

Solving wireless sensor network coverage problem using LAEDA

Shirin Khezri¹, Mahdi Nazaari A²

¹Department of Computer Engineering and Information Technology, Payame Noor University, Iran

²Department of Mathematics, Payame Noor University, Iran

Article Info

Article history:

Received Aug 28, 2019

Revised Nov 2, 2019

Accepted Nov 16, 2019

Keywords:

Distributed sensor network

LAEDA

Sensor placement

Wireless sensor network

ABSTRACT

Coverage improvement is one of the main problems in wireless sensor networks. Given a finite number of sensors, improvement of the sensor deployment will provide sufficient sensor coverage and save cost of sensors for locating in grid points. For achieving good coverage, the sensors should be placed in adequate places. In this article, estimation of distribution algorithm based on learning automata is presented for solving the sensor placement (LAEDA-SP) in distributed sensor networks by considering two factors: 1) the complete coverage and 2) the minimum costs. The proposed algorithm is a model based on search optimization method that uses a set of learning automata as a probabilistic model of high-quality solutions seen in the search process. It is applied in a various area with different size. The results not only confirmed the successes of using the new method in sensor replacement but also they showed that the proposed method performs more efficiently compared to the state-of-the-art methods such as simulated annealing (SA) and population-based incremental learning algorithms (PBIL).

*Copyright © 2020 Institute of Advanced Engineering and Science.
All rights reserved.*

Corresponding Author:

Shirin Khezri,

Department of Computer Engineering and Information Technology,

Payame Noor University,

POBOX 19395-3697, Tehran, Iran.

Email: sh.khezri@pnu.ac.ir

1. INTRODUCTION

In distributed sensor networks, the sensor placement is NP-complete for arbitrary sensor fields and it is one of the most important issues in the research fields. A sensor network can arrange in two ways, one as a random placement and the second as a grid-based placement. Once the surrounding is unknown the random placement is the only option and the sensors may be disintegrated everywhere but when the features of the network were known before, then the sensor placement could be done with great scrutiny and we could guarantee the quality of providing services along with satisfying the limitations. The strategy of sensor placement depends on the application of the distributed sensor network (DNS). In this article, the focus is on the grid-based placement.

Recent years have witnessed an increased interest in the use of wireless sensor networks (WSNs) in numerous applications such as forest monitoring, disaster management, space exploration, factory automation, secure installation, border protection, and battlefield surveillance [1-6].

In [7-10], some literature survey are presented to address number of subjects such as, the challenges in WSN, different security mechanisms to protect data from attackers, and reduction of the gap between application and technology. The structure of sensor nodes is presented in [11-12], and [13-14] discuss about how the WSNs work.

Several deployment strategies have been studied for achieving an optimal sensor network architecture which would minimize cost, provides high sensing coverage, be resilient to random node failures, and so on. Some of the deployment algorithms try to find new optimal sensor locations after an initial random placement and move the sensors to those locations, achieving maximum coverage. In [15], a systematic grid distribution of outdoor sensor distribution is proposed to find a sufficient number of sink nodes (gateways) to provide connectivity. The objective of this paper is to evaluate the performance of long range (LoRa) shadowed radio links, typical in urban and semi urban centers, together with node grid distribution and optimal sink node placement using measures of connectivity and packet loss ratios. In [16] and [17], they present a resource-bounded optimization framework for sensor resource management under the constraints of sufficient grid coverage of the sensor field. In [18], they formulate the sensor placement problem in terms of cost minimization under coverage constraints. In [19] Node placement in heterogeneous WSN is formulated using a generalized node placement optimization problem to minimize the network cost with lifetime constraint and connectivity. In [20] they formulate and solve the sensor placement problem for efficient target localization in a sensor network, they develop a mathematical framework for the localization of the missile using multiple sensors based on Cramer-Rao Lower Bound (CRLB) analysis. In [21] they present the practical problem of optimally placing the multiple PTZ cameras to ensure maximum coverage of user-defined priority areas with optimum values of parameters like pan, tilt, zoom and the locations of the cameras. Moreover, in [22] a heuristic algorithm is proposed based on Simulation Annealing Algorithm to solve this problem considering the coverage and cost limitations.

In this article, the Learning Automata based Estimation of Distribution Algorithm (LAEDA) [23] is applied for solving these NP-complete problems. This algorithm as an estimation of distribution algorithm for a class of EDAs in which there is no dependency between variables. The LAEDA is a simple EDA that ignores all the variables interactions. Since this algorithm belongs to no dependency model, it will be compared with PBIL that is the most famous algorithm of the class no dependency model and simulated annealing algorithm [22].

The rest of the article is organized as follows. In Section 2, we address the definition of sensor placement problem and its mathematical model. In Section 3, we present the proposed algorithm. The results and discussion are addressed in Section 4 and finally in Section 5 the conclusions will be presented.

2. SENSOR PLACEMENT PROBLEM

In this section, we first address the definition of sensor placement and then present its mathematical model.

2.1. Definition of Sensor Placement

The sensor network based on grid-based could be considered as a two or three-dimensional network [24]. A set of sensors are settled on the grid points to monitor the sensor area. In this article, we consider the detection model of a sensor to be a 0/1 coverage model. Now if the Euclidean distance between the grid point and the sensor is less than the detection radius of the sensor ($d < r$), so the coverage is assumed to be full (1); otherwise, the coverage is assumed to be ineffective (0). If any grid point in a sensor field can be detected by at least one sensor, we call the field is completely covered, as shown in Figure 1. A power vector is defined for each grid point to indicate whether sensors can cover a grid point in a field. In Figure 1, a completely covered and discriminated sensor field of 7*4 with radius =1 is illustrated, that a target can be detected at any place in the field. In Figure 2, the power vector for point 19 is (0, 0, 0, 1, 0, 1, 0, 0) corresponding to sensor 3, 7, 8, 12, 14, 18, 23 and 27. In a completely covered sensor field, when each grid point is identified by a unique power vector, the sensor field is said to be completely discriminated, as shown in Figure 1. In this case, as soon as a target occurs in a grid of sensor field, it can be located by the back-end according to power vector of the grid.

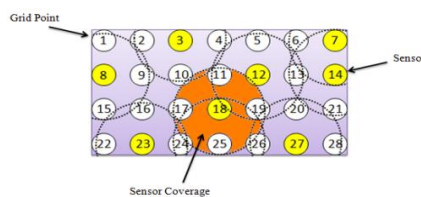


Figure 1. A complete covered and discriminated sensor field with radius =1, achieved by the proposed algorithm

2.2. Mathematical Model

The sensor placement problem is an NP-complete problem and is formulated here as a combinatorial optimization problem. The formulation can plan a sensor network that provides either complete or high, discrimination, depending on the cost limitation.

Given Parameters:

$A = \{1, 2, \dots, m\}$: Index set of the sensor's candidate locations.

$B = \{1, 2, \dots, n\}$: index set of the location in the sensor field, $m \leq n$.

r_k : Detection radius of the sensor located at k , $k \in A$.

d_{ij} : Euclidean distance between location i and j , $i, j \in B$.

c_k : The cost of the sensor located at k , $k \in A$.

G : Total Cost limitation

Decision Variables:

y_k : 1, if a sensor is allocated at location k and 0 otherwise, $k \in A$.

$pv_i = (pv_{i1}, pv_{i2}, \dots, pv_{ik})$: The power vector of location i , where pv_{ik} is 1 if the target at location i can be detected by the sensor at location k and 0 otherwise, where $i \in B, k \in A$.

Objective Function:

Objective Function is cost limitation and the complete coverage that cost limitation formula is in (1).

$$\sum_{k=1}^m c_k y_k \leq G \quad (1)$$

3. PROPOSED ALGORITHM

A branch of population-based non-deterministic revelation algorithms has been proposed, called "distribution estimation algorithms" which like genetic algorithms, do not require a smooth search space and complex differential equations, and in addition solved many problems of genetic algorithms. In distribution estimation algorithms, by constructing a probabilistic model of the genome components, the velocity increases to the optimal solution of the problem. In these algorithms, new populations are not created using mutation and crossover operators. New genomes are estimated based on probabilistic distribution and are sampled and made based on selected genomes from previous generations.

In [13], a model of estimation of probability distribution algorithms, namely LAEDA is introduced by Rastegar and Meybodi. LAEDA algorithm can be represented as a seven-dimensional vector as $\langle N, Se, \mu, f, M, \phi, \psi \rangle$, N number of genomes in each generation, Se number of selected genomes, μ penalty probability parameter, f evaluation function, M sets of learning automata corresponding to genome constructor variables, ϕ reward mechanism to learning automata and finally function ψ that maps the learning automata actions to the variables value.

In this algorithm, the assumption is that genome variables are independent, and a learning automaton is used for each variable in the genome. The number of learner automata operations is equal to the number of permitted values for the corresponding variable. To build each genome sample, we first ask the learning automaton of each variable to select the desired action and then assign its corresponding variable to the corresponding value of the selected action. Therefore, the probability of constructing the genome $X = (x_1, \dots, x_n)$ is given by eq.2.

$$P(X = x) = \prod_{i=1}^n P(X_i = x_i) = \prod_{i=1}^n Grad_i^j \quad (2)$$

That $Grad_i^j$, $1 \leq j \leq r_i$ is the probability of choosing action j corresponding to x_i using the i -th learning automata. At each step, using the learning automata based on the population, N genomes are constructed.

Then a new population is evaluated by the evaluation function, then the best Se genomes are selected. After applying a mechanism that depends on the learning automata environment model, a reinforcement signal vector is constructed and done learning about each learning automaton. After the new generation learning is done, the above steps are repeated until the stop condition is reached. The LAEDA algorithm is extended to solve the sensor placement problem in Figure 2 as follows.

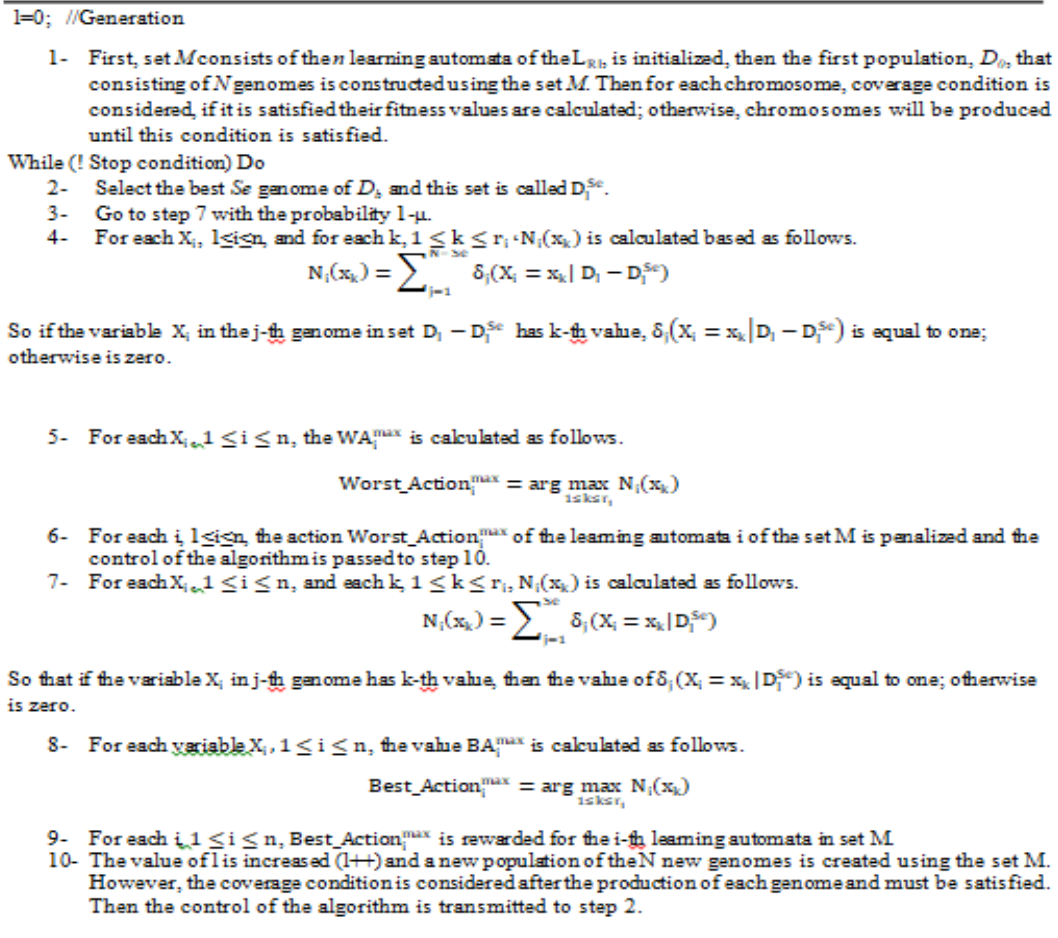


Figure 2. The proposed LAEDA-SP

4. RESULTS AND DISCUSSION

In this section, we perform several experiments to compare the performance of LAEDA-SP to several state-of-the-art methods using several different area.

4.1. Experimental Setup

This section presents the computational results. First, the performance of the proposed algorithm is evaluated when small sensor fields are deployed. The purpose of the experiment is to examine whether the algorithm can find the optimal solution under a minimum cost constraint. Then, the performance results in the case of larger sensor fields are presented under various cost constraints.

The parameters of PBIL and LAEDA-SP are set as Table 1. In the table, *Pop-Size* means population size in each generation, *Pm* means mutation probability, *LR* means learning rate and *Se* is selection genomes for next generation across current generation.

In LAEDA and PBIL algorithms, a high value of *Se* genomes has chosen for updating the genome's probability model. In all experiments, we assume the value of *Se* as a value equals to half of the population of each generation and Learning Rate is 0.01. In SA algorithm, the parameters of the cooling schedule are $\alpha=0.75$ and $\beta=1.3$. The initial values of r and t are respectively $5n$ and 0.1 and n is the number of grids in the sensor field. The frozen temperature, t_f , is $t_0/30$. Each algorithm runs 10 times for each problem and average results for different areas are calculated and compared in Table 2. The algorithms are implemented in Matlab (v 7.6) on a personal computer (3G).

Table 1. The Parameters of PBIL and LAEDA

| Parameters | Pop-Size | Pm | LR | Se |
|------------|----------|-----|------|-------|
| LAEDA-SP | 50 | - | 0.01 | Pop/2 |
| PBIL | 50 | 0.2 | 0.01 | Pop/2 |

4.2. Result I

Experiment I evaluates the performance of the proposed algorithm for smaller rectangular sensor fields that have no more than 30 grid points. The results are compared with SA [22] and PBIL [25].

First, we find a minimum sensor density for a completely covered and discriminated sensor field. Then, an attempt is made to obtain the better result by using the proposed algorithm under a sensor density constraint.

Table 2 shows the number of sensors used by three algorithms when they cover the sensor field with various areas completely. In all cases, the proposed algorithm achieves the best deployment with a minimum sensor density. The required sensor density is between 25% and 37.5%. Figure 3 confirms the superiority of the proposed algorithm against the PBIL and SA algorithms considering Sensor density (in #Sensors) vs. target area parameter.

Table 2. Comparison of two algorithms and the proposed algorithm for some target area values

| Area | #Sensors | | | LAEDA-SP's Sensor Density |
|------|----------|------|-----------|---------------------------|
| | SA | PBIL | LAEDA-SP | |
| 4*3 | 6 | 6 | 4 | 0.33 |
| 4*4 | 7 | 6 | 4 | 0.25 |
| 6*3 | 8 | 8 | 6 | 0.33 |
| 6*4 | 10 | 9 | 7 | 0.29 |
| 7*3 | 9 | 8 | 7 | 0.33 |
| 8*3 | 10 | 10 | 9 | 0.375 |
| 9*3 | 11 | 10 | 9 | 0.33 |
| 5*3 | 6 | 6 | 5 | 0.33 |
| 5*5 | 10 | 10 | 9 | 0.36 |
| 6*5 | 12 | 11 | 10 | 0.33 |
| 7*4 | 12 | 11 | 9 | 0.32 |
| 10*3 | 12 | 12 | 11 | 0.36 |

As all sensors have the same deployment cost, the cost constraint, constraint (1), can be express as a limit on the number of sensors. This section uses a normalized term, sensor density, in the constraint. Sensor density is defined in (3).

$$Sensor\ density(\%) = \left(\sum_{k=1}^m \frac{y_k}{n} \right) \times 100\% \tag{3}$$

Where: $y_k = \begin{cases} 1, & \text{if a sensor is allocated at location } k \\ 0, & \text{otherwise} \end{cases}$, n is the number of grids in sensor field.

The proposed algorithm can achieve completely covered placement at a very low sensor density.

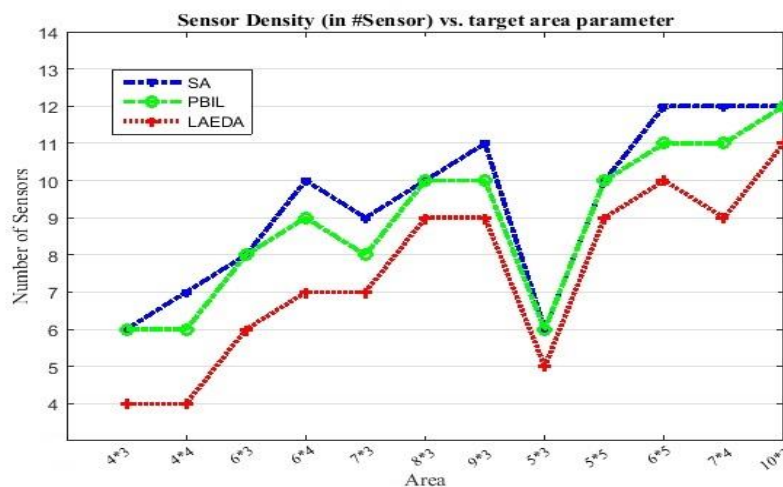


Figure 3. Sensor density (in #Sensors) vs. target area

4.3. Result II

In this experiment, a larger sensor area, with 15×15 grid points is considered. The radius of each sensor is one. The results obtained using the proposed algorithm is compared with the best solution obtained by the PBIL approaches. The best solution that has a minimum objective value is founded in 1000 arbitrarily generated solutions. Figure 4 shows that the required density for the desired solution obtained by the proposed algorithm 51% in 1000 arbitrarily generation. In contrast, the other approach is associated with a relatively high density (58% and 62%). The proposed algorithm can achieve completely covered placement at a very low sensor density. LAEDA-SP gives better results especially in larger networks compared to PBIL algorithm due to using algorithm's evolution rate, so it can operate better than PBIL and SA in scalability parameter.

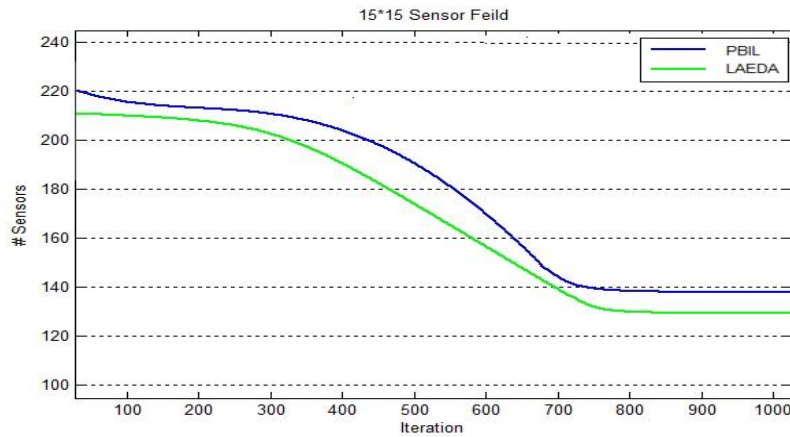


Figure 4. Sensor density (in #Sensors) for 15*15 sensor field

In following, the sensor environment is plotted for various size of an area, resulting from the proposed algorithm for better representation. Figures 5 and 6 show sensor network 6*4 and 4*3 respectively that the proposed algorithm with 7 and 4 sensors can cover respectively under the minimum cost and full coverage.

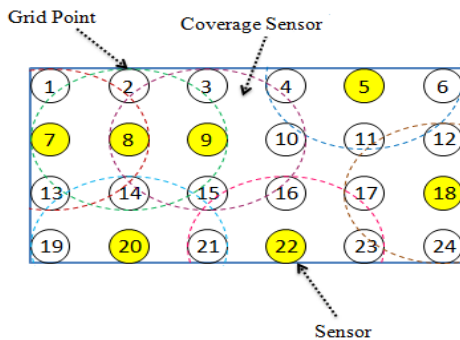


Figure 5. A complete covered in area 6*4

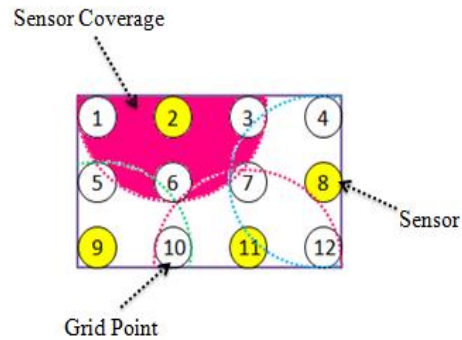


Figure 6. A complete covered in area 4*3

5. CONCLUSION

In this article, we describe the sensor deployment problem for locating targets under constraints (complete coverage of sensor network with minimum number of used sensors for coverage). We use the proposed method of LAEDA-SP for solving the problem. The results show the proposed algorithm is more efficient than other methods like PBIL and SA in solving the optimization problem in large sensor fields. The proposed algorithm can achieve completely covered placement at a very low sensor density. Since sensor deployment in the Wireless Sensor Networks (WSN) is important, more efficient intelligent algorithms should be found.

REFERENCES

- [1] I.F. Akyildiz, W. Su., Sankarasubramaniam, E. Cayirci, "Wireless Sensor Networks: a survey", Computer Networks, Georgia Institute of Technology, *IEEE* 38 (2002) 393-422.
- [2] C-Y. Chong, S.P. Kumar, "Sensor Networks: Evolution, Opportunities, and Challenges", Proceedings of the IEEE 91 (8) (2003) 1247-1256.
- [3] Quoc-Anh, G., Dinh-Chinh, N., Duc-Nghia, T., "Wireless Technology for Monitoring Site-specific Landslide in Vietnam", International Journal of Electrical and Computer Engineering (IJECE), Vol.8, No.6, pp. 4448-4455, 2018.
- [4] Salih Ali, N., Alkareem Alyasseri, Z.A., Abdulmohson, A., "Real-time Heart Pulse Monitoring Technique Using Wireless Sensor Network and Mobile Application", International Journal of Electrical and Computer Engineering (IJECE), Vol.8, No.6, pp. 5118-5126, 2018.
- [5] Basavaraj G.N, Jaidhar C.D, "Low latency and energy efficient cluster based routing design for wireless sensor network," Indonesian Journal of Electrical Engineering and Computer Science (IJECS), Vol. 13, No. 2, 2019.
- [6] A. Davis and H. Chang, "A Survey of Wireless Sensor Network Architectures," International Journal of Computer Science and Engineering Survey, vol. 3, pp. 1-22, 2012.
- [7] T. Bala, et al., "A Survey: Issues and Challenges in Wireless Sensor Networks", International Journal of Engineering and Technology, vol. 7, pp. 53-55, 2018.
- [8] R. Sudha and B. Shamile, "A Survey on Wireless Sensor Networks," International Journal of Engineering Science and Research Technology, vol. 6, pp. 66-71, 2017.
- [9] N. Singh and K. Rautela, "Literature Survey on Wireless Sensor Network," International Journal of Engineering and Computer Science, vol. 5. pp. 17544-17548, 2016.
- [10] K.T. Kishor, et al., "A Fundamental Implementations and Working Principles of Wireless Sensor Networks," Comp-soft, vol. 4, pp. 2030-2035, 2015.
- [11] K. N., Jyoti Metan, K. N. Narashinha Murthy, "N-tier modelling of robust key management for secure data aggregation in wireless sensor network", International Journal of Electrical and Computer Engineering (IJECE), Vol. 9, No. 4, pp. 2682-2690, 2019.
- [12] A. Basim, A. Yasser Kareem, "Lifetime enhancement for clustering protocols in heterogeneous wireless sensor networks", Indonesian Journal of Electrical Engineering and Computer Science (IJECS), Vol. 14, No. 3, pp. 1305-1314, 2019.
- [13] J. Youngjun, et al, "Design and implementation of heterogeneous surface gateway for underwater acoustic sensor network", International Journal of Electrical and Computer Engineering (IJECE), Vol. 9, No. 2, pp. 1226-1231, 2019.
- [14] H.M.A. Fahmy, "Protocol Stack of WSNs. "Wireless Sensor Networks", Springer, Singapore, 2016. 55-68.
- [15] Bt. Zainal, N. A., Habaebi, M. H., Chowdhury, I. J., Rafiqul Islam, M., "Gateway sink placement for sensor node grid distribution inLoRa smart city networks", Indonesian Journal of Electrical Engineering and Computer Science (IJECS), Vol. 14, No. 2, pp. 834-842, 2019.
- [16] S.S. Dhillon, K. Chakrabarty, and S. Iyengar, "Sensor Placement for Grid Coverage under Imprecise Detections," Proc. of the Fifth International Conference on Information Fusion, 2002, Vol. 2, No.3, pp. 1581-1587, July 2002.
- [17] S.S. Dhillon and K. Chakrabarty, "Sensor Placement for Effective Coverage and Surveillance in Distributed Sensor Networks," Proc. of IEEE WCNC 2003, Vol. 3, pp. 1609-1614, March 2003.
- [18] K. Chakrabarty, S.S. Iyengar, H. Qi, and E. Cho, "Grid Coverage for Surveillance and Target Location in Distributed Sensor Networks," IEEE Trans. on Computers, Vol. 51, No. 12, Dec. 2002.
- [19] Sasikumar, P., Vasudevan, S. K., Vivek, C., Subashri, V., "Heuristic Approaches with Probabilistic Management for Node Placement in Wireless Sensor Networks", International Journal of Recent Trends in Engineering, Vol. 2, No. 4, November 2009.
- [20] Rajagopalan, R., Niu, R., Mohan, Ch. K., Varshney, P. K., Drozd, A.L., "Sensor placement algorithms for target localization in sensor networks", IEEE Radar Conference, pp. 1-6, 2008.
- [21] Indu, S., Chaudhury, S., Mittal, N. R., Bhattacharyya, A., "Optimal Sensor Placement for Surveillance of Large Spaces", Distributed Smart Cameras, Third International Conference on Digital Object Identifier, pp. 1-8, ICDCS 2009.
- [22] Frank Y. S. Lin and P. L. Chiu, "A Near-Optimal Sensor Placement Algorithm to Achieve Complete Coverage/Discrimination in Sensor Networks", IEEE Communication letters, Vol. 9, No. 1, January 2005.
- [23] Rastegar, R., and M. R. Meybodi, "A New Estimation of Distribution Algorithm Based on Learning Automata", To Appear in the Proceedings of IEEE Conference on Evolutionary Computation, UK, 2005.
- [24] Dhillon, S.S., Chakrabarty, K., Iyengar, S.S., "Sensor Placement for Grid Coverage under Imprecise Detections", Proceedings of the Fifth International Conference on Information Fusion, (2002).
- [25] Baluja, S., "Population Based Incremental Learning: A Method for Integrating Genetic Search Based Function Optimization and Competitive Learning", Technical Report CMU-CS-94-163, Carnegie Mellon University, Pittsburgh, Pennsylvania (1994).