Multi-Objective Energy Efficient Optimization Algorithm For Coverage Control In Wireless Sensor Networks

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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 activenodes 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 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 inthe 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 andcoverage 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.
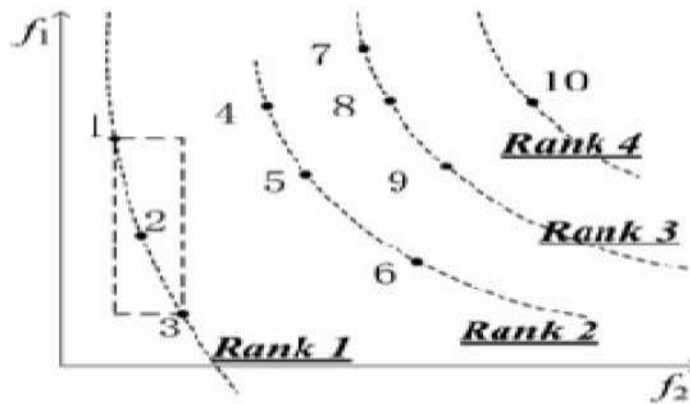
Pareto Concepts

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

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
$+1)$ from $S^{(k)}$ by applying the genetic operators.
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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.

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 isassigned in the solution and this bit represents the working state of corresponding node as (6):

$$x = (x_1, x_2,\ldots, x_i,\ldots, x_K) \quad x_i = \begin{cases} 1, & \text{If the sensor is selected} \\ 0, & \text{Otherwise} \end{cases}$$

(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.
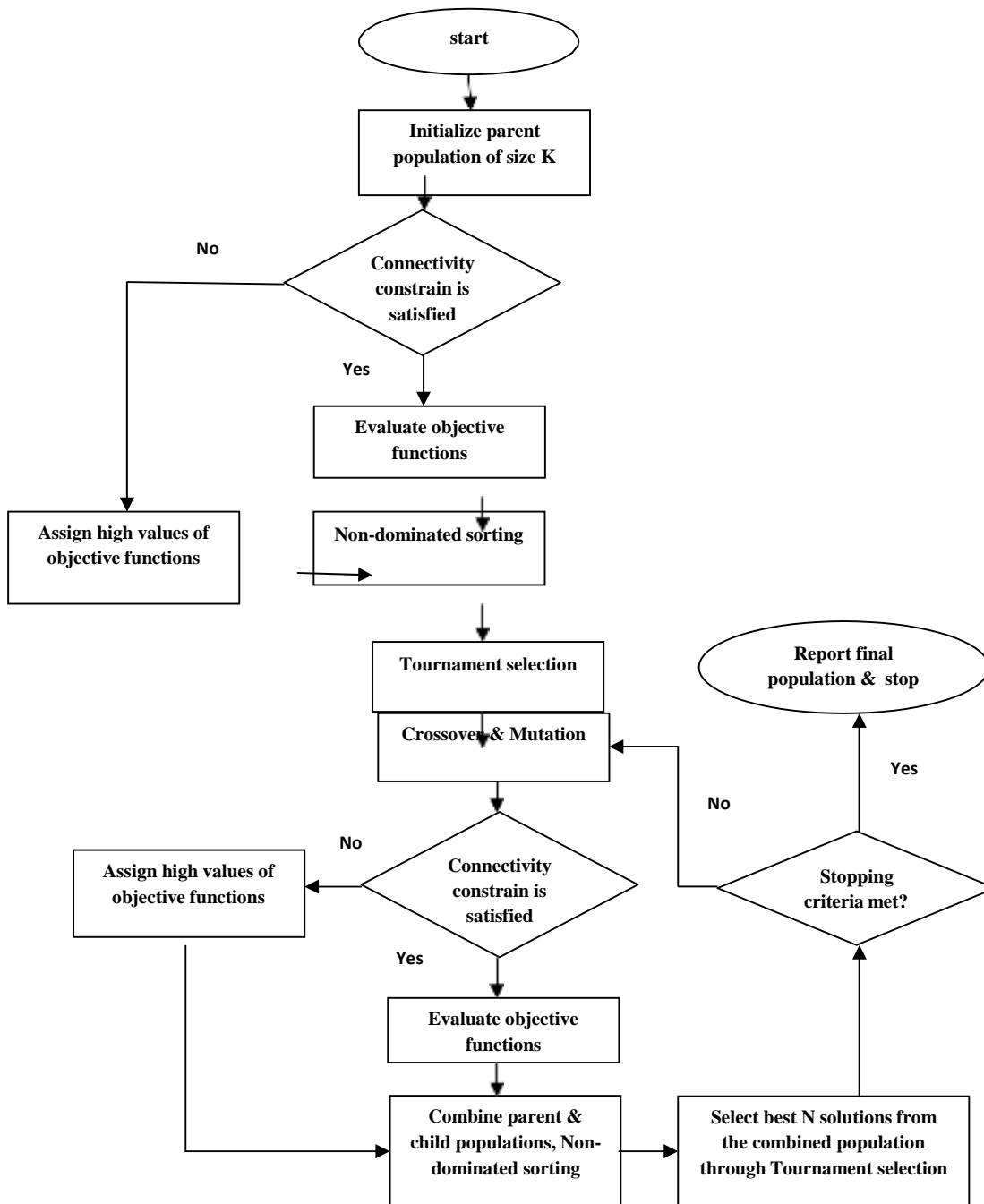
Figure 2. The flowchart for the proposed algorithm

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.

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.

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