Hard Constrained Vertex-Cover Communication Algorithm for WSN

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Abstract. The communication problem is to select a minimal set of placed sensor devices in a service area so that the entire service area is accessible by the minimal set of sensors. Finding the minimal set of sensors is modeled as a vertex-cover problem, where the vertex-cover set facilitates the communications between the sensors in a multi-hop fashion keeping in mind the limited communication range and battery lifespan of all sensors. The vertex-cover is a subset of the coverage set of sensors; therefore, we transform the search space from a continuous domain into a discrete domain. We encoded the vertex-cover problem into the evolutionary domain, where the objective function is to select a minimal set of sensors out of the coverage sensors to act as the vertex-cover set so that its communication range covers all the coverage sensors. The experimental results demonstrate the feasibility of our evolutionary approach in finding minimal vertex cover set, which is less than 37% of total sensors used as communication sensors, in under 14 seconds with 100% coverage of the sensor nodes in wireless sensor network.

Keywords: Wireless sensor network, communication, vertex cover, discrete space, optimization, evolutionary approach.

1 Introduction

The wireless sensor network (WSN) has emerged as a promising platform to monitor an area with minimal human interventions. Advancements in low-power micro-electronic circuits, wireless communications, and operating systems have made WSN into feasible platforms that are used in many applications. Initially, the WSN applications were dominated and funded by the military applications, such as monitoring the activity in a battle field. Now, many civilian applications, such as environmental and habitat monitoring have emerged to benefit from the usage of WSN.

There are two core problems that should be considered by deployment of any wireless sensor networks. These problems are the coverage and communication problems. The coverage problem is to place sensor devices in a service area so that the entire service area is covered. In a previous work [17], we proposed a heuristic model that maps the coverage problem into two sub-problems: floorplan and placement, which are mimicking the placement and integration modules of integrated circuit (IC) into a circuit board. The floorplan problem is to divide the circuit board into well-defined geometric cells, and then the placement problem determines the best cells to place the IC modules into them with minimal total wire connections. A combined optimization of floorplan and placement was coded in an evolutionary approach and found good coverage solutions as defined by the measure of quality of coverage [18].

In this work we focus on the communication problem, which will assume that sensor networks consist of two types of sensor devices. The first type of sensors (coverage sensors) is responsible for sensing/monitoring the surrounding environment, and generates data packets periodically. Those are the sensor devices that we got as a result of applying our evolutionary coverage algorithm. They are also responsible for forwarding the data they receive from other sensors towards a second type of sensors (named communication sensors). Communication sensors are responsible for collecting all the data generated by the coverage sensors. Communication sensors have sufficient processing capability and more power supply that make their communication ranges cover the whole service area. One of the challenges imposed by such sensor networks, is the communication sensor placement problem. We define the communication sensor placement problem as how to select the minimal number of communication sensors out of the set of the coverage sensors while maximizing the communication range of the communication sensors in the service area taking into consideration the traffic intensity distribution in the area. Communication sensors have significant impact on sensor network performance. Despite its significance, results on this problem remain limited, particularly theoretical results that can provide performance guarantee.

In this work, we develop a heuristic algorithm that is based on the vertex cover approach. The vertex cover problem is the optimization problem of finding a vertex cover of minimum size in a graph, where we assume that each vertex cover represents a communication sensor and the covered nodes are the rest of the coverage sensors. Finding the minimum vertex cover is an NP-complete problem. However, by using some heuristics we can obtain a vertex cover set, which is in the worst case at most twice that of the optimal. Our algorithm provides solutions specifying coverage sensors that can be used as communication sensors and minimizes the number of the communication sensors, while providing a satisfactory quality of service to the users. This is accomplished by trying to cover the largest set of the coverage sensors, and hence covering a maximum possible part of the service area. The goodness of a solution depends on how it minimizes the number of the communication sensors while maximizing the communication coverage of the sensors in the service area. In the rest of the paper, we will use the terms base stations and communication sensors interchangeably.

The rest of the paper is organized into five sections. Section 2 describes the related work with respect to the coverage problem and communication problem in wireless sensor networks. Section 3 contains the mathematical formulation of the communication problem. Section 4 describes our evolutionary approach in solving the communication problem. Section 5 illustrates our experimental results generated by the proposed evolutionary methodology. Section 6 contains the conclusion and future directions.

2 Related Work

Recently, many researchers have been investigating and developing deployment strategies that give the optimal base stations placement for guaranteed coverage, connectivity, bandwidth and robustness, taking into consideration numerous factors such as traffic density, channel condition, interference scenario, the number of base stations, …etc. The objectives are either minimizing the number of base stations deployed, minimizing the total cost, minimizing the energy consumption, or maximizing the number of served sensors by a base station, maximizing network lifetime, and maximizing the network utilization.

Therefore, many researchers have focused their efforts on reducing network traffic of these sensor networks [2, 5, 7, 11, 12, 15]. Many other researchers have focused on minimizing the number of base stations [2, 5, 8, 13, 16], where others used a predefined fixed number of base stations [1, 9, 11, 12, 14]. Also, some researchers have focused on maximizing the number of sensors served by a base station [3]. However, most of the above researches have assumed that the number of sensors served by any base station is fixed [1, 2, 5, 9, 12].

The base stations in these applications may be arranged in wired networks, and may in general pose considerable technical problems in data processing, communication, and management. The base stations can also be arranged into wireless networks. This even pose more technical challenges because of their dynamic structures and more constrained energy and bandwidth capabilities. Thus, the base stations placement has been formulated in various ways.

The strategy reported in [1] aimed to find a base station configuration that ensures each user to communicate with a satisfactory signal to-interference ratio (SIR) in a wireless CDMA system. The solution is guaranteed to be optimal and considered coverage, capacity and cost but not interference. The work in [2] is an adaptation to the recent bio-inspired optimization approach, Particle Swarm Optimization (PSO), to form a suitable algorithm that converges with a faster rate than genetic algorithms. Two important factors are considered simultaneously, coverage and economic. Another work in [3] describes an application of combinatorial optimization to the problem of designing cellular mobile telephone wireless networks. The goal of the network design problem is to cover the maximum number of subscribers in an effective and efficient manner. Work [6] focuses on the problem of where to place base stations to yield high capacity and efficiency in term of channel quality and spectral. One of the key objectives is to allow many users to co-exist in a relatively small area while maintaining spectral efficiency, system capacity and channel quality. New dynamic base station selection technique for overlapping cell placement based on robust traffic performance for personal communication systems in fluctuating and heavily tapered traffic is suggested in [7]. The proposed technique improves the blocking probability and carried traffic performance. It enhances the robustness of a system for congested traffic due to moving of the subscribers even if the base station has few channels. The authors in [8] addressed the problem of placing the sensor nodes, relay nodes and base stations in the sensor field such that each point of interest in the sensor field is covered by a subset of sensors of desired cardinality. Several deployment strategies to determine optimal placement of the nodes for guaranteed coverage, connectivity, bandwidth and robustness are considered in this paper.

The authors of paper [9] have studied two phases of installation process, the placement of the base stations and assignment of frequency channels in WLAN networks. They aimed to reduce installation costs, minimize interferences of signals between channels and improve the network throughput. The processes that have been taken to choose the best placement of base stations are to map the demand area by dividing it into small quadrangular pieces of demand points. Next, choose candidate locations that offer low cost of installation and good attendance area. Then signal measurement for the signal level received by each candidate base station on each demand point. Finally, they defined the computational model which is developed using integer linear programming computational model. Limited number of base stations and candidate locations are used. The strategy represented in [10] aimed to find optimization methods for base station placement in wireless applications. The authors suggest that Nelder-Mead method or some other direct search method will be highly effective for many formulations, particularly as reliable problem-specific initialization heuristics are developed. A set of non linear programming models are developed based on the Hooke and Jeeves method, quasi Newton, and conjugate gradient search algorithms to search the optimal location of transmitters to serve specified distributions of receivers. In [12] the authors considered an alternate objective, that is, to determine the base station positions and transmission power levels so as to maximize the minimum throughput among the mobiles, according to their study both of them determine the coverage area and the signal to interference ratio, and hence influence the system capacity. In [13] an approach for automatic base station placement is presented. An optimization strategy forms the core of the automatic process which not only determines the number of base stations and their locations but also base station configurations. It aims at designing a high-quality network that guarantees the system performance; i.e. meets the requirement of the coverage capacity, and interference level, while trying to minimize the required bandwidth and the cost involved in building such a network. The number of base stations and their locations and the transmissions power are defined. In [15] the authors analyzed the problem of automatic base station placement and used a hierarchical approach to solve the problem. A fuzzy expert system was developed to determine the optimal base station parameters. A numerical experiment was made for adjusting the transmitted power to reduce the interference and to distribute traffic equally to the cells so that the frequency cost is minimized. The objective function was based on several weighted factors, such as covered area, interference area, and mean signal path loss. The authors in paper [16] have developed a computer aided planning tool known as POPULAR, which stands for a planning of Pico cellular radio. Planning must take into account the specifics of radio wave propagation at the installation site. POPULAR computes the minimal number of base stations and their locations given a blueprint of the installation site and information about the wall and ceiling materials. The internal technique within POPULAR, depends on the number of assigned test points inside the building to be covered.

In this work, we consider similar formulation of the coverage problem as discussed in [17, 19, 20]. However, we have assumed that the cell size is not fixed, and the service area can be floorplanned in arbitrary ways. Also, we used object-oriented classes to represent chromosomes and their genes. Our evolutionary methodology is attached with a sensor device library with heterogeneous features, such as the radius of coverage (ranging from 1 meter to 50 meters) and cost (ranging from $50 to $1000).

3 Communication Problem Formulation

We are given a two-dimensional service area (A) with width (W) and height (H) as shown in Figure 1. The service area is an obstacle-free. Also, the service area A is already divided into M x N cells, where each cell can possibly contain a sensor device at its center of mass. All the centers of mass represent demand points, which were considered as the candidate locations for the sensor devices for the coverage problem. Thus, a set of placed sensors for the coverage problem, B, is given as an input to the communication problem. Each element in the set B is a tuple, b_i, consisting of six ordered parameters, $b_i = <S_j, C_{MxN}, RC, SC, CR, BL>$. The parameter S_j refers to the sensor identification, which was allocated from the sensor device library S. The parameter C_{MxN} represents the physical cell location of the placed sensor within the service area. The indices M and N refer the column and row numbers respectively of the floorplan of the service area, as shown in Figure 1. The parameter RC indicates the radius of coverage in meters of the placed sensor S_j. The parameter SC refers to the initial installation and deployment cost in Dollars ($) of the placed sensor S_j. The parameter CR refers to the communication radius that the radio signal within the placed sensor (S_j) can reach in meters. The range of CR varies with the consumption of power. The last parameter BL indicates the current battery level of the placed sensor S_j.

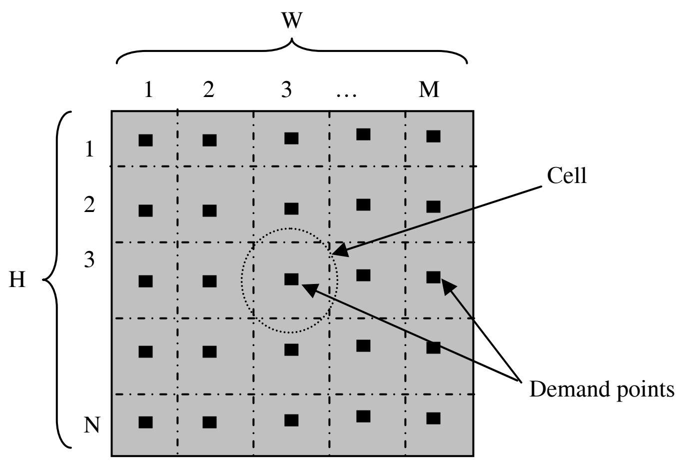

Fig. 1. A service area to be monitored by WSN.

Also, the total coverage (TC), which represents the ratio of the total non-overlapping of all placed sensors' radius of coverage over the total area of service area (WxH), is given as an input to the communication problem. The communication problem is to determine a minimal subset C of B ($C \subseteq B$) such that the communication radiuses (CRs) of all selected sensors (vertex covers) within B can reach all other sensors in $\hat{C} = B - C$; moreover, the sensors in $\hat{C}$ should be as far as possible away from the radius of coverage of all selected vertex covers in C, as illustrated in Figure 2. There are three possible relations between the communication radius (CR) and the radius of coverage (RC) of a sensor:

1. CR = RC,
2. CR < RC, and

3. CR > RC.

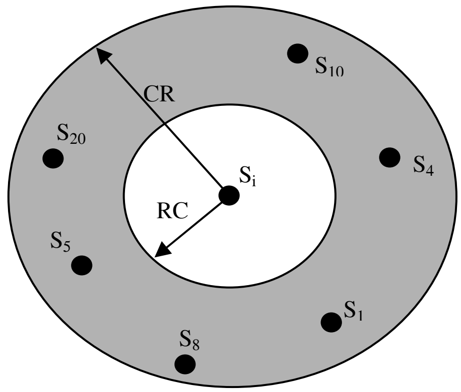

Fig. 2. The relationship between the communication and coverage ranges of s vertex-cover.

The first two relations, where the communication radius is equal or less than the radius of coverage respectively, are not considered in this paper. According to the leading company in the development of WSN [21], the relations 1-2 are not considered due to their impractical usage in the field. In this paper, we considered the third relation (CR > RC), where the communication radius is greater than the radius of coverage (sensing range). If a sensor is selected as a vertex cover, then there should be a minimal number of sensors in its sensing range (within the white-circle $\pi \times RC^2$) as illustrated in Figure 2. Also, all the sensors within the shaded circle $((\pi \times CR^2) - (\pi \times RC^2))$ can be bound to the vertex cover S_i. Our objective function is to achieve a minimal vertex cover set as stated in Equation (1). δ_k represents an allocation variable of a vertex cover; $\delta_k = 1$ indicates that a sensor device *k* has been allocated to be used as a vertex cover. This objective function is subject to a set of constrains (2), (3), (4), (5), (6), (7) and (8).

$$\min \sum_{k \in B} \delta_k \qquad (1)$$

$$1 \le |C| \le \frac{|B|}{z} \qquad (2)$$

$$1 \le \sum_{k \in C} \omega_{k,j} \le |C|, \text{for given sensor } j \in \hat{C} \qquad (3)$$

$$L \le \sum_{j \in \hat{C}} \omega_{k,j} \le U, \text{for given vertex cover } k \in C \qquad (4)$$

$$\left(\omega_{k,j} \times C_{w,h}\right) \notin \left(\delta_k \times \left(\pi \times RC_k^2\right)\right), \text{for } \forall k \in C, \forall j \in \hat{C} \qquad (5)$$

$$\left(\omega_{k,j} \times C_{w,h}\right) \in \left(\delta_k \times \left(\pi \times CR_k^2 - \pi \times RC_k^2\right)\right), \text{ for } \forall k \in C, \ \forall j \in \hat{C} \quad \textbf{(6)}$$

$$\left(\delta_i \times \left(\pi \times RC_i^2\right)\right) \cap \left(\delta_j \times \left(\pi \times RC_j^2\right)\right) \cong \phi, \text{ where } i \neq j \text{ and } i, j \in C \quad \textbf{(7)}$$

$$\delta, \omega \in \{0,1\} \quad \textbf{(8)}$$

Constraint (2) ensures that the cardinality of the vertex cover set C is bound between one and the cardinality of the entire sensors set B divided by some given value (z). Constraint (3) ensures that each sensor, which is not selected as a vertex cover, must be bound to at least one vertex cover. $\omega_{k,j}$ is a binding variable; $\omega_{k,j}$ = 1 indicates that a sensor j is bound to a vertex cover k. Otherwise, the sensor j is bound to different vertex cover. Constraint (4) ensures that the bound sensors to an allocated vertex cover are restricted between a lower (L) and upper (U) values. The values of L and U are determined by the designers, and also they are used to create a load-balance workload for each vertex cover. Constraint (5) ensures that the number of sensors located within the sensing range of a vertex cover is minimized and cannot be more than the total number of vertex cover sensors. Moreover, Constraint (6) ensures that a sensor is located within the communication range of its vertex cover excluding its sensing range. Constraint (7) ensures that the coverage ranges of two vertex cover sensors are not overlapping, hence, ensures that no vertex cover sensor is located within the sensing range of another vertex cover sensor. Finally, Constraint (8) defines the allocation (δ) and binding (ω) variables as a Boolean.

4 Evolutionary Approach for Solving the Communication Problem

The selection problem of communication sensors requires an enormous computational effort to achieve optimal solutions. Therefore, we have selected the Genetic Algorithm (GA) to search the discrete design space for good solutions. GA uses a population of chromosomes, which represent the candidate solutions, to evolve toward better solutions. Through some genetic operators such as a mutation and crossover, these chromosomes would reach the optimum or near-optimum solutions. The evolution process starts from a population of chromosomes generated by applying the coverage algorithm, and occurs over a number of generations. In each generation, multiple chromosomes are stochastically selected from the current population, modified using different operators to form a new offspring, which becomes the new chromosomes in the next iteration of the algorithm. The basic structure of GA, as shown in Figure 3, is a powerful search technique that is used to solve many combinatorial problems.

The genetic algorithm starts with an initial population P (t=0) of solutions encoded as chromosomes. Each chromosome is made of a sequence of genes and every gene controls the inheritance of specific attributes of the solution's characteristics. A fitness function measures the quality of the chromosome (number of communication sensors, and number of sensors covered by their sensing and communication ranges). A fit chromosome suggests a better solution. In the evolution process relatively fit chromosomes reproduce new chromosomes and inferior chromosomes die. This process continues until a chromosome with desirable fitness is found. These selected chromosomes, known as parents, are used to reproduce the next generation of chromosomes, known as offspring.

```
Genetic Algorithm:
begin
       t = 0;
       initialize chromosomes P(t);
       evaluate chromosomes P(t);
       while (termination conditions are unsatisfied)
       begin
         t = t + 1;
         select P(t) from P(t-1);
         mutate some of P(t);
         crossover some of P(t);
         evaluate chromosomes P(t);
       end
end
```

Fig. 3. The basic structure of Genetic Algorithm.

The evolution process involves two genetic operations namely, mutation and crossover. A mutation operator arbitrarily alters one or more genes of a randomly selected chromosome. The intuition behind the mutation operator is to introduce a missing feature in the population. Our mutation replaces an existed communication sensor device with a new one from the list of coverage sensors.

A crossover operator combines features of two selected chromosomes (parents) to form two similar chromosomes (offspring) by swapping genes of the parent chromosomes. The intuition behind the crossover operator is to exchange information between different potential solutions.

4.1 Chromosome Representation

We represent a solution of communication sensors selection problem as three object-oriented link lists, as shown in Figure 4. The first link-list represents the population, which contains all chromosomes. The second link-list, which is attached with every chromosome class, represents how many sensor devices have been allocated and bound to a chromosome. The third link-list, which is attached with every chromosome class, represents the vertex cover nodes.

We combined all chromosomes in the population of size P into one data structure, which comprises of one link list representing all chromosomes and each chromosome has one link list representing all its genes, where each gene symbolizes a sensor device that is allocated as a base station. Two types of nodes are declared as two different classes, where first class represents a chromosome's attributes and the second class represents a gene's features. Also, we maintain a dynamic matrix to illustrate all cells and demand points.

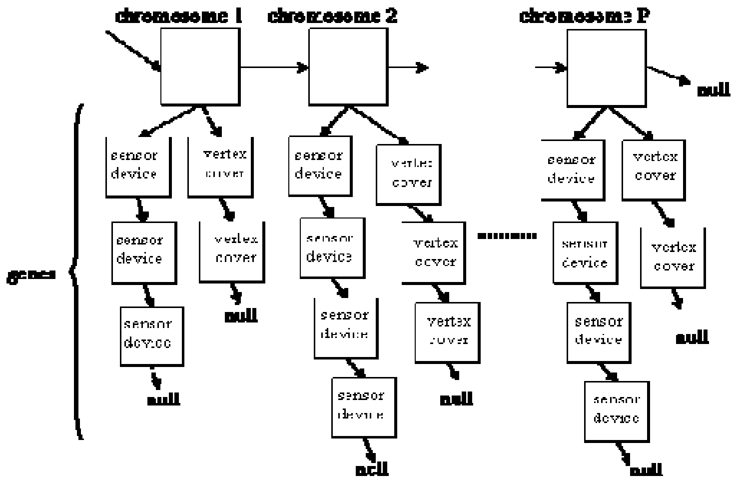

Fig. 4. A population of Chromosomes.

5 Experimental Results

To test our evolutionary methodology for the communication problem in wireless sensor networks, we first ran our previously developed code for the coverage problem to find a good solution to the coverage problem of a sensor wireless network. We have coded the coverage within WSN using the evolutionary methodology, which searches for good solutions using JAVA as a programming language. For this experiment, we assigned the population size, the number of generations, the crossover rate and mutation rate to be 100, 1000, 0.45, and 0.25 respectively. The budget threshold *C* is set to $150,000, and we have used a cell size of 30 meters by 30 meters; moreover, we maintained 10 cells by 10 cells as a service area. We choose the solution that consisted of 45 sensors with an average cost of $25,334, and an average coverage ratio of 86.71% of the service area. The coverage ratio represents the total amount of service area that is covered by the sensing range of the sensor devices. Next, we ran our developed methodology for the communication problem on the previous network setup to pick up the least number of the coverage sensors as vertex cover (communication) sensors that would have the maximum communication ratio. The communication ratio represents the total number of coverage sensors that are covered by the communication range of the sensor devices considered as vertex cover (communication) sensors.

For the next experiments, we started by assuming that all the coverage sensors are considered as communication sensors (vertex covers). Hence, 100% of the coverage sensors are covered by the vertex covers, i.e., the communication sensors would have the exact same coverage ratio as the coverage sensors. Then, we applied our evolutionary methodology to reduce the number of required vertex covers, while maintaining the exact same coverage ratio. To achieve such a coverage ratio, we only used the mutation operation that removes or replaces a vertex cover sensor from a solution if and only if the 100% coverage ratio is not affected. In addition, we have ignored the crossover operation, since we cannot guarantee that we end up with a solution that has 100% coverage ratio as we started with. All the experiments are executed on a PC platform and each experimental run for 1000 generations of the communication problem took under 14 seconds. Moreover, in all of our experiments, as the number of generations increased, the behavior of our algorithm changed and then it reaches a plateau after 240 generations. In each of the Figures 5, 6, and 7, we illustrate six curves that tracked the average behavior of the whole population with respect to the number of vertices chosen as vertex covers and how many other vertex covers are in their communication range. This behavior is measured as the number of generations increased.

Figure 5 illustrates two curves that tracked the behavior of the whole population with respect to the average percentage of coverage sensors chosen as vertex covers, and the average percentage of coverage sensors covered by the vertex covers. As the number of generations increased, the average number of coverage nodes chosen as vertex covers decreased from 100% of the coverage sensors to around 16% of the coverage sensors. In addition, the second curve illustrates that our methodology managed to cover all the coverage sensors by the set of the vertex covers (100% coverage ratio) as the number of generations increased. The average ratio of the number of vertex covers out of the total number of coverage sensors was around 37% and those vertex covers covered 100% of the original 45.

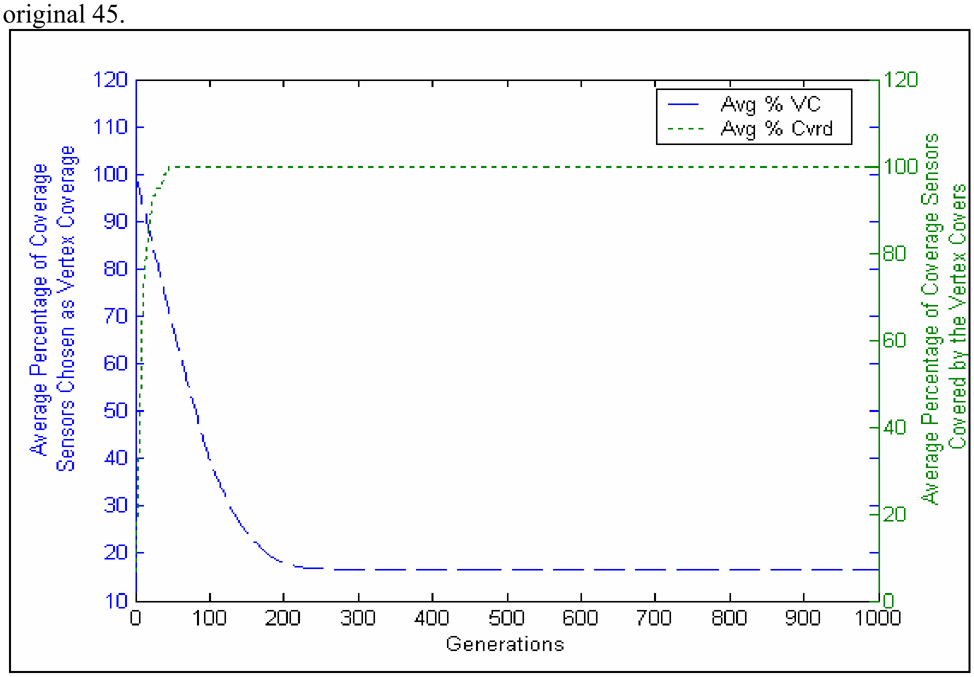

Fig. 5. Relation between the average percentage of coverage sensors chosen as vertex covers, the average percentage of coverage sensors covered by the vertex covers and the number of generations.

In Figure 6, the curve tracked the behavior of the whole population with respect to the average number of vertex covers in the range of other vertex covers. Since we began with a solution that considers every coverage sensor as a vertex cover, and given the communication ranges of those vertex covers, a large percentage of the vertex cover sensors are covered by the communication ranges of other vertex covers. However, as the number of generations increased, this ratio dropped to almost 0%. Thus, our methodology was able to optimize the solution to a minimum set of vertex covers that cover the whole coverage sensors and at the same time they do not cover each other by their communication ranges (i.e., minimized their intersections.)

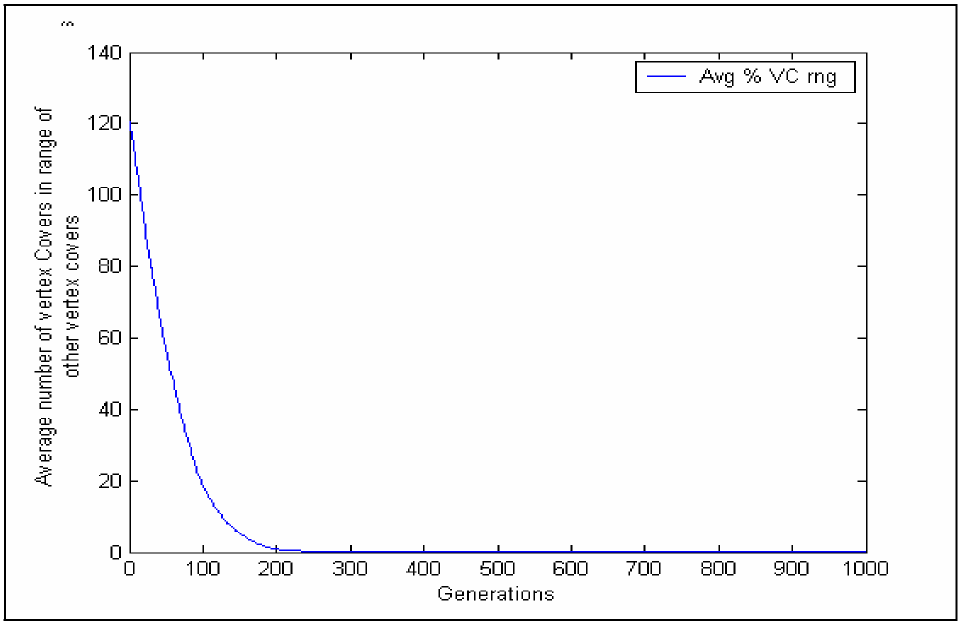

Fig. 6. Relation between the average number of vertex covers in range of other vertex covers and the number of generations.

Figure 7 illustrates three curves that track the best, the average, and the worst percentage of sensors chosen as vertex covers as the number of generations increased. All the three curves show a consistent behavior of our methodology in choosing the optimum number of sensors as vertex covers, and that the number of VCs decreases with the increasing number of generations. We concluded from these early experiments that our methodology managed to produce a near optimal number of vertex cover sensors that cover all the coverage sensors, and this was accomplished in less than 14 seconds.

Finally, in Figures 8 and 9 we show snapshots of our Sensor CAD Visualizer. It provides a graphical user interface that lets the user control the genetic algorithm, visualizes the solutions graphically, shows how it would look like in real life, and lets you go through different generations that were produced by the GA. Figure 8 shows the result of applying our evolutionary coverage GA, while Figure 9 shows the result of applying our evolutionary communication GA.

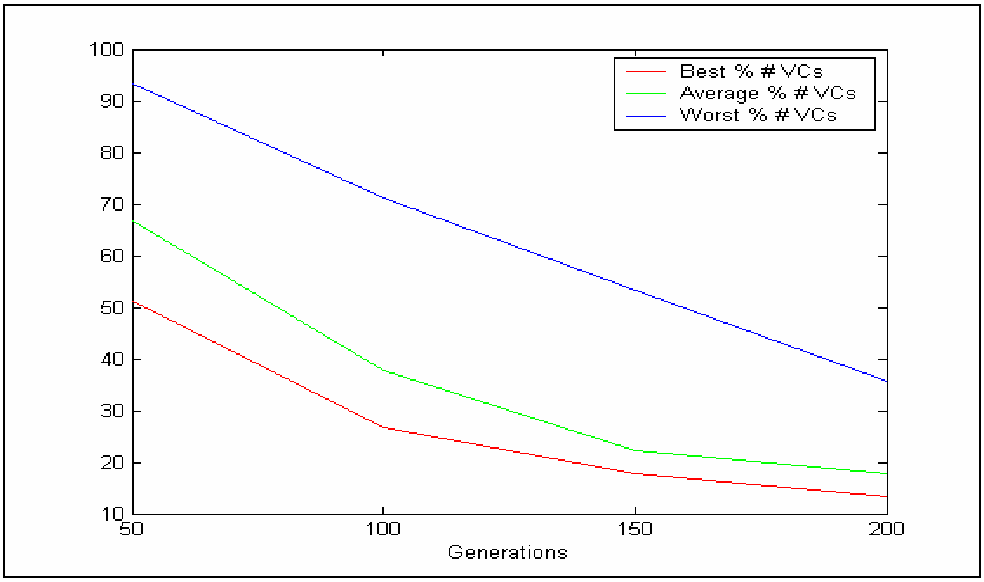

Fig. 7. Relation between the best, average and worst number of vertex-cover sensors and the number of generations.

Fig. 8. A snapshot of the Sensor CAD Visualizer, which shows that after 631 generations of applying the coverage GA found 45 sensors as the best coverage at a cost of $30,430 while having a coverage ratio is equal to 99%.

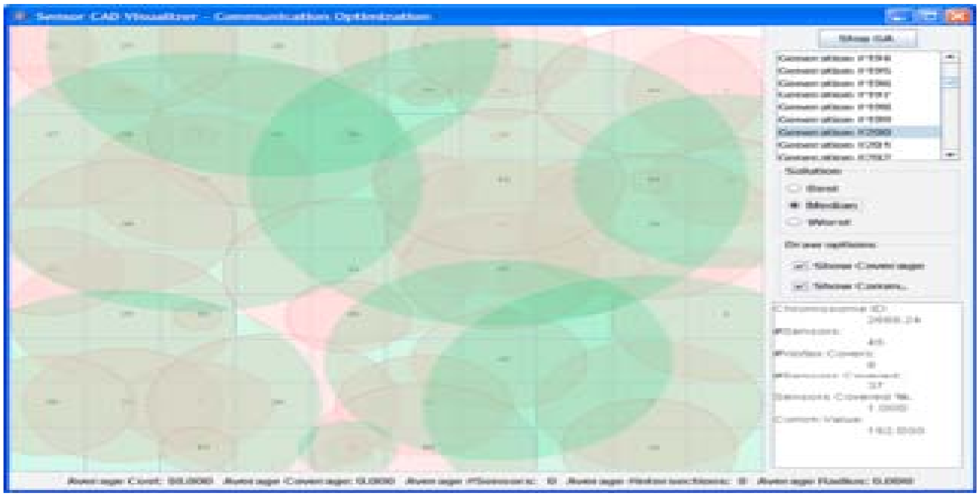

Fig. 9. A snapshot of the Sensor CAD Visualizer, which shows that after 200 generations of applying the communication GA found 8 sensors as the best vertex-cover sensors that cover all coverage sensors.

6 Conclusion and Future Directions

We have extended our previously proposed model for the coverage problem in the wireless sensor networks by introducing a new model for the communication problem. As with the coverage model, our communication modeling has reduced the solution space into a discrete optimization problem so that it can achieve the maximum communication possible with the least number of the coverage sensors (i.e., vertex covers) and at the same time guarantees that all the coverage sensors are covered by the vertex covers. Our early experiments with our new evolutionary model demonstrate very promising results. We will continue to improve our methodology by trying to solve both the coverage and communication problems simultaneously, and hence try to increase the transmission power during the coverage problem while reducing the energy utilization and reducing the over all cost of constructing the sensor network. Furthermore, we want to run our evolutionary communication GA using both the mutation and crossover operations. We want to study the effect of using both operations on the number of vertex cover sensors and the time required to get such optimal solution.

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