Pareto Optimal Solution for Multi-objective Optimization in Wireless Sensor Networks

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Abstract. A wireless sensor network (WSN) consists of small sensors with limited sensing range, processing capability, and short communication range. The performance of WSNs is determined by multi-objective optimization. However, these objectives are contradictory and impossible to solve optimization problems with a single optimal decision. This paper presents multi-objective optimization approach to optimize the coverage area of sensor nodes, minimize the energy consumption, and maximize the network lifetime and maintaining connectivity between the current deployed sensor nodes. Pareto optimal based approach is used to address conflicting objectives and trade-offs with respect to non-dominance using non-dominating sorting genetic algorithm 2 (NSGA-2). The tools we have used for simulation are: NS2 simulator, tool command language script (TCL) and C language and Aho Weinberger keninghan script (AWK) are used. We have checked the coverage area, packet deliver ratio, and energy consumption of sensor nodes to evaluate the performance of proposed scheme. According to the simulation results, the packet delivery ration is 0.93 and the coverage ratio of sensor to region of interest is 0.65.

Keywords: Pareto optimal · Multi-objective · Energy consumption · Coverage · Wireless sensor networks

1 Introduction

WSN is an emerging and fast growing technological platform in many working environments. Nowadays, it has attracted a lot of research attention in many application areas. WSNs contain a collection of sensors that can be deployed rapidly and cheaply for various applications such as environment monitoring, object tracking, traffic and crime surveillance and ground water monitoring [10]. Deployment of sensors is a crucial issue in WSN design. Technologies have made the development of sensor to be small, low power, low-cost distributed devices, which can make local processing and wireless communication in reality. Sensor nodes failure may cause connectivity loss and in some cases network partitioning. This can cause serious damage in some environments that need critical monitoring [2]. WSN's quality is determined by optimizing multi objectives [1, 5, 7]. Since multi-objective optimization (MOOP) are contradictory and impossible to

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solve optimization problems with a single optimal decision. Sensor nodes are equipped with non-rechargeable and irreplaceable batteries. In addition, sensors have limited sensing range, processing and communication range. Hence, Optimizing the basic network metrics such as network lifetime, energy consumption, sensing coverage at once while maintaining connectivity between each sensor node and sink leads conflicting objectives.

The aim of this paper is to find non-dominated Pareto-optimal points in multi-objectives optimization problems to design WSNs. It tries to minimize energy consumption, maximize coverage area, maintain active communication within sensor nodes, and get better fitness by finding the balance trade-off point. This paper solves MOOP by finding the Pareto solutions for the system to optimize conflicting objectives and quantifying trade-off.

2 Related Works

Recently, a number of research contributions have addressed diverse aspects of WSNs including routing, energy conservation and network lifetime [1]. The growing demand of usage of wireless sensor applications in different aspects makes the quality-of services to be one of paramount issue in wireless sensor applications. In [6] authors studied the sensing range of WSNs. On the paper, a large numbers of sensor nodes were deployed in the target area to mitigate node replacement problem and to effectively monitor the field. However, number of sensor nodes increased on the specific area and it needs more cost to deploy. The authors classified WSN area coverage into the three types: area coverage, point coverage and barrier coverage [3]. Characterization of the coverage varies depending both on the underlying models of each node's field of view and on the metric used for appraising the collective coverage. To achieve their objectives; they used several models for different application scenarios.

Network connectivity is another metric criterion for efficient functioning of WSNs which depends on the selected communication protocol [3]. Two sensor nodes are directly connected if the distance of the two nodes is smaller than the communication range. Connectivity requires the location of an active node to be within the communication range of one or more active nodes. So that all active nodes can form a connected communication.

3 Methodology

We assumed sensor nodes are deployed in a square region area and all sensor nodes can sense and communicate within the region. Every sensor nodes have direct or indirect link to the sink node and sensing range of node n is assumed to be circular with radius r. The paper focused to optimize the following performance metrics (parameters') of WSNs: coverage area, energy consumption and network lifetime. The performance metrics we considered are: coverage area, energy consumption, packet delivery ratio, and network lifetime. Coverage area: describes the region WSN sensing area ranges. Stationary sensor nodes are randomly deployed at the target area. Sensor Si is deployed at point (xi, yi).

For any point p at (x, y), the Euclidean distance between Si and p can be calculated by the equation:

$$\mathrm{d}(\mathrm{s}_i, \mathrm{P}) = \sqrt{(x_i - x)^2 + (y_i - y)^2} \quad (1)$$

Each sensor has sensing range within the circular sensing radius r by using binary sensing model. Area A covered in a sensor networks [7]

$$\mathrm{A_{Cover}} = \sum\nolimits_{i=1} \frac{(d[(s_i, p)])^2}{\text{total\_area}} \quad (2)$$

Among the sensing models, binary disk sensing model describes a node whether it senses the point on its sensing range or not. The sensing range of each node within the circular sensing radius r

$$\mathrm{C_{xy}}(\mathrm{si}) = \begin{Bmatrix} 1\ if\ d(si, p) < r \\ 0 \quad otherwise \end{Bmatrix} \quad (3)$$

Energy consumption: each sensor contains limited battery power, so sensor nodes need to increase the network lifetime. Energy consumed by a sensor i in time t is:-

$$\mathrm{E_i}(\mathrm{si, ti, ri, I}) = \mathrm{s(si) + t(ti) + r(ri) + I} \quad (4)$$

Where s(si) is the energy consumed at sensing, t(ti) is the energy consumed at transmitting, r(ri) is the energy consumed at receiving and i energy consumed at idle state in given time t. To maximize coverage area with connectivity: coverage Function.

$$\mathrm{F(X) = f1(x1),\ f2(x2) \ldots f(xn)}$$

Maximize C_{area} *Subject to:*

$$\mathrm{C_{xy}}(\mathrm{si}) = \begin{Bmatrix} 1\ if\ d(si, p) < r \\ o \quad otherwise \end{Bmatrix}$$

Connectivity must exist within area. To minimize energy consumption, the energy consumed by each sensor node need to be: energy consumption function

$$\text{Minimize}\ (\mathrm{Ei(Si, ti, ri, i)})$$

The Total Energy consumption on sensing radius si of node ni with u factor is formulated as:

$$\mathrm{E(total[si])} = \sum\nolimits_{i=1}^{n} * r$$

$$\mathrm{E(total[ti])} = \sum\nolimits_{i=1}^{n} * r$$

$$\mathrm{E(total[ri])} = \sum\nolimits_{i=1}^{n} * r$$

3.1 Non-dominated Sorting Genetic Algorithm-II (NSGA2)

It's computational intelligence which applies the principle of natural selection and survival of the fittest to find near optimal solution in the search space. There are many Multi-objective optimization algorithms among them:- Multi-Objective evolutionary algorithm (MOEA), Strength Pareto evolutionary algorithm (SPEA), Pareto envelop Strategy algorithm (PESA), and improved Non-dominated Sorting Algorithm (NSGA-II) [12].

In this paper, NSGA-II algorithm is used, because it has better performance than others. NSGA-II uses an elitist principle, diversity preserving mechanisms and emphasizes the non-dominated solutions. NSGA-II working based on genetic operators such as, crossover and mutation to MOOP.

To analysis non-dominance points and ranking population of sensor node deployment works in the following logic (Fig. 1 and Table 1).

- Item Take all sets of solutions of node population p
- Item any i^{th} solution (xi) which belongs to p
- Item Set of solutions which dominates (S) the solution xi and number of solutions (ni) which dominates xi.
- Item Any non-domination front (PK) at K^{th} level.

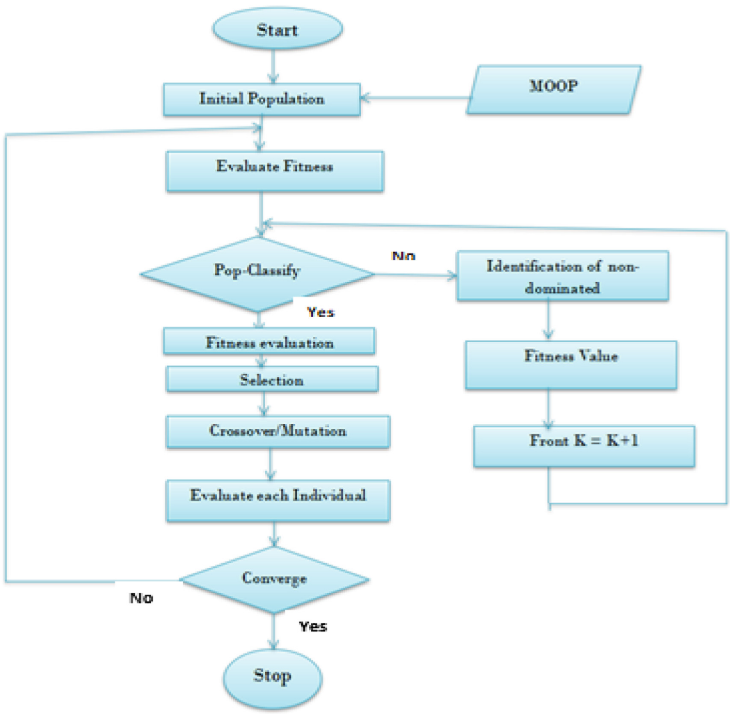

Fig. 1. Flow chart of NSGA-II

Table 1. NSGA-II parameter's list

Parameter	Value
Population size	20
Maximum generation	50
Mutation probability	0.1
Crossover probability	0.9

4 Simulation Setup and Results

We have installed NS2.35 simulator on 8 GB, RAM of Ubuntu Linux operating system. Initial population of stationary sensor nodes deploy randomly. The following simulation parameters used to find balanced trade-off between objective function. In the above section, the details of the proposed algorithm is described; A non-dominated sorting genetic algorithm II (NSGA-II) was first proposed in [4] as a biological heuristics algorithm which usually used to solve complex industrial optimization problems. This algorithm has been wide attention by authors due to its faster convergence, stronger robustness, and better draw near the true Pareto-optimal front.

Begin

Input: Population P; Maximum Generation *GMax*;

Cross probability Pc; mutation probability Pm

Initial: compute objective values, fast non-dominated

sort, selection, crossover and mutation.

Generation = 1;

While Generation≤ *GMax* do

Combine parent and offspring population, compute

objective values and make non-dominated sort.

Made selection

If rand-num()≤ Pc

Crossover operation;

End

If rand-num() ≤ Pm

Made mutation;

End

Generation = Generation + 1;

End

Output: best individuals

End

At the beginning, we made some assumptions: the nodes are deployed randomly, each one are static and knows its own location using some location systems [9]. The simulation region is a square area with the size of 401 m by 401 m in all the experiments, and 20 sensor nodes are deployed randomly in this two dimensional area.

The packet delivery ratio indicates how much the sensor networks are communicated with each other. According to the simulation result, we have achieved a packet delivery ratio of 92.89 which indicates the existence of better connectivity within the network system. Figure 3 shows the evaluation of energy consumption fitness function (Table 2).

Table 2. Definitions and values of simulation parameters

Parameter	Definition	Value
X	Maximum width of RoI	401 m
Y	Maximum length of RoI	401 m
Rc	Communication radius	10 m
Rs	Sensing radius	250 m
Ns	Number of sensors	20
IE	Initial energy	10 J
Si	Sensing energy for node i	0.6 mA
TEi	Transmission energy for node i	0.9 mA
REi	Reception energy	0.7 mA
I	Idle	0.1 mA

Figure 2 below shows the design layout of the 20 sensor nodes in 401 m by 401 m is plotted as shown below in NS2 working simulation environments.

The best Pareto optimal solutions are find by using [11] NSGA-II. In NSGA-II algorithm, its main operation consists of two components like; one part of genetic algorithm includes the operation, such as crossover, selection, and mutation. The other part refers to the unique non-dominated sorting operation in the multi-objective optimization algorithm. The selection operation can contain the better individuals with their fitness values. The mutation operation is designed according to the genetic mutation in the biology, in order to ensure that the algorithm has strong global convergence ability. And, the

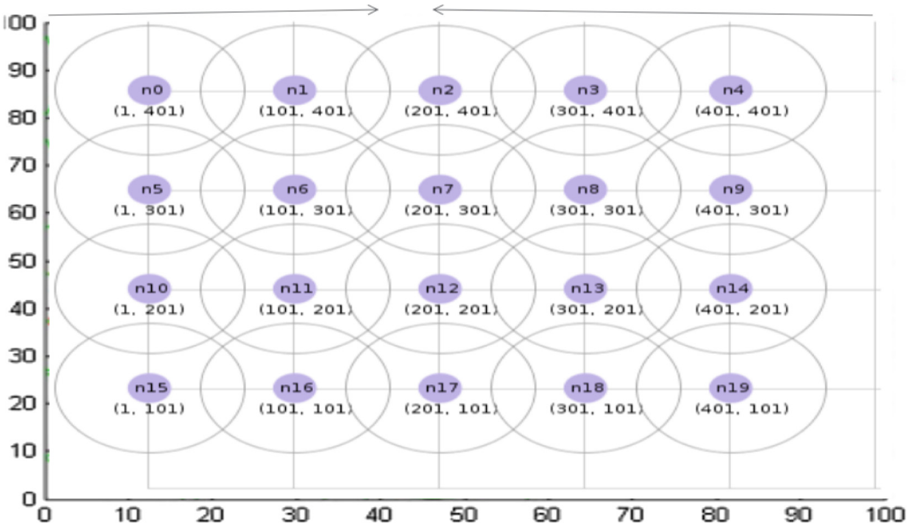

Fig. 2. Design of the deployed sensor nodes in the area

crossover operation is designed based on the principle that homologous chromosomes cross to generate new improve the algorithm search ability.

As the result shows the sensing coverage of each sensor nodes are varies depending on its location from the sink node; it's location is at the center of deployment area. The more near to sink node, the more energy dissipate to cover its sensing region. The coverage area of Fitness for every sensor has their own sensing capacity; for example node1 has 0.91, node2 has 0.93, node3 has 0.94 and node12 has 1.0 etc. According to [8], it's ratio of the number of packets sent by the source node and the number of packets received by the destination node. The packet delivery ratio within our deployed sensor nodes is quantified in the simulation from 591 sent packet, 549 is received packets.

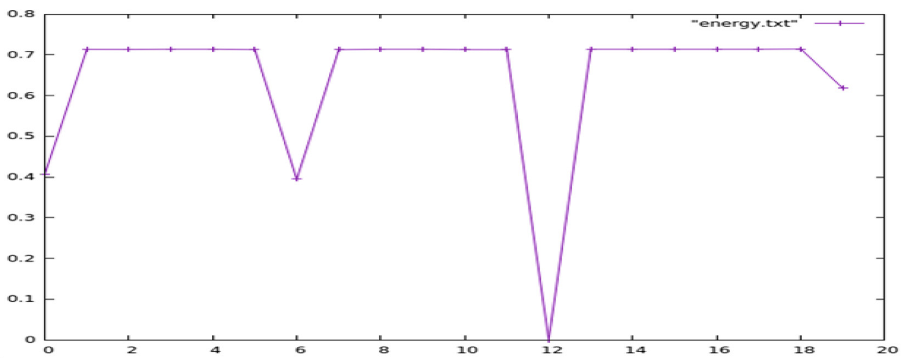

Fig. 3. Energy consumption of each sensor fitness function

5 Conclusions

In this Paper we have proposed Pareto optimal based approach to simultaneously optimize the basic performances metrics of WSNs: area of coverage, energy consumption and network lifetime. NS2 simulation tool is used to evaluate the performance of the proposed scheme. According to the simulation results; the packet delivery ratio is 0.93 and the coverage ratio of sensors to region of interest is 0.65.

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