Comparative Representations of a Genetic Algorithm to Locate Unmanned Aerial Vehicles in Disaster Zones

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Abstract—**Our economy and society depend on the continuous operation of the internet and other wireless networks. However, during or after a natural disaster, communications infrastructure can be affected and even interrupted. Effective planning of emergency operations in these scenarios can play an essential role in saving lives. Recently, the use of Unmanned Aerial Vehicles (UAVs) has been proposed to provide broadband connectivity. UAVs can be rapidly deployed as aerial base-stations over the affected area and provide connectivity between victims and emergency operators. However, one of the challenges for their deployment in emergency scenarios is finding their optimal locations to provide the largest number of communication services. This paper introduces an optimization model which positions UAVs in such a way as to maximize their coverage (the number of mobile users covered), thus guaranteeing a successful voice service in an LTE network. A genetic algorithm (GA) with a steady-state population configuration is used to find optimal locations of the UAVs. We present the results of the GA using two different representations: binary and floating-point. The results indicate that the genetic algorithm with a steady-state model performs better using a binary representation.**

Index Terms—**Binary representation, Floating-point representation, Genetic algorithms, Unmanned aerial vehicles**

I. Introduction

COMMUNICATIONS infrastructure can play an important role during natural disasters and keeping it active during catastrophes is a challenge faced by service providers, emergency services and the government [1]. During such events, communications systems can collapse. For example, Hurricane Katrina in 2005 destroyed 2000 base stations and 911 emergency services were severely damaged, leaving emergency operators without a reliable network to coordinate rescue operations [2]. The East Japan earthquake and the tsunami in 2011 damaged 1.9 million landlines and 29,000 base stations. The partial restoration took a month, while the complete restoration took 11 months [3]. In October 2012, Hurricane Sandy, in the United States of America, left 25% of base stations without service. As a consequence the affected population did not have the essential services of the network for several weeks, hindering rescue operations [4]. In 2014 in México, Hurricane Odile affected the peninsula of Baja California. It devastated the electrical and communications infrastructure such that people could not request emergency services during the first critical hours, and they could not communicate with friends and family for several weeks.

The efficient management of emergencies in scenarios where communication is interrupted by a natural disaster depends to a large extent on the ability of Public Safety Communications (PSC) to coordinate and share critical information. Currently, PSC uses the narrow band, which limits their interoperability, coverage, and service. The Federal Communications Commission (FCC) has established that it will use broadband technologies to enable PSCs to offer voice, video and data services in order to save lives, reduce damages and prevent criminal activities in the wake of natural disasters [5]. The Third Generation Partnership Project (3GPP) is working on Long Term Evolution (LTE) to support broadband requirements in PSC with the aim of creating a reliable and interoperable network [6]. Diverse studies as in [6], show LTE as a technology that has strong potential to support specific requirements of emergency scenarios.

One opportunity for improving PSC with LTE is to use UAVs as aerial base stations. The UAVs have mobility and self-organization capabilities [5], [6], [7] that offer an agile and low-cost communications infrastructure [8]. However, their use in communications networks faces some challenges. These challenges include achieving an optimal deployment of the devices, interference management, trajectory planning, network design, and channel model. [8], [9].

During an emergency, the deployment of UAVs to optimal locations is key to providing reliable network coverage. If a UAV is placed randomly within the affected area, it will not guarantee that the greatest number of victims have connectivity. On the other hand, if they are located in optimal positions, then network coverage can be maximized, ensuring that the largest number of victims have access to communication services. In emergency scenarios the number of UAVs and the number of transmission channels are usually limited; therefore, resources have to be used efficiently.

Finding locations for UAVs that maximize network coverage is the problem addressed by this research. According to the theory of computational complexity, this type of problem is considered as NP-Hard because of the large number of combinations of locations that a UAV can have [10], [11]. Metaheuristics are used to deal with this type of optimization problem, delivering suitable solutions within a reasonable time-frame [12]. Genetic algorithms (GAs) belong to this class of metaheuristics; the population evolution inspires them [13]. By applying selection, crossing and mutation

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operators, populations evolve [14]. GAs are robust techniques to solve complex problems. While they do not guarantee an optimal solution, they do find solutions very close to it. They are global search algorithms, and if a local optimum that is not useful is found, they can easily discard it and continue to explore other options. Other techniques have to restart the work. One of the challenges for their implementation is a representation of the solutions. This leads to choosing if it is appropriate to represent the solutions that the GA will process as binary, integer, floating-point or permutations strings. The information of these strings is relevant, given that they must allow for simple mapping with the objective function and support in faithfully representing the phenomenon studied. Representation of solutions has a high impact on the performance of the GA regarding execution time and quality of the solutions. For some problems, a commitment to these performance factors is observed. In this work, two representations are compared in the GA: binary and floating-point.

Several studies have addressed the problem of the location of UAVs for scenarios where communication is interrupted. For example, in [5], UAVs are used to provide communication between emergency services and victims. It studies two PSC scenarios in large and small scale to optimize the deployment of UAVs, maximizing throughput in the network with signal-interference ratio restrictions. A brute force search technique is used to solve the problem. This same technique is also at work in [15], where a device-to-device (D2D) communication system is proposed and assisted by a UAV. The UAV is deployed to aid communication between the base station (EB) and a terminal device (DT). The UAV is sent to an optimal position to maximize the data rate between the EB and the DT. However, brute force algorithms are time-costly due to the necessary evaluation of all potential locations for the UAVs. Particularly in scenarios where lack of connectivity compromises human lives, time is of the essence.

In [16] the optimal deployment of UAVs is used to create an aerial wireless network. UAVs are used to maximize network coverage. A GA with a generational population model (GAG) and a Hill Climbing Algorithm (HCA) are combined to find the optimal locations of UAVs. The GAG finds global locations of the UAVs, while the HCA is used as a complement to the local search of the positions found by GAG. However, executing the combination of the two techniques has a high computational cost.

Some studies address the problem of optimal positioning of UAVs in contexts other than emergencies. For example, in [17] a UAV is used to meet the required needs of land users in a given area. The objective is to find the optimal location for the UAV in order to minimize the total power of transmission required. It is based on the Facility Location Problem (FLP) used to find the optimal locations of the UAVs. The Optimal Transport Theory (OTT) is applied to the locations found, to verify that the UAVs' locations minimize the total transmission power; otherwise, the FLP is applied again until the objective is achieved. The OTT is a powerful mathematical framework of probability theory. However, applying it to NP-Hard type problems is not appropriate, since it is too time-inefficient. In [18] UAVs are used to improve the capabilities of the wireless network. The objective is to find positions for the UAVs that can maximize coverage of the downlink with a minimum transmission power. This study developed a deterministic method for the optimal deployment of UAVs, based on a classic optimization problem called Circle Packing. However, when the number of UAVs increases, the developed method may not solve the problem in a reasonably fast time, due to the increase in computational complexity. The study [19] uses UAVs as relay nodes to improve network connectivity and communications system performance. UAVs should be optimally positioned to improve the worst connection in the network and improve overall performance between equipment. The Particle Swarm Optimization (PSO) algorithm is used to locate the optimal locations for the UAVs. However, PSO easily falls into local optima in spaces of high dimensionality.

This paper contributes to state-of-the-art with an optimization model based on two representations of a GA that allows locating UAVs in disaster zones. We developed a GA with a steady-state population model (GAE) to find those optimal locations for the UAVs in order to maximize network coverage. The GAE processes only a part of its population with the selection, crossing and mutation operators. This makes the cost in time to be less than the cost of algorithms such as brute force, PSO, HCA or GAG. Remember that reducing the time to find a solution is a priority in emergency scenarios. Unlike the works of [16], [18], Quality of Service (QoS) is considered in this study to provide voice services. This requirement is fundamental in emergency scenarios because communication must be guaranteed. In this research, QoS is considered in terms of the Signal-to-Interference Ratio (SIR).

This paper is organized as follows: Section 2 shows an overview of GAs. Section 3 describes the system model. Section 4 describes the proposed algorithm for UAVs' placement. Section 5 shows the achieved experiments and results. Finally, in Section 6 the conclusions are provided.

II. Overview of Genetic Algorithm

A GA is a classic evolutionary algorithm that uses techniques inspired by natural evolution [13]. Evolution occurs through natural selection and reproduction; they are essential processes that improve the survival capabilities of the fittest. The individuals that best adapt to the environment are the ones that survive the most and reproduce the most.

GAs belong to the class of population-based metaheuristic algorithms that improve solutions through iterative processes [12]. The population is formed by a set of potential solutions, called individuals. Individuals that are most likely to generate offspring are usually the individuals that are best adapted to the environment. To generate offspring, some individuals are selected to evolve and reproduce; this is achieved by applying crossing and mutation strategies. Several components, such as coding of solutions (representation), the objective function (FO), population initialization, selection mechanism of individuals and variations of reproduction operators (crossing and mutation) influence the GA search process. It is necessary to specify each component to implement a GA. Additionally, to stop the algorithm, a stop condition must be provided. The simple GA is shown in Algorithm 1.

The simple genetic algorithm starts by creating a population of individuals in a random way (STEP 1). In STEP

Algorithm 1: Simple genetic algorithm

```
1 Initialize population;
2 Evaluate each individual in the population;
3 while Stop condition=True do
4     Select parents;
5     Recombine pairs of parents;
6     Mutate resulting offspring;
7     Evaluate new individuals;
8     Replace individuals with the new generation created;
9 end
```

2, each of the individuals is evaluated in the FO. In STEP 4, the individuals that will be mated are selected. These individuals are called parents. To carry out this process, a selection operator is used. Once the parents are selected, the crossover operating factor is executed in STEP 5. A recombination probability is necessary to obtain the offspring, which indicates if the strings recombine or not. If the recombination must take place, the corresponding operation is applied given the representation.

Then, in STEP 6, the resulting offspring mutate given a representation. This process occurs if a probability of mutation is fulfilled. In STEP 7, the offspring are evaluated in the FO. Finally, in STEP 8, parents are replaced by their offspring. The processes between STEPS 4 and 8 are executed while the stop condition is true. This stop condition can be defined by the maximum number of generations, the execution time, the error rate and even the optimal solution (if known).

The GA has two different models of population management: the generational model and the steady-state model [13]. In the generational model, the offspring are the same size as the population, so that each generation is replaced in its entirety by the offspring. In this way, each individual only exists in a single generation of GA. In contrast, in the steady-state population model, the population is not modified in its entirety, but rather only a part of it is replaced. Thus the offspring are superimposed on the population. In particular, the steady-state population model was introduced by Whitley's GENITOR algorithm [20]. In the steady-state population model, the idea of iteratively reproducing one or two new descendants and inserting them directly into the initial population means that there are not generations but cycles.

III. System Model

Figure 1 represents a natural disaster, such as an earthquake, tsunami or hurricane. This illustrates the area where communication is interrupted in its entirety. The emergency services have some UAVs that can be used as air base stations to maintain connectivity between victims and emergency personnel. To be able to maximize the coverage of the UAVs, they must be deployed in optimized locations. Once the optimized locations are found, the UAVs are quickly deployed in the affected area. UAVs function as an LTE access point, which allows information to be routed through the network. It is expected that LTE technology will become the broadband system of the PSCs [6].

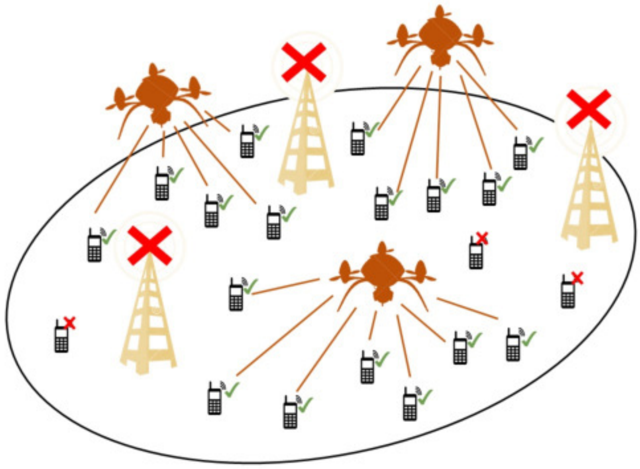


Fig. 1: Typical scenario after a natural disaster

Figure 2 illustrates the scenario in which the simulation is developed. The area affected by the natural disaster is represented by a two-dimensional area limited by $[-X_{max}, X_{max}]$ and $[-Y_{max}, Y_{max}]$, with origin in $(0, 0)$. A set of mobile users $\{MU_1, MU_2, \cdots, MU_n\}$, are located within the area, each mobile user is represented by a Cartesian coordinate (X_n, Y_n), where n is the index of the mobile user. A set of UAVs $\{U_1, U_2, \cdots, U_m\}$ must provide service to the area, their positions are Cartesian coordinates (X_m, Y_m), where m is the index of the UAVs.

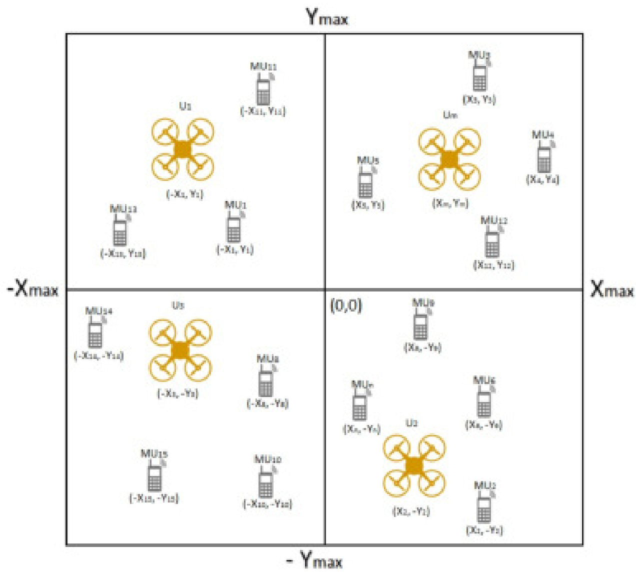


Fig. 2: Simulation scenario

A. Objective function

The FO is a mathematical function that evaluates a candidate solution (individual). The optimized locations of the UAVs that provide the maximal network coverage C, is given by:

$$Maximize\ C = V/N \tag{1}$$

where V is the number of mobile users covered by the set of UAVs $\{U_1, U_2, \cdots, U_m\}$ and N is the total of mobile users within the affected area ($N \neq 0$). For example, having a total of 300 mobile users (N) and the UAVs only serve 180 mobile users (V), then $C = \frac{180}{300} = 0.6$, the value obtained is the coverage offered by the UAVs, that is, the candidate solution's measure of fitness. The optimal value is 1, which means that 100% of the population is covered.

B. Restrictions

This paper analyzes the downlink and considers mobile users that transmit on the same channel at the same time as interfering transmitters. The downlink refers to the analysis performed on the transmitted signal from an U_m to a MU_n.

A propagation model predicts the loss suffered by the signal when the transmission channel sends it. This study uses a Hata propagation model for urban areas. Other studies such as [21] show that this propagation model makes predictions with a margin of error of less than 10 dB with respect to the real values of a communications network for frequencies of operation f_c of 700 MHz. The proposed emergency LTE network uses this frequency. Therefore, the path loss Lp_{nm} of the signal between a MU_n and a U_m is given by:

$$Lp_{nm}(dB) = A + B\log_{10}(d_{nm}) \tag{2}$$

where A and B are constant values calculated in [22], and are based on f_c and the heights of U_m and MU_n. d_{nm} is the Euclidean distance between the U_m and MU_n.

This study considers the QoS based on the SIR in dB, which indicates how much interference is perceived by a MU_n when a set of mobile users is using the same channel. Figure 3 shows the calculation of the SIR in the MU_1 of a UAV that makes up the system, U_1, where the interfering MUs are those that are using the same transmission channel as the MU_1. The SIR guarantees a successful voice transmission. So, the SIR in a MU_n can be expressed by:

$$SIR_n = (P_{tx}/ld^{\delta})/(\sum_{k\in\varphi} P_k/id(k,n)^{\delta})) \tag{3}$$

where P_{tx} is the transmission power of the U_m. δ is the attenuation factor that the signal suffers and takes a value between 2 and 4. P_k is the transmission power of the MU interfering k, MU_k. ld is the distance between U_m and MU_n. id is the distance between MU_k to MU_n. φ is the set of the MU_k using the same channel. k refers to the index of interfering transmitters that have been assigned the same channel.

Then, in order to consider that a MU_n is covered by a U_m, it must comply with the following restrictions:

$$MU_n = 0 \tag{4}$$

$$R_m \leq 2000m \tag{5}$$

$$Lp_{nm} < 120dB \tag{6}$$

$$SIR_n \geq 3dB \tag{7}$$

The restriction in (4) ensures that a MU_n is only associated to an U_m. If a MU_n has a value of zero, it means that it is not associated with any U_m. On the contrary, if it has a value greater than zero, it indicates that the MU_n is already associated with an U_m. Inequality (5) guarantees that the MU_n is within the R_m radius of coverage of the U_m. The restriction in (6) indicates the pathloss between a MU_n and an U_m. The threshold value of R_m and Lp_{nm} are derived from characterization to reduce interference for a defined area of 10,000,000 m^2. The restriction in (7) guarantees a successful voice transmission.

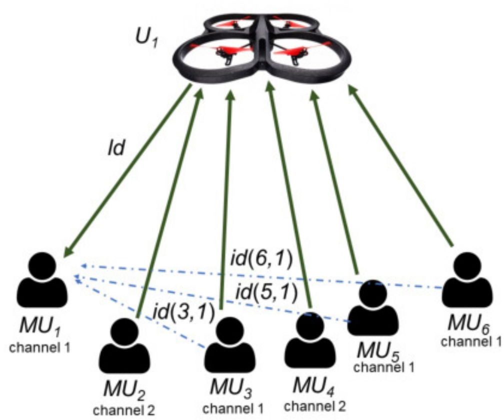


Fig. 3: Calculation of the SIR in a mobile user

IV. Proposed Algorithm for UAVs Placement

For an efficient deployment of a set of UAVs $\{U_1, U_2, \cdots, U_m\}$, the GAE, proposed in [23], is applied, where a tournament selection is used to select two parents. Then, two offspring are created, and following that, the two best individuals of the two parents and the two offspring are reintroduced into the population. The deployment of UAVs to optimal locations in this paper is proposed by means of two representations of the GAE: binary GAE (GAEB) and floating-point GAE (GAEF).

The process followed by the GAEB and GAEF for the deployment of UAVs in optimal locations is shown in Algorithm 2.

Algorithm 2: GAEB and GAEF algorithm

Require: total number of mobile users (N), total number of UAVs (M), population size (P), recombination probability (P_c), mutation probability (P_m) and total number of cycles (T_c).
Ensure: Maximum coverage (C)
1: Randomly generate the positions of N
2: Randomly initialize P
3: **while** *number_of_cycles* $< T_c$ **do**
4: Select two parents using a tournament selection
5: Crossover parents by using *two*-points
6: Mutate the resulting offspring
7: Evaluate new individuals in (1)
8: Select the two best individuals of the two parents and the two offspring. Name these two best individuals as M_1 and M_2 respectively
9: Replace the two parents with the M_1 and M_2 individuals
10: Keep the most suitable individual in the population
11: **end while**
12: Select the most suitable individual of the total number of cycles T_c

In STEP 1, the scenario is created by locating N mobile users in the area affected by the disaster. Then in STEP 2,

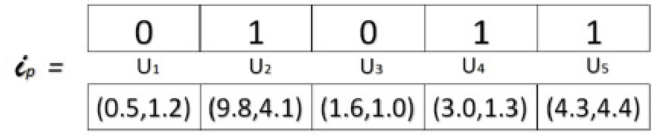


Fig. 4: Codification of individuals i_p of the GAEB

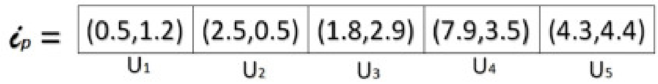


Fig. 5: Codification of individuals i_p of the GAEF

the size P population is generated randomly and is made up of a set of individuals $\{i_1, i_2, \cdots, i_p\}$, where p is the index of the individual. Each i_p individual represents a candidate solution to the problem.

An i_p for the GAEB is composed of two vectors (see Figure 4). The first is a binary vector where a bit with value 1, denotes that the $m-th$ UAV is selected and a bit with value 0 means that it is not. The second vector has different UAV positions in Cartesian Coordinates U_m = (X_m, Y_m). Each individual of the population has different positions of the U_m. In the case of the GAEF, each i_p contains a different combination of U_m positions and their coding as shown in Figure 5. Once the population is initialized, in STEP 4 the tournament selection operator is applied (tournament size T = 2). The process begins by randomly selecting two i_p of the population; the one with the best fitness will be the first father $P1$. The same process is repeated to assess the second father $P2$. In order to obtain the fitness of the competitors of the tournament, the individual must be evaluated in the FO described in (1). The process that must be followed to evaluate the individuals in the FO is shown in Algorithm 3. This process starts by verifying that the $m-th$ position of the binary vector of the individual i_p is selected (bit = 1) for the GAEB case. If this is fulfilled, it is verified that the $n-th$ MU is not associated with any U_m. This is MU_n = 0. If this is fulfilled, we continue to calculate the Euclidean distance d_{nm} between MU_n and U_m. If d_{nm} complies with the constraint of (5), then we must calculate the pathloss Lp_{nm}. If Lp_{nm} satisfies the condition from (6), then we proceed to calculate the SIR of the MU_n. If the signal to interference ratio SIR_n of the MU_n complies with the constraint of (7), then the MU_n is associated with the U_m. To finish the process, the MU_n that were covered by the U_m of the individual i_p are added to obtain the value of V, and the fitness of the selected i_p individual is calculated.

Once the parents are selected, STEP 5 is applied, where the parents create two new individuals called offspring. A 2-point crossover operator [13] is used for the GAEB case while the arithmetic crossover operator is used for the GAEF [13]. In STEP 6, a bit-flip mutation operator is applied for the GAEB [13]. In the case of GAEF, the MPTM mutation operator is applied [24].

As indicated in STEP 7, the new offspring are evaluated, under the procedure of Algorithm 2. Then, in STEP 8, the fitness of the two parents and the two offspring is compared, and the two individuals with the highest fitness are selected. These are called M_1 and M_2. In STEP 9, the vectors of

Algorithm 3: Evaluation of individuals in the FO

Require: total number of mobile users (N), total number of UAVs (M)
Ensure: Maximum coverage (C)

```
m = 0
while m < M do
    n = 0 {For the GAEF go to STEP 5}
    if U_m = 1 then
        while n < N do
            if MU_n = 0 then
                Compute Euclidian distance d_nm between U_m and MU_n
                if d_nm ≤ 2 then
                    Compute pathloss Lp_nm
                    if Lp_nm < 120dB then
                        Compute SIR of the MU_n
                        if SIR_n ≥ 3dB then
                            Associate MU_n to U_m
                        end if
                    end if
                end if
            end if
            n = n + 1
        end while
    end if
    Add associated MU_n
    m = m + 1
end while
Return C
```

parents P_1 and P_2 are replaced by vectors M_1 and M_2, respectively. In STEP 10, the most suitable individual in the population is searched and saved. The process is repeated until the stop condition is met. In this case, the total number of cycles T_c is used. When the number of cycles is met, the solution to the problem is the individual with the highest fitness of the total number of cycles T_c. This solution contains the optimal locations for the UAVs.

V. Simulation Results

The experiments in this study were carried out using GAEB and GAEF. The purpose was to determine which genetic coding representation is most efficiently positioned UAVs in disaster zones. The experiments were divided into two cases:

- Case 1. The worst-case scenario. Here, each UAV had only one transmission channel to provide connectivity to mobile users.
- Case 2. The best-case scenario. The UAVs were assigned more resources; i.e., they had more than one transmission channel to serve affected mobile users.

In both cases, each experiment was executed 50 times to show which representation was the best one statistically.

For Case 1, the worst-case scenario, each UAV has one transmission channel, and there are a total of 500 mobile users within the affected area (N=500). The name of each experiment is listed in Table I, first column. The names include a capital letter and an underscore symbol, along with the type of representation (GAEB or GAEF) applied. The capital letter represents the mobile user configuration, that is, the number of UAVs deployed and the size of the service area. In the second column of the table is the number of UAVs used, represented by M. The third column indicates the size of the service area.

TABLE I: Case 1, worst-case scenario

Experiment	Total number of UAVs (M)	Area (m^2)
A_GAEB	5	10,000,000
A_GAEF	5	10,000,000
B_GAEB	10	10,000,000
B_GAEF	10	10,000,000
C_GAEB	5	1,000,000
C_GAEF	5	1,000,000
D_GAEB	10	1,000,000
D_GAEF	10	1,000,000

For Case 2, the best-case scenario, each UAV had five transmission channels and there were a total of 500 mobile users within the affected area (N=500). Table II shows the name of the experiment, the total number of UAVs used (M), and the size of the service area.

TABLE II: Case 2, best-case scenario

Experiment	Total number of UAVs (M)	Area (m^2)
E_GAEB	5	10,000,000
E_GAEF	5	10,000,000
F_GAEB	10	10,000,000
F_GAEF	10	10,000,000
G_GAEB	5	1,000,000
G_GAEF	5	1,000,000
H_GAEB	10	1,000,000
H_GAEF	10	1,000,000

Table III shows the best parameter selection for running the GAEB and GAEF algorithms. The size of the initial population directly affects the production and diversity of individuals, therefore, P = 100. The stop criteria for both algorithms is 1000 iterations (T_c = 1000 in Algorithm 2).

Table IV shows the values used to design the emergency network. The transmission power of a mobile user is PT_n while the transmission power of each UAV is PT_m, the suggested values in [6] were used. We carried out preliminary tests to set heights for each U_m and MU_n; therefore, the values shown in Table IV for these parameters are the ones which led to lower path-losses. The frequency f_c has a value

TABLE III: Parameters used for GAEB and GAEF

Parameter	GAEB	GAEF
Selection	Tournament	Tournament
Crossover	Two-points	Arithmetic
Mutation	Bit flip	MPTM
Crossover probability P_c	0.5	0.7
Mutation probability P_m	0.1	0.1
Population size P	100	100
Number of cycles T_c	1000	1000

which is expected to be used by the PSC to provide LTE broadband communication [6].

TABLE IV: Parameters used in the emergency LTE mobile network

Parameter	Values
MU_n transmit power PT_n	24 dBm
U_m transmit power PT_m	73 dBm
Altitude of U_m	150 m
Height of MU_n	1.5 m
Frequency f_c	700 MHz

In the experiments, for a service area of 10,000,000 m^2, the restrictions of (5) and (6) were satisfied using the restriction values shown in these equations; i.e., $R_m < 2000$ m and $Lp_{nm} < 120$ dB. However, any change to the service area must be followed by a detailed interference analysis to provide the best values. For example, for a service area of 1,000,000 m^2, the new restriction values will be $R_m <$ 250 m and $Lp_{nm} < 90$ dB.

Table V shows the performed experiments for Case 1 using GAEB and GAEF. Each experiment was executed 50 times to obtain statistical values. For each experiment, the best and worst solutions found in both coding representations were reported. All the solutions provided good results. However, as expected, the best solutions are those that locate the UAVs closest to the optimal position, thus providing the best coverage. This table shows that in all the cases, the statistical distribution of solutions has a small standard deviation from the average, indicating that, most of the time, the solutions will be very close to the optimal increasing the coverage.

Table V shows that as the number of UAVs increases, the number of mobile users that can be covered also increases. This is demonstrated by "average fitness" of each experiment: B_GAEB, B_GAEF, D_GAEB, and D_GAEF. Therefore, the more UAVs deployed, the more mobile users can have connectivity. It is also observed that the average fitness obtained by the GAEB (A_GAEB, B_GAEB, C_GAEB, and D_GAEB) is better than that obtained by the GAEF (A_GAEF, B_GAEF, C_GAEF, and D_GAEF). Furthermore, in smaller areas (1,000,000 m^2) better solutions were obtained than in the experiments carried out in large areas of 10,000,000 m^2. For example, average fitness reported in experiments C_GAEB (1,000,000 m^2 and M=5) and C_GAEF (1,000,000 m^2 and M=5) is better than average fitness in experiments A_GAEB (10,000,000

TABLE V: Case 1. Worst-case scenario results. Experiments using GAEB and GAEF to test the performance of both methods. GAEB provided the best results.

Experiment	Best solution found	Worst solution found	Average	Standard deviation
A_GAEB	0.414	0.352	0.382	0.012
A_GAEF	0.408	0.358	0.378	0.011
B_GAEB	0.696	0.572	0.627	0.022
B_GAEF	0.622	0.546	0.575	0.016
C_GAEB	0.438	0.376	0.408	0.013
C_GAEF	0.424	0.380	0.402	0.010
D_GAEB	0.696	0.610	0.657	0.020
D_GAEF	0.674	0.572	0.610	0.020

m^2 and M=5) and A_GAEF (10,000,000 m^2 and M=5). This observation is also true for average fitness in D_GAEB (1,000,000 m^2 and M=10) and D_GAEF (1,000,000 m^2 and M=10) vs. B_GAEB (10,000,000 m^2 and M=10) and B_GAEF (10,000,000 m^2 and M=10). This is because in a smaller area more users can be covered by the UAV.

Table VI reports the average execution time of the experiments considering the worst-case scenario. As is shown, the smaller the area in which UAVs are located, the longer it takes for the GAEB and the GAEF to execute. Take, for example, experiments that have the same number of UAVs to deploy, such as C_GAEB and C_GAEF vs. A_GAEB and A_GAEF. C_GAEB and C_GAEF have higher average execution time than A_GAEB and A_GAEF. The same is shown in experiments D_GAEB and D_GAEF vs. B_GAEB and B_GAEF. Average execution time is higher in experiments D_GAEB and D_GAEF than experiments B_GAEB and B_GAEF. This indicates that there is a relationship between execution time and the extension of the area where the UAVs are to be located.

TABLE VI: Case 1. Execution times for the worst-case scenarios

Experiment	Average execution time (s)	Total number of UAVs (M)	Area (m^2)
A_GAEB	184.8	5	10,000,000
A_GAEF	188.4	5	10,000,000
B_GAEB	269.4	10	10,000,000
B_GAEF	235.8	10	10,000,000
C_GAEB	210	5	1,000,000
C_GAEF	211.8	5	1,000,000
D_GAEB	290.4	10	1,000,000
D_GAEF	276.6	10	1,000,000

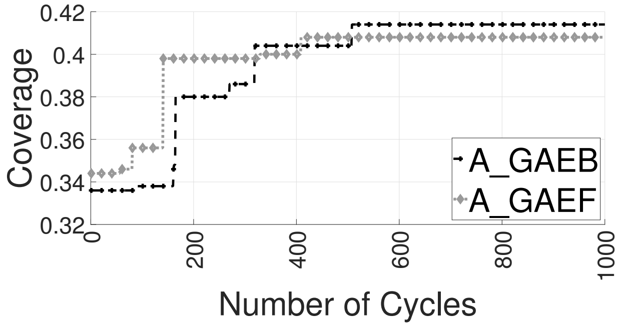
Figure 6 shows the convergence of the "best solution found" as reported in Table V. When compared with one another, the experiments that execute the GAEB are shown to generate more improvements as the number of iterations increase. In contrast, the experiments executing the GAEF have fewer improvements or none as the number of iterations increase. This suggests that experiments executing GAEF got stuck in local maxima and they will require a mechanism to escape from traps and more cycles to improve their performances. In a GAEF, the UAVs' locations change by very small margins as compared to those of GAEB.

Table VII shows the performed experiments for Case 2; i.e. the best-case scenario with five transmission channels per UAV. To obtain statistical values, each experiment was run 50 times and the best and worst solutions for each scenario were recorded. Then the average values and standard deviation were calculated for each case. In general, the average solution is considered a very good solution because the UAVs were located very close to the optimal places. The standard deviation for all the experiments is very low, indicating that, most of the time, the algorithms obtain solutions very close to the optimal.

TABLE VII: Case 2. Best-case scenario results. Experiments using GAEB and GAEF to test the performance of both methods. GAEB provided the best results.

Experiment	Best solution found	Worst solution found	Average	Standard deviation
E_GAEB	0.450	0.388	0.425	0.015
E_GAEF	0.442	0.398	0.421	0.010
F_GAEB	0.730	0.632	0.686	0.020
F_GAEF	0.670	0.578	0.622	0.018
G_GAEB	0.498	0.428	0.452	0.017
G_GAEF	0.472	0.438	0.454	0.009
H_GAEB	0.786	0.660	0.722	0.028
H_GAEF	0.722	0.616	0.671	0.021

Table VII shows that suitability of the solutions improves when the number of transmission channels per UAV increases, as compared to the solutions reported in Table V from Case 1, worst-case scenario (one transmission channel per UAV). This happens because mobile users are distributed among the assigned channels, causing less interference, which in turn allows more mobile users to link with the UAVs. Therefore, there is a relationship between the number of assigned channels and the coverage delivered: the more channels assigned, the greater the number of services that can be provided. It should also be noted that, in smaller areas (1,000,000 m^2) better solutions are obtained than in large areas (10,000,000 m^2). For example, consider the experiments with the same number of UAVs but different area sizes in which to deploy them: G_GAEB and G_GAEF vs. E_GAEB and E_GAEF. Average fitness in experiments G_GAEB (1,000,000 m^2) and G_GAEF (1,000,000 m^2) is better than average fitness in experiments E_GAEB (10,000,000 m^2) and E_GAEF (10,000,000 m^2). Similarly, average fitness in experiments H_GAEB (1,000,000 m^2)



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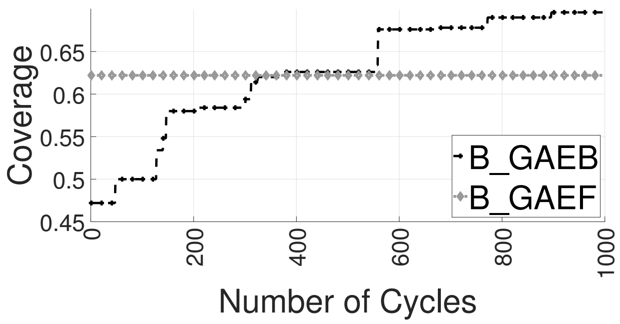

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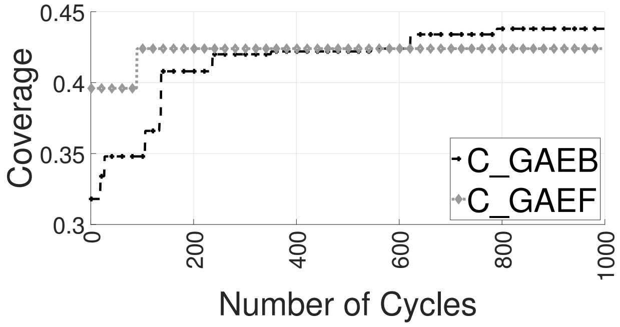

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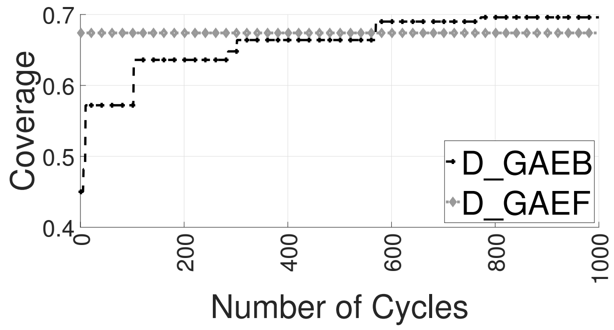


(d)

Fig. 6: Convergence of the "best solution found". (a): A_GAEB vs. A_GAEF, (b): B_GAEB vs. B_GAEF, (c): C_GAEB vs. C_GAEF, (d): D_GAEB vs. D_GAEF

and H_GAEF (1,000,000 m^2) is better than average fitness in experiments F_GAEB (10,000,000 m^2) and F_GAEF (10,000,000 m^2). This is an expected performance given that, in a smaller area, more mobile users are covered with the UAVs that are in place. In general, the average fitness obtained by the GAEB (experiments E_GAEB, F_GAEB, G_GAEB and H_GAEB) is better than that obtained by the GAEF (experiments E_GAEF, F_GAEF, G_GAEF and H_GAEF).

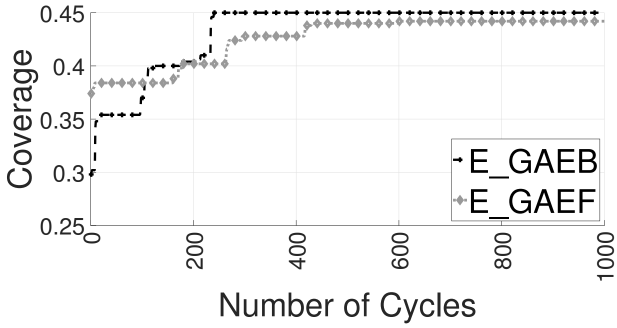
Table VIII shows the average execution time of the GAEB and GAEF when testing the experiments of Case 2, best-case scenario. Just as in Case 1, it can be seen that the smaller the area in which the UAVs are located, the longer the GAEB and the GAEF take to execute. For example, experiments G_GAEB and G_GAEF (both with 1,000,000 m^2 and M=5) have higher average execution times than experiments E_GAEB and E_GAEF (both with 10,000,000 m^2 and M=5). Likewise, experiments H_GAEB and H_GAEF (both with 1,000,000 m^2 and M=10) have higher average execution times than experiments F_GAEB and F_GAEF (both with 10,000,000 m^2 and M=10).

TABLE VIII: Case 2. Execution times for the best-case scenario

Experiment	Average execution time (s)	Total number of UAVs (M)	Area (m^2)
E_GAEB	98.4	5	10,000,000
E_GAEF	105.6	5	10,000,000
F_GAEB	142.8	10	10,000,000
F_GAEF	141.6	10	10,000,000
G_GAEB	107.4	5	1,000,000
G_GAEF	112.2	5	1,000,000
H_GAEB	156.6	10	1,000,000
H_GAEF	159.6	10	1,000,000

Figure 7 illustrates the convergence of the "best solution found" as reported in Table VII. The experiments executing the GAEB generate more improvements as the number of iterations increase. Contrasting Figures 6 and 7, we observe that the number of channels per UAV was a factor that helped the experiments executing the GAEF to generate more improvements as the number of iterations increased. Even though the number of channels per UAV affect the fitness of GAEF, the UAVs' locations still change to a lesser degree than a GAEB. Similar to the findings in Figure 6, in a GAEF, a mechanism to escape from local traps and more iterations are required to improve its fitness. This fact is independent of the number of channels, number of UAVs and size of the area.

To verify the quality of our solutions, we carried out other experiments in order to compare our results with those reported in [11]. The authors in [11] showed that 8 base stations can serve up to 698 mobile users in a service area of 1,000,000 m^2. Even though the context of [11] differs from this research, that is, UAVs were not used as base stations and were not studied in emergency situation, it is referenced here to measure the quality of the solutions of this proposal. Then, we performed the experiments I_GAEB and I_GAEF for Case 1, worst-case scenario (one transmission channel). In contrast, the experiments J_GAEB and J_GAEF are for Case 2, best-case scenario (five transmission channels). Each experiment was executed 50 times; the 698 mobile



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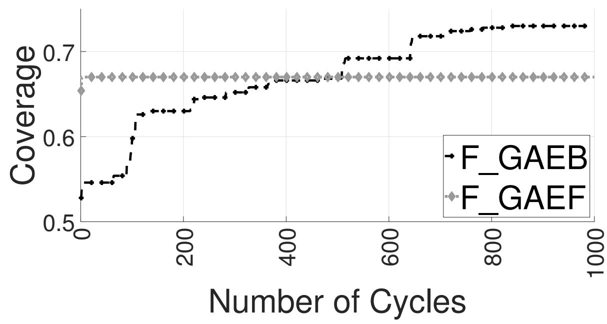

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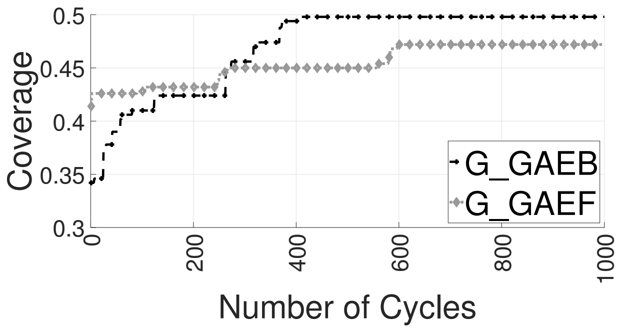

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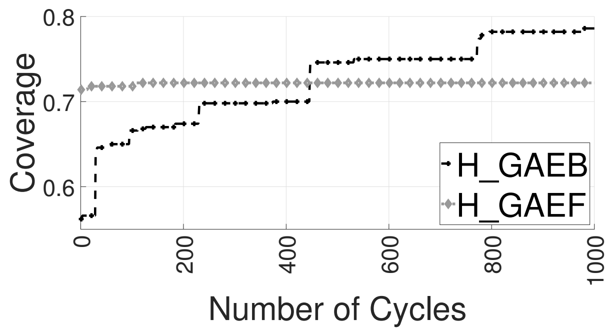

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Fig. 7: Convergence of the "best solution found". (a): E_GAEB vs. E_GAEF, (b): F_GAEB vs. F_GAEF, (c): G_GAEB vs. G_GAEF, (d): H_GAEB vs. H_GAEF

users locations were kept fixed within the affected area and each individual (candidate solution) has different eight UAVs locations. The parameter values for the emergency LTE mobile network are specified in Table IV for GAEF and GAEB. Table IX shows the results of the experiments.

Our algorithm covers on average more than 40% of mobile users as in the experiments I_GAEB and I_GAEF show in

TABLE IX: Results obtained by Case 1 and Case 2

Experiment	Best solution found	Worst solution found	Average	Standard deviation
I_GAEB	0.450	0.388	0.425	0.016
I_GAEF	0.442	0.398	0.421	0.017
J_GAEB	0.730	0.632	0.686	0.016
J_GAEF	0.670	0.578	0.622	0.018

Table IX. Increasing the channels to five, as in the J_GAEB and J_GAEF experiments in Table IX, covers on average more than 60% of the 698 mobile users. This suggests that the main factor that helps UAVs to improve coverage is the number of channels. From Table IX we observe that the GAEB (experiments I_GAEB and J_GAEB) obtains better solutions than the GAEF (experiments I_GAEF and J_GAEF).

The "best solution found" for I_GAEB and I_GAEF experiments reported in Table IX, is the best deployment of the eight UAVs to cover the maximum number of mobile users (see Figure 8). In contrast, Figure 9 shows the "best solution found" (or the best deployment of the eight UAVs) for J_GAEB and J_GAEF reported in Table IX. In Figures 8 and 9, the eight UAVs are symbolized by big squares in different colors while the small squares paired with a number are colored in the same color as the UAVs; these represent the mobile users to whom the UAV provides a voice service. The red squares are mobile users who could not be considered because they did not comply with the restrictions. Contrasting deployments in Figures 8 and 9, we observe more complete circle patterns when the GAEB is applied, that is, in I_GAEB and J_GAEB. Irregular circle patterns are observed when GAEF is applied, as in I_GAEF and J_GAEF. This observation confirms that when the GAEF is used, it leads to small changes in where the UAVs are located.

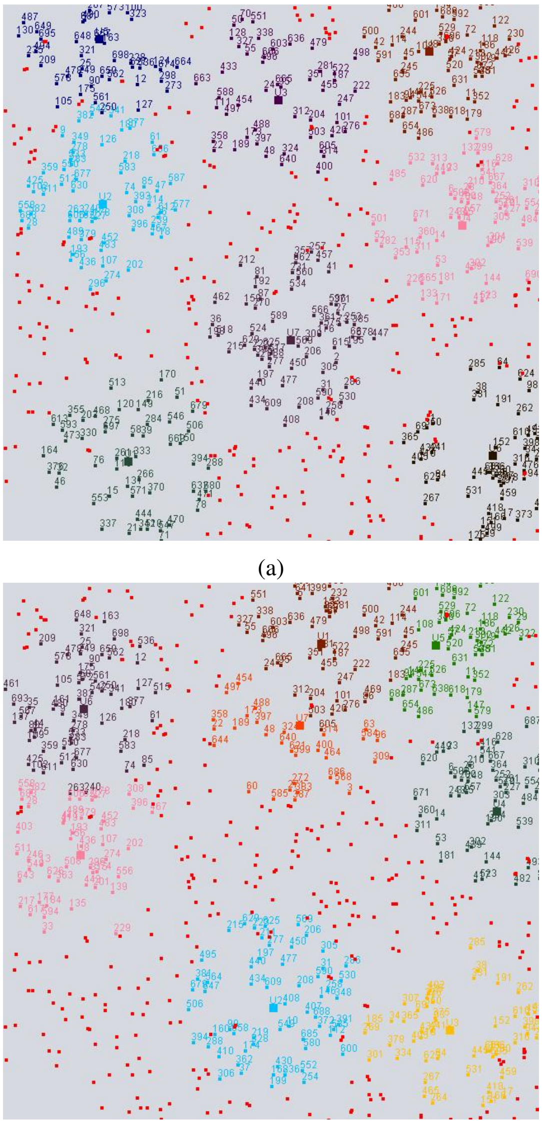
VI. Conclusion and Future Work

This research contributes to the state-of-the-art in meta-heuristics in the identification of optimal locations to which a limited number of UAVs can be deployed to provide communication in an LTE network to as many mobile users as possible in an area where communications are interrupted by a natural disaster. To do so, we developed an optimization model based on a GA with a steady-state population using two different representations: binary and floating-point. A GA with a steady-state population model was chosen to reduce execution time.

According to the results of this study, the worst-case and the best-case scenarios, we conclude that the solutions obtained by the GAEB are of better quality than the solutions obtained by the GAEF.

The results suggest that the GAEF needs to execute more iterations in order to improve it's solutions. This is because changes in UAVs locations are smaller compared to the GAEB.

The more transmission channels and UAVs assigned to an area, the more extensive the coverage achieved. This is because mobile users can be better distributed among a



(a)

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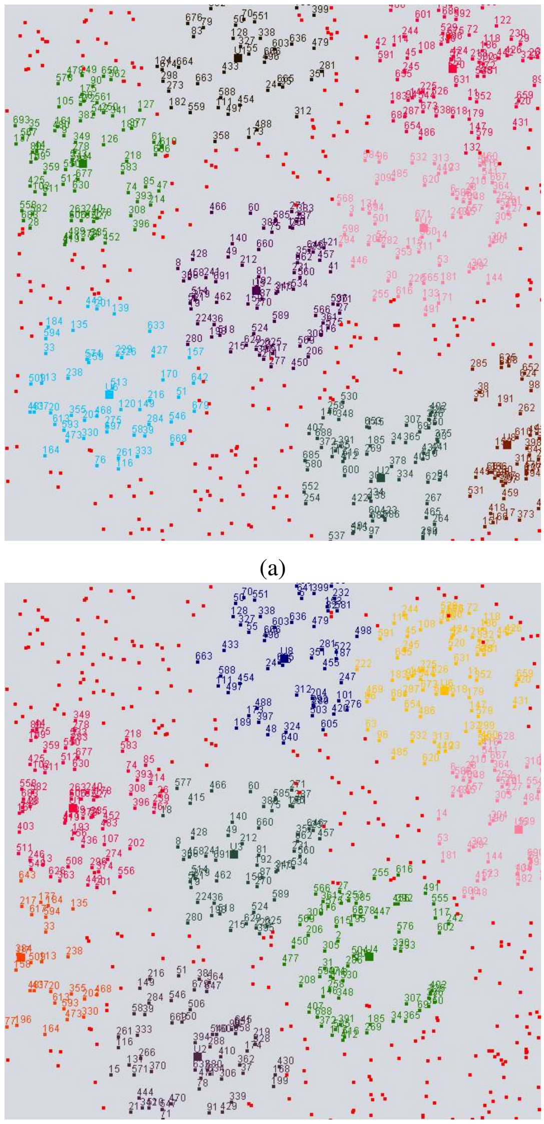
Fig. 8: Deployments of the "best solution found". (a): I_GAEB, (b): I_GAEF



(a)

(b)

Fig. 9: Deployments of the "best solution found". (a): J_GAEB, (b): J_GAEF

greater number of UAVs and channels, thus decreasing the amount of interference in signal.

According to execution times reported in both cases of study, there can be seen a relationship between the execution time and the extent of the area in which the UAVs need to be located: the smaller the area, the longer the execution time. In a small area, users are more crowded which in turn makes it more difficult for the algorithm to find the set of mobile users who do not interfere with each other.

We also compared our results with cutting-edge results from a related study in which the authors reported that 8 base stations could serve 698 mobile users in the area of 1,000,000 m^2. In this context, the GAEF and GAEB covered on average more than 40% of mobile users considering the worst-case scenario (Case 1). In contrast, the GAEF and GAEB covered on average more than 60% of mobile users in the best-case scenario (Case 2). These results indicate that the number of channels is a crucial factor in improving coverage.

For future work, we plan to apply other types of bio-inspired algorithms to improve the quality of the solutions. The restriction of intra-tier interference, which is the interference that mobile users receive from UAVs by reusing the same frequencies, will also be integrated into this optimization model.

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