UAVs deployment in Disaster Scenarios based on Global and Local Search Optimization Algorithms

D. G. Reina, S. L. Toral
Electronic Engineering Department
University of Seville
Seville, Spain

H. Tawfik
School of Computing, Creative Technologies & Engineering
Leeds Beckett University
Leeds, UK

***Abstract*— The advancements in UAV related technologies and wireless communications pave the way for the deployment of wireless mesh networks in the air. These air mesh networks can be suitable for providing communication services in disaster scenarios to ground nodes such as victims and first responders. However, the optimal deployment of UAVs is not an easy as the number of possible scenarios to position the UAVs may reach a computationally challenging level. The combination of global and local search optimization algorithms can be considered as a powerful way for dealing with the massive number of possible solutions. We propose a deployment approach based on a global search algorithm such as the genetic algorithm and a local search algorithm namely the hill climbing algorithm. We show that the combination of both optimization techniques provides promising results for optimal positioning of UAVs in disaster scenarios based on simulation examples.**

Keywords—Disaster Scenarios, UAVs, Artificial Intelligence, Wireless Communications

I. INTRODUCTION

During the aftermath of a disaster scenario many people may remain isolated and uncommunicated due to the damages in the cellular communication infrastructure [1]. Reports on previous disaster scenarios confirm that people were unable to use their mobile and/or smartphones in a normal way [2]. This situation can cause dramatic consequences for people's welfare. Therefore, the research network communication community started to think about other networks that allow citizens to establish communications in disaster scenarios. In the last decade, alternative and self-deployed networks like Mobile Ad Hoc Networks (MANETs) have been envisioned as a promising possibility to be used for disaster relief operations [3][4]. However, MANETs have not had a significant impact on the communication market yet [5]. The main reason is that the configuration of portable devices like smartphones in ad hoc mode is not easy task in the current operating systems.

Recently, Unmanned Aerial Vehicles (UAVs) have been proposed for relief operations in disaster response scenarios [6][7]. The first idea was to use single UAV systems for search and tracking operations. However, the significant advances in the equipment for UAVs have made possible to incorporate wireless capabilities to them. This fact has also enabled the cooperation of multiple UAVs forming swarms. These swarms of UAVs can form mesh networks that provide communication services to people on the ground. Consequently, the UAV can act as access points to the air mesh network that will allow its users to make calls or connect to the Internet.

The deployment of the UAVs is of paramount importance in order to provide reliable communication services to the ground nodes [8]. This paper is focused on the use of artificial intelligence based algorithms such as genetic and hill climbing algorithms to position the UAVs in disaster scenarios. The main objective is to cover as many victims as possible. Secondary goals include maximizing robustness and minimizing redundancy. The genetic algorithm (GA) is used to first deploy a swarm of UAVs in the disaster area. To accomplish such aim, we assume the availability of some global information that has to be collected before the arrival of UAVs in the disaster area. Then, we apply a local search algorithm like the Hill Climbing Algorithm (HCA) for improving the previous first deployment according to the real conditions of the disaster scenario. We demonstrate that the combination of global and local search is suitable for the optimization of UAVs' positions.

The main contributions of this paper are combining local and global search based methodology for positioning UAVs in disaster scenarios to maximize the number of covered ground nodes, and the evaluation of different mutation and moving direction schemes for GA and HCA implementations.

The rest of this paper continues as follows, Section II includes related studies existing in the scientific literature. Section III states the coverage problem addressed in this work and the main assumptions considered. Section IV describes the proposed approach and Section V includes the simulation results obtained. Finally, this paper concludes with Section VI.

II. RELATED WORK

Global and local search algorithms have been widely used to optimize several tasks in disaster response scenarios [8]0[10]. In 0, the authors use a genetic based approach to place auxiliary nodes in disaster scenarios so as to improve the global connectivity of rescue teams. The authors demonstrate that GAs can be successfully used for offline optimization problems in disaster scenarios. In [10], a local search algorithm such as the Simulated Annealing Algorithm (SAA) is used to find optimal positions of a connected swarm of

UAVs. The SAA is used as the core of the online optimization mechanism that tries to maximize the number of covered victims. Moreover, the authors used dissimilarity metrics among UAVs to define the tactical movements.

In [11], a multi-hop UAVs network is used to connect two separated ground nodes. The ground nodes are located far from each other and they cannot connect directly. UAVs act as relaying nodes between them. In the initial stage of this application, the UAVs only know the location of one of the ground nodes. Thus, they initially perform a search strategy in order to locate the second ground node. After knowing the position of both nodes, an algorithm calculates the best locations for the UAVs in order to maximize the RSSI. Although the scenario application is not specifically stated, the behavior of the UAVs which search for a ground node and establish a connection bridge with another one resembles to the communication links between first responders in disaster scenarios.

The deployment problem of Wi-Fi wireless routers, using GAs, has already been studied in several works [12][13][14]. However, this study differs from the previous work for several reasons. Firstly, the previous work does not consider that the Wi-Fi routers have to form a connected mesh network. Secondly, they assume that the Wi-Fi routers have to be placed in a grid so the discrete search space is reduced compared with a continuous search space as the one considered in this work. Thirdly, in some studies, including [13][14], the authors do not limit the number of clients that a Wi-Fi router can serve simultaneously.

This work is also different from the ones presented in 0[10][11] in a number of ways. First, we consider that the information on the target scenario is limited. Second, the deployment of drones should guarantee that the drones form a connected mesh network. Third, we also limit the number of clients that can be served by the same Wi-Fi router. Fourth, this work is a combination of an offline deployment based on GA and an online deployment based on HCA.

III. Problem Statement

The problem consists of finding the optimal positions for a number of drones so that they can cover the maximum number of ground nodes (victims and/or first responders) and also form a connected mesh network.

The assumptions made about the scenario under consideration are:

- The transmission range of nodes (drones and ground nodes) is a circle of radius *r*. Consequently, the drones' transmission range is given by πr^2 m^2. A drone is connected to other wireless devices (drones and ground nodes) provided they are within the drone's transmission range.
- The height of the drones in the air is not considered. and the problem is bi-dimensional (2D).
- We consider quadcopter drones so they can remain in a stable position without implying significant movements. This fact is important to provide communication services to ground nodes.
- The number of maximum connections between ground nodes and a drone is 15. There are some studies that confirm that above a certain threshold the quality of communications worsens significantly [15].
- The drones form a connected mesh network as long as it is possible to find a communication path between any two drones in the network. We define this condition as the network connectivity condition.
- The positions of certain ground nodes are known in advance. The percentage of known victims is defined as the *K* value. We consider a known victim as a ground node, which location is known before the arrival of the UAV at the disaster area.
- The ground nodes are static.

IV. Proposed Solution

In order to solve the aforementioned problem, we propose a two-phase based approach. During the first phase, which is named as first deployment, a global search algorithm such as a GA is used to deploy the drones in the disaster area. The *K* value is used as input for the GA, which will be responsible for proving the optimal positions of drones according to the *K* value. During the second phase namely 'fine-tuning', the drones will move around the positions provided by the GA in order to explore ways to further maximize the covered victims. The movements will be based on a local search algorithm namely HCA. The network connectivity condition considered in the previous section should be met during the two phases of the proposed approach. Figure 1 illustrates the proposed solution.

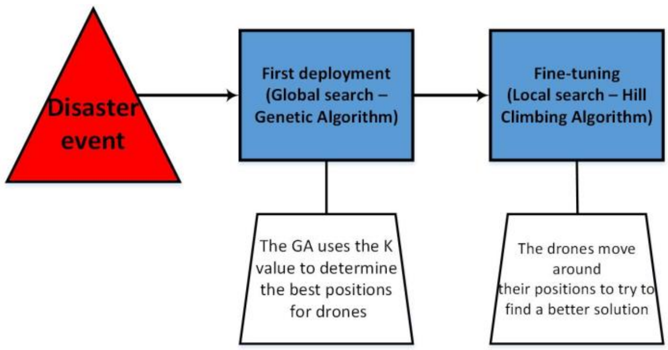

Figure 1. A proposed Global and local search based proposed solution

A. First deployment based on GA

The GA is a type of metaheuristic and probabilistic algorithm based on the Darwinian theory of natural evolution **Error! Reference source not found.**. From an algorithmic point of view, the GA is a global search algorithm that encodes potential solutions in a chromosome-like structure. Then, two genetic operators are used to explore the search space such as crossover and mutation. These operations are probabilistic and used to avoid the solutions being stuck at a local optimum. In our problem, the potential solutions are the 2D positions of the drones in the disaster scenario. The potential solutions, which are also known as individuals, are evaluated using a fitness function. This determines the quality of each possible solution.

The crossover operation consists of swapping the genetic information of two potential solutions, which are also known as parents. The selection of parents is based on the quality of the solution. A 'survival of the fittest' inspired rule ensures that the higher the quality, the higher the probability of being selected as a parent. As a result of the crossover operation two new individuals are created based on the parents' genetic information. Tournament and probability roulette are two possible approaches for parent selection.

The mutation operation consists of the modification of an individual. Consequently, a new individual is created by slightly changing the genetic information of an individual. Both crossover and mutation are probabilistic operations (Pc and Pm in Figure 2). On the one hand, by using crossover we explore deeply the search space. On the other hand, mutation is suitable for checking the surrounding research space of a given individual. Figure 2 shows the GA flow.

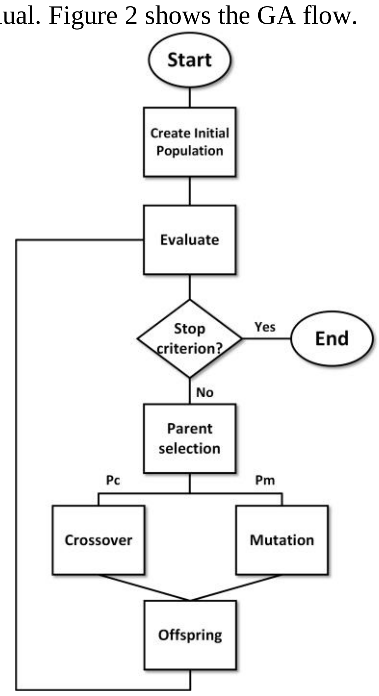

Figure 2. Genetic algorithm flow

The initial population should have a size that guarantees a high degree of exploration. Regarding the fitness function used to evaluate the quality of the individuals, the following expression is used:

$$f = k_1 V_c + k_2 C \quad if\ Net = 1$$
$$f = -1 \quad otherwise \qquad (1)$$

Where V_c is the number of victims covered by the drones considering the limitation of 15 connections per drones, C is the number of possible connections between drones and victims without considering the limitation in the number of connections. In addition, *Net* in above (1) denotes the connectivity conditions. Therefore, if the network formed by the drones is not connected, the solution will be penalized. Notice that the term C have been added to account for robustness in the solutions. Finally, the constants k_1 and k_2 weight the importance of the terms *Vc* and *C*. We consider covering the maximum number of victims as the primary objective of our approach. For this purpose, we select the values of k_1 and k_2 as follow:

$$k_2 = \frac{k_1}{|I|*|I|*|P|} \qquad (2)$$

Where $|I|$ is the number of drones and $|P|$ is the number of victims to be covered. Notice that $|I| * |I| * |P|$ is the total number of possible connections among victims and drones. By selecting the value of k_2 using (2), we always guarantee that $k_1 V_c > k_2 C$ in (1).

Regarding the crossover operation, we use a two-point mechanism. Two points are selected to exchange the genetic information of two selected parents.
As for the mutation operation, we use three different types of mutation schemes:

- **Shuffle Indexes:** It shuffles the attributes of the input individual and return the mutant. The attrubutes of our invividuals are the *X* and *Y* coordinates.
- **Swapping Coordinates:** It swaps the coordinates *X* and *Y* of a drone in the solution.
- **Shifting:** It shifts a coordinate of a drone in the solution over a given quantity.

The idea is to evaluate the proposed intial deployment considering different mutation schemes and select the most suitable one. With regard to the stop criterion, we stop the GA after the completion of a fixed number of generations.

B. Finetuning of the serach based on HCA

HCA is a mathematical optimization technique that falls into the category of local search optimization algorithms **Error! Reference source not found.**. It is an iterative algorithm that starts with an arbitrary solution to a problem, then attempts to find a better solution by incrementally changing a single element of the solution. If the change produces a better solution, an incremental change is made to the new solution, and the process is repeated until no further improvements can be found. In our optimization problem, a better solution means that the new solution increases the proposed fitness function (1).

Figure 3 shows the different steps that are followed by a generic implemetation of HCA. In the proposed approach the initial solution is obtained from the best individual provided by the GA.
In order to implement the moving direction scheme, we explore two approaches:

- **Group movement:** In this case each drone selects an independent movement.
- **Single movement:** Only one of the drones is selected to execute the movement.

In both cases, the movement of a drone is represented by the speed vector comoposed of the magnitude (speed in m/s) and moving angle.

The HCA is executed until the end of the simulation is reached. Consquently, in our implementation of HCA the termination criterion is a maximum number of iterations in the case of HCA and maximum number of generations in the case of GA..

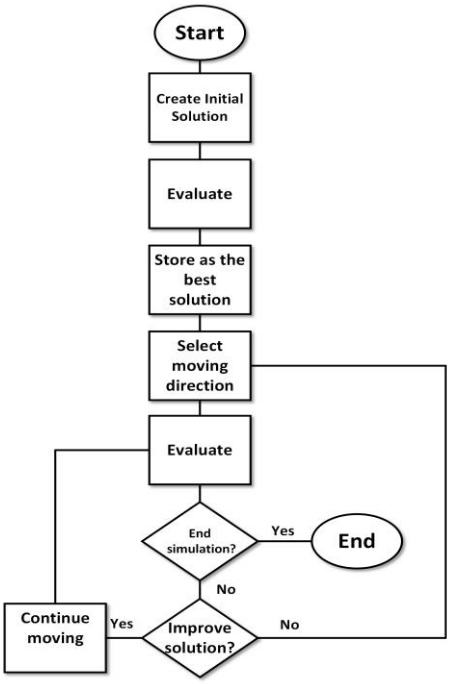

Figure 3. Hill climbing algorithm flow chart

V. Performance Evaluation

This section is focused on obtaining the simulation results of the proposed positioning approach in a disaster scenario. The disaster scenario considered attempts to emulate a disaster scenario in a rural area. Therefore, it is assumed that the drones can move freely throughout the whole disaster scenario. In this case the victims are distributed around the four corners of a square simulation scenario and they are static. The value of K in a real scenario will depend on the data collected in the aftermath of the disaster event. In practice, there are several mechanisms to obtain such data such as satellite images and phone call from people who live around the disaster area. Figure 4 represents the considered scenario; each black point indicates the positions of the victims.

Table 1 includes the main simulation parameters of the considered scenario. V_m refers to the maximum number of connections that can accept a drone. We consider 10 drones since this quantity should be sufficient to service all the ground nodes.

It is worth highlighting that the elitism mechanism has been applied in order to guarantee that the best individuals past to the following generation. According to Table 2, the 10% best individuals pass directly to the next generation. The other 90% are generated by crossover and mutation operations. The selection of parents is carried out using the probability roulette, which assigns a selection probability to the individual proportionally with its fitness.

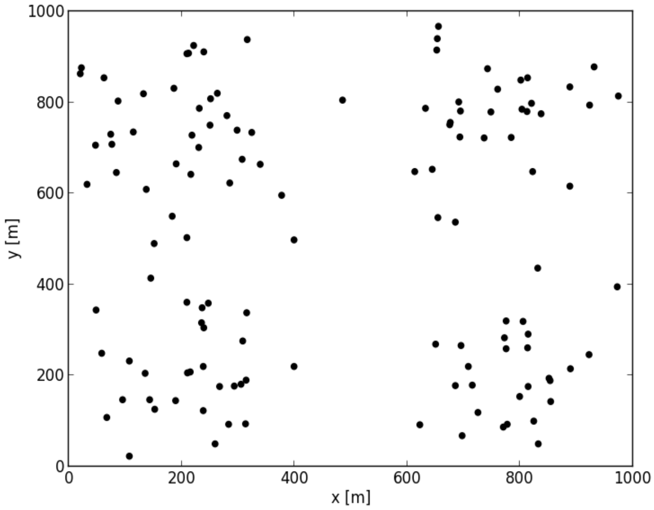

Figure 4. The simulation disaster scenario

TABLE 1. SIMULATION SCENARIO PARAMETERS

Scenario parameter	Value
Total Nº Victims	125
Mobility of victims	Static
Total Nº Drones	10
V_m	15
Drone's transmission radio range	250 m
Disaster area	1000 m x 1000 m

TABLE 2. GA CONFIGURATION PARAMETERS

Configuration parameter	Value
Population size	100
% Generated by crossover and mutation	90%
% Generated by elitism	10%
Type of selection	Roulette
Type of crossover	Two points
Crossover probability	80%
Type of mutation	shuffle indexes, swapping coordinates, shifting
Mutation probability	1%
Fitness function	Equation (1)
Nº Generations	100

TABLE 3. HCA CONFIGURATION PARAMETERS

Configuration parameter	Value
Simulation time	5000 s
Simulation step time	1 s
Drone's maximum speed	10 m/s
Moving direction scheme	Group movement, single movement
Fitness function	Equation (1)

Error! Reference source not found. includes the main configuration parameters used for the HCA implementation. It is important to highlight that the considered simulation time is high enough to guarantee the convergence of the HCA.

Table 4 contains the simulation results obtained by the GA for two different K values. Table 4 includes the maximum fitness (Max.) and the average value (Ave.) for the 50 trials conducted. We can observe that the simulation results are good for the three mutation schemes considered. The maximum fitness for K= 0.8 is obtained by the shifting scheme and it is equal to 9801.864. This result means that 98 victims are found. Notice that the maximum for K= 0.8 is 100 victims. The 1.868 presents the robustness of the solution according to Equation (1). For K= 0.6, the shuffle indexes scheme obtained the best results.

TABLE 4. SIMULATION RESULTS FOR THE FIRST DEPLOYMENT PROBLEM USING GA, K= 0.6 AND K= 0.8

Mutation Scheme	K= 0.6		K= 0.8	
	Max.	**Ave.**	**Max.**	**Ave.**
Shuffle Indexes	7501.704	7163.668	9801.816	9237.943
Swapping Coordinates	7401.720	7139.571	9801.864	9205.865
Shifting	7301.736	7101.578	9801.976	9386.860

Figure 5 shows the evolution of the best individual for each generation of the GA. It can be observed the suitable performance of the GA and its convergence.

Table 5 contains the simulation results obtained by the HCA for two different K values. Again, Table 5 includes the maximum and averages values obtained. Notice that the initial positions used by the HCA are taken from the best results shown in above Table 4 for each K value (Shuffle Indexes for K= 0.6 and Shifting for K= 0.8). According to the results included in Table 5, the group movement scheme achieves better results than the single movement scheme. The difference is more noticeable for K= 0.6, where group movement scheme outperforms its counterpart by 7.21 %. It is also worth it to highlight that for K= 0.8 the 88 % of victims are serviced. In the case of K =0.6 this value is decreased up to 83 %. Figure 6 shows the evolution of the best solutions found by the HCA for K= 0.8 and group movement scheme. Up to 22 different steps are provided by the HCA

Figure 7 shows the optimal positions of the drones obtained by the GA and HCA for K=0.8. It also shows the links among drones (red dotted lines) and the links among the drones and the victims (yellow and green dotted lines).

TABLE 5. SIMULATION RESULTS FOR THE FINE-TUNING UNSING HILL CLIMBING ALGORITHM

Moving Scheme	K=0.6		K=0.8	
	Max	**Average**	**Max**	**Average**
Group movement	10402.184	10000.138	11002.064	10900.036
Single movement	9702.112	9684.099	10902.032	10870.012

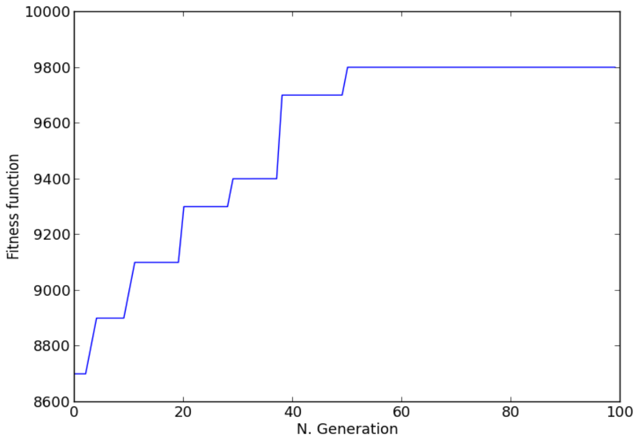

Figure 5. Evolution of the best individual of each generation in the GA (best run), K = 0.8 and shifting mutation scheme

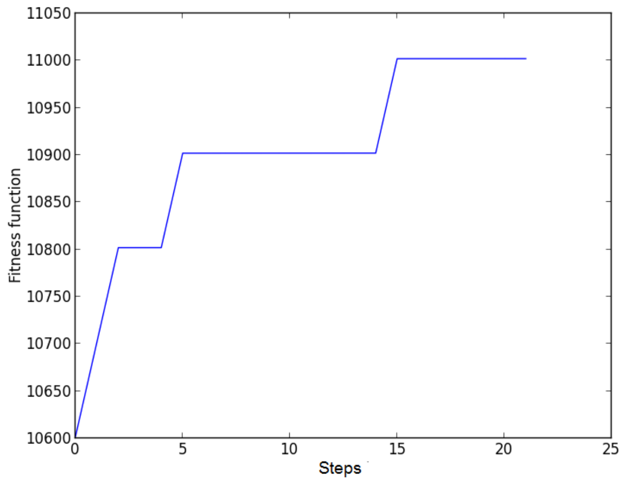

Figure 6. Evolution of the best solution in HCA, K = 0.8 and group movemebt scheme

VI. CONCLUSIONS

This paper presents a novel approach to position a group of UAVs in a disaster scenario. We propose to use the combination of global and local search algorithms, which is based on GA and HCA respectively. The proposed approach provides promising results in the considered scenario. The vast majority of victims are covered with the proposed search and deployment. We evaluate up to three different mutation schemes for the GA implementation and two moving directions schemes for the HCA implementation. We have not seen significant differences in the mutation scheme used by the GA. However in the HCA case, group movement scheme clearly outperforms the single movement scheme. As future work, we aim at evaluating other global and local search algorithms such as particle swarm optimization, simulated annealing, and Tabu search algorithms.

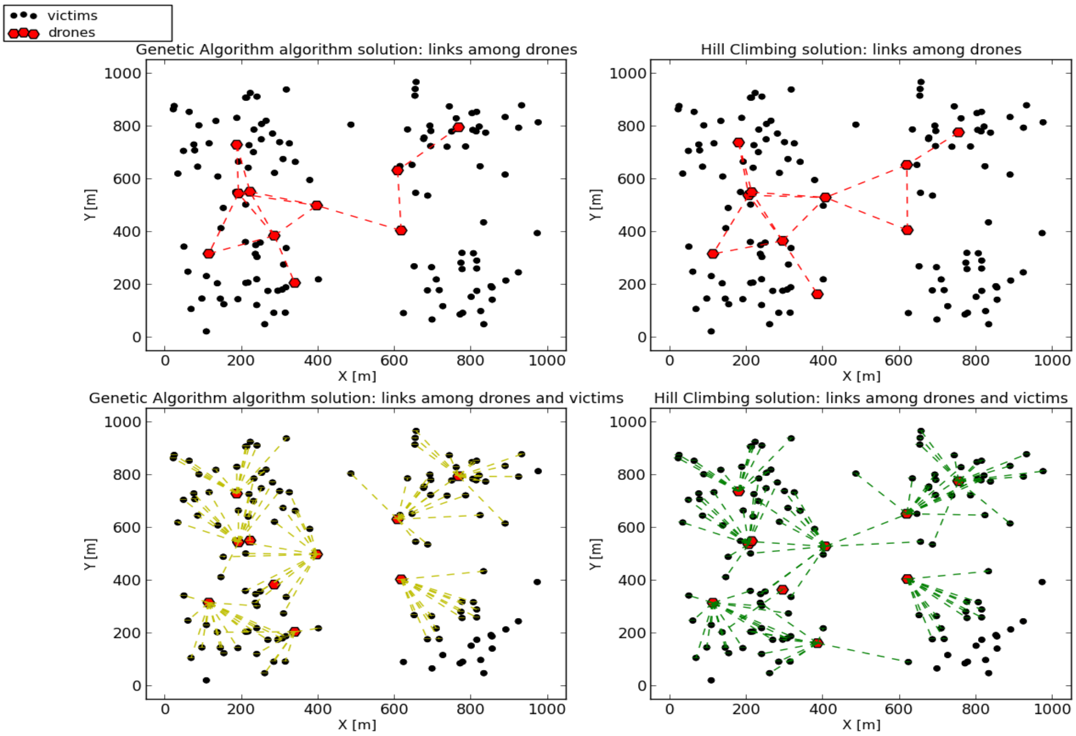

Figure 7. Optimal positions of the drones provided by the GA and the HCA for K = 0.8

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