Optimization of Massive Connections in 5G Networks for IoT

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Abstract— The expected traffic demands for the coming years requires a major technology development. Indeed, from 2017 to 2022, the global annual traffic growth is estimated to reach 220%. This annual growth leads in turn to an increase in the number of users connected to IP networks, going from 2.4 to 3.6 devices connected per person. Currently, 4G networks are capable of handling this load, but the irruption of the 5G breakthroughs, expected to be at full operation by 2020, is visible. However, 5G technologies may come along with a considerable power consumption if they are not devised properly. As a consequence, a key issue in the developing of these networks is to make them energetically sustainable. In this work, a preliminary study of the optimization of various aspects of the 5G system is presented. It addresses the configuration of the different basic parameters of the system and optimizes the power transmitted by the base stations to obtain simultaneous improvements in system capacity and its power consumption for a massive connections scenario. To the best of our knowledge, this is the very first time this type of 5G scenario is optimized with these two performance criteria.

Keywords—IoT, massive connections, 5G networks, optimization.

I. INTRODUCTION

In recent years, the world has experimented the evolution towards the second, third and fourth generation of wireless networks [1, 2]. This progress responds to the capacity demand of new technologies and applications, like high quality video streaming, online gaming, or e-healthcare. However, the new era of communications is still in its infancy. New use cases such as augmented reality, 3D visualization, tactile Internet, remote monitoring, road safety or real-time control place poses new challenges that have driven the development of the fifth generation (5G) mobile networks.

Moreover, the Internet of Things (IoT) adds an additional dimension to connectivity [3], increasing considerably the number of agents in the network. Intelligent "common objects" and accessories like smart wearable devices (e.g., bracelets, glasses, watches), smart home appliances, autonomous cars, etc. will be enabled in this new scenario, generating a hyper-connected smart world. Predictions estimate that users may download terabytes of data annually. Furthermore, future services like the ones introduced above require hundreds of Mbps each, summing up more than 1 Gbps per User Equipment. Considering such significant future traffic demands, the industry aims to increase today's networks capacity by a factor up to 1000x. In fact, in early 2012 ITU-R initiated the definition and research of 5G with the development of IMT-2020 systems. In order to improve network capacity, an increase of the spectrum, spectral efficiency, and spatial reuse are presented as the main three existing paradigms.

This new vision of the network and its requirements have also a big impact on the system architecture, that is facing new challenges and opportunities [4]. Apart from reusing and/or renovating old 4G technologies, future 5G networks will introduce a few changes in the network architecture. The two major ones are, on the one hand, the division of the 4G evolved packed core (EPC) into new core and Multi-access Edge Computing (MEC) and, on the other hand, the introduction of a new structure with a central unit (CU) and a distributed unit (DU). However, the exigency of the new 5G features and requirements configure a broader range of more complex challenges and enablers. According to experts [5], there are at least six challenges that are not sufficiently addressed by Long Term Evolution-Advanced (LTE-A) networks. Some of these challenges and enablers are discussed in below:

- System Capacity and Data Rate: Current trends forecast a huge increase in data rates, also at high mobility and crowded areas [6]. This capacity-demanding not only in the radio access network, but also in the front- and backhaul, and the back bone.
- End-to-End Latency: New agents and scenarios like remote controlled robots or drones require real-time applications and rapid feedback control cycles. This is also critical for some applications like augmented and virtual reality as well as for vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications. For enabling all these technologies, an improvement in the End-to-End (E2E) latency is needed. An illustrative target value has been proposed in [7]: 1ms. Other techniques like well-tailored NAS protocols or NAS-access stratum (AS) integration could help to reduce the E2E latency.
- Massive Number of Connections: New 5G technologies suppose a considerable increase in the number of connections. For example, an actual deployment of IoT implies providing connectivity to thousands of devices [8]. But the challenge goes even further if we consider
the enormous diversity of service requirements and device types that should be supported in an efficient and scalable manner.

- **Cost:** As it has been motivated above, capacity and data rate are two of the main challenges to address in 5G deployments. However, some of the most suitable enablers for that, like network densification, increase the infrastructure costs reasonably.

- **QoE:** 5G network traffic will be dominated by challenging video applications like ultra-high-definition (UHD) [9]. In order to handle that, demanding user- and application-specific requirements have to be met by adopting Quality of Experience.

In this work, two studies of 5G network optimization are presented. In the first one, several parameters of the 5G system are optimized: system capacity, power consumption, and signaling costs. It aims at showing the influence of different assignments between users and base stations. Based on these results, a second study is undertaken for massive connection assignments between users and base stations. Based on these results, a second study is undertaken for massive connection scenarios which would be the future scenario for IoT.

The structure of this paper is as follows. Section II presents the configuration of the system, detailing the different models used to compute the signal power, capacities and costs of the different elements. Also, in Section II, the different association strategies for assigning users to bases stations are described. In Sections III and IV, the two optimization studies to be undertaken are shown, respectively. Finally, Section V provides the reader with conclusions drawn in the work.

## II. SYSTEM MODEL

This section aims to describe the underlying modelling on which all optimization and experiments undertaken are based. It is important to remark that this is just a basic model, which has been taken from a previous work by Valenzuela et al. [10]. The main characteristics of the considered scenario are the following. The working area is a terrain of 500x500 m². Both the base stations (BSs) and the users equipments (UEs) are randomly deployed on the scenario, but the users are not static: they move using a random waypoint model.

Different types of base stations are used. Their characteristics (macro, micro or femto) are depicted in Table 1. With the aim of modelling different propagation conditions, ten different regions have been defined in the following way: each region is defined by an attraction point (i.e., a given coordinates) that is further used by a Voronoi tessellation. On each region, the propagation parameters are generated randomly (the path loss and the channel type).

| Table 1: Specifications of the different types of base stations |
|---------------------------------------------------------------|
| Frequency (GHz) | 2 | 5 | 28 |
| BW (MHz) | 10 | 25 | 140 |
| Gain (dBi) | 15 | 5 | 5 |
| Max Power (dBm) | 46 | 25 | 20 |
| PIRE (dBm) | 61 | 30 | 25 |
| Heigh (m) | 25 | 10 | 6 |

### A. Received power

In order to compute the received power at each point (Prx), the following formula has been used:

\[
P_{\text{Rx}}[\text{dBm}] = P_{\text{Tx}}[\text{dBm}] + G[\text{dB}] - L_{\text{PATH LOSS}}[\text{dB}]
\]

where Prx and Ptx are the received and transmitted power (in dBm). The signal losses depend on the propagation region and are represented as L_{PATH LOSS}[dB]. They are computed as:

\[
L_{\text{PATH LOSS}}[\text{dB}] = L_{\text{SPACE}}[\text{dB}] + L_{\text{SHADOW FADING}}[\text{dB}]
\]

where L_{SPACE} is the signal loss due to the distance between the base station and the user, and decays following an attenuation exponent. L_{SHADOW FADING} is the variation in attenuation due to multiple variables such as multipath propagation, the distribution of which follows a log-normal distribution. These transmission path losses have been modeled in six different ways following three transmission models [11], UMi (Urban Microcells), UMa (Urban Macrocells), RMa (Rural Macrocells) for two possible cases, LOS (Line-Of-Sight) and NLOS (Non-Line-Of-Sight).

### B. Signal to interference plus noise ratio (SINR)

The signal to interference plus noise ratio (SINR) for UE k, is calculated as follows:

\[
\text{SINR}_k = \frac{P_{\text{Rx},i,k}[\text{mW}]}{(\sum_{n\neq j}^{M} P_{\text{Rx},n,k}[\text{mW}]) + P_{\text{NO}}[\text{mW}]}
\]

In this calculation, the power received by the UE k from the BS j is denoted by P_{Rx,j,k}.

The summation in the denominator is the total received power by the UE k from all the BSs that operate at the frequency that the BS j does, except the BS_j. Finally, the noise power is denoted by P_{NO}, computed as:

\[
P_{\text{NO}} = 174 + 10 \log_{10} \text{BW}_j
\]

being BW_j the bandwidth assigned to the BS j. For assigning the bandwidth of the different stations, the criteria followed is to define it as the 5% of the operating frequency that depends on the cell type.

### C. System Capacity

Once the SINR has been calculated, the capacity of the system will be calculated using the well-known formula for MIMO systems:

\[
C_{\text{rx}} = \log_2(\det(I_R + \frac{\text{SNR}}{I} \times H_{\text{rx}} \times H_{\text{rx}}^H))
\]

where R is the number of the receiver antennas, t is the number of antennas in the transmitter, IR is the identity matrix of RxR dims and H is the matrix of the channel. In this work we have used a randomly generated Rayleigh matrix.

### D. Power Consumption

This work uses a model that considers both the consumption between the UE and the BS, and the consumption between the BS and the access router [12-13]. The regular power consumption of an BS, which will be denoted as Pbc, can be expressed as:

\[
P_{\text{bc}} = \alpha \star P + \beta + \delta \star S
\]
where $P$ represents the transmitted or radiated power of each BS. The coefficient $\alpha$ denotes the power transmission efficiency due to an RF amplifier and feeder losses, while $\beta$ represents the power dissipated due to signal processing, $\delta$ is a constant denoting a dynamic energy consumption per unit of data, and $S$ is the data rate. The detailed parametrization of the different cell types considered is included in Table 2.

**Table 2: Power model parameters for cells**

|                  | Macrocell | Small cells |
|------------------|-----------|-------------|
| $\alpha$         | 21.45     | 5.5         |
| $\beta$          | 354.44    | 38          |
| $\delta$         | 2         | 0.2         |
| $p[W]$           | 1         | 1           |

The transmitted power is the sum of the powers of the different transmitters plus the energy consumed by the backhaul (PBH) that needs to be included [14], which is defined as:

$$Pt = \sum Pbc + PBH$$

### E. BS-UE Pairments

Once the configuration of the system parameters are modeled, as well as the subsequent computation of the different network measures, we proceed to detail two strategies for pairing UEs and BSs, that is, planning the assignments of UEs to BSs.

They are presented from the simpler case to the more complex one, both of them having as the goal of maximizing the SINR. These association could have considered other objectives, such as minimizing the distance or maximizing the received power between UEs and BSs, but the chosen one (maximization of the SINR) is what allows us to obtain the best results in terms of system capacity, providing the user with higher connection speeds to the network. Two different strategies are used:

Planning 1: the UE is paired with the BS that provides the highest SINR among all those available in the scenario.

Planning 2: Avoids the continuous jump between BSs. To do this, it pairs the UE with the BS that provides the highest SINR among all those available in the scenario whenever the change causes an improvement in the SINR above a certain threshold.

### III. MULTILAYER OPTIMIZATION

In this first approach to optimization of a 5G system, the parameter to be configured is the transmission power of the different BSs, i.e., the maximum transmitted power reflected in Table 1. The Matlab multi-objective toolbox has been used as the optimization engine, where different objectives have been set.

The number of BSs and UEs are deployed with three possible configurations each: 20, 40 and 50 UEs and 5, 14 and 20 BSs, respectively. Regarding the connections of these UEs, they follow a Poisson process with an average arrival ratio of $\lambda=0.2$, and the duration of a session follows an exponential distribution with an average of $\mu=10$ s. In this scenario, BSs are connected to an access network where routers offer IPv6 connectivity to mobile users.

First the experiment conducted has considered 2 objectives: the total capacity of the system and the power consumed, when using the two different UE-BS association strategies, i.e., Planning 1 (red) and Planning 2 (blue). Figure 1 shows the different Pareto fronts obtained. The set of non-dominated solutions shows different compromise solutions (points). It can be seen how Planning 1 obtains much better results as much higher capacities are obtained with the same consumed power. This is due to the fact that, by using a power threshold to minimize the signaling, and thus lowering the number of handovers, the SINR decreases and therefore the capacity decreases. Figure 2 shows the bits per Joule obtained for this same set of solutions. Now, the solutions obtained for Planning 1 are very similar to the solutions obtained by Planning 2. It is also clearly shown how in the chosen bit/w metric in Planning 1 is much better than that of Planning 2.
IV. MASSIVE CONNECTIONS OPTIMIZATION

In this second study, genetic optimization is applied to optimize the performance of the network over massive IoT deployments in terms of capacity, power consumption and satisfaction of user demand. This is tackled by addressing the so-called cell Switch-Off problem (CSO). This section is structured as follows: first, the addressed problem is defined. Second, the genetic algorithm used is described. Then, the configuration settings are shown and, finally, the results obtained are presented.

A. The Cell Switch Off problem

The CSO (Cell Switch-Off) problem consists on switching off a subset of small base stations (SBSs) of the network in order to address the problem of energy consumption. In our approximation is represented by a binary string $s \in \{0,1\}^{|B|}$, where $s_i$ indicates whether the SBS $i$ is activated or not, being $|B|$ the whole set of SBSs deployed. The CSO Problem has been treated as an optimization problem several times in the literature. A similar approximation was made by Luna et.al. in [16]. In this work, we have formulated the CSO problem as a multi-objective problem with three different objective functions. These are:

1. Network capacity: Total aggregated capacity of the system in Mb/s (maximize).
2. Power consumption: Total consumed power by the network, computed as the aggregation of the consumed power of every cell (minimize).
3. User’s satisfaction rate: represents the relative number of users whose traffic demand is satisfied, in % (maximize).

B. Algorithm

The algorithm used is the Non-Dominated Sorting Genetic Algorithm II, NSGA-II [15], which is based on generating a new population from the original one by applying the typical genetic operators (selection, crossover, and mutation); then, the individuals in the new and old population are sorted according to their rank, and the best solutions are chosen to create a new population. In case of having to select some individuals with the same rank, a density estimation based on measuring the crowding distance to the surrounding individuals belonging to the same rank is used to get the most promising solutions.

C. Experiment settings

Four scenarios with different users and cells densities have been addressed. The detailed parametrization is included in Table 3, in which the names in the first column (L,H) represent the deployment densities of devices and small cells.

| $|\lambda_{\text{small cells}}|$ | Num devices |
|---|---|
| L (Low) | 500 | 1000 |
| H (High) | 1000 | 2000 |

In the case of the users, the values represent the number of active IoT devices within the covered area (500m²). Regarding the cells, a unique macrocell is considered in all cases, whereas the number of small cells (type “micro”, see Table 1) varies. This variation is denoted by the $|\lambda_{\text{small cells}}|$ parameter of the PPP distribution (SBSs/km²).

The NSGAII algorithm uses, as genetic operators, Two Point Crossover with a crossover rate of 0.9, and Bit Flip mutation with a mutation rate of 1/L, where $L = |B|$, the number of SBSs of the UDN. Binary tournament is the selection operator and the stopping condition is to compute 50000 function evaluations.

D. Results

This section has been further structured into two different subsections for a better organization of the discussion of the results. The first one provides a visual inspection of the approximated Pareto front reached. Then, a comparison of the performance obtained in every of the considered scenarios is given.

1) What type of solutions provides the CSO problem?

A graphical overview of the distribution of the solutions to the CSO problem provided by the NSGAII algorithm is shown in Figure 5. In the form of a Pareto Front, solutions are characterized in terms of power consumption and capacity.

![Figure 5: Pareto Front of the NSGAII algorithm for the CSO problem.](image-url)
satisfaction rate as the third objective of the problem, which forces the algorithm to search for solutions that satisfy the users’ demand of the network.

2) Performance over different scenarios

As it has been introduced in a previous section, the experimentations have been run over for different scenarios, varying the deployment densities of users and base stations. Table 4 shows an overview of the results obtained in every of the instances in terms of capacity, power consumption and satisfaction rate.

Table 4: Specifications of the different types of base stations

|        | LL  | HL  | LH  | HH  |
|--------|-----|-----|-----|-----|
| Capacity | 10.8 | 12.7 | 22.3 | 28.7 |
| Power consumption | 12821.7 | 13367.3 | 23096.8 | 25094.75 |
| Satisfaction rate | 99 | 99 | 98.8 | 98 |

As expected, solutions computed over high-density scenarios imply a higher capacity and power consumption. However, it is remarkable that increasing the number of cells (LH and HH instances) has a greater impact than doing the same with the number of users (LL and HL). A second interesting finding is that the algorithm was able to provide satisfaction rates above 98% in all scenarios, which can be of special interest for network operators.

V. CONCLUSIONS

In this work, the optimization of a 5G system with different configuration parameters has been proposed. Two different multi-objective problems have been formulated that account for the network consumption, its capacity and the cost of signaling due to the handover induced by UE mobility. In these preliminary optimizations it is shown how to improve one parameter it is necessary to harm another, but efficient, compromise solutions of valuable impact for the network designer can be reached. Future work is on the line of developing new planning algorithms that maximize efficiency of the system.

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