Multi-Objective Green Optimization for Energy Cellular Networks Using Particle Swarm Optimization Algorithm

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December 7, 2021

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***Abstract*—The energy consumption of cellular networks is essential and this consumption increases with the development of generations of networks and the expansion of the database. The volume of data grows to very large volumes, in terms of the number of users covered by the base stations of this network. Some of the important limitations of cellular networks are the excessive production of carbon dioxide by base stations and the cost of installing enough base stations for good coverage. Our goal in this paper is threefold. Indeed, the cost of installing base stations must be minimized, CO_2 emissions must be reduced and network coverage must be maximized. So we have a problem with three conflicting goals. We have modeled this problem as a multi-objective optimization problem. To resolve it, we propose a method based on Particle Swarm Optimization (PSO) algorithms. To evaluate the effectiveness of the proposed algorithm, experiments are performed on a data set. The results showed that our approach improves the coverage of cellular networks, reduces carbon dioxide production, and reduces the cost of base stations installed, simultaneously.**

***Index Terms*—Particle swarm optimization, Green multi-objective problem, Energy cellular networks**

I. Introduction

With the rapid development of cellular networks, the explosive growth of data traffic and applications has forced these networks to face enormous challenges for researchers and developers.

To manage this traffic, Mobile operators use a maximum number of base stations (BSs) to obtain considerable coverage and capacity. We are now in the fifth generation (5G) which offers many advantages over previous generations of mobile networks. It offers low energy consumption and provides very high frequencies and wider bands compared to 4G thanks to sophisticated techniques [8].
The demand for user traffic for existing wireless networks is extraordinarily high in this modern world. The increase in user traffic has two reasons. The first one is the increase in the number of users during the day due to the increase in the use of mobile devices. The second reason is the mobility of these users, resulting in an increase in capacity. In the years to come, wireless devices will undoubtedly experience rapid growth and provide very high data traffic. To cope with this type of traffic, mobile operators use the maximum number of base stations (BSs) for coverage and high capacity, resulting in extremely high power consumption in the network and therefore an alarming amount of carbon dioxide. The direct and most effective way to solve the problem of power consumption and to reduce CO_2 emissions is to reduce the number of base stations used or to put the base station in standby mode during low load periods. But this leads to a deterioration in quality and disruption of service for users. To solve this problem, [1], [2] discussed the concept of multi-objective optimization and the on/off strategy to minimize the number of BSs.

Our goal in this paper is to propose a solution to satisfy three different objectives:

- reduce the number of base stations in order to reduce energy consumption and to reduce CO_2 emissions,
- minimize the total cost of installing base stations,
- maximize network coverage.

The first objective is different from the second objective because the installation cost varies from one base station to another. On the other hand the first two objectives are contradictory with the third objective.
In this paper, we consider the green radio network planning (RNP) problem for cellular networks. Our aim is to satisfy the three conflicting objectives mentioned above. For this we have modeled this problem as a multi-objective optimization problem and then we have transformed it into a mono-objective one using dynamic weights. To resolve the NP-hard problem, we propose a method based on Particle Swarm Optimization (PSO) algorithms.

The structure of this paper is as follows. In Sect. II, a brief overview of former related works is made. In Sect. III, we introduce a multi-objective mathematical model of our problem. In Sect. IV we present a solution based on particle swarm optimization algorithm. In Sect. V, we provide an application of our approach, and then, we present the obtained numerical results . Sect. VI concludes this paper.

II. Related works

In recent years, much research has been done on appropriate methods and technologies to save energy and reduce carbon dioxide (CO_2) production in networks. Several studies have investigated the allocation of resources in a part of a network with a few base stations. For instance, the authors in [3] propose a switching on-off strategy based on genetic algorithm method to solve the NP-hard problem. The authors in [5] addressed the same problem using fuzzy logic. The authors of [6] proposed a methodology to reduce energy consumption by reducing the number of active base stations, which will also reduce the production of CO_2 using genetic algorithm. The authors of [5] presented an optimal strategies for turning power-saving base stations on and off in the wireless access network when some base stations are powered by power supplies. The authors of [6] used base station shutdown (BS_s) technology during a low load period to provide power to the cellular network without sacrificing user traffic demand. In [4], the authors presented an exact algorithm for solving the channel assignment problem in cellular telephony networks. In [7], the authors formulated an optimization problem that aims to maximize the profit of LTE cellular operators and minimize the CO_2 emissions in green wireless cellular networks without affecting the desired quality of service (QoS). In [9], the authors addressed the problem of planning the universal mobile telecommunication system base stations location for up-link direction using fuzzy logic.

The main aim of our study is to develop an efficient multi-objective mathematical model that maximizes the total covered traffic , reduces energy consumption by minimizing the number of operational BS_s and minimizes costs of base station.

III. Problem statement and model presentation

A. Problem statement

Consider a territory to be covered by a LTE service. Let $S = \{1, \cdots, m\}$ be a set of possible base station (BS) sites, and $I = \{1, \cdots, n\}$ be a set of mobile stations (MS_s). Each base station BS_j (with $j \in S$), has a cost of installation denoted by c_j. We denote by u_i the required number of simultaneously active connections for a MS_i and by K_{BS} the maximum number of MSs served by a BS.

An illustrative example is presented in Figure 1. In this example, we have four possible BS sites and nine MSs. We see that the BS_4 is not installed and the MS_4 is not covered. MS_1, MS_2 and MS_3 are affected to BS_1, MS_5 and MS_6 are assigned to BS_2. MS_7, MS_8 and MS_9 are assigned to BS_3. In addition, each base station BS has a cost of installation, for example a cost of installation of BS_1 is c_1.

B. Model presentation

we have two decision variables:

$$x_i = \begin{cases} 1 & \text{if } BS_i \text{ is selected} \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

and

$$y_{k,i} = \begin{cases} 1 & \text{if MS}k \text{ is served by BS}i \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

Since we want to maximize the network coverage, minimize the number of installed base stations and also minimize the total cost of installing base stations, the problem can be formulated as follows :

$$\begin{cases} \min \sum_{i=1}^{m} x_i \\ \\ \max \sum_{k=1}^{n} \sum_{i=1}^{m} u_k y_{k,i} \\ \\ \min \sum_{i=1}^{m} c_i x_i \end{cases} \tag{3}$$

Subject to:

$$x_i P_{k,i} - SINR_{thr,k} \sum_{j=1, j\neq i}^{m} x_j P_{k,j} - SINR_{thr,k}\sigma^2 \geq \left(-SINR_{thr,k} \sum_{j=1,j\neq i}^{m} P_{k,j} - SINR_{thr,k}\sigma^2\right)(1 - y_{k,i}) \quad \forall k \in I, \forall i \in S \tag{4}$$

$$y_{k,i} \leqslant x_i \quad \forall k \in I, \forall i \in S \tag{5}$$

$$\sum_{i=1}^{m} y_{k,i} \leqslant 1 \quad \forall k \in I \tag{6}$$

$$\sum_{k=1}^{n} y_{k,i} \leqslant K_{BS} \quad \forall i \in I \tag{7}$$

where $P_{k,i}$ is the received power for MS_k by its serving BS_i, $SINR_{thr,k}$ is the minimum threshold value that the signal-to-noise and interference ratio (SINR) must exceed in order that MS_k to be served, and σ^2 is the thermal noise power.

The quality of service of the MS is denoted by constraint (4). We ensure by constraint (5) that we cannot assign a mobile station to a base station (BS_i) if BS_i is not installed. We guarantee by constraint (6) that each mobile station is covered by at most one BS. Constraint (7) guarantees that each BS can serve at most K_{BS} mobile stations.

C. Improved problem formulation

In this section, we transform the multi-objective problem 3 into a mono-objective one using the weighted sum method as follows.

$$\min \left(\alpha \sum_{i=1}^{m} x_i - \beta \sum_{k=1}^{n} \sum_{i=1}^{m} u_k y_{k,i} + \gamma \sum_{i=1}^{m} c_i x_i \right) \tag{8}$$

subject to the constraints (4), (5), (6) and (7), where α , β and γ are positive weights of objective functions satisfying the condition $\alpha + \beta + \gamma = 1$.

In [10] and [11] , the authors introduce dynamic weights instead of constant ones. As a result, the mathematical modeling of our problem becomes :

$$\begin{cases} \min (\alpha(t) \sum_{i=1}^{m} x_i - \beta(t) \sum_{k=1}^{n} \sum_{i=1}^{m} u_k y_{k,i} + \gamma(t) \sum_{i=1}^{m} c_i x_i) \\ |\alpha(t) \sum_{i=1}^{m} x_i + \beta(t) \sum_{k=1}^{n} \sum_{i=1}^{m} u_k y_{k,i}| < \epsilon \\ |\alpha(t) \sum_{i=1}^{m} x_i - \gamma(t) \sum_{i=1}^{m} c_i x_i| < \epsilon \\ |\gamma(t) \sum_{i=1}^{m} c_i x_i + \beta(t) \sum_{k=1}^{n} \sum_{i=1}^{m} u_k y_{k,i}| < \epsilon \end{cases} \tag{9}$$

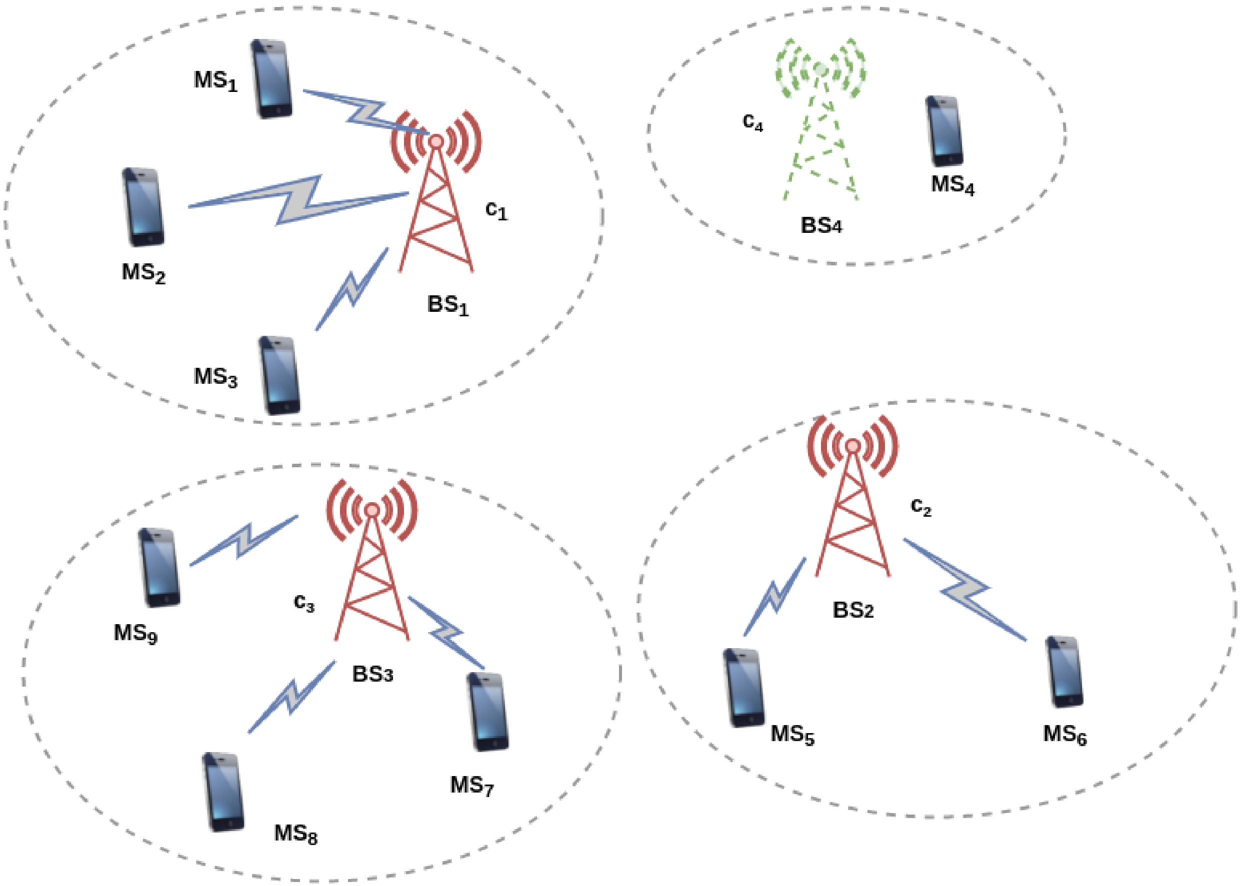

Fig. 1. Illustration of our problem with nine mobile stations and four possible base station sites

subject to constraints (4) to (7), where ϵ is a positive number very close to 0, t is a time step (here we consider t to be an iteration of the particle swarm optimisation), $\alpha(t)$, $\beta(t)$ and $\gamma(t)$ are the dynamic weights of the three objective functions.

IV. Particle swarm optimization solution

A. Particle swarm algorithm

The particle swarm is composed of n particles and the position of each particle represents a solution in the search space. The particles change their state according to the following three principles:

- Keep its inertia,
- Change state according to its most optimal position,
- Change state according to the most optimistic position of the group.

The position of each particle is affected by both the most optimistic position in its motion (individual experiment) and the position of the most optimistic particle in its neighbourhood (global experiment). The update of the position $x_i(t)$ and velocity $v_i(t)$ of a particle P_i is represented by equations 10 and 11.

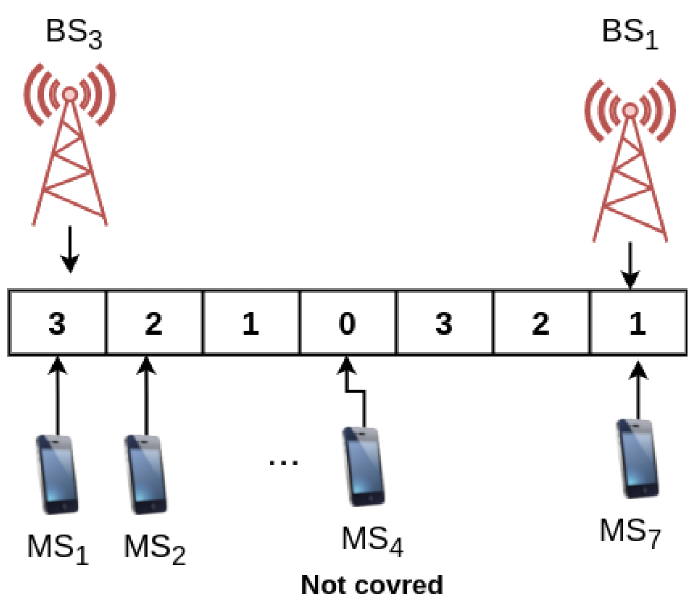

Fig. 2. Example of particle representation

$$v_i(t+1) = \omega v_i(t) + c_1[pbest_i(t) - x_i(t)] + c_2[gbest(t) - x_i(t)] \quad (10)$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (11)$$

where ω is the inertia, c1 and c2 are random coefficients numbers in the range $[0, 1]$, chosen at each iteration, $gbest_i(t)$ is the best solution found up to time t and $pbest_i(t)$ is the best solution found by the particle P_i. Let $f(x)$ be the objective function to be optimised (fitness) and n the number of particles The essential steps of the particle swarm optimisation are presented by Algorithm 1.

Algorithm 1 PSO algorithm

Initializing the parameters and size (S) of the swarm
Initializing the population and velocities of the particles.
for each particle, put $pbest = P$ (with P:(position of the particle))
calculate $f(P)$ of each particle
while the stop condition is not checked **do**
  for $1 < i < S$ **do**
    calculate the new velocity using Eq.10,
    Calculate the new position using Eq. 11,
    calculate $f(P)$ of each particle
    if $f(P)$ is better than $pbest$ **then**
      $pbest = P$
    end if
    if $f(P)$ is better than $f(pbest)$ **then**
      $gbest = pbest$
    end if
  end for
end while
Display the best solution gbest.

B. Particle representation

To represent our problem, we use an integer encoding. Each particle is represented as an array of integers, where the value of each element of the array is between 0 and m. For example in Figure 2 the MS_1 is assigned to BS_3, the MS_7 is assigned to BS_1 and BS_s 1, 2 and 3 are installed. We also see that the MS_4 is not covered by any BS.

C. Main components of particle swarm optimisation

Step1: (Initialize particles)
Initial population. Consider m BS_s and n MS_s. To represent each particle in the population, we generate n random number as integers in the set $\{0, \cdots, m\}$. A population is a set of particles.

Step2:
For each particle, calculate the fitness value of each particle according to Eq. 9. If the fitness value is better than the best fitness value (pbest), set the current value as the new pbest. Then, Choose the particle with the best fitness value of all particles as the most gbest.

Step3:
For each particle, calculate the velocity of the particles using the velocity update equation

$$V_{k+1} = (\omega \otimes V_k) \oplus (c1 \otimes (pBest \ominus P_k)) \oplus (c2 \otimes (gBest \ominus P_k)). \quad (12)$$

Then, update the position of the particles using to the position update equation

$$P_{k+1} = P_k \oplus V_{k+1} \quad (13)$$

Step4:
Find Gbest.
Where:

- V_{k+1} and V_k are the velocities of the particle at iteration k and k+1.
- pbest is the best position of the particle
- gbest is the best position of its neighbourhood at iteration k.
- P_k is the position of the particle at iteration k.
- ω is the inertia.
- c2, c3 are two coefficients randomly generated at each iteration.

D. Operators

- operator $\oplus$
  This operation is applied between a position X and a velocity V and returns a position. The result is obtained by successive permutations of the elements of X taking into account those of V. It is only used when updating the position.
- operator $\otimes$
  This operation is applied between a real k and a velocity V and the result is a velocity. Different cases are to be considered depending on the real. If k belongs to the interval $]0, 1[$ then V is truncated by $E(k * |V|)$ where $|V|$ is the number of elements of V and $E(x)$ is the upper integer part of x.
  If k is an integer, then k permutations of V are performed, using speed addition.
  If $k > 1$ then we separate the integer and decimal parts, where $k = n + x$ where n and x are the integer and decimal parts respectively to the integer and decimal parts of k. We then return for each part to the previous cases.
  If $k < 0$, we take its absolute value.
- operator $\ominus$
  The subtraction is applied between two positions and returns the Velocity from the first position to the second.

V. Application

A. Data description

We consider a network to be covered with the following information:

- the total number of MSs to be served is 400,
- the number of base stations is 120,
- The number of required simultaneously active connections for each mobile station is 1,

- The maximum transmission power is equal to $20W$,
- the power of thermal noise is equal to $5.97 \times 10^{-15}W$,
- the carrier frequency is equal to $2000MHz$,
- the maximum number of MS that can be served by each BS is equal to 50,
- and the minimum threshold value that SINR must exceed to serve a MS is equal to $-5dB$.

B. *Results and discussion*

The algorithm is coded in the Java programming language and implemented on a machine with an Intel Core $i5-5200U$ at $2.20GHz$ and $8GB$ of RAM. The parameters for particle swarm optimization (PSO) are shown in Table I, where:

TABLE I
PARAMETERS PSO

Parameters	**values**
Population size	30
Max iterations	500
ω	$(\omega_{max} - ((\omega_{max} - \omega_{min}) * iter))/itermax$
c2	Randomly generated
c3	Randomly generated

- itermax is the maximum number of iterations,
- iter : iteration,
- ω_{max} : the maximum value of ω, $\omega_{max} = 0.9$,
- ω_{min} : the minimum value of ω, $\omega_{min} = 0.4$.

In Table II, we have compared the results obtained by using the existing approach which neglects the cost of installing base stations, and by using our approach which considers the three objectives mentioned above. We performed 10 executions of each method and we compared the best and average values of each objective function.

For the best of cases, our approach finds the solution that minimizes the cost without degrading the other two objectives. On average, our approach manages to better minimize the cost and the number of base stations with a very small degradation of the network coverage compared to the existing method.

TABLE II
NUMBER OF MSS COVERED AND BSS INSTALLED FOR 120 BSS AND 400 MSS

		N. of BSs installed	N. of MSs covered	Cost	Time (ms)
Existing approach	Best	114	397	5724	6.7
	mean	114.7	397.3	5716	
Our approach	Best	114	397	5690	7.4
	mean	114.4	396.3	5677.1	

C. *Green optimization*

In this part, we analyze the CO_2 emission.

$$\mathrm{CO}_2 = \frac{N \times P_{\mathrm{BS}} \times T \times 620}{10^6} \tag{14}$$

This equation calculates the emitted quantity in [$kgCO_2$/day], of CO_2 in one day, where:

- the Number of BSs chosen is denoted by N
- the total consumption of the BS in Watt(W) is denoted by P_{BS}. When transmitting with a maximum transmit power of 20W, $P_{BS} = 140W$ (see [2])
- Here $T = 24h$ (one day)
- In this formula, we consider that electricity energy is derived from fuel oil where each $1KWh$ represents $620gr$ of CO_2

We can now calculate the average CO_2 emissions for:

- Existing approach:

$$\mathrm{CO}_2 = \frac{114.7 \times 140 \times 24 \times 620}{10^6} = 238.94$$

- Our approach:

$$\mathrm{CO}_2 = \frac{114.4 \times 140 \times 24 \times 620}{10^6} = 238.31$$

.

Therefore, the CO_2 emission is decreased using our approach compared to the existing approach.

VI. CONCLUSION

Energy efficiency is a growing concern, especially in the wireless communication networks of today and tomorrow. This is due to the sharp increase in the number of users and the continued needs of these networks.

In this paper, we have studied the problem of planning cellular networks by meeting three important objectives. (i) reduce the total cost of base stations, (ii) reduce the energy consumption of these base stations, and (iii) maximize total coverage in order to maintain quality of service. We have modeled this problem as a multi-objective problem under some constraints. Then, we proposed a resolution method based on the particle swarm optimization (PSO) algorithm to solve this problem.

The simulation results show the effectiveness of our approach to solve the problem while simultaneously satisfying the three objectives mentioned above.

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