Multi-objective genetic algorithm for the automated planning of a wireless sensor network to monitor a critical facility

Damien B. Jourdan[*], Olivier L. de Weck
Dept. of Aeronautics and Astronautics, Massachusetts Institute of Technology
77 Massachusetts Ave., Cambridge, MA, USA 02139

ABSTRACT

This paper examines the optimal placement of nodes for a Wireless Sensor Network (WSN) designed to monitor a critical facility in a hostile region. The sensors are dropped from an aircraft, and they must be connected (directly or via hops) to a High Energy Communication Node (HECN), which serves as a relay from the ground to a satellite or a high-altitude aircraft. The sensors are assumed to have fixed communication and sensing ranges. The facility is modeled as circular and served by two roads. This simple model is used to benchmark the performance of the optimizer (a Multi-Objective Genetic Algorithm, or MOGA) in creating WSN designs that provide clear assessments of movements in and out of the facility, while minimizing both the likelihood of sensors being discovered and the number of sensors to be dropped. The algorithm is also tested on two other scenarios; in the first one the WSN must detect movements in and out of a circular area, and in the second one it must cover uniformly a square region. The MOGA is shown again to perform well on those scenarios, which shows its flexibility and possible application to more complex mission scenarios with multiple and diverse targets of observation.

Keywords: Multi-objective genetic algorithm, wireless sensor network, network planning, node placement, facility monitoring, coverage.

1. INTRODUCTION

Recent military operations demonstrated the limitations of surveillance missions performed by high-altitude platforms (UAV, U2, satellite) even when equipped with state of the art sensors. Most of these limitations are inherent to this type of long-distance surveillance and cannot be resolved with any improvement in the onboard-sensor technology. Indeed these techniques are useful to detect features on the ground (such as facilities or vehicles), but they are often insufficient for identifying them with certainty and monitoring their activity. In order to gain a clear understanding of the situation on the ground, it is vital to observe from close range using remote sensing devices placed around the feature of interest, e.g. Wireless Sensor Networks (WSN). Since these missions will be performed in hostile areas, the placement of such sensors needs to be done without human personnel involved, e.g. via aerial deployment from an aircraft. Once the sensors are deployed on the ground, their data is transmitted back to the home base to provide the necessary situational awareness.

The deployed units (the wireless sensors, called sensors in the following) fulfill two fundamental functions: sensing and communicating. The sensing can be of different types depending on the feature to observe (seismic, acoustic, chemical, optical, etc.), and the communication is performed wirelessly. However, the small size and energy storage capacity of the sensors prevent them from relaying their gathered information directly to the base. It is therefore necessary that they transmit their data to a high-energy communication node (HECN) able to provide the transmission relay to an aircraft or a satellite. All sensors must be able to transmit their data to this node, either directly or via hops, using nearby sensors as communication relays. In this paper an idealized model for the two characteristics of the sensors is used; they can communicate with one another if they are within a fixed distance R_{COMM}, and they can sense anything within their sensing radius $R_{Sensing}$. All sensors in the WSN are assumed to be identical. They also must be connected to

[*] jourdan@mit.edu; phone 1-617-253-3905; fax 1-617-258-8364.

This research is funded by the Charles Stack Draper Laboratory through the MIT/Draper Technology Development Partnership Program.

the HECN in order to transmit their data to the base. This is illustrated in Fig. 1, where the area covered by each sensor is shown as a circle (sensing disk) and arrows represent the communication links present between sensors. The HECN is placed on top of a building.

Three case studies are conducted. In the first one (Case 1), the feature to monitor is a facility served by two roads. The WSN must provide a good coverage of the facility, i.e. it must be able to detect movement along the roads (where it is most likely to occur), but also around the facility as a whole. Moreover, since the area is hostile, the survivability of the WSN depends on whether the sensors will be detected or not. The closer to the facility sensors are placed, the greater the probability that they will be discovered. Finally the network is deployed from an aircraft that can only carry a limited payload, so the number of sensors must be minimized. In the second study (Case 2), movements in and out of a circular area are to be detected. This is akin to Case 1, except that this time there are no threats to the sensors. In the third one (Case 3), a square area is to be uniformly covered by the WSN, so that every point in it can be monitored. Note that in this last case the definition of 'coverage' is different than in the previous cases, since it is not limited to an ability to detect movement in and out, but everywhere in the area. These three case studies are basic mission scenarios that can form the building blocks (or primitives) of a more complex mission scenario. For example, consider a factory suspected to manufacture dangerous chemicals. An area close to it may have been identified as a possible location for waste disposal, and chemical sensors are to cover it uniformly in order to analyze the soil (Case 3). Also, seismic sensors placed around the plant can detect the movements in and out of it, which gives and indication of the plant's activity (Case 1 or 2, depending on the threat level). All these sensors must then relay their data to a HECN placed nearby.

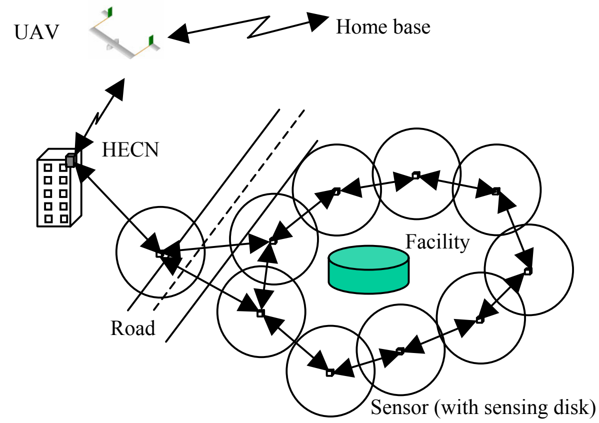


Fig. 1. Example of the use of a WSN to monitor a facility, with the High Energy Communication Node (HECN) placed on top of a building.

A Multi-Objective Genetic Algorithm (MOGA) is used to find Pareto-optimal network layouts for these three case studies, layouts that maintain the communication connectivity between every sensor and the HECN. In Case 1 the coverage and survivability are maximized and the number of sensors is minimized, while in Cases 2 and 3 only the coverage and the number of sensors are considered. It is shown that the exact same MOGA works in all cases, which shows its flexibility and its possible use for more complex missions built upon these basic building blocks.

2. LITERATURE REVIEW

From the early 1990's to a few years ago, a large body of research was devoted to the Base Station (BS) location problem for cellular phone networks. At that time the problem was to find the optimal location of BS (transmitters) in order to satisfactorily cover subscribers. Although this problem differs in many aspects from the sensor network planning problem (notably because in WSN the sensors ("BS") also need to communicate with each other (connectivity)), it is insightful to review the methods used. These range from Dynamic Programming[1], to Genetic Algorithms[2,3] and Tabu Search[4]. Virtually every type of optimization technique was tested on this problem, many of which dealt with multiple objectives (though often blended into a single objective function, except Meunier[3] who uses Pareto optimality) while using non-trivial communication models taking the terrain into account.

The BS location problem is part of the larger topic of Facility Location in Operations Research[5]. Here a set of demand points must be covered by a set of facilities (which corresponds in WSN to covering an area with a set of sensors). The goal is to locate these facilities so as to optimize a certain objective (e.g. minimize the total distance of demand points to their closest facility). A classic example close to the WSN problem is the Maximal Covering Location Problem[6,7] (MCLP), where as many demand points as possible must be covered with p sensors of fixed radius. It is also referred to as a location-allocation problem, since each demand point must be assigned to a certain sensor. Again in all these discussions, the main difference with WSN is that the nodes are not required to be connected. Another problem of interest is the Facility Location-Network Design problem, where facilities positions need to be determined (just as in

MCLP) and the network connecting these facilities must also be optimized. Unfortunately, in WSN design it is impossible to decouple sensor placement and network design, since the location of the sensors determines the network topology.

The past three years have seen a rising interest in sensor network planning, focusing mostly on optimizing the location of the sensors in order to maximize their collective coverage (a problem almost identical to the BS location problem). Several techniques were used, but the research on BS location is never mentioned. Chakrabarty[8] used Integer Programming, while Bulusu[9], Dhillon[10] and Howard[11,12] devised different greedy heuristic rules to incrementally deploy the sensors. Zou[13] adapted Virtual Force Methods (often used for the deployment of robots[12]) for the sensor deployment. Only one objective is optimized in these methods, although in the greedy algorithms referenced above it is possible to obtain the trade-off between number of sensors and coverage (e.g. by continuing to add sensors and noticing how much coverage is gained each time). Particular to WSN is the relationship between optimal WSN layout and the ratio between the sensors sensing and communication radius. This interaction is studied in Jourdan[14].

Current work on WSN gives little or no attention to the communication requirement between sensors. Also, only a single objective is considered (almost always coverage), whereas it seems other considerations are also of vital practical importance in the choice of the network layout (survivability, robustness to node failure, etc.). This paper presents a method that starts addressing these gaps, while testing it on realistic (although simplified) scenarios.

3. MODELING

3.1 WSN Modeling

The area considered is a flat square of side 10 (in arbitrary units), centered on the origin. The sensors are identical and are characterized as follows. They can monitor anything within $R_{Sensing}$ and they can communicate with any other sensor located within R_{COMM}. The HECN, with which each sensor must communicate (either directly or through hops using nearby sensors) is assumed to have been placed beforehand (presumably in a location with good line of sight to the relay aircraft or satellite). In this paper it is placed at the upper right corner of the area. This assumption is for convenience and does not prevent generalizability.

The design variables correspond to the horizontal and vertical coordinates of the sensors, and the maximum number of sensors *MAX_NUM* is a parameter fixed by the operator (it may correspond to the total number of available sensors). The vector *DV* containing the design variables is of size *2 x MAX_NUM*:

$$DV = \begin{bmatrix} x_1 & y_1 & \dots & x_{MAX\_NUM} & y_{MAX\_NUM} \end{bmatrix} \tag{1}$$

Although *DV* is of constant size, the number of sensors actually present in each design vector is allowed to vary (this is important for the optimization described below). For a WSN containing less than *MAX_NUM* sensors, the remaining entries are set to 0. So if x_i and y_i are both equal to 0, it signifies that there is no i^{th} sensor. Therefore, for a WSN containing n sensors (with n less than *MAX_NUM*), *MAX_NUM-n* pairs of entries of *DV* will be equal to 0. Equation 2 is an example of a design for a network with at most 4 sensors, where only 2 sensors are present (the first and third sensors).

$$DV = \begin{bmatrix} x_1 & y_1 & 0 & 0 & x_3 & y_3 & 0 & 0 \end{bmatrix} \tag{2}$$

3.2 Objectives Calculation

The operator designating the features of interest has the choice to select what type of surveillance action (s)he wishes to take. For example, the movements in and out of a facility may be of interest in order to identify the use of the compound (Case 1). It may also be the case that a "suspect" area has been selected, and the operator wishes to discover what kind of activity is taking place there. He may wish to monitor the movements in and out of it without placing sensors directly inside it, corresponding to perimeter monitoring (Case 2), or he may decide to cover it uniformly in order to have complete coverage (Case 3). These three cases illustrate possible mission scenarios for the WSN, and the following sections detail how the objectives are calculated in each case. In all cases, only the sensors connected to the HECN are taken into account in the calculation of the objectives.

3.2.1 Case 1: Monitoring movements in and out of a facility served by two roads

The facility is modeled as a circle of radius 1 centered at the origin. It is assumed that any sensor placed inside the facility will not be able to operate, so any entry (x_i,y_i) of DV belonging to this unit circle will not be taken into account in the calculation of the objectives (it is as if this sensor was not present). Two roads serve the facility, one horizontal going East, one vertical going North. This is illustrated in Fig 2a.

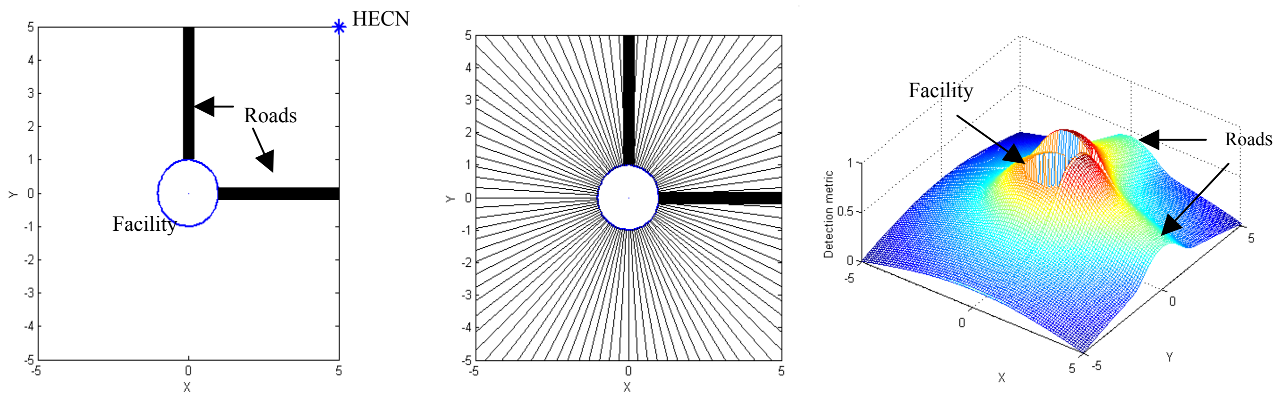


Fig. 2. Framework for Case 1: facility served by two roads (a, left); lines used to calculate the coverage objective (b, center); mapping of the probability of detection used for the survivability objective (c, right)

The first objective is the coverage, by which is meant the ability of the network to monitor movements in and out of the facility. A series of radial lines stemming from the facility are generated, and represent the possible directions from which agents can enter or exit the facility. A sensor covers a line if its distance with the line is less than $R_{Sensing}$, i.e. if the line crosses its sensing disk. The coverage is equal to the number of lines covered by the sensors, divided by the total number of lines (so it is between 0 and 1). This is illustrated in Fig 2b.

$$Max : J_1 = Coverage = \frac{Lines\ \ covered}{Total\ number\ of\ lines} \tag{3}$$

Since two roads serve the facility, it is likely that the activity in and out of the facility takes place mostly along them. Therefore, more lines are generated along these roads, so that these directions carry a greater weight and priority is given to covering the roads.

The second objective is the survivability of the network, by which is meant the likelihood that sensors will not be found. Each point in the area is assigned a probability of detection $P_{detection}$. This probability depends on the proximity of the facility or the roads. It is assumed that if a sensor is placed close to a road (where most of the activity takes place) or to the facility, it is more likely to be found and disabled. In this paper the mapping (Fig. 2c) is generated using some exponential function decaying with the distance to these features (4). It is the sum of three components $P_{Facility}$, P_{roadX} and P_{roadY}, corresponding to the three features that present a threat (facility and two roads).

$$P_{detection}(X) = [\ P_{Facility}\ (x,y) + P_{roadX}\ (x,y) + P_{roadY}\ (x,y)\ ]\ /\ 4 \tag{4}$$

$$with \begin{cases} P_{Facility}(x,y) = 2 \cdot \left[1 - \dfrac{\sqrt{x^2+y^2} - R_{Facility}}{\sqrt{2}\cdot(L/2 - R_{Facility})} \right] + \exp(-0.5\cdot(\sqrt{x^2+y^2} - R_{Facility})^3) \\ P_{road_X}(x,y) = \exp(-0.5\cdot|y|^3) \\ P_{road_Y}(x,y) = \exp(-0.5\cdot|x|^3) \end{cases}$$

where L is the side of the area, $R_{Facility}$ the radius of the facility and P_{roadX} (P_{roadY}) is taken into account if $x > R_{Facility}$ ($y > R_{Facility}$). Note that $P_{detection}$ is maximum at the "gates" (where the roads meet the facility, see Fig. 2c).

It should be noted that any mapping is acceptable to the optimization method presented in this paper (MOGA, described below), since MOGA do not have any requirement about the continuity of the objectives. There is therefore great freedom for the user in setting this probability profile. The survivability of the network is obtained by finding the sensor with maximum probability of detection, and subtracting this value from 1 (5). Note that since this metric only takes into account the sensor with highest probability of detection, it will not discriminate layouts where all sensors are highly detectable and layouts where only one is.

$$Max : J_2 = Survivability = 1 - \underset{connected\ sensors}{Max}(P_{detection}) \tag{5}$$

Finally the third objective is the number of connected sensors, which is to be minimized.

$$Min : J_3 = Number\ of\ sensors \tag{6}$$

The first two objectives (coverage and survivability) are competing. For a fixed number of sensors, in order to have more coverage the sensors need to come closer to the facility and to the roads. However doing so decreases the survivability of the network. Likewise large survivability is obtained when all the sensors are far away from the roads and the facility, yielding a poorer coverage. Also, the more sensors the more coverage and the closer to the edges of the area the WSN can spread (yielding a good survivability). So the third objective is competing with the two others.

3.2.2 Case 2: Monitoring movements in and out of a circular perimeter

The area considered is a circle of radius 3, centered on the origin, as shown in Fig. 3a. It is assumed that there are no threats to the sensors, the goal is to obtain as much coverage with as few sensors as possible.

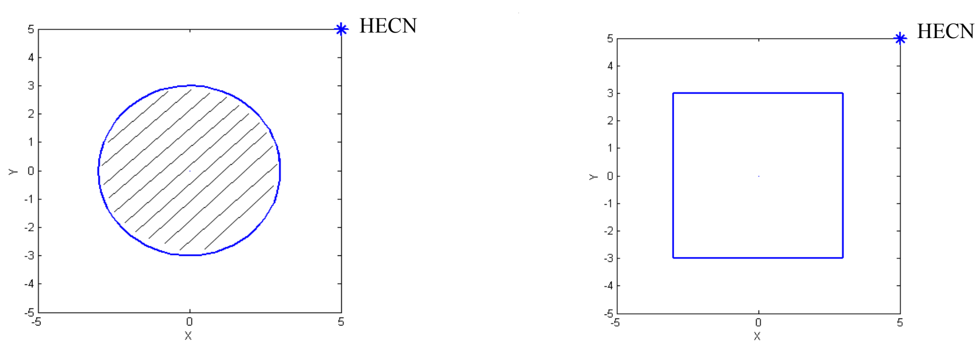


Fig. 3. Framework for Case 2 (a, left) and Case 3 (b, right)

The first objective is the coverage, as defined in Case 1. Lines are generated around the circle, and the calculation is similar. Sensors placed inside the circle are not taken into account.

$$Max : J_1 = Coverage = \frac{Lines\ covered}{Total\ number\ of\ lines} \tag{7}$$

The second objective is the number of sensors, to be minimized.

$$Min : J_2 = Number\ of\ sensors \tag{8}$$

Again, these two objectives are competing since placing more sensors yields a better coverage.

3.2.3 Case 3: Uniform monitoring of a square area

The area is a square of side 6, centered on the origin (Fig. 3b). The two objectives are those considered in Case 2, but this time the coverage is calculated differently. The goal is to cover uniformly the whole square, that is the WSN must be able to detect any movement inside the area, not only in and out. A point is covered if it is within $R_{Sensing}$ to a sensor, so that the total coverage is equal to the intersection of the square with the union of all sensing circles, normalized by the square area.

$$Max: J_1 = Coverage = \left[\bigcup_{connected\ \ sensors} \left[\pi . R^2_{Sensing} \ \ (x_i, y_i) \right] \right] / \ Area \tag{9}$$

The second objective is the number of sensors, to be minimized.

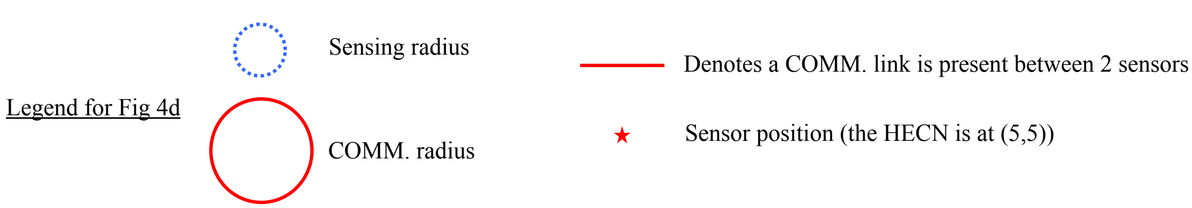
$$Min\ : J_2 = Number\ \ of\ \ sensors \tag{10}$$

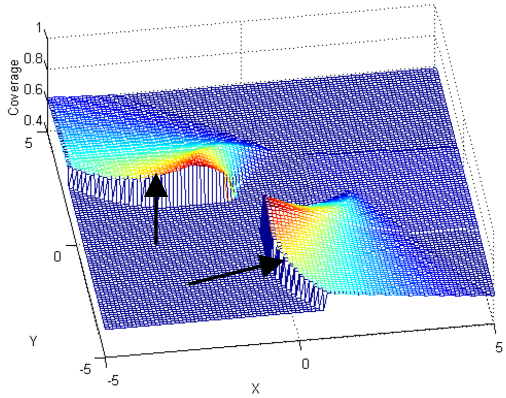
These two objectives are again competing.

4. MULTI-OBJECTIVE GENETIC ALGORITHM DESCRIPTION

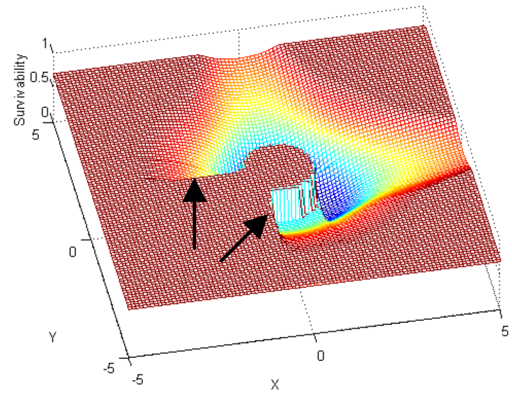
Although the terrain considered (flat surface) is idealized, the design space of the WSN optimization remains highly non-linear. This is due notably to the binary nature of the communication connectivity requirement between sensors; moving a sensor by a small amount can cause large changes in all the objectives, especially if it becomes disconnected. This is illustrated in Fig. 4 on a scenario from Case 1. Four sensors are fixed (Fig. 4d), while the fifth one is moved throughout the area; the objectives are mapped according to this sensor position. Discontinuities can be observed in all three objectives, although only one sensor is moved in this example. These discontinuities correspond to positions where the fifth sensor becomes disconnected to the rest of the network. As shown in Fig. 4d, as long as it is inside the communication region of one of the fixed sensors (solid circles), its coverage contributes to the overall coverage (when it is in places not already covered by the fixed sensors). But once it leaves this region, it cannot communicate anymore with the WSN (and therefore it cannot transmit its data to the HECN) so the coverage drops abruptly. The maximum for the coverage and the survivability is found on a sharp edge of the design space, with a sudden drop on one side. The same is observable for the number of sensors. The combined effect of all sensors renders these discontinuities even more severe.

In addition, the number of sensors is discrete, which makes the optimization harder. Therefore Genetic Algorithm (GA) was chosen as the optimization tool, because it has proven to work well for non-linear problems. It also handles multiple objectives easily. As we will see in the next section, it is also very flexible and can be used without any modifications on different scenarios with different objectives. The MOGA is aimed at providing the end-user with a set of Pareto-optimal layouts from which to choose. This is interesting because it expresses the trade-off between the objectives. For example it provides the amount of additional coverage that can be attained by deploying an additional sensor, and the operator, depending on his preference, can decide whether it is worth it or not. Because it explores the whole search space, the MOGA will find Pareto-optimum network topologies (structure of the network). Local search methods can then be used to refine these "raw" results by fine-tuning the position of each sensor; this will not be treated in this paper.

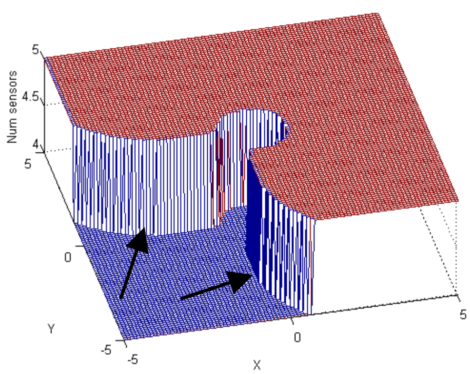




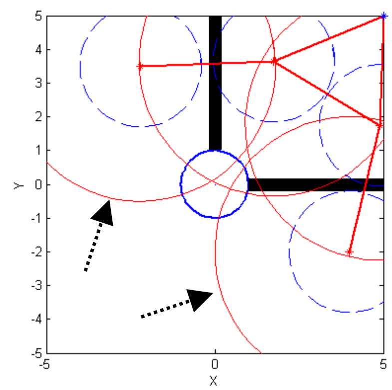
(a) Coverage (maximize)



(b) Survivability (maximize)



(c) Number of sensors (minimize)



(d) Layout of the 4 fixed sensors

Fig. 4. Design space analysis conducted on a Case 1 scenario, with arrows pointing at discontinuities

Due to the homogeneity of the design variables (the coordinates of all sensors), there is no need for encoding as is done in traditional GA. The design vector *DV* (1) is therefore used as it is as a chromosome in the GA. The GA is taken from Han[2], where the number of sensors per chromosome varies dynamically (as indicated before, a sensor is present at (x_i,y_i) if this pair is different from $(0,0)$). An initial population of N parent individuals (represented by their chromosome) is generated, where the number of sensors present in each individual as well as the positions of the sensors are chosen at random. Each parent is then mated with another (crossover) to produce two children, with the crossover point chosen at random. The children are then mutated with probability m, so that each element of *DV* is modified with a probability m. The mutation affects the coordinates of the sensor as well as whether or not this sensor is kept at all in the chromosome[2]. The objectives of these children are then computed, and a fitness value is assigned to every parent and children. This fitness is based on the Pareto dominance developed by Fonseca[15], and is proportional for

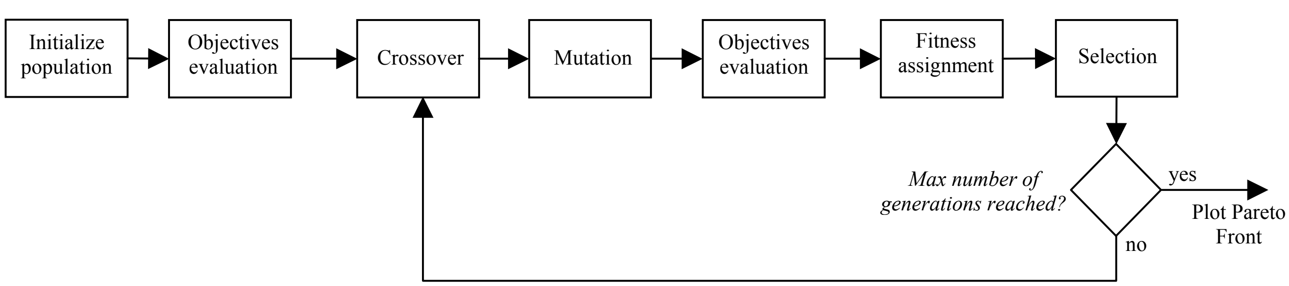
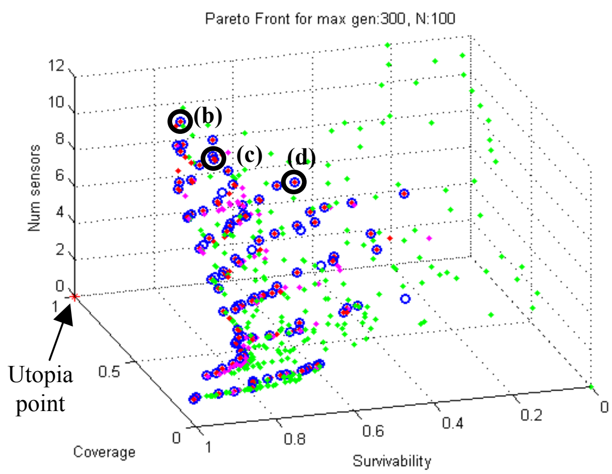


Fig. 5. MOGA description

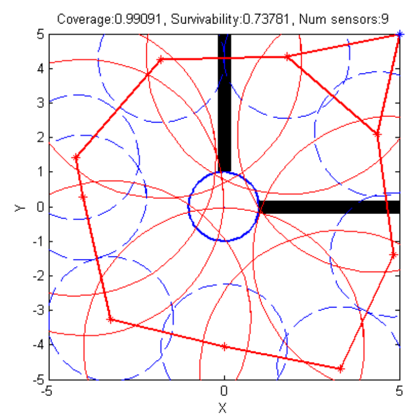
each individual to the number of individuals that dominate it (in the Pareto sense). The selection in the pool of parent and children is done using deterministic elitism, so that the N individuals with best fitness are passed on to the next generation. This enables the Pareto-optimal individuals to be passed on to the next generation, so that the population keeps improving while maintaining its diversity. The process continues until the maximum number of generations is reached. This is summarized in Fig. 5.

5. CASE STUDIES RESULTS

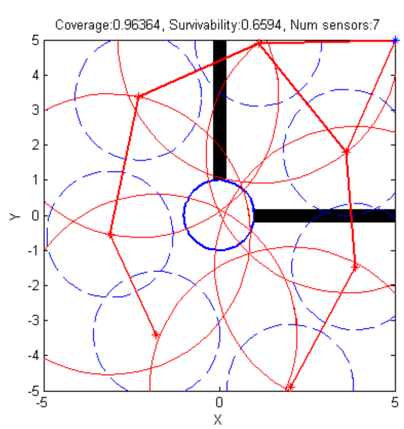
The values chosen for the sensors properties are 1.8 for $R_{Sensing}$ and 4 for R_{COMM} (the sensing range is about half the communication range). For a discussion on the influence of these parameters on the optimal layout of the WSN, see Jourdan[14]. The MOGA optimizations were performed with 300 generations, a population of 100 individuals (N) and a mutation rate of 0.1 (m). They were implemented using MATLAB 6.1 on a computer with a Pentium 4 processor running at 1.8 GHz.



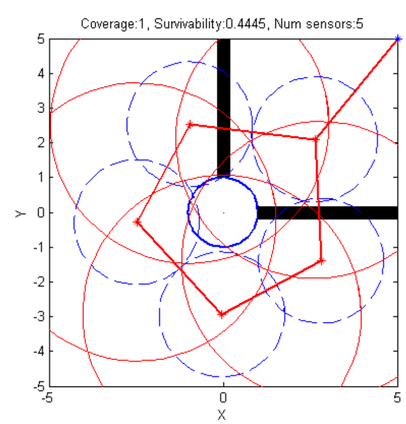
(a) Objectives graph with Pareto-optimal designs marked with small circles



(b) Pareto-optimal layout with 9 sensors



(c) Pareto-optimal layout with 7 sensors



(d) Pareto-optimal layout with 5 sensors

Fig. 6. MOGA results for Case 1. Objectives graph with Pareto Front and instances of Pareto-optimal WSN layouts (see legend of Fig. 4d)

5.1 Case 1

The objectives graph is shown in Fig. 6a, where the objectives of the individuals from all 300 generations are plotted. The approximate Pareto Front can be observed, from which the user can view the trade-off between the three objectives and choose a design based on his or her preference. The utopia point is where coverage and survivability are 1, and the number of sensors is 0. The remaining plots of Fig. 6 are examples of Pareto-optimal designs, to illustrate the trade-off between coverage, survivability and number of sensors. This optimization took 24 minutes to complete.

These results confirm the intuition about this problem. Higher survivability is achieved by placing the sensors far away from the facility and the roads (Fig. 6b), and to maintain full coverage of the movements more sensors are needed (compare (b) and (d)). The cost for using less sensors (and requiring the same full coverage) is a lower survivability: it drops of 39% from that with 9 sensors (0.73) to that with 5 sensors (0.44). The layouts selected in Fig. 6 all have a coverage value close to 1. However it may be the case that the survivability is the greatest concern for a particular mission (e.g. if we want the WSN to stay on site for a long time), so that we are ready to sacrifice some coverage in order to gain some survivability. Given a certain number of sensors (from 9 to only 1), Pareto-optimal layouts with the largest survivability are found to have the same structure as in Fig. 6b, with the coverage decreasing as more and more sensors are removed from the original layout shown in Fig 6b.

5.2 Case 2

The objectives graph is shown in Fig. 7a, this time with only two objectives, coverage and number of sensors. The approximate Pareto Front is plotted as a black line. It shows the trade-off between coverage of the area versus number of sensors. This optimization took 20 minutes to complete.

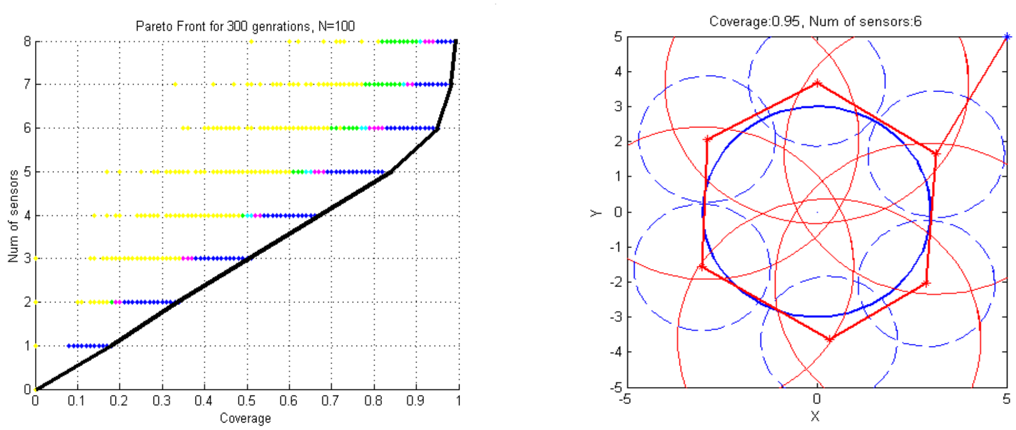
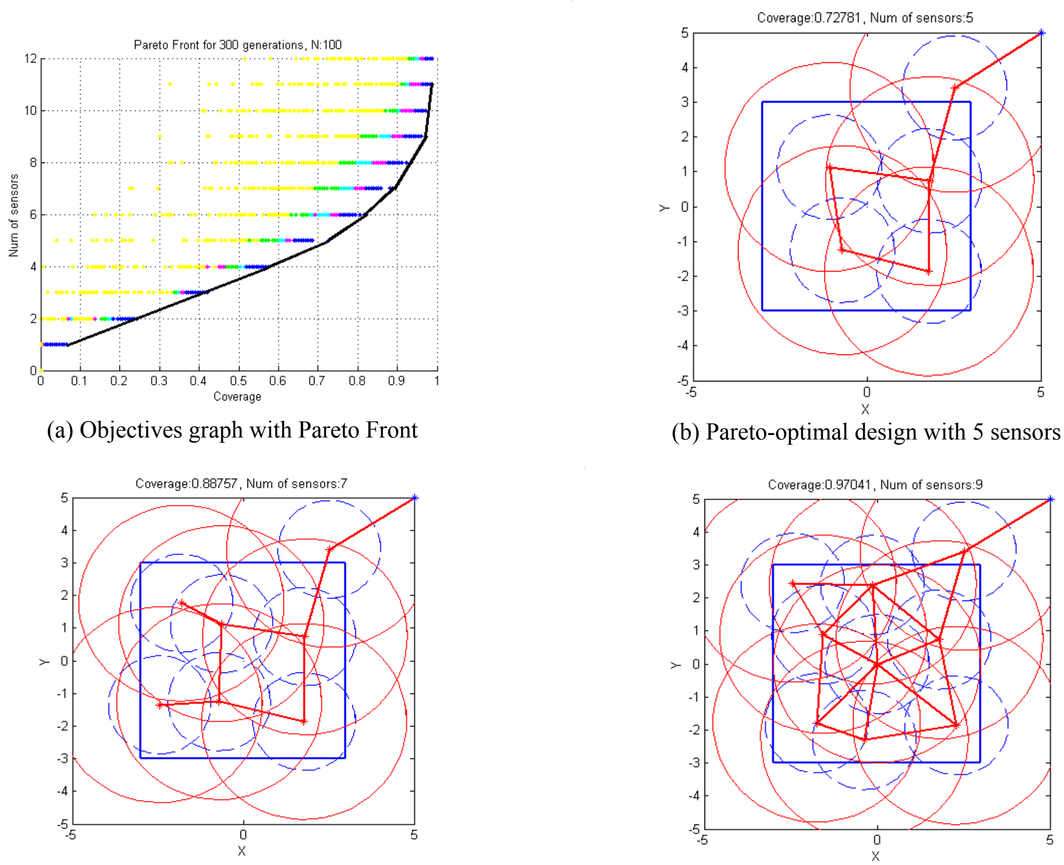


Fig. 7. MOGA results for Case 2: Objectives graph with Pareto Front (a, left) and WSN layout with 6 sensors (b, right)

Fig. 7b displays the layout with almost full coverage (obtained with 6 sensors). These results are intuitive, the MOGA provides the actual numerical values of the trade-off. The goal of this example is to show that the same MOGA than in Case 1 can be used. This is shown again in the following example.

5.3 Case 3

Results of the MOGA are shown in Fig. 8. These results agree again with the intuition, showing that the MOGA finds optimal layouts (notice the symmetrical structures that appear). Although in this case study the coverage is calculated in a different way, the very same MOGA used in Cases 1 and 2 works well. This illustrates the flexibility of this algorithm to the modeling and the choice of objectives. This optimization took 25 minutes to complete.



(a) Objectives graph with Pareto Front

(b) Pareto-optimal design with 5 sensors

(c) Pareto-optimal design with 7 sensors

(d) Pareto-optimal design with 9 sensors

Fig. 8. MOGA results for Case 3

6. CONCLUSIONS AND FUTURE WORK

The automated planning of WSN will become crucial in the near future. However, little research has gone into devising a planner that accounts for the specificities of WSN (e.g. the communication connectivity requirement between sensors and the multi-objective aspect). Also, the variety of missions that WSN will be asked to perform calls for a flexible optimization technique.

In this paper we first described the modeling used for the terrain and the sensors, and then three mission scenarios were proposed: the monitoring of the movements in and out of a facility served by two roads (with hostile threats to the WSN), the monitoring of the movements in and out of a perimeter, and the uniform monitoring of an area. These three examples are not comprehensive of all scenarios that will come up in reality, but they provide important basic building blocks of more complex missions.

The Multi-Objective Genetic Algorithm (MOGA) used to perform the optimization was then described, and the results on the three above scenarios were presented. It was shown that the MOGA successfully generated the Pareto Front of non-dominated network designs, providing the decision-maker with useful trade-off information between the objectives. Also, the very same algorithm was used in all three instances, where the only change is in the objective functions. This shows the flexibility of the algorithm chosen, and it is promising for more complex scenarios.

More work is required on the MOGA itself in order to increase its efficiency, especially by tailoring it more to the specificities of WSN. Also, a case study involving several of the basic mission scenarios described in this paper, as well as multiple HECN, should be performed. Other objectives such as the robustness of the WSN to node failure should also be explored. The fact that the network will be dropped by an aircraft is also of major importance, since it will incur some uncertainty in the final positions of the sensors. Integrating the airdrop uncertainty in the WSN planner will provide more robustness to the deployment process and increase the chances that the WSN actually placed on the ground will perform as planned. Finally a more realistic model for the terrain should be implemented, where an uneven terrain produces non-circular sensing and communicating ranges.

REFERENCES

1. R. Rose, "A smart technique for determining base-station locations in an urban environment," *Proc. IEEE Vehicular Technology Conference*, vol. 50, pp. 43-47, Jan. 2001.
2. J. K. Han, B. S. Park, Y. S. Choi and H. K. Park, "Genetic approach with a new representation for base station placement in mobile communications," *Proc. IEEE Vehicular Technology Conference*, vol. 4, pp. 2703-2707, Oct. 2001.
3. H. Meunier, E. Talbi, P. Reininger, "A multiobjective genetic algorithm for radio network optimization," *Proc. Congress on Evolutionary Computation*, vol. 1, pp. 317-324, July 2000.
4. E. Amaldi, A. Capone, F. Malucelli, F. Signori, "UMTS radio planning: optimizing base station configuration," *Proc. IEEE Vehicular Technology Conference* , vol. 2, pp. 768-772, Sept. 2002.
5. Z. Drezner, H. W. Hamacher (editors), *Facility location: applications and theory*, Springer-Verlag, Berlin, 2002.
6. R. Church, C. ReVelle, "The maximal covering location problem," *Papers of The Regional Science Association*, 32: 101-118, 1974.
7. A. Mehzer, A. Stulman, "The maximal covering location problem with facility placement on the entire plane," *Journal of Regional Science*, vol. 22, no. 3, 1982.
8. K. Chakrabarty, S. S. Iyengar, H. Qi and E. Cho, "Grid coverage for surveillance and target location in distributed sensor networks," *IEEE Transactions on Computers*, vol. 51, pp. 1448-1453, Dec. 2002.
9. N. Bulusu, J. Heidemann and D. Estrin, "Adaptative beacon placement," *Proc. Int. Conf. on Distributed Computing Systems*, pp. 489-498, Apr. 2001.
10. S. S. Dhillon, K. Chakrabarty and S. S. Iyengar, "Sensor placement for grid coverage under imprecise detections," *Proc. Int. Conf. on Information Fusion*, vol. 2, pp. 1581-1587, Jul. 2002.
11. A. Howard, M. J. Mataric and G. S. Sukhatme, "An incremental self-deployment algorithm for mobile sensor networks," *Autonomous Robots Special Issue on Intelligent Embedded Systems*, vol. 13, no. 2, pp. 113-126, 2002.
12. A. Howard, M. J. Mataric and G. S. Sukhatme, "Mobile sensor network deployment using potential fields: a distributed, scalable solution to the area coverage problem," *Proc. Int. Conf. on Distributed Autonomous Robotic Systems*, pp. 299-308, 2002.
13. Y. Zou and K. Chakrabarty, "Sensor deployment and target localization based on virtual forces," *Proc. IEEE Infocom Conference*, vol. 2, pp. 1293-1303, Apr. 2003.
14. D. B. Jourdan and O. L. de Weck, "Layout optimization for a wireless sensor network using a multi-objective genetic algorithm," to appear in *Proc. IEEE Vehicular Technology Conference*, Milan, May 2004.
15. C. M. Fonseca and P. J. Fleming, "Genetic algorithms for Multiobjective optimization: formulation, discussion and generalization", *Genetic Algorithms: Proc. Fifth International Conference*, pp 416-423, Morgan Kaufmann, 1993.