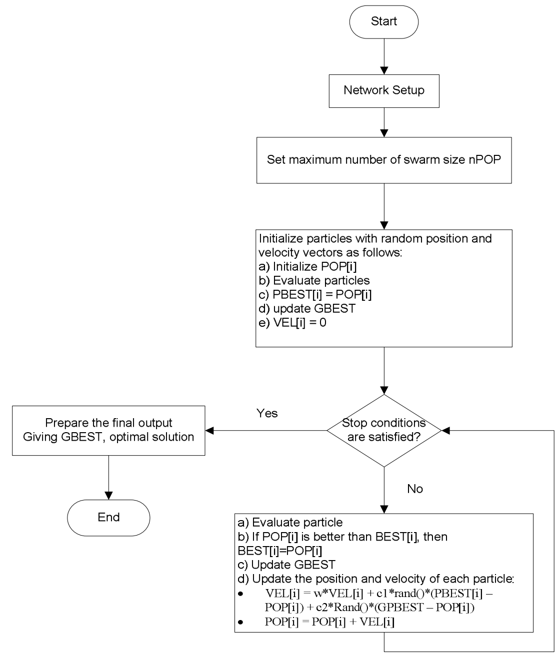

Fig. 1 Flowchart of the proposed methodology

The algorithm was applied in a grid area $10*10$. The following are the results of our simulations. The progress of optimization process is shown during the increasing of population size. Fig. 1 is presented the evolution of the fitness function during the optimization of the designs till the 500th particles.

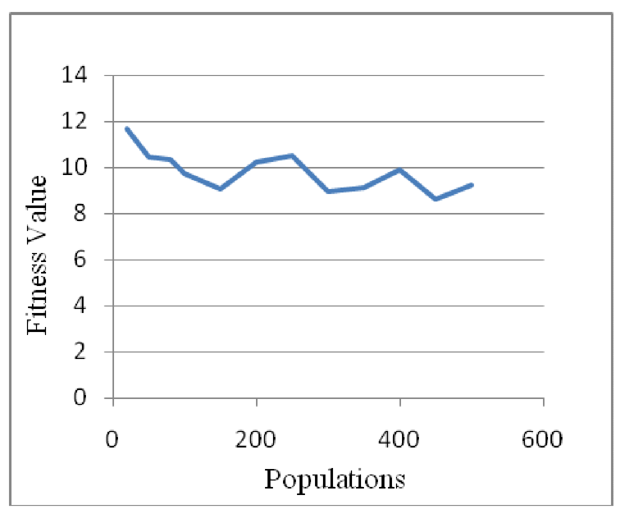

Fig. 2 Optimization of fitness function during the iteration of the algorithms

[1] $\lfloor x \rfloor$ represents floor of x, which equals to greatest number, less than or equal to x.

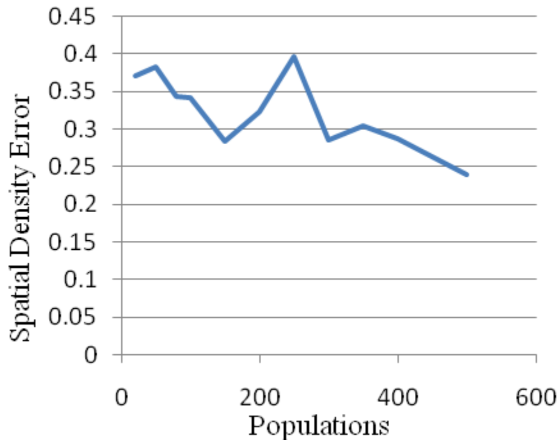

Fig. 3 Optimization of Spatial Density Error (SDE) parameter

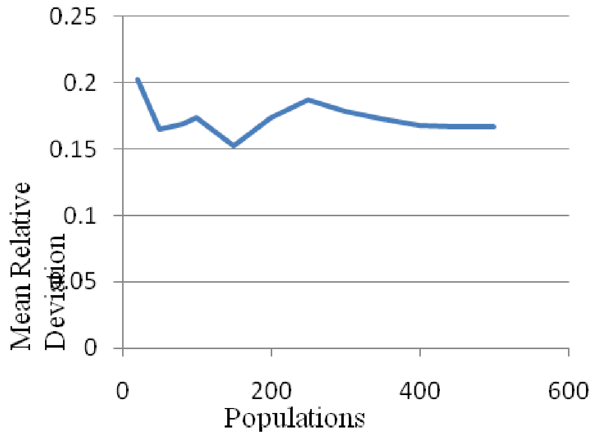

Fig. 4 Optimization of Mean Relative Deviation (MRD) parameter

As it can be seen in figures 2 and 3 the algorithm tries to minimize the error of uniformity in the area of interest. The minimization of energy consumption is easily observed in figures 5 and 6 while figures 7, 8 show the optimization process of connectivity parameters.

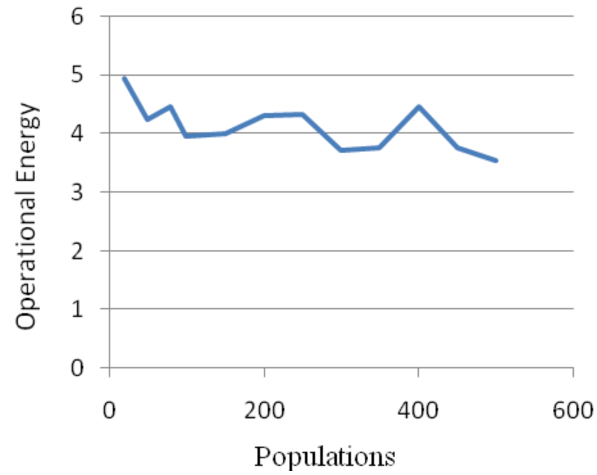

Fig. 5 Optimization of Operational Energy (OE) parameter

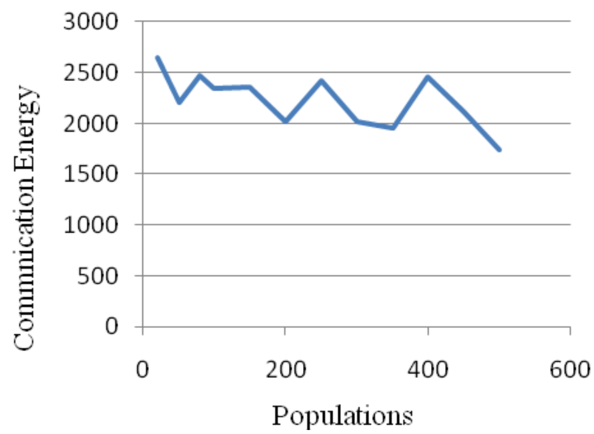

Fig. 6 Optimization of Communication Energy (CE) parameter

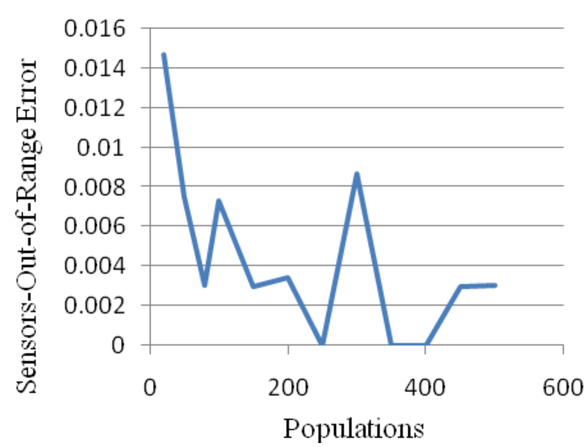

Fig. 7 Optimization of Sensors-Out-of-Range Error (SORE)

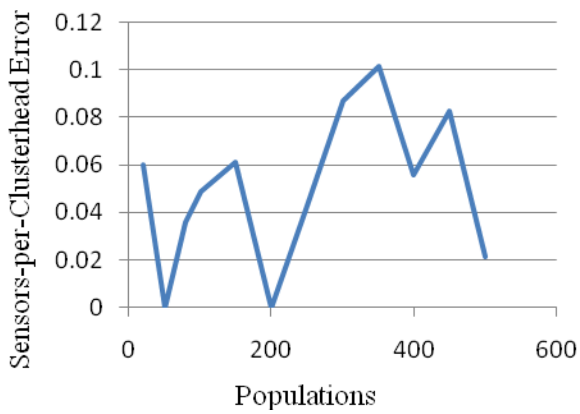

Fig. 8 Optimization of Sensors-per-Clusterhead Error (SCE) parameter

V. Conclusion

In this paper an optimal wireless sensor network design is presented by the use of PSO approach. This method is presented for a fixed wireless network while a periodic data gathering is needed such as agriculture application. A homogeneous network is assumed. Sensors may be either active or inactive. An active sensor may operate as a CH, HSR or LSR. The primary goal of the algorithm is to find the best operational mode for each sensor. Optimal sensor network constructed by the algorithm satisfied the most important parameters of the network. For future work there is an extend scope for using metaheuristic methodologies in different aspect of wireless sensor networks.

References

[1] F. Akyildiz, W. Su, Y. Sankarasubramaniam, E. Cayirci, "Wireless sensor networks: a survey", Computer Networks, Vol. 38, pp. 393-422, 2002.

[2] J. Yick, B. Mukharejee, D. Ghosal, "Wireless sensor netwok survey", Computer Networks, Vol. 52, pp. 2292–2330, 2008.

[3] A. Mainwaring, J. Polastre, R. Szewczyk, D. Culler, "Wireless sensor networks for habitat monitoring", Proc. ACM International Workshop on Wireless Sensor Networks and Applications (WSNA'02), Sep. 2002, pp. 88–97.

[4] http://www.swarmintelligence.org

[5] M. Younis, M. Youssef, K. Arisha, "Energy-Aware management in Cluster-Based Sensor Networks," Computer Networks, Vol. 43, No. 5, pp. 649-668, 2003.

[6] A. Abbasi, M. Younis, "A survey on clustering algorithms for wireless sensor networks", Computer. Communications, Vol. 30, pp.2826-2841,2007.

[7] S. S. Dhillon, K. Chakrabarty, "Sensor placement for effective coverage and surveillance in distributed sensor networks," Proc. IEEE Wireless Communications and Networking Conference (WCNC'03), March 2003.

[8] W. Xiaoling, S. Lei, Y. Jie, X.Hui, J. Cho, S. Lee," Swarm Based Sensor Deployment Optimization in Ad Hoc Sensor Networks",Proc. International Conference on Embedded Software and Systems (ICESS), Dec 2005, pp.533-541.

[9] S. Jin, M. Zhou, A. S. Wu, "Sensor network optimization using a genetic algorithm," Proc. 7th World Multiconference on Systemics, Cybernetics and Informatics, 2003.

[10] S. Hussain, A. Wasey Matin, O. Islam, "Genetic algorithm for hierarchical wireless sensor networks," Journal of Networks, VOL. 2, NO. 5, pp. 87-97, 2007.

[11] D.B. Jourdan, O.L. de Weck, "Layout optimization for a wireless sensor network using a multi-objective genetic algorithm", Proc. IEEE Semiannual Vehicular Technology Conference, pp. 2466-2470, May 2004.

[12] K. P. Ferentinos, T. A. Tsiligiridis, "Adaptive design optimization of wireless sensor networks using genetic algorithms", Computer Networks 51 (2007), pp. 1031–1051

[13] R. Poli , J. Kennedy · T. Blackwell "Particle swarm optimization An ocerview", Swarm Intell, pp.33-57,2007

[14] Y. Shi, R. C. Eberhart: "Empirical study of Particle Swarm Optimization" Proc. Evolutionary Computation, Vol. 3, Jul. 1999.

[15] R. Eberhart, J. Kennedy, "A new optimizer using particle swarm theory", Proc. 6th international symposium on micro machine and human science, Oct. 1995, pp. 39–43.