MULTI-OBJECTIVE ENERGY EFFICIENT OPTIMIZATION ALGORITHM FOR COVERAGE CONTROL IN WIRELESS SENSOR NETWORKS

Seyed Mahdi Jameii[1] and Seyed Mohsen Jameii[2]

[1]Department of Computer Engineering, Shahr-e-Qods Branch, Islami Azad University, Tehran, Iran.
Jamei@Qodsiau.ac.ir
[2]Department of Computer Engineering, Qazvin Branch, Islami Azad University, Qazvin, Iran.
Jamei@Ariapardazesh.ir

ABSTARCT:

Many studies have been done in the area of Wireless Sensor Networks (WSNs) in recent years. In this kind of networks, some of the key objectives that need to be satisfied are area coverage, number of active sensors and energy consumed by nodes. In this paper, we propose a NSGA-II based multi-objective algorithm for optimizing all of these objectives simultaneously. The efficiency of our algorithm is demonstrated in the simulation results. This efficiency can be shown as finding the optimal balance point among the maximum coverage rate, the least energy consumption, and the minimum number of active nodes while maintaining the connectivity of the network.

KEYWORS

Wireless Sensor Networks, Multi-objective Optimization, Coverage, Lifetime

1. INTRODUCTION

Wireless Sensor Networks (WSNs) are very suited for doing the surveillance tasks. The processing and wireless communication capabilities and battery power of each sensor in this kind of networks are limited and replacing the battery of nodes is impossible in applications such as habitat monitoring and monitoring civil structures.[1-2]

Coverage is a key problem in WSNs and it focuses on determining the portion of the field that is monitored by active nodes [3-7].

For deployment of sensor nodes some of the key objectives that need to be satisfied are

DOI : 10.5121/ijcseit.2013.3403

The portion of covered area, the number of active nodes, energy consumed by nodes, and network connectivity are key objectives in the area of WSNs. Selecting the optimal set of active nodes has been proved as an NP-complete problem in [8].

In the real world, Optimization Problems (OP) is usually with multiple attributes. Commonly, multiple objectives should be optimized simultaneously; however, there exists conflicts among the multiple objectives. For example, product quality and cost are two conflicting objectives in the production activity. In order to achieve the total optimization, some conflicting objectives should be compromised [9]. Some good algorithms have been put forward such as NSGA-II[10], PESA [11], PAES [12], SPEA2 [13] ,etc. NSGA has better diversity and faster convergence in solutions.

In this paper, we propose a NSGA-II based multi-objective algorithm for optimizing all of these objectives simultaneously. The efficiency of our algorithm is demonstrated in the simulation results. This efficiency can be shown as finding the optimal balance point among the maximum coverage rate, the least energy consumption, and the minimum number of active nodes while maintaining the connectivity of the network. The remaining of this paper is organized as follows: In Section 2 we present the related work related to coverage in WSNs. In Section 3 we introduce the NSGA-II algorithm briefly. Section 4 describes the proposed algorithm. Simulation results are shown in section 5 and the proposed algorithm is evaluated in this section. The paper concludes with Section presents some 6.

2. RELATED WORKS

Maximizing the coverage and lifetime objectives individually was the main focus of several studies in the past. Although coverage is the key objective in WSNs but for better efficiency it should not be optimized separately. The proposed approaches in [14-17] optimize the lifetime and coverage objectives individually and sequentially, or by constraining one and optimizing the other. This often results in ignoring and losing “better” solutions since WSN coverage and lifetime are conflicting objectives [18]. Therefore, there is not a single solution to maximize both objectives simultaneously and a decision maker [19] needs an optimal trade-off of candidate solutions.

In a Multi-objective Optimization Problem (MOP), a candidate trade-off solution is often called non-dominated or Pareto optimal. The set of all Pareto optimal or non-dominated solutions in the search space, also called Pareto Set (PS), is often mapped to a Pareto Front (PF) in the objective space [20]. Multi-objective Evolutionary Algorithms (MOEAs) could obtain such an approximate PF in a single run. This is mainly due to the fact that MOEAs accommodate different forms of operators to iteratively generate a population of solutions. In the literature, several general purpose MOEA frame- works are used for dealing with MOPs in WSNs [21–24] such as the Non-dominated Sorting Genetic Algorithm-II [25] (NSGA-II).

3. NON-DOMINATED SORTING GENETIC ALGORITHM-II

NSGA-II [10] has been demonstrated as one of the most efficient multi-objective optimization algorithms. Pareto optimality is an integral part of NSGA-II and will be introduced first.

3.1. Pareto Concepts

Multi-objective optimization can be expressed as (1):

Min f_i (x), i = 1, 2, . . . , m $x \in x$
(1)

where $f_i(x)$ denotes the i^{th} objective function, m is the number of objectives and x represents the feasible search space.

Definition 1: A solution x_1 is said to dominate x_2 (denoted by x1 ‹ x2) if and only if:
$i \in \{1, 2 ... m\} : f_i(x_1) \leq f_i(x_2) \wedge \quad j \in \{1, 2 ... m\} : f_j(x_1) , f_j(x_2)$
(2)

Definition 2: For S = {x_i, I = 1,…., n}, solution x is said to be a non-dominated solution (Pareto solution) of set S if $x \in S$ and there is no solution $x' \in S$ for which x′ dominates x.

Definition 3: Assume that set P contains all the non-dominated solutions of S, then PF= $\{v \mid v= [f_1(x), f_2(x). . .f_m(x)]^T, x \in P\}$ is a Pareto front of set S.

3.2. Fitness Assignment Schemes in NSGA-II

In the fitness assignment procedure, NSGA-II allocates a rank value r_i to each solution. The non-dominated solutions are identified and assigned the rank value 1. After removing those solutions from the population, new non-dominated solutions are assigned rank value 2. This procedure continues iteratively.

Fig. 1 provides a graphic example. It represents rank values for a population (size 10). First, the non-dominated solutions 1, 2 and 3 receive rank value 1, then solutions 4, 5 and 6 receive rank value 2 and the procedure continues.

To promote the solutions in the sparse region, crowding distance D_i is assigned to each candidate solution. D_i is the average distance of two points on either side of the solution i along each of the objectives. For objective dimension two, D_i for solution i is determined by a rectangle formed by two nearest neighbours of i, as shown in Fig. 1. For solution 2, solutions 1 and 3 are the two neighbours in the same rank, defining the boundary rectangle. D_2 would be the average side length of the rectangle. With assigned r_i and D_i, any two solutions in the population can be compared by solution i is superior than solution j $\Leftrightarrow \{r_i < r_j\}$ or $\{r_i = r_j$ and $D_i > D_j\}$ (3)

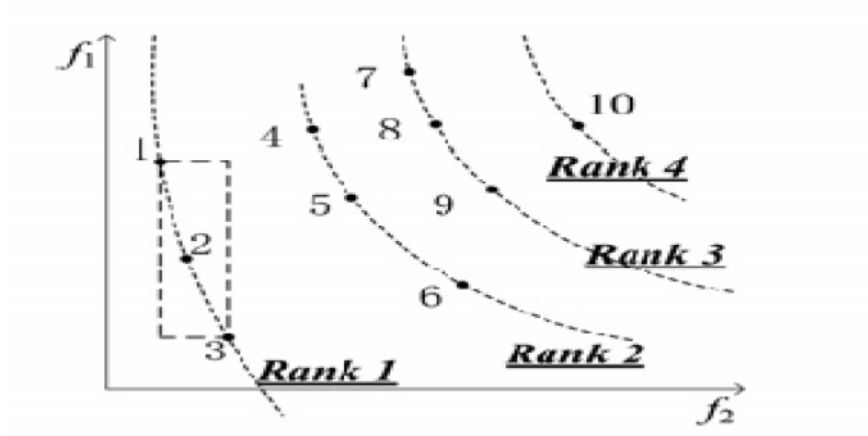

Figure 1. Fitness assignment of NSGA-II in a two-objective Space

3.3. Procedure of NSGA-II

In any generation of NSGA-II, there are two steps: evolving and filtering. An evolving process generates the temporary new population $S_1^{(k+1)}$ from $S^{(k)}$ by applying the genetic operators.

1. Coding: A real-coding scheme is adopted because of difficulties of binary representation when dealing with continuous search space with large dimensions. A decision variable is represented by a real number within its lower limit and upper limit. Since parts of decision variables are discrete, a procedure is imposed to round discrete variables of newly generated solutions to the nearest valid value.

2. Crossover and mutation: A blend of crossover- α operator and normally distributed mutation operator [26] is employed for the real-coding scheme.

After genetic operators, the filtering procedure combines $S^{(k)}$ and $S_1^{(k+1)}$, and then chooses solutions by applying (3) to form the new population $S^{(k+1)}$.

4. PROPOSED ALGORITHM

In this section, the details of the proposed algorithm are described. At first, we made some assumptions: the nodes are deployed randomly, each one are static and knows its own location using some location systems [27]. In the proposed algorithm, such as [28], the transmission radii of sensors are assumed to be at least twice the sensing radii for assuring the connectivity of the network.

We introduce a cluster-based optimization scheme which is scheduled into rounds. In each round, firstly, the target area is divided into several clusters. The LEACH [29] algorithm is used for clustering and selecting the cluster heads. The cluster-head has full control of its cluster and run the NSGA-II algorithm for optimizing the following objectives subject to the connectivity constrain:

Objective 1: Maximizing the network coverage:
Max $f_1(x)= A_{coverd} / A$
(4)
where $A_{covered}$ is the covered area by the active sensors and A is the whole area of the sensor field.

Objective 2: Number of active sensors that is desirable to be minimize, so can be converted to the objective for maximization as follow:
Max $f_2(x)= 1- |K'|/ |K|$
(5)
In this equation, $|K'|$ is the number of active nodes and $|K|$ is the number of all nodes.
We have used a bit string with size K for representing the solution. For each sensor node 1 –bit is assigned in the solution and this bit represents the working state of corresponding node as (6):

$x = (x_1, x_2,\ldots, x_i,\ldots, x_K)$

$$x_i = \begin{cases} 1, & \textit{If the sensor is selected} \\ 0 & \textit{Otherwise} \end{cases}$$
(6)

In fig.2, the flowchart of the proposed algorithm is shown. The recombination operator used in this paper is two-point crossover, which is a typical recombination for binary or other string-like chromosomes, and the crossing points are selected at random. The mutation operator is applied for each new generated child after crossover. It works by complementing some genes in the child's chromosome randomly. The mutation operator swaps the bits of each string (0 becomes 1 and vice versa) means that a sleep sensor node becomes active and vice versa.

After a new population has been produced through the genetic operators, selection is done in an extended space composed of all parent and offspring individuals. This extended sampling space allows large probability of mutation and crossover while keeping the population relatively stable. Assign each individual having two fitness functions (coverage rate and number of active sensors), by introducing the non-dominated sorting, crowded distance operator and elitism. Selecting the individuals as a parent for producing the next generation is proportional to its fitness value.

Each time there are two solutions of different non-domination ranks, we prefer the higher one. If there are two solutions with the same non-domination ranks, we prefer the one which has larger crowded distance. Also the elitism mechanism is used in our algorithm to prevent destroying the best individual of each generation by the crossover and mutation operators during the evolution process. This means that the current best individual at each generation of the algorithm can be easily transferred to the next generation.

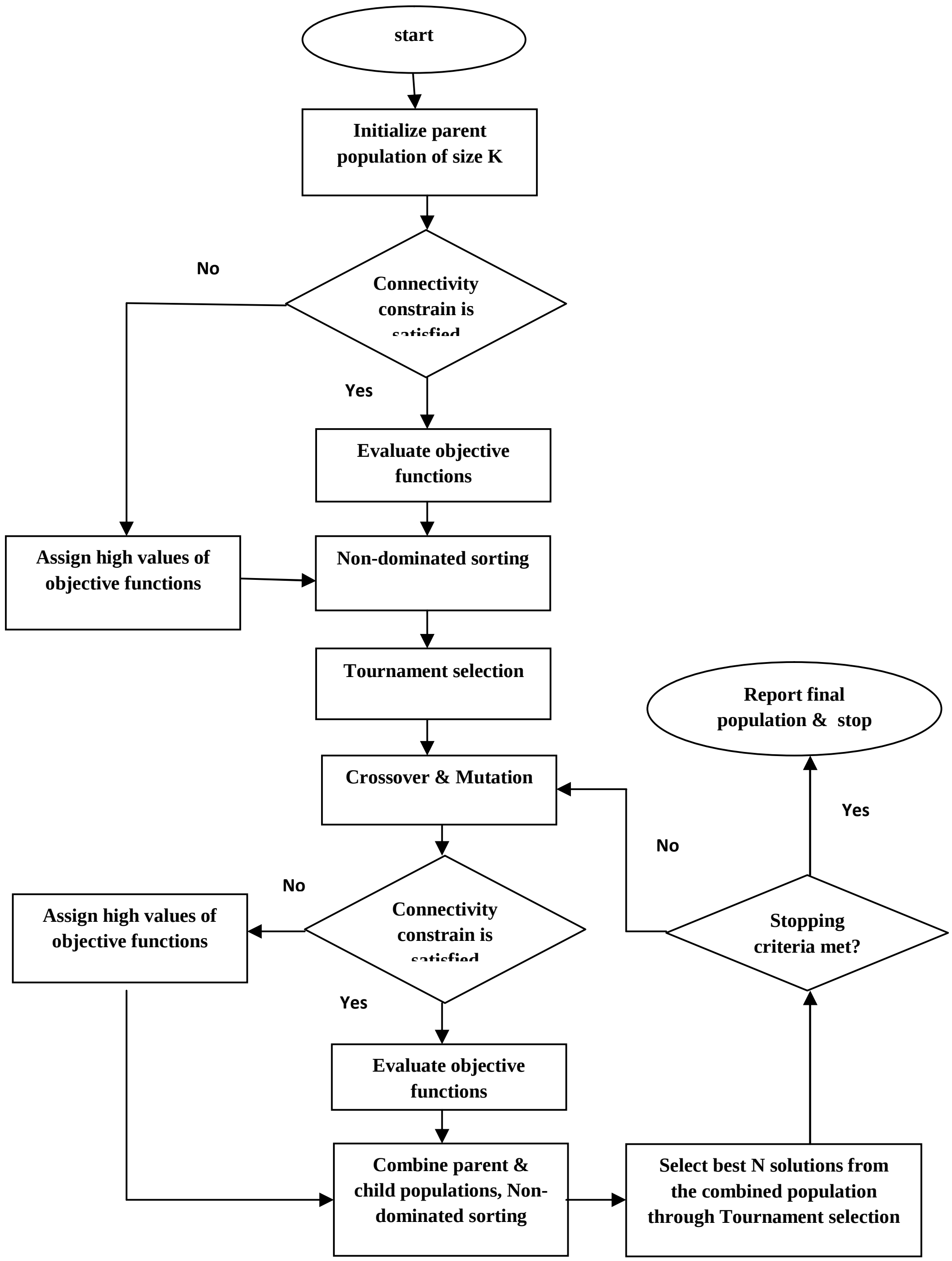

Figure 2. The flowchart for the proposed algorithm

5. SIMULATION RESULT

In this section, our proposed algorithm is simulated using NS-2 simulator [30]. To evaluate the proposed protocol, the coverage algorithm is implemented using single objective genetic algorithm (SGA) and the proposed algorithm is compared with it. In the simulations, we assume a target area with a size of 150×150 m^2. We deployed the sensor nodes randomly in the target area. The number of nodes, K, in the first experiment are considered as 100, 150, 200, 250, 300, 350, 400, 450, 500 respectively. As shown in Fig. 3 and 4, due to the proposed algorithm accuracy in selecting the active sensor set, it is able to provide the full coverage in sparse deployment. Also, with increasing the nodes density, the proposed protocol decreases the energy consumption of the sensor networks.

In the last experiment, the number of nodes is considered as 100 and coverage rate with different number of working nodes are depicted in Fig. 5. As can be seen in this figure, with the same number of working nodes, the proposed algorithm can achieve higher coverage rate compared to the SGA algorithm. This is because of in the proposed algorithm both of the coverage rate and number of working sensor are considered simultaneously as objectives.

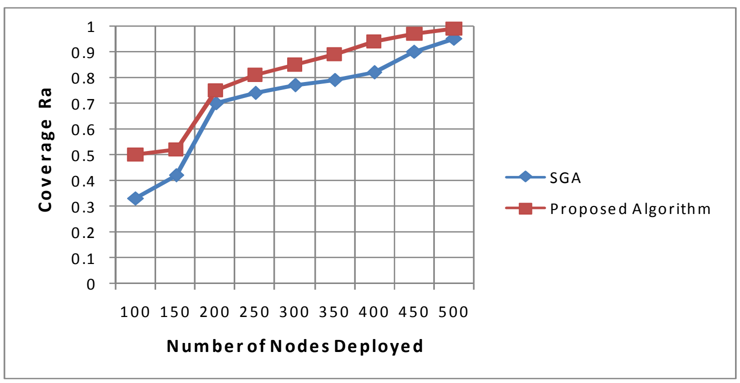

Figure 3. Coverage Rate of Sensor Set in Different Configuration

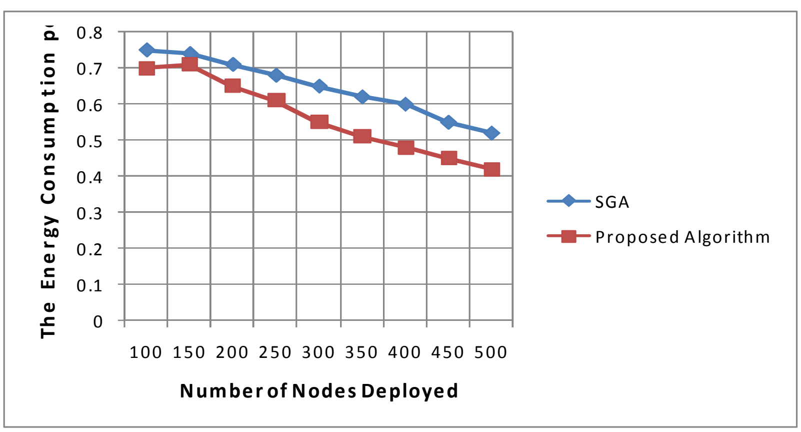

Figure 4. The Energy Consumption per Area in Different Configurations

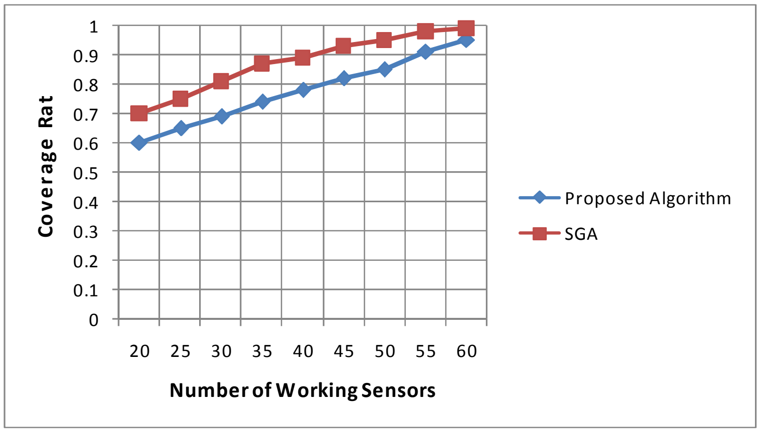

Figure 5. Coverage Rate Vs. Number of Working Sensors

6. CONCLUSION:

In this paper we proposed a NSGA-II based multi-objective algorithm for optimizing the area coverage, number of active sensors and energy consumed by nodes in wireless Sensor networks while maintaining the connectivity simultaneously. For evaluating the proposed protocol, the coverage algorithm is implemented using Single objective Genetic Algorithm (SGA) and the proposed algorithm is compared with it. As shown in the simulation results, many more non-dominated solutions are found in the proposed algorithm and these solutions are better than the solutions obtained by the SGA algorithm.

ACKNOWLEDGEMENTS

The authors wish to thank Islamic Azad University, Shahr-e-Qods branch for supporting this work through grants.

REFERENCES

[1] E. Shih, S. Cho, N. Ickes, R. Min, A. Sinha, A. Wang, A. handrakasan, Physical layer driven protocol and algorithm design for energy-efficient wireless sensor networks, in: Proc. of the 7th Annual International Conference on Mobile Computing and Networking, Rome, Italy, pp. 272_287, 2001.

[2] I.F. Akyildiz, W. Su, Y. Sankarasubramaniam, E. Cayirci, A survey on sensor networks, IEEE Communications Magazine 40, pp. 102_114, 2002.

[3] S. Meguerdichian, F. Koushanfar, M. Potkonjak, and M. Srivastava, “Coverage Problems in Wireless Ad Hoc Sensor Networks,” Proc. IEEE INFOCOM, 2001.

[4] X. Wang, G. Xing, Y. Zhang, C. Lu, R. Pless, and C. Gill, “Integrated Coverage and Connectivity Configuration in Wireless Sensor Networks,” Proc. ACM First Int’l Conf. Embedded Networked Sensor Systems (SenSys), 2003.

[5] X. Bai, S. Kumar, D. Xuan, Z. Yun, and T.-H. Lai, “Deploying Wireless Sensors to Achieve both Coverage and Connectivity,” Proc. ACM Int’l Symp. Mobile Ad Hoc Networking and Computing (MobiHoc), 2006.

[6] H. Zhang and J. Hou, “Maintaining Sensing Coverage and Connectivity in Large Sensor Networks,” J. Ad Hoc and Sensor Wireless Networks, vol. 1, pp. 89-124, 2005.

[7] G. Kasbekar, Y. Bejerano, and S. Sarkar, “Lifetime and Coverage Guarantees through Distributed Coordinate-Free Sensor Activation,” Proc. ACM MobiCom, 2009.
[8] M. Cardei and J. Wu, “Energy-efficient coverage problems in wireless ad-hoc sensor networks,” Computer Communications, vol. 29, no. 4, pp. 413–420, 2006.
[9] Cui xunxu, Multiobjective Evolutionary Algorithms and their Applications, Beijing:National Defense Industry Press, pp10-15, 2006.
[10] K. Deb, A. Pratap, S. Agarwal, T. Meyarivan, A fast and elitist multi-objective genetic algorithm: NSGA-II, IEEE Transactions on Evolutionary Computation, vol. 6, pp. 182_197, 2002.
[11] Come D W. “The parate envelope-based selection algorithm for multiobjective optim ization,” Lecture Notes in Computer Science, pp839-848, 2000.
[12] Joshua D. Knowles and David W Corne, “The pareto Archived evolution strategy: a new baseline algorithm for multiobjective optimization,” In 1999 Congress on Evolutionary Computation. Washington.D.C, pp98-105, 2000.
[13] E.Zitzler, M.Laumanns, L.Thiele. SPEA2, “Improving the strength pareto evolutionary algorithm,” Technical Report TIK-Report 103, Swiss Federal Institute of Technology Zurich (ETH).May,2001.
[14] S. Meguerdichian, F. Koushanfar, M. Potkonjak, M.B. Srivastava, Coverage prob- lems in wireless ad-hoc sensor networks, IEEE INFOCOM, vol. 3, pp. 1380–1387, 2003.
[15] P. Cheng, C.N. Chuah, X. Liu, Energy aware node placement in wireless sensor networks, IEEE Global Telecommunications Conference vol. 5, 3210–3214, 2003.
[16] X. Liu, P. Mohaparta, On the deployment of wireless data back-haul networks, IEEE Transactions on Wireless Communication vol. 6, No 4, pp. 1426–1435, 2007.
[17] Y. Chen, C.-N. Chuah, Q. Zhao, Network configuration for optimal utilization efficiency of wireless sensor networks, Elsevier Ad Hoc Networks Vol. 6, pp. 92–107, 2008.
[18] D.B. Jourdan, O.L. de Weck, Layout optimization for a wireless sensor network using amulti-objective genetic algorithm, IEEE Semiannual Vehicular Technol- ogy 5, pp.2466–2470, 2004.
[19] S. Chaudhuri, K. Deb, An interactive evolutionary multi-objective optimiza- tion and decision making procedure, Applied Soft Computing, Vol.10, No.2, pp.496–511, 2010.
[20] K. Deb, Multi-objective Optimization Using Evolutionary Algorithms, Wiley and Sons, 2002.
[21] R. Rajagopalan, P.K. Varshney, C.K. Mohan, K.G. Mehrotra, Sensor placement for energy efficient target detection in wireless sensor networks: a multi-objective optimization approach, in: Conference on Information Sciences and Systems, Baltimore, Maryland, 2005.
[22] S.C. Oh, C.H. Tan, F.W. Kong, Y. S. Tan, K.H. Ng, G.W. Ng, K. Tai, Multiobjec- tive optimization of sensor network deployment by a genetic algorithm, IEEE Congress on Evolutionary Computation, pp.3917–3921, 2007.
[23] J. Jia, J. Chen, G. Chang, Z. Tan, Energy efficient coverage control in wireless sensor networks based on multi-objective genetic algorithm, Computers and Mathematics with Applications 57 (11–12), pp. 1756–1766, 2007.
[24] J. Jia, J. Chen, G. Chang, Y. Wen, J. Song, Multi-objective optimization for coverage control in wireless sensor network with adjustable sensing radius, Computers and Mathematics with Applications 57 (11–12), pp.1767–1775, 2009.
[25] K. Deb, A. Pratap, S. Agarwal, T. Meyarivan, A fast and elitist multiobjective genetic algorithm: NSGA II, IEEE Transactions on Evolutionary Computation Vol.6, No. 2, pp.182–197, 2006.
[26] ABRAHAM A., JAIN L., GOLDBERG R.: ‘Evolutionary multiobjective optimization: theoretical advances and applications’, 2005.
[27] N. Bulusu, J. Heidemann, D. Estrin, GPS-less low-cost outdoor localization for very small devices, IEEE Personal Communications 7, pp.28_34, 2000.
[28] H. Zhang, J.C. Hou, Maintaining sensing coverage and connectivity in large sensor networks, Ad-hoc and Sensor Wireless Networks Vol. 1, pp.89_124, 2005.
[29] W. Heinzelman, A. Chandrakasan and H. Balakrishnan, Energy-Efficient Communication Protocol for Wireless Microsensor Networks, Proceedings of the 33rd Hawaii International Conference on System Sciences (HICSS '00), January 2000.
[30] The Network Simulator - NS-2. http://www.isi.edu/nsnam/ns/.