Anonymous selection optimization approach for covering Targets in wireless sensor networks

RAJA RAVISANKAR.R, J. MANGAYARKARASI & R. SUJATHA

Abstract— **In recent scenario, wireless sensor network made a vital role in communication stream. Coverage of target with prolonged life time in the sensor nodes makes a large gap of development stairs. When we go for target coverage of sensor nodes, it leads to two different paths. One, the time domain optimization of sensor coverage with some lack of improved life time span and also the more complexity of optimized process. Second, the space domain optimization which require less complexion with high level of prolonged life time process and improved target coverage too. The study portrays about the introduction of upper bound on the network life time from time based formulation. From that the conversion process is made with set coverage pattern based solution, where it converts the time domain solution into space domain solution. At last the target coverage with prolonged lifetime is optimized using Anonymous selection Optimization process in the space domain process. The result gave the most high level life span process for the sensor nodes with highest target coverage compared with the previous optimized process.**

Keywords: *Time domain optimization, Target coverage, Pattern based set cover method, Space domain optimization, Particle Swarm Optimization.*

I. INTRODUCTION

In the past decades, wireless sensor network (WSN), one of the fastest growing research areas, has been attracted a lot of research activities. Due to the maturity of embedded computing techniques and wireless communication techniques, significant progress has been made. Typically, a WSN consists of a large number of small sensors that can sense and monitor the physical world, and thus it is able to provide rich interactions between a network and its surrounding physical environment in a real-time manner. More recently, the cyber physical system (CPS) has also emerged as a promising way of bridging the physical and virtual worlds [4]. A CPS may involve multiple WSNs and other types of networks like mobile ad hoc network (MANET), wireless mesh network (WMN), vehicular ad hoc network (VANET), etc. Connecting these heterogeneous networks usually relies on the Internet. Therefore, CPS is featured by cross-domain cooperation, heterogeneous information flow, and intelligent decision.

- *Mr. Raja Ravisankar.R is currently pursuing masters degree program in Communication Systems engineering in Anna University, Tamilnadu, India,PH-919942421464. E-mail: ravisankar82@gmail.com*
- *Mrs. Mangayarkarasi .J is currently working as a Asst. Professor in Dept. of Electronics & Communication Engineering in Anna University, Tamilnadu, India.*
- *Mrs. Sujatha .R is currently working as a Asst. Professor in Dept. of Electronics & Communication Engineering in RVS College of Engineering, Tamilnadu. India.*

The time is divided into time slots and we assume that the sensors have synchronized clocks which notify them at the beginning of each time slot. Sensor has an initial energy and, as normalization, we assume that every sensor consumes *e* units of energy in each time slot in which it is active. For saving energy, a sensor may be in a sleep mode, in which it does not communicate with its neighbors nor sense its vicinity. A senor in the sleep mode consumes only negligible unit energy, which is assumed to be zero. This is also called duty-cycling WSNs.

II. ENERGY-EFFICIENT COVERAGE (EEC) PROBLEM

A. Probabilistic Sensor Detection Model

We introduce here the probabilistic sensor detection model, a model that has a more realistic approach to solving the EEC problem compared to previous models. Practical sensors detect the event being monitored (e.g., heat, pressure, force, etc.). The probabilistic sensor model considers the uncertainty of event detection, unlike the Boolean disc model, and assumes that the detection probability is a continuously and exponentially decreasing function of the distance between the PoI and the center of the sensor. Wireless Sensor Networks (WSNs) are based on the cooperation of a number of typically tiny sensors that consist of four parts: sensor, processor, transceiver, and battery (as energy source). The sensor gets information from the surrounding areas or from target points, and the processor changes the analog information obtained to digital information. Then, the transceiver transmits the converted information to the gateway (or base station) directly, or through neighboring sensors. This device is a low-cost, low-power, and multifunctional tiny embedded system.

In recent years, the field of embedded systems has grown exponentially, and there is currently an active study of WSNs. WSN applications are used to monitor the surrounding environment in a wide range of areas, for example, medical, security, military, and agricultural industries; in air pollution monitoring to detect the concentration of dangerous gases; in greenhouse monitoring to control temperature and humidity levels inside greenhouses; water/wastewater monitoring to detect pollutants; to control the water levels in dams, among Others.

The Efficient-Energy Coverage (EEC) problem is one of the important issues to consider in WSN implementation. The sensors in most WSNs typically use batteries, but it is generally infeasible to replace or recharge all the batteries. Many techniques have been proposed to conserve energy and prolong the network's lifetime. Among them, scheduling methods, which reduce energy consumption by planning the activities of the devices, have been shown to be effective. These activity scheduling methods need to have devices densely deployed in an interest area. Then, only part, or a subset, of the devices accomplish the sensing task, while the other devices can be scheduled into a sleep state to save energy. By scheduling the devices' activities from active to sleep, or *vice versa*, this method needs only a subset of the devices for monitoring an area of interest at any time. Therefore, the lifetime of the WSN is prolonged. To achieve a longer lifetime, it is important to find the maximum number of disjoint subsets of devices in the scheduling method. Many scheduling algorithms have been proposed to solve the EEC problem.

The EEC problem was converted into a binary integer programming problem to make a greedy algorithm. Intelligent optimization algorithms were also used to schedule The devices activities, includes Genetic Algorithms (GAs), Anonymous Selection Optimization (ASO) algorithms and Ant Colony Optimization (ACO) algorithms. In this paper, we propose an alternative method to solve the EEC problem by an ACO algorithm unlike the ACO algorithm in, where the ACO algorithm simply followed the lead of the previous entity that applied it the first time and is hence, not optimized for better performance. The ACO algorithm is based on swarm intelligence, where complex collective behavior emerges from the behavior of many simple agents. The first Ant System (AS) algorithm was successfully applied in combinatorial optimization problems, such as the Traveling Salesman Problem (TSP) and the Quadratic Assignment Problem (QAP).The EEC problem, with scheduling, is also an applicable combinational optimization problem.

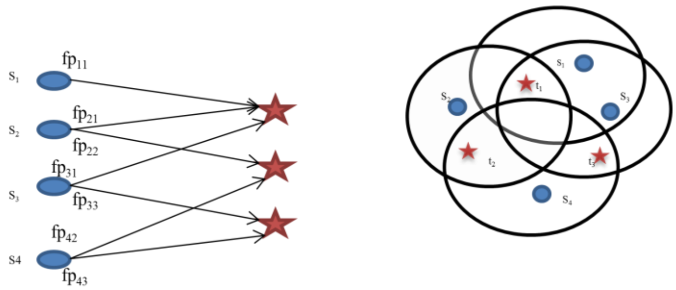

Fig. 1 Example with three targets and four sensors

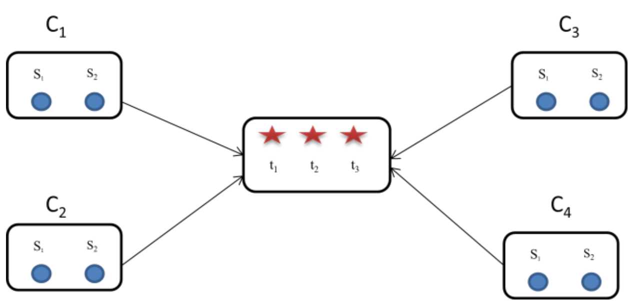

Fig. 2 Illustration of four sensor covers

B. Experiments on Area-Coverage Problems

The characteristics of the nine area-coverage cases with different numbers *N* of sensors and sensing ranges *R* are Presented in the area-coverage cases, the grid size *d* is set so that the resolution of grids is big enough. The value of n_F shows that the number of target fields to be covered in the area-coverage problems is

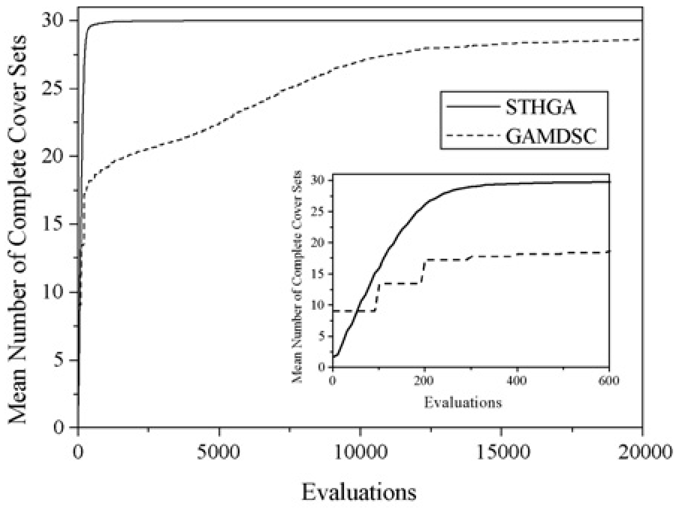

Fig.3 Average optimization curves of STHGA and GAMDSC when solving the point-coverage Case 1 (N = 90 and the maximum number of disjoint cover sets is 30). The inner figure shows more details within the first 600 evaluations.

Much larger than the number of targets in the point-coverage Problem in the previous subsection. By comparing the time used by STHGA and MCMCC for achieving the optimal solution, the computation speed of STHGA is much faster than that of MCMCC. Take Case 5 as an example, the average time used by STHGA 767 ms, which is shorter than 1s, whereas MCMCC needs 766 ms, which is approximately 82s. The reason why MCMCC uses a longer time than STHGA is because of its mechanism in building cover sets. MCMCC builds each cover set by successively adding a sensor to the set until all fields have been covered. Before each step for choosing a sensor, a new critical field that is formed by the remaining sensors to the uncovered fields must be determined. Then each of the sensors that cover the new critical field is evaluated by an objective function. The sensor that has the maximum function value is selected into the cover set. The worst runtime of MCMCC is O (N_2) and it needs to calculate the values of its objective function several times for choosing an unselected sensor to a new cover set. Because the update of the critical field and the calculation of the objective function are time-consuming, MCMCC generally uses a long time before termination. When the number and positions of sensors are fixed in the target area, the sensing ranges of sensors influence the lifetime of the WSN. Without considering the energy consumption by different sensing ranges, a sensor deployment with 400 sensors using sensing ranges from 1 to 50 is checked. The numbers of complete cover sets that are achieved by the three algorithms are the same when *R* = 6 to 8. However, for the larger sensing ranges (*R* > 8), the performance of GAMDSC becomes worse than both STHGA and MCMCC. Fig. 3 shows that the results obtained by STHGA and GAMDSC are identical when *R* = 6 to 32. When *R* = 33 to 50, STHGA performs better than GAMDSC. The computation time of STHGA increases rapidly after $R > 33$, during which MCMCC fails to find the optimal solution. Even though MCMCC has terminated with a suboptimal solution, STHGA continues to search for better solutions.

III. Problem Description

The formal definition of the minimum energy network connectivity (MENC) problem is given as follows given a set of n wireless nodes $V = \{n_1,\ldots,n_n\}$ and a set E of edges or links constructed in such a manner that there is a directed edge only if u can reach v using its maximum transmission power. The graph $G(V, E)$ sets an upper bound on the maximum connectivity that a wireless network can have. The MENC problem consists in to determinate a topology T (a sub graph of G) strongly connected such that, the total energy consumption of the network is minimized. The total energy is computed as follow:

$$TE = \sum_{i=1}^{n} p_i, \qquad (1)$$

Where p_i denotes the power assigned to sensor node n_i. The network model and energy consumption follow the Similar assumptions. The sensors in the network are stationary and located in a two dimensional plane (the location of each sensor is fixed after deployment). The location information will be used for calculating the distance between two sensor nodes.

The sensors radiate and receive equally in all directions (omni directional antenna). If a sensor i transmit with a power level

$$p_i = d^2, \qquad (2)$$

Then any sensor within the distance d can receive the signal. Suppose there are two nodes n_i and n_j then the distance between these two nodes can be calculated by using the Euclidean distance,

$$d = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}, \qquad (3)$$

Where (x_i, y_i) e (x_j, y_j) are the position coordinates of Sensors n_i and n_j, respectively. Sensor nodes can operate in different initial power levels, with a lower and an upper bound.

IV. CG AND ASO BASED APPROACH

CG-Based Approach

The CG-based approach is effective in the feasible domain and requires some initial basic feasible solutions (BFSs) to start with. The effectiveness of this approach can be enhanced by the quality of the initial BFS. Therefore, to achieve a high convergence speed, it is important to develop methods for obtaining good initial BFS. Here, we use the random-selection algorithm (Algorithm 1) that was proposed in our previous paper. The complexity of the random-selection algorithm is O(n), where n is the number of sensors. Generally speaking, for one instance, the convergence speed of the CG-based approach increases as the number of initial patterns increases. Thus, it is preferable to use RSA to generate multiple initial coverage patterns.

ASO Based Approach

The ASO algorithm is initialized with a population of Random candidate solutions, conceptualized as particles. Each particle is assigned a randomized velocity and is iteratively moved through the problem space. It is attracted towards the location of the best fitness achieved so far by the particle itself and by the location of the best fitness achieved so far across the whole population (global version of the algorithm).

The ASO algorithm includes some tuning parameters that greatly influence the algorithm performance, often stated as the exploration–exploitation tradeoff: Exploration is the ability to test various regions in the problem space in order to locate a good optimum, hopefully the global one. Exploitation is the ability to concentrate the search around a promising candidate solution in order to locate the optimum precisely. Despite recent research efforts, the selection of the algorithm parameters remains empirical to a large extent.

Algorithm ASO

```
01. Generate a population of N particles {x_1^0, ..., x_N^0};
02. For each particle i, (i := 1,...,N) set xb_i^0 := x_i^0;
03. t := 0;
04. While StoppingCriterion = false do
    05. For each particle x_i^t, apply repairing procedure
        (if necessary) and improving procedure;
    06. Find the global best particle g^t;
    07.  t := t + 1;
    08. For each particle i, update the velocity v_i^t and
        the position x_i^t;
    09. For each particle i, find the personal best
        position xb_i^t;
10. End-While.
11. Return the best particle g^(t-1)
```

Figure 4. Pseudo-code of the ASO heuristic.

V. RESULTS AND DISCUSSION

We use both CG-based and ASO based approaches to solve this instance, and the results are shown in Fig. 6 (UPP stands for the lifetime upper bound). to determine the optimal lifetime within 63 iterations. On the other hand, in the case of the revised CG-based approach, 0.78s are required for determining the same optimal solution within 11 iterations. In the CG-based approach, the lifetime obtained. The present work gives some additional insight into the PSO parameter selection topic. It is established that some of the parameters add no flexibility to the algorithm and can be discarded without loss of generality. Results from the dynamic system theory are used for a relatively simple theoretical analysis of the algorithm which results in graphical guidelines for parameter selection. The user can thus take well-informed decisions according to the desired exploration–exploitation tradeoff: either favor exploration by a thorough sampling of the solution space for a robust location of the global optimum at the expense of a large number of objective function evaluations or, on the contrary, favor exploitation resulting in a quick convergence but to a possibly non-optimal solution. Not surprisingly, the best choice appears to depend on the form of the objective function. The newly established parameter selection guidelines are applied to standard benchmark functions.

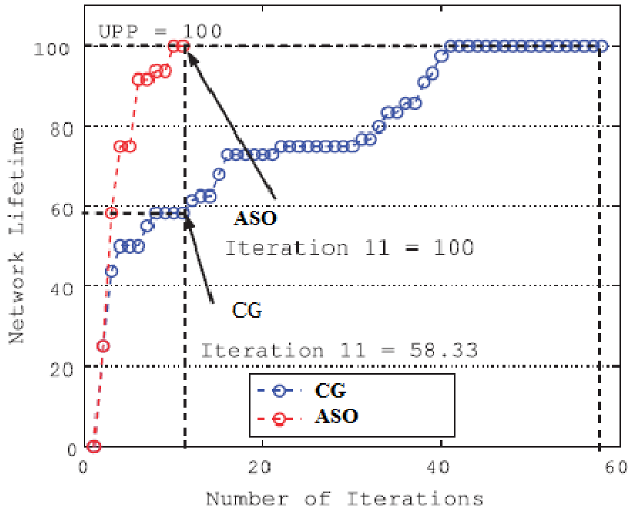

FIG 5. COMPARISON OF ASO & CG BASED APPROACH

VI. CONCLUSION & FUTURE WORK

In this paper, we have built a general framework to analyze and tackle the target coverage problem in sensor networks. We studied the problem in time domain and obtained several unique results. First, we showed that by exploiting the time-dependant formulation we can obtain a lifetime upper bound in a LP form, which could serve as a performance benchmark. Then, by transforming the problem from time to space domain, we have verified the set cover based method that has been widely used in previous work. Lastly, we have developed a specialized particle swarm optimization approach to solve the problem in information, and can be performed faster .The theoretical results in this paper can serve as performance benchmark to evaluate these algorithms. routing and coverage problem. One of our future work will focus on building distributed algorithms which do not require global the problem of delivering sensed data among the network. Therefore, it would be better to jointly consider the joint data method. We prove that this method maintains the optimality while reducing computation complexity significantly.

As for future work, there are several potential extensions. For example, in this paper, we have not considered The sub optimization, which is the hardcore of the whole problem, has been solved by a novel relaxation and rounding space domain optimally. It decomposes the space-based formulation into sub formulations that are then solved iteratively.

ACKNOWLEDGMENT

I thank Dr. V.Malathi, Dean and Mrs.J. Mangayarkarasi, Asst. Professor of ECE in Anna University, Regional Centre-Madurai for their support in guidance and also I thank our staffs and Students for their timely help.

REFERENCES

[1] I.F. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci, “A Survey on Sensor Networks,” IEEE Comm. Magazine, vol. 40, no. 8, pp. 102-114, Aug. 2002.
[2] W. Song, R. Huang, M. Xu, B.A. Shirazi, and R. Lahusen, “Design and Deployment of Sensor Network for Real-Time High-Fidelity Volcano Monitoring,” IEEE Trans. Parallel and Distributed Systems, vol. 21, no. 11, pp. 1658-1674, Nov. 2010.
[3] C. Liu, K. Wu, and J. Pei, “An Energy-Efficient Data Collection Framework for Wireless Sensor Networks by Exploiting Spatiotemporal Correlation,” IEEE Trans. Parallel and Distributed Systems, vol. 18, no. 7, pp. 1010-1023, July 2007.
[4] E.A. Lee, “Cyber Physical Systems: Design Challenges,” Proc. IEEE Symp. Object Oriented Real-Time Distributed Computing (ISORC), May 2008.
[5] F.-J. Wu, Y.-F. Kao, and Y.-C. Tseng, “From Wireless Sensor Networks Toward Cyber Physical Systems,” Pervasive and Mobile Computing, vol. 7, no. 4, pp. 397-413, Aug. 2011.
[6] M. Cardei and J. Wu, “Energy-efficient Coverage Problems in Wireless Ad Hoc Sensor Network,” Computer Comm. J., vol. 29, no. 4, pp. 413-420, Feb. 2006.
[7] Q. Tang, L. Yang, G.B. Giannakis, and T. Qin, “Battery Power Efficiency of ppm and fsk in Wireless Sensor Networks,” IEEE Trans. Wireless Comm., vol. 6, no. 4, pp. 1308-1319, Apr. 2007.
[8] Z. Yuan, L. Wang, L. Shu, T. Hara, and Z. Qin, “A Balanced Energy Consumption Sleep Scheduling Algorithm in Wireless Sensor Networks,” Proc. Seventh Int’l Wireless Comm. & Mobile Computing Conf. (IWCMC ’11), 2011.
[9] M. Cardei and D.-Z. Du, “Improving Wireless Sensor Network Lifetime through Power Aware Organization,” ACM Wireless Networks, vol. 11, pp. 333-340, May 2005.