A Joint Algorithm for Base Station Deactivation and Mobile User Reassignment in Green Cellular Networks

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Abstract: The proliferation of smartphones has led to an increase in the cellular infrastructure, due to efforts by mobile operators to meet the rising demand. Given that the planning of cellular networks is carried out according to demand during peak hours, a large number of base stations must be deployed to maintain a constant number of base stations even when traffic intensity is reduced. This strategy has brought about increased energy levels in cellular networks, affecting the networks' operating expenses and contributing to the problem of carbon emissions in the atmosphere. This work shows an algorithm that deactivates base stations for cellular networks and reassigns mobile users. We use the interruption probability to analyze the effect of base-station-deactivation on mobile users. We perform two approaches: one using a homogeneous network and the other a heterogeneous network. The homogeneous network is a macro-cell deployment, whereas the heterogeneous network comprises macro-cells and femto-cells. A genetic algorithm is used to find the set of base stations to deactivate and continue offering the demand services. As the carrier-to-interference ratio increases, the results show that few base stations need deactivating in a heterogeneous network with high traffic demand.

Keywords: Genetic algorithm; Green network; Sleep mode

1 Introduction

Currently, there are mobile applications for almost any activity performed on smartphones, from carrying out banking operations to measuring kilometers traveled during a walk. The applications work automatically, anywhere, and at any time. As a result, smartphones have gained popularity among the world's population, as shown by the fact that, in 2018, 66% of the said population had a mobile device. Following this trend, it is estimated that by the year 2023, the percentage will increase to 71% [1]. These devices provide voice and text messaging services and focus on online services such as data storage and social networks, as well as music and video transmissions, all of which generate more data traffic.

Network operators' strategy to meet the demand for data is to increase the number of base stations in a network [2]. This proposal is known as network densification [3]. It implies that many base stations (BSs) are deployed to handle high traffic status. However, the same number of active BSs is maintained even when traffic intensity is reduced. BSs use between 60% and 80% of the total energy utilized in a cellular network [4], and are responsible for 70% of the network's carbon dioxide emissions, making BSs the most energy-consuming devices in a network [5]. On a global scale, the information and communications technology industry contribute 2% to the world's CO_2 emissions [6].

In essence, there is one important reason why the development of green cellular networks has been proposed to address the imbalance between energy performance and energy consumption: the need for environmentally friendly cellular networks [7]. Researchers in the communications industry have focused on improving energy efficiency because BSs are the primary consumers of energy in a cellular network. Some solutions to reduce energy consumption involve BS hardware modifications or intelligent management of the elements of a network based on variations in traffic load [7]. Other solutions, reported in [7], propose reducing power amplifier operation periods, deploying heterogeneous networks, or switching BSs on/off.

The number of active BSs can be optimized by shutting down underused BSs and loading all users from the off BSs to the active BSs through a reassignment process [8]. To deactivate BSs within a network, it is necessary to find the minimum set of active BSs needed to continue offering the services in demand. This problem is not a trivial problem, given that various factors influence which BS should be active, such as radius coverage of the BS, available channels, and interference. On the other hand, the significant number of BSs in a network increases the possible combinations of active BSs, i.e., possible solutions to the problem. Therefore, minimizing active BSs in a cellular network is considered an NP-Hard [9] type problem since the time spent looking for a feasible solution is substantial. It should be mentioned that the optimal solution to this problem has not been found because there are potentially many, and the solution depends on multiple factors.

User reassignment adds complexity to the problem. A decision must be made about which subset of BSs to disable and which mobile users to associate with each active BS. These are yet more factors to consider when modeling the system.

The protocol for the assignment of mobile users should not be confused with that of their reassignment. The former has already been widely studied and reflected in standards mentioned in [4] [10] [11], whose improvements are focused on energy efficiency and load balancing. Whereas the latter, the user-reassignment, arises due to the BS being shut down.

The present work proposes an algorithm for BS deactivation and mobile user reassignment. The algorithm uses an optimization model designed to minimize the number of active BSs by using the fundamental processes of an artificial intelligence technique called a Genetic Algorithm (GA) [12]. The use of GAs has proven to be appropriate in the context of this research topic, as shown in [2] and [6]. Reassigning users is an extensive process as all BSs search for the best service conditions for their users. For this reason, we apply a steady-state population model [12] of the GA to reduce the number of times the processes of crossover, mutation, and selection are carried out.

The GA for deactivating BSs and reassigning mobile users is responsible for evaluating the network at a given moment. It finds the minimum set of active BSs needed and performs the user reassignment process to maintain a low interruption probability (PI) value. To achieve this, in the optimization model, we explicitly consider the PI to analyze how BS deactivation affects users' service. The energy saved in this type of algorithm will depend on the number of deactivated BSs. If many BSs are deactivated, the energy saved can be substantial [7].

This paper is organized as follows: Section 2 presents the related work. Section 3 describes the system and optimization models. Section 4 explains the base station deactivation and mobile user reassignment algorithm. Section 5 discusses our experiments and their results. Finally, we present the conclusion, and address implications for further research.

2 Related Work

In the existing literature, several papers seek to reduce energy consumption in cellular networks by minimizing the number of active BSs. For example, in [9], an optimization framework is proposed that chooses a minimum set of BSs. It allocates mobile users accordingly (reassignment process) while meeting their target Signal-to-Interference-plus-Noise Ratio (SINR) constraints. It involves two approaches: the proactive approach and the reactive approach. The former begins with a low traffic load. As traffic increases, BSs are turned on. The latter starts with a high traffic load, and BSs are turned off as traffic decreases. The problem is transformed to one of full linear programming for small and medium networks and is solved with a branch and bound algorithm. For larger networks, a heuristic solution is proposed: each time the algorithm tries to eliminate a BS, it constructs a new Voronoi tessellation, calculates the SINR for each BS and mobile user pair, and also calculates the interruption probability. Unlike [9], our algorithm can be adapted to any network size. It considers a PI threshold in the model.

In [2], BSs shut down in a specific order, not necessarily beginning with the lower load BSs, and a smaller number of BSs are allowed to remain active. The authors propose an approach to minimize the number of active BSs. The reassignment process assigns a mobile user to a BS with the highest spectral efficiency without violating the bandwidth constraints; otherwise, the mobile user is blocked. It is a centralized cell zooming approach based on work in [13], in which a GA finds an ordering which results in more BSs being switched off. Even though cell zooming techniques focus on the energy consumption of the whole network, they may cause inter-cell interference and gaps in coverage [13]. In contrast, our algorithm does not deactivate BSs because they have smaller loads. Instead, it leaves active those BSs that can receive more users from their neighboring BSs, i.e., those located in areas with more users.

Similarly, work in [14] applies a binary Social Spider algorithm to solve the problem of BS deactivation by minimizing the number of active BSs. To shut down the BSs, the algorithm penalizes the fitness function according to the cell traffic load of the available neighboring BSs. If the neighboring BSs can serve the traffic load initially handled by deactivated BSs, the penalty value is lower; if not, it is higher. They do not include PI constraint in the original optimization problem. Our algorithm also applies a penalty function, but, unlike the work in [14], we increase the fitness value of a candidate solution if it cannot achieve the PI threshold. We guarantee that the BS set selected by the GA serves 99% of mobile users.

Work in [4] couples its approach to BS deactivation with user association. It proposes a fitness function that minimizes the trade-off between energy consumption and flow-level performance. Two problems arise from this: 1) a user association problem for which a policy is defined that guarantees that mobile users associate with the BS in an energy-efficient manner, taking into account the load balance; 2) a BS switching on/off problem that is solved employing a greedy algorithm. On the other hand, our algorithm evaluates the network-wide impact of BS deactivation on mobile users using the PI.

An algorithm that switches BSs off and on in a heterogeneous network (cellular network and wireless local area network) has been proposed [10]. Its cost function minimizes energy consumption and maximizes network revenue. To make it tractable, the authors divide the problem into two sub-problems (user association and BS switching on/off). On the one hand, the user association algorithm connects users to BSs or access points (APs) depending on their energy efficiency and revenue. For the BS deactivation problem, work in [10] proposes two greedy algorithms: the first one is based on the cost function (it turns off the BS that yields the maximum cost gain), and the second one is based on the density of access points within the coverage of each BS (it turns off the BS with the most significant number of mobile users associated with APs). However, this approach does not evaluate the impact of the switching on/off strategy on mobile users or Quality of Service (QoS) degradation. Moreover, greedy algorithms have a very high computational cost [15].

Work in [6] proposes to resize an LTE green network, determining the minimum number of active BSs needed given a specific traffic load, with restrictions on QoS. The number of active BSs represents energy reduction. A random number representing the number of active BSs is generated and, based on already proposed disconnection patterns, the active BSs are selected. A GA is applied to solve the problem. The user association or reassignment process is considered in the optimization model. Their approach introduces user outage per BS in the optimization model instead of presenting it at the network system level.

The work presented in [11] uses a BS on/off algorithm to reduce energy consumption in a cellular network. It establishes that BSs be deactivated one at a time since this minimally affects the load of the other BSs. Each time a BS is turned off, the load increment in neighboring BSs is evaluated. To do this, the algorithm considers the type of region (urban, metropolitan, etc.), the location of the BS, and its coverage. It proposes a sequential algorithm called Switching-on/off based Energy Saving (SWES). It is based on sharing information (feedback) between BSs and mobile users, such as system load and signal strength. When a BS is switched off, users are reassigned to the new BS with the second-best signal strength. However, the feedback may generate a large amount of data to send along with the information required by each user. Additionally, it does not quantify how mobile users are affected by the switching-off process (user outage).

The studies mentioned above addresses the reassignment process either jointly with or separately from the BS deactivation algorithm. We propose a joint algorithm for base station deactivation and mobile user reassignment, but, as opposed to the works discussed above, we use the PI metric in the optimization model to quantify how the BS switching-off process affects the mobile users in a network system. Then, in the GA processes, we add a penalty function to increase the fitness value of a candidate solution if it cannot achieve the PI threshold imposed in the optimization model. We guarantee that the BS set selected by the GA serves 99% of mobile users. Also, unlike the previous works, we analyze the performance of our proposed approach in heterogeneous and homogeneous networks at different traffic loads (number of mobile users). Another difference is that our work exploits the spectrum sharing approach to reuse frequencies in BSs. This efficiently exploits the channels available in a given BS since a set of mobile users can transmit over the same channel simultaneously [16].

3 System Model

Fig. 1 shows a cellular system network composed of several BSs and mobile users deployed over a two-dimensional area. Each base station (BS_j) and mobile user (UT_i) have random Cartesian coordinates that follow a uniform distribution. To differentiate the coordinates of these two components, a BS_j uses the notation

(x_j, y_j); on the other hand, a UT_i uses (u_i, v_i). The total BSs and mobile users in a network at a given moment are indicated by J and I, respectively.

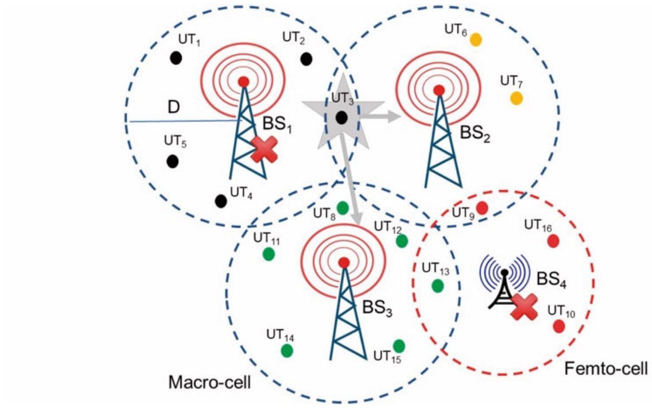

Figure 1
System scenario

Mobile users (UTs) assigned to a BS are delimited within their coverage radio D (see Fig. 1). The BS can be one of two types: macro-BS and femto-BS. The coverage radius of a femto-BS will always be less than the coverage radius of a macro-BS. When a BS is switched off (see BS_1 and BS_4 in Fig. 1) and some UTs linked to it cannot be reassigned to a new BS, the UTs are considered without service.

The Euclidean distance between a BS_j and a UT_i is denoted as $d_{i,j}$ and is calculated by applying Equation 1:

$$d_{i,j}(km) = \sqrt{\left(u_i - x_j\right)^2 - \left(v_i - y_j\right)^2} \quad (1)$$

Each BS_j provides service to several UT_i simultaneously; to know this relationship, the User-Base Station Relationship (RBU) matrix was created, as shown in Fig. 2, where the rows represent the BS_j and the columns represent the UT_i. If $RBU_{j,i} = 1$, the BS_j serves the user UT_i; otherwise, there is no relationship between BS_j and UT_i. In this way, a switched-off BS is made evident, as in the case of BS_4 (row 4), since there are only zeros in its elements.

It is also possible to know which UTs are not associated with any BS, as in the case of UT_{10}, since all the cells that represent it have values of zero. A BS can only allocate a specific number of C channels and service a certain number of UTs. MTU is the maximum number of UTs that a BS can serve. Macro-cells can serve more mobile users than femto-cells.

The binary vector Solutions for BS control (SBS) represents a GA's candidate solution (individual). Its length is equal to the value of J. The BS_j is switched-on if the SBS_j element has a value of 1 and turned off otherwise.

Base Station Number	Mobile Users													
	1	2	3	4	5	6	7	8	9	10	11	12	13	...	*I*
1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Figure 2
RBU matrix

Fig. 3 shows an individual and the scenario it refers to; it proposes that BS_2, BS_3, BS_4 remain switched on. On the other hand, the vector CU of a length equal to I contains the channel identifier that each UT_i has been assigned to by the BS that serves it. The elements in CU can take a value from 1 to C. It is essential to mention that index k refers to an individual or SBS vector specific to the GA population. Index j refers to one particular BS and index i is a particular UT of the network.

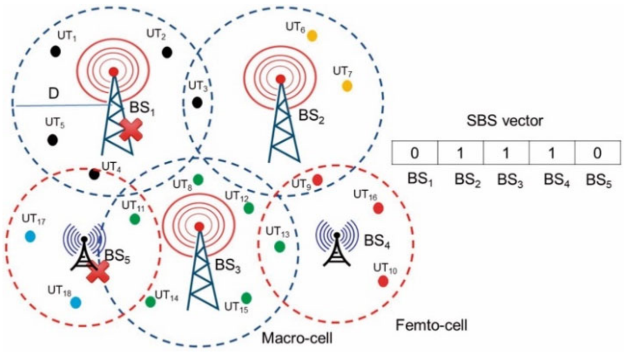

Figure 3
An individual and its proposed scenario

The carrier-to-interference ratio (CIR or C/I), expressed in dB, is the ratio between the average received modulated signal power (i.e., $PR_{i,j}$) and the sum of co-channel interference power received from other transmitters (I_{Total}) [17]. CIR value can also be used as a deciding factor in the channel allocation to UTs [18]. The CIR perceived in BS_j is calculated based on the following expression:

$$CIR_j(dB) = PR_{i,j} - I_{Total} \tag{2}$$

Where, $PR_{i,j}$ is the received power from UT_i to BS_j. I_{Total} is the total interference caused by UTs using the same channel as UT_i (interference co-channel due to spectrum sharing).

From Equation 2, the total interference I_{Total} can be determined as follows:

$$I_{Total}(dB) = \sum_{m \in \varphi} PR_{m,j} \tag{3}$$

where $PR_{m,j}$ is the received power from UT_m to BS_j. m refers to the index of interfering transmitters that have been allocated to the same channel as UT_i. φ is the set of UT_m using the same channel.

The received power $PR_{i,j}$ in dB from UT_i to BS_j is determined as follows:

$$PR_{i,j}(dB) = PT_i - PL_{i,j} \tag{4}$$

where PT_i is the transmission power of the UT_i (uplink). $PL_{i,j}$ is the path loss expressed in dB. It represents the power reduction (attenuation) of the signal as it propagates through space between UT_i and BS_j. The path loss can be calculated using Hata's model for the urban area [19], which is specified as follows:

$$PL_{i,j}\,(dB) = A + B\,log_{10}(d_{i,j}) \tag{5}$$

where:

$$A = 69.55 + 26.16\,log_{10}(f_c) - 13.82\,log_{10}(h_j) - a(h_i) \tag{6}$$

$$B = 44.9 - 6.55\,log_{10}(h_j) \tag{7}$$

f_c is the carrier frequency, h_j is the BS antenna height, and h_i is the UT antenna height. We set A=50 and B=40, as did [20].

From Equation 3, the received power $PR_{m,j}$ from UT_m to BS_j is:

$$PR_{m,j}(dB) = PT_m - PL_{m,j} \tag{8}$$

where PT_m is the transmission power of the UT_m (uplink). $PL_{m,j}$ is the path loss between UT_m and BS_j given by:

$$PL_{m,j}\,(dB) = A + B\,log_{10}(d_{m,j}) \tag{9}$$

Fig. 4 depicts the CIR metric in BS_1. When BS_2 is switched off, its UTs are reassigned to neighbor BS_1. Then, each UT in BS_2 computes the received power in the channel that BS_1 allocates. This is shown in UT_6. Its interfering signals are those from UT_2 and UT_3, due to the fact that they are using the same channel as UT_6.

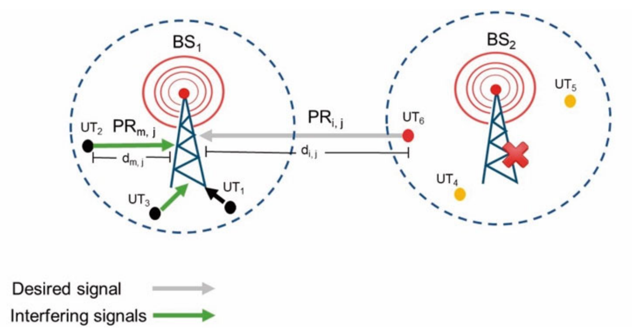

Figure 4
CIR metric in BS_1

The following optimization model accounts for the problem of optimizing the resources of a BS that is turned on according to the reassignment success of UTs. In order to obtain the minimum number of active BSs needed in a cellular network, the objective function is defined in Equation 10:

$$Minimize \sum_{j=1}^{J} SBS_j \tag{10}$$

As shown in Equation 10, the solution is an SBS vector that determines the lowest number of BSs to keep turned on. On the other hand, for a solution to be considered feasible, it must comply with the following restrictions:

$$\sum_{j=1}^{J} RBU_{j,i} = 1 \tag{11}$$

$$On_j = 1 \tag{12}$$

$$d_{i,j} \leq D \tag{13}$$

$$\sum_{i=1}^{I} RBU_{j,i} \leq MTU \tag{14}$$

$$CIR_j \geq \alpha \tag{15}$$

$$PI_k \leq \beta \tag{16}$$

Restriction (11) limits a UT_i to a single BS_j. Restriction (12) establishes that only active BSs may provide service to the reassigned UT; this is represented by the equation $On_j = 1$ if restriction (11) > 0 and $SBS_j = 1$, otherwise $On_j = 0$. The distance between a BS_j and a UT_i to which service is provided is limited in restriction (13), where it cannot be greater than the coverage radius threshold D of the BS_j. In (14), a BS is required not to exceed the maximum number of mobile users that it can service. The value of CIR_j represents interference perceived by a BS_j , and it must be greater or equal to a threshold as set in (15). Lastly, the percentage of mobile users without service when the BSs are turned off in the k^{th} SBS vector must be lower than the threshold complying with (16). This percentage is the value of PI.

4 Algorithm for Base Station Deactivation and Mobile User Reassignment

The procedure to find the minimum set of active BSs to maintain service for at least 99% of UTs is described below. In STEP 1, the initial scenario is built: BSs have a fixed location, whereas the UTs within the coverage area are randomly deployed.

Each mobile user UT_i is assigned to a BS_j if it meets the following conditions: (1) the total number of UTs served by the BS_j is less than MTU and (2) the distance $d_{i,j}$ is less than or equal to D. The least used channel of the BS_j is assigned to each UT_i and the identifier of that channel is stored in vector CU in position i. According to the spectrum sharing technique, two or more UTs can share the same channel [16].

In STEP 2, binary values are randomly set for each element of the SBS vectors (individuals) that make up the population. NS identifies the size of the population.

In STEP 3, the k^{th} SBS vector k^{th} individual is evaluated. A_k represents its fitness. The following actions are carried out in this step:

1. Identify turned-off BS_j i.e. the elements of the SBS vector where $SBS_j = 0$
2. Based on the initial scenario, reassign to an active BS the UTs associated with the BS that is turned off in the k^{th} SBS vector, thereby complying with the conditions shown in Equations (11-15)
3. Calculate PI_k by applying Equation (17). PI_k is the percentage of UTs in the network that are out of service, i.e., those UTs that could not be reassigned to any of the active BSs in the k^{th} SBS vector. A UT_i is considered without service if all the cells in column i in the RBU matrix have a value equal to 0

$$PI = \left(I - \sum_{j=1}^{J} \sum_{i=1}^{I} RBU_{j,i} \right) * 100 \Big/ I \tag{17}$$

4. Evaluate the sum in Equation (10) to obtain the value of A_k, counting the elements of the k^{th} SBS vector, where $SBS_j = 1$

Input: Population size, crossover probability, mutation probability, and number of iterations. Total number of UTs, the maximum number of UTs per macro-cell, the transmission power of UTs, interruption probability threshold, number of femto-cells, width and height of the terrain, coverage radius for macro-cell/femto-cell, number of channels per macro-cell/femto-cell, and maximum number of UTs per femto-cell.

Output: The lowest number of BSs turned on and UTs reassignment.

```
1:    BUILD initial scenario
2:    INITIALIZE population with random individuals
3:    EVALUATE each individual in Equations (10) to (16)
4: repeat
5:    SELECT two parents by using tournament selection
6:    RECOMBINE pairs of parents
7:    MUTATE the two-resulting offspring
8:    EVALUATE parents and offspring in Equations (10) to (16)
9:    SELECT the two best individuals out of the two parents and two offspring.
      Call those best individuals, best1 and best2
```

10: REPLACE parents with *best1* and *best2* respectively
11: **until** *Number_of_cycles* < *Total_number_of_cycles*
12: SELECT the fittest individual from the population

If the PI_k value exceeds the threshold established in Equation (16), the k^{th} SBS vector will be penalized. That is, its fitness value will increase based on a penalty function. The k^{th} feasible vector can have a maximum value of $A_k = J$ (all active BSs). Therefore, the infeasible or penalized vectors will be added ($J + 1$) to their fitness value.

Each SBS vector corresponds to an RBU matrix that shows the reassignment of UTs to the active BS, the UTs without service (if they exist), and the deactivated BSs.

In STEP 4, the GA performs a cycle which is the process of selecting parents, crossing them, mutating offspring, and replacing parents.

In STEP 5, two parents are selected employing the tournament technique [12]. Two individuals are randomly picked, and the winner of these two individuals is selected as a parent (the individual with the lowest value of A_k). The process is then repeated (to generate a total of two parents).

Then, in STEP 6, a random number is generated within [0, 1], which is compared to the Crossover Probability (PC). If this random number is less than or equal to PC, two new individuals (offspring) are generated with a combination of the bits or elements of the parents. Specifically, we apply two-point crossover [12], where *c1* and *c2* are integers ranging from 1 to *J*.

In STEP 7, some bits of the offspring are mutated. A mutation is the inverse value of the bit. To decide which bits are to be mutated, a random number within the range of [0, 1] is generated for each element of the offspring. If this value is less than the mutation probability (PrM), the bit changes.

Once the offspring have been mutated, the algorithm proceeds in STEP 8 to evaluate these individuals and the parents. It also applies the four actions mentioned in STEP 3.

In STEP 9, the A_k values of the two parents and two offspring are compared. If those individuals are feasible solutions, the two individuals with the best fitness value are *best1* and *best2* [21]. Otherwise, if infeasible individuals are compared, the two individuals with the worst fitness value (the highest) are chosen to survive. Those two individuals are also called *best1* and *best2*. The replacement strategy applied when comparing infeasible individuals is another contribution from the present work.

In STEP 10, *best1* and *best2* are inserted into the population, replacing the parents.

There are different stop conditions for a GA with a steady-state population model. For example, if the optimal solution is known in the problem, the algorithm can be forced to perform the necessary cycles to find that solution or one very close to it.

In the case of a GA with a steady-state population model, a stop condition may be to carry out the necessary cycles so that all individuals in the population are replaced at least once by their offspring. Given that the optimal solution to the proposed problem is unknown and changing all the individuals could require too many cycles, the stop condition in the present work is a certain number of cycles, as mentioned in STEP 11.

STEP 12 is the result of STEPS 1 through 11. It determines the lowest number of required active BSs and reassigns those UTs whose BSs have been deactivated.

5 Results

Table 1 shows the values of the simulation parameters that were maintained in all the experiments carried out in this research. The aim was to simulate an LTE network. For this reason, parameters such as the transmission power of UTs were defined based on the work in [22].

The DeJong configuration presented in [23] was initially used regarding the GA parameters. It is a standard for many GAs, and this parameter combination has been found to work better for optimizing a function than many other parameter combinations.

However, to reduce the probability that the initial population is composed only of infeasible solutions, we increased the population size from 50 to 100 individuals. We also increased the number of cycles from 1000 to 2000, because we had observed decreases in fitness after cycle 1000. Finally, the GA parameters used for this specific problem are shown in Table 2.

A sensitivity analysis was carried out to observe the impact of the CIR variations on the PI values. In other words, we tried to figure out the trade-off between CIR and PI to achieve a service percentage of 99%.

Table 1
Simulation parameters

Parameter	Value
Transmission Power of UT	-40 dB
Area	25000000 m^2
Coverage radius D for macro/femto	1500 m/750 m
Number of channels per BS	10 channels
Interruption probability threshold	1%
Maximum number of users per macro-cell	150 UTs
Maximum number of users per femto-cell	75 UTs

Table 2
Parameters used in GA

Parameter	Value
Population size	100
Crossover probability	0.6
Mutation probability	0.001
Number of cycles	2000

Table 3 describes the characteristics of the experiments performed for sensitivity analysis. Regarding the type of network, two cases were considered: (i) a homogeneous network (only macro-cells) and (ii) a heterogeneous network (macro-cells and femto-cells). Two traffic statuses were established, a low one where there were only 500 UTs, and a high one where 1000 UTs were located within the cellular network. In each of the 12 experiments, the algorithm was run 50 times. As reported in [7], heterogeneous networks were used for the femto-cells to support the macro-cells in high-traffic status. The femto-cells were then deactivated at a low-traffic level.

Table 3
Parameters used in experiments for analyzing PI

Experiment	I	Type of network	Number of macrocells	Number of femtocells	CIR threshold (dB)
1	500	Homogeneous	10	-	3
2	1000	Homogeneous	10	-	3
3	500	Homogeneous	10	-	7
4	1000	Homogeneous	10	-	7
5	500	Homogeneous	10	-	14
6	1000	Homogeneous	10	-	14
7	500	Heterogeneous	5	5	3
8	1000	Heterogeneous	5	5	3
9	500	Heterogeneous	5	5	7
10	1000	Heterogeneous	5	5	7
11	500	Heterogeneous	5	5	14
12	1000	Heterogeneous	5	5	14

Table 4 shows the average fitness value for each experiment, the standard deviation, the lowest number of active BSs found in the best performance (best fitness obtained), and the highest number of activated BSs (worst fitness obtained). In addition, for experiments with heterogeneous networks, the fourth column (best found) specifies the number of activated macro-BSs (indicated by the letter M) and the number of activated femto-BSs (indicated by the letter F).

The data in Table 4 demonstrate that when the system network presents a low traffic status (experiments 1, 3, 5, 7, 9, and 11), the algorithm decides to turn off more BSs.

On average, these experiments kept around 6 BSs turned on. On the other hand, when the system network has high traffic (the remaining six experiments), the algorithm turns off fewer BSs. The latter experiments left about seven turned-on.

When the average number of active BSs is contrasted with the CIR threshold, it is clear that the higher the CIR threshold (14 dB) and traffic, the more BSs are turned on to maintain only 1% (PI threshold) or less of UTs without service.

Table 4
Fitness or number of activated BSs per experiment

Experiment	Average fitness	Standard deviation	The best found	The worst found
1	6.72	0.54	6	8
2	8.02	0.14	8	9
3	7.04	0.57	6	8
4	8.08	0.27	8	9
5	7.28	0.61	6	8
6	8.3	0.51	8	10
7	6.8	0.61	4 M + 2 F = 6	8
8	9.46	0.50	5 M + 4 F = 9	10
9	6.78	0.71	4 M + 1 F = 5	8
10	9.44	0.50	5 M + 4 F = 9	10
11	7.1	0.50	4 M + 2 F = 6	9
12	9.6	0.49	5 M + 4 F = 9	10

In each of the 12 experiments, when determining if a BS would remain active, the algorithm considers the BS's location concerning UTs. When a BS is centered in or close to an area with many UTs, and no other BS covering the majority of the UTs, the algorithm will likely keep the BS active. For example, the cellular network system in Experiment 1, shown in Fig. 5. The uppercase letters represent the macro-BSs, and the ones inside a red square represent the deactivated macro-BSs. It can be seen that J macro-BS is one of the farthest from the rest of the BSs, which makes it the only one that can cover certain UTs in its area. We observe that some BSs remain active in all the experiments, such as the J macro-BS. In contrast, macro-BSs A and D are chosen interchangeably in some experiments to cover the same area.

The above observations affirm that the algorithm prefers a BS with higher capacities. However, it cannot be ignored that the BSs are also chosen for the suitability of their locations. There have been cases where a femto-BS, situated in an important area to serve certain UTs, remained turned on even when traffic was low. Take, for example, the case of BS J. In experiments with heterogeneous networks, it became a femto-BS and was activated. The same happened in experiments 7 and 11.

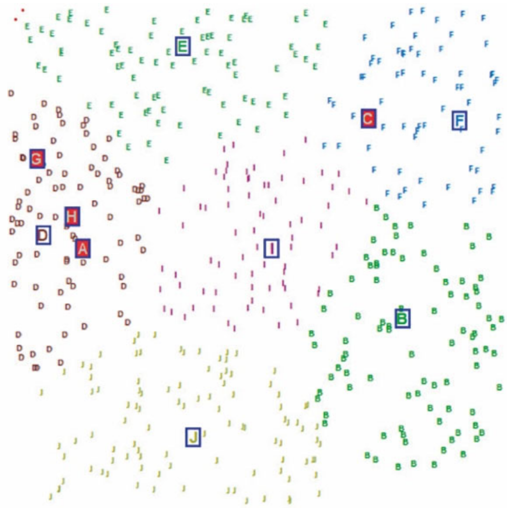

Figure 5
Cellular network system from experiment 1 after executing the algorithm

A completely different situation is seen when comparing the two types of networks in experiments with high traffic situations. Here the difference in fitness is very marked. For example, in Experiment 2, the average number of activated BSs was 8.02, whereas, in Experiment 8, the average was 9.46. We can infer that, in high traffic situations, the algorithm has to leave more BSs turned on when dealing with heterogeneous networks and fewer with homogeneous networks. This is due to the macro-BSs covering a larger area and a more significant number of UTs than the femto-BSs. For this reason, when the cellular network system is composed of femto-BSs and has high traffic, the algorithm is forced to keep more BSs active.

In terms of convergence, most experiments with low traffic status showed a trajectory similar to that shown in Fig. 6. In this case, since there were relatively few UTs, the algorithm found feasible solutions in early cycles. In contrast, most of the experiments with high traffic showed a convergence similar to that of Fig. 7. In that case, there were more UTs, so it was more challenging for the algorithm to find feasible solutions in the initial population. That performance was also due to the penalty function and the replacement strategy used when comparing infeasible individuals. The two worst individuals carried over to the next cycle because of this replacement strategy. Its effect was to increase fitness in early cycles, but as the cycles ran their courses, fitness decreased, resulting in a feasible solution. The improvement or deterioration in fitness was also a function of traffic. Take the experiment in Fig. 7 as an example. It had 1000 UTs. Once a feasible solution was obtained, the algorithm made few changes to reach a solution with fewer active BSs. In contrast, most of the experiments with 500 UTs, the algorithm made more changes to find solutions with inferior fitness (see Fig. 6).

In each of the 12 experiments, the solutions provided by the algorithm maintained the PI at 1%. Under the conditions specified in each experiment, at least one solution was found with a minimum percentage of UTs without service.

Finally, we evaluated other GA variants to compare performance. The experiment consisted of a homogeneous network (20 BSs, 500 UTs, and α = 3 dB). The experiments were carried out using GA with the generational model and GA with the generational model using elitism. Those GA variants have two-point crossover and bit-flipping mutation. Their parameters are the ones shown in Table 2. Each GA variant executed 30 runs. The results are reported in Table 5.

Table 5 shows that the GA with the steady-state model outperforms the other GA variants. Consequently, the GA with the steady-state model has robustness since it has the lowest variation.

Table 5
Comparison of GA variants

GA variant	Average fitness	Standard deviation	The best found
GA with the steady-state population model	8.46	0.63	7
GA with the generational model	8.8	2.07	8
GA with the generational model using elitism	9.53	0.81	8

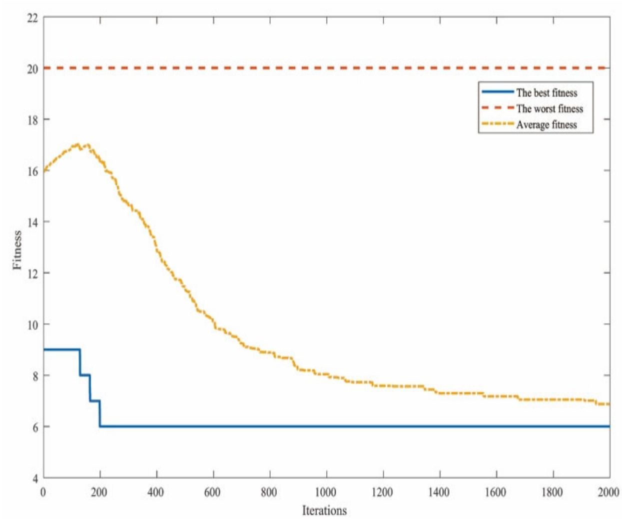

Figure 6
Convergence of the algorithm with low traffic (500 UTs)

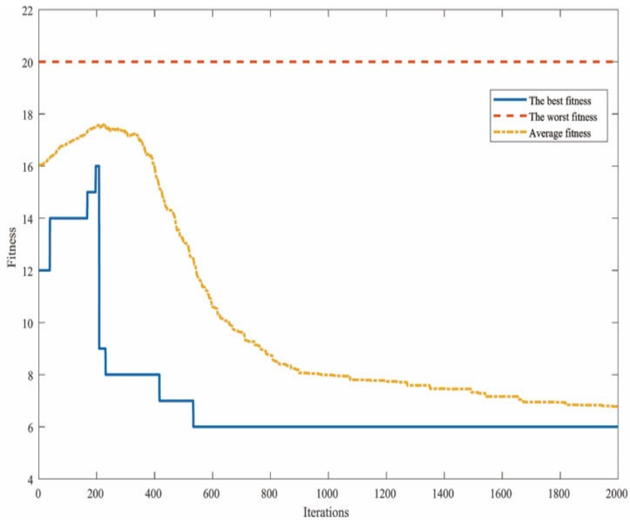

Figure 7
Convergence of the algorithm with high traffic (1000 UTs)

Conclusions

To take full advantage of dense 5G deployments, while still meeting the required QoS, sustainable management techniques are needed, to provide eco-friendly and cost-effective mobile architectures. A sustainable design of 5G systems includes sleep modes, that is, the capacity to turn off some of the BSs when the traffic load is low. Given the said context, we present our base station deactivation and user reassignment algorithm.

Based on the experiments carried out, our conclusions are as follows:

- One of the significant challenges of a deactivation and user-reassignment algorithm is to prevent the complete shutdown of all BSs in a network. For this reason, it is important to consider a mechanism that prevents infeasible solutions in the algorithm without compromising its performance.
- A deactivation algorithm based on a steady-state GA can successfully find a minimum set of active BSs because it shuts down 10-50% of the BSs present in a cellular network system and maintains service for at least 99% of users.
- In a cellular network, a reassignment process must be carried out to deactivate some BSs and maintain service for 99% of its UTs; not carrying out this process would leave up to 20% of UTs without service.
- An essential factor in the decision to deactivate a BS is the PI as the number of UTs without service in a cellular network. When considering this factor in regards to the optimization model, it is possible to switch off BSs according to the success of the UT reassignments and network traffic. When there is less traffic in the network, the number of active BSs is smaller.

- In all the proposed scenarios, even in those where the CIR threshold was equal to 14 dB, our proposed algorithm was able to find a solution where at least one BS was deactivated, and 99% of users were serviced.
- In heterogeneous networks, the algorithm deactivates more femto-BSs than macro-BSs when traffic is lower. This scheme supports the existing literature, which shows that the use of femto-BSs is more beneficial when the heterogeneous network presents high traffic status.

Going forward in our research, we will apply other metaheuristics to evaluate their performance in solving the problem addressed in this paper. We will pose the optimization model as a multi-objective problem, i.e., minimize the interruption probability and the number of active BSs. We plan to use the Page's Trend Test

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