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Research Article

Self-Planning of Base Station Transmit Power for Coverage and Capacity Optimization in LTE

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A computationally efficient self-planning algorithm for adjusting base station transmit power in a LTE system on a cell-by-cell basis is presented. The aim of the algorithm is to improve the overall network spectral efficiency in the downlink by reducing the transmit power of specific cells to eliminate interference problems. The main driver of the algorithm is a new indicator that predicts the impact of changes in the transmit power of individual cells on the overall network Signal to Interference plus Noise Ratio (SINR) for the downlink. Algorithm assessment is carried out over a static system-level simulator implementing a live LTE network scenario. During assessment, the proposed algorithm is compared with a state-of-the-art self-planning algorithm based on the modification of antenna tilt angles. Results show that the proposed algorithm can improve both network coverage and capacity significantly compared to other automatic planning methods.

1. Introduction

In recent years, mobile communications have experienced a rapid increase in the number of users and services, which has led operators and manufacturers to develop systems with greater capacity. In parallel, the complexity and size of these systems have increased exponentially, making network management a very challenging task. To deal with such complexity, operators demand automatic tools for configuring network parameters, as a flexible solution to improve network capacity without new investments. This trend has stimulated research and standardization activities in the field of Self-Organizing Networks (SON) [1].

Network Coverage and Capacity Optimization (CCO) has been identified by operators as one of the most important use cases of SON [2]. The aim of CCO is to provide optimal (i.e., maximum) coverage and capacity. In legacy radio access technologies (e.g., Global System for Mobile communication, GSM), CCO can be solved easily as coverage and capacity are decoupled by means of frequency planning. This is not the case for Long Term Evolution (LTE) technology, where all cells in the same layer use the same frequency band. This tight frequency reuse scheme makes the closest cells also the most interfering ones, so that a wider coverage usually leads to a higher interference, a lower spectral efficiency, and, ultimately, less capacity. As a result, network coverage and capacity in LTE are strongly linked, so a tradeoff between them is necessary [3].

Power control (PC) is a powerful strategy for dealing with the CCO problem. The aim of PC is to reduce the amount of interference from neighbor cells while ensuring that enough power is transmitted to (or received from) User Equipment (UE) to maintain an acceptable link quality [4, 5]. In LTE, fractional power control is used in the UpLink (UL) to dynamically change UE transmit power [5]. Moreover, several self-planning methods have been proposed to adapt UpLink Power Control (ULPC) parameters in LTE to local network conditions [6–10]. However, for the downlink (DL) of LTE, power planning is the simplest solution to solve CCO issues in the absence of a power control scheme.

Changing the base station transmit power is as costly as changing any other radio access network parameter since both actions only require modifying the network parameter file. However, there remains the problem of finding the optimum transmit power settings. A tradeoff exists between ensuring a good connection quality for users served by the

cell changing its transmit power while reducing interference in its neighbor cells. Thus, power planning can be formulated as a large-scale nonseparable multiobjective optimization problem. To find the optimal power plan, many search algorithms have been proposed in the literature [11–16]. To check the quality of a plan, analytical network models can be used [14]. However, analytic approaches fail to reflect relevant network conditions (irregular spatial traffic distribution, base station configuration, channel conditions, clutter type, etc.). To solve this limitation, a system-level simulator is often used in network planning tools [11–13, 15, 16]. However, system-level simulations are time consuming. Thus, it is essential to have an automatic search algorithm that finds the best parameter plan in a few attempts. To the authors' knowledge, no previous work has derived a simple rule to modify an existing power plan ensuring that the resulting solution is indeed the best solution.

In this work, a novel self-planning algorithm for modifying DL transmit power in a LTE system is presented. The proposed algorithm aims to improve the overall network SINR by adjusting DL transmit power on a per cell basis. The algorithm is designed as a set of controllers (one per cell), whose input is a new cell performance indicator. This novel indicator, which is the core of the proposal, reflects if a higher (or lower) transmit power in a particular base station increases (or decreases) the overall network SINR in DL. The algorithm is validated on a static system-level simulator implementing a real LTE dense urban scenario. During the analysis, the proposed algorithm is compared with a state-of-the-art self-planning approach based on remote electrical tilt.

The rest of the work is organized as follows. Section 2 presents the state of research in the CCO problem. Section 3 presents the problem formulation from which the new indicator is derived. Section 4 outlines the proposed method for adjusting DL transmit power on a cell basis. Section 5 shows the results of simulations carried out to validate the algorithm. Finally, Section 6 presents the main conclusions of the work.

2. Related Work

Depending on their purpose, SON methods can be classified as self-planning, self-optimization, or self-healing [17, 18]. *Self-planning* methods are conceived for the planning stage, when the network is not deployed yet. Consequently, self-planning algorithms make use of network models to estimate the quality of a network parameter plan. In the search of the best plan, many different parameter settings have to be tested. For this purpose, classical optimization methods are used to find the best solution (e.g., brute-force enumeration [19], simulated annealing [13], Taguchi [6], and genetic [20]). To check the quality of a plan, analytical [14] or simulation models [5] can be used. *Self-optimization* (a.k.a. self-tuning) methods are designed to adapt network parameters to changing network conditions during the operational stage [11–13, 15, 16]. Self-optimization algorithms usually consist of a controller that iteratively modifies network parameters based on certain network performance indicators. Unlike self-planning, self-optimization algorithms do not need a system model but make use of measurements from the live network to adjust network parameters. Finally, *self-healing* methods aim to detect, diagnose, and compensate problems caused by abnormal events in the network [21–23].

SON methods can also be classified in terms of the modified network parameter. In particular, CCO is usually performed by changing antenna bearings [6, 19, 20, 24–30] or power settings [11–13, 15, 16]. Strategies to modify antenna bearings include both self-planning [6, 19, 24–26] and self-optimization methods [20, 27–30]. Although most of these methods modify antenna tilt angles, a few of them simultaneously set tilt and azimuth angles [6, 24, 26]. Regarding power-based CCO methods, a power control algorithm is proposed in [11] for adjusting power levels according to the needs of UEs. The algorithm tunes DL transmit power based on signal quality measurements from UEs to ensure that all UEs experience adequate transmission quality. The algorithm also detects when UEs experience a transmission quality greater than required, so that transmit power is decreased to minimize interference in neighbor cells. In [12], the previous algorithm is extended by solving convergence problems through starting planning with maximum cell power levels for all transmitters. In [13], a decentralized algorithm for adjusting the transmit power of base stations in LTE is also presented. In this case, each neighbor cell searches for the optimal setting of the transmit power of the cell, keeping the power setting of the rest of cells unaltered. The algorithm relies on the knowledge of the interference produced by a base station in its neighbor cells at different transmit power levels. In [15], a more sophisticated algorithm is proposed to jointly tune transmit power and antenna tilt. In this algorithm, cells are classified in three groups depending on the ratio of covered UEs and carried traffic. Parameter changes are calculated based on the performance of the worst cell, and changes are simultaneously executed for all cells in the same group. Therefore, this method does not exploit the fact that network parameters can be set on a cell-by-cell basis. In [16], a decentralized self-optimization algorithm is proposed to adjust both transmit power and tilt on a cell basis to maximize both cell-average and cell-edge UE throughput of the whole network. The algorithm is implemented as a controller based on fuzzy reinforcement learning. Inputs are the current transmit power and tilt settings of the optimized cell, and the average relative differences in load and spectral efficiency with neighbor cells. A central controller enables cooperative learning by sharing the result of the adaptation process among cells. Controller parameters are adapted based on the result of random parameter changes. A major drawback is the fact that the algorithm needs many iterations to converge and can temporarily degrade network performance.

Likewise, power replanning is also used in self-healing algorithms to solve localized problems caused by network failures. Unlike self-optimization approaches, the aim of healing is not to achieve optimal system performance, but to bring a faulty cell to acceptable service levels. The most common application is Cell Outage Compensation (COC) [21–23]. The main limitation of these methods is the assumption

that, in normal operation, base stations do not fully utilize the available transmit power. However, in live networks, base stations are generally set to the maximum power to provide maximum coverage. Moreover, these algorithms are mainly focused on improving coverage, with less emphasis on intercell interference or signal quality.

A major drawback of most SON algorithms is the lack of an optimality proof. Most self-planning methods are based on heuristic approaches that reduce the size of the solution space to be explored to reduce computation time. Likewise, most self-optimization algorithms rely on heuristic control rules based on the knowledge of an experienced operator. Although some advanced self-optimization algorithms include unsupervised learning methods (e.g., Q-Learning [16]), simplifying assumptions often cause that there is no guarantee that optimal system performance is reached. Thus, the goodness of tuning is usually assessed based on convergence speed and stability issues [31]. Only in very rare cases, the optimality conditions can be reformulated as a control problem (e.g., [32], where the problem of traffic sharing in GSM is formulated as a balancing problem between adjacent cells).

In this work, the global CCO problem is formulated as a balancing problem by considering the tradeoff between the performance of a cell and its neighbors when increasing the transmit power of the cell under study. From the analysis of optimality conditions, a new indicator is derived that reflects the overall SINR gain in the vicinity of a cell increasing its transmit power. Thus, it is ensured that changes in power settings performed on a cell-by-cell basis always improve the overall system performance. The main contributions of this work are (a) a new indicator used to detect if increasing the transmit power of a particular base station increases (or decreases) the total system SINR in DL, (b) an algorithm for adjusting base station transmit power in a LTE network to increase the coverage area and overall spectral efficiency based on the previous indicator, and (c) a thorough comparison of the proposed algorithm with classical CCO algorithms in a realistic scenario taken from a live network.

3. Problem Formulation

In the following paragraphs, variables in logarithmic units are written in uppercase, whereas variables in natural units are written in lowercase. Likewise, the term DL is omitted hereafter for brevity.

CCO should be treated as a classical multiobjective optimization problem, since both coverage and capacity must be maximized. However, it is common practice to assign a higher priority to either coverage or capacity, since both features cannot be simultaneously optimized. In most cases, optimization is focused on network capacity, provided that a minimal network coverage is ensured [8]. In network planning, network capacity is often evaluated in terms of spectral efficiency, which is given by the signal quality in terms of SINR. Nonetheless, several objective functions have been proposed in the literature to measure the overall signal quality of a network, depending on how the performance of users and cells is aggregated:

(a) Overall user mean, considering all users equally. Thus, more populated cells tend to dominate the figure for merit.

(b) Cell arithmetic mean, where all cells are treated the same, regardless of their size and traffic. Such a figure of merit is simple to compute and easy to interpret, being the preferred option for operators. From the Shannon bound, it can be inferred that the average SINR in a cell (in dB) is a rough approximation of its average spectral efficiency [34]. Thus, the arithmetic mean of the average SINR across cells approximates the average maximum cell capacity, provided that all cells have the same system bandwidth.

(c) Cell harmonic mean [6], where cells with small SINR values render the mean value small. Thus, cells with worse performance tend to dominate the figure for merit.

In this work, the arithmetic mean of the average SINR per cell in dB is considered. Thus, the objective function to be maximized is the total system SINR (in dB), computed as

$$\begin{aligned} &\text{Maximize} \quad \Gamma_t = \sum_i \overline{\Gamma}(i) \\ &\text{subject to} \quad \overline{\Gamma_{\text{ce}}}(i) > \Gamma_{\text{ce}_{\min}}(i), \end{aligned} \tag{1}$$

where $\overline{\Gamma}(i)$ and $\overline{\Gamma_{\text{ce}}}(i)$ are the average SINR of users in cell i and in the cell-edge of cell i, respectively. In (1), $\Gamma_{\text{ce}_{\min}}(i)$ is the minimal value of $\overline{\Gamma_{\text{ce}}}$ required in cell i. The decision variables are cell transmit powers, $P_{TX}(i)$, which determine the value of $\overline{\Gamma}(i)$. In this work, $P_{TX}(i)$ is defined as the transmit power level per Physical Resources Block (PRB). It is assumed that $P_{TX}(i)$ is the same for all PRBs.

In the absence of constraints, any local minimum must satisfy the stationary condition, that is,

$$\frac{\partial \Gamma_t}{\partial P_{TX}(i)} = 0 \quad \forall i. \tag{2}$$

If it is assumed that changing the transmit power of a cell only affects a limited number of neighbor cells, the stationary condition can be rewritten as

$$\frac{\partial \Gamma_t}{\partial P_{TX}(i)} \approx \frac{\partial \left(\overline{\Gamma}(i) + \sum_{j \in N(i)} \overline{\Gamma}(j)\right)}{\partial P_{TX}(i)}, \tag{3}$$

where $N(i)$ is the set of neighbors of cell i. The terms in the numerator reflect the tradeoff between the SINR of a cell and its neighbors. Specifically, increasing the transmit power of a cell increases the SINR of users served by that cell, that is,

$$\frac{\partial \overline{\Gamma}(i)}{\partial P_{TX}(i)} > 0, \tag{4}$$

at the expense of decreasing the SINR of users in neighbor cells, that is,

$$\frac{\partial\left(\sum_{j\in N(i)}\overline{\Gamma}(j)\right)}{\partial P_{TX}(i)}<0. \tag{5}$$

To find a local maximum, a simple gradient ascent method can be used. For this purpose, the slope of the objective function with respect to each decision variable must be obtained. Such an indicator, $\beta(i)$, reflecting the gain in the total system SINR obtained by increasing the transmit power of a cell i is estimated as follows.

3.1. Novel Indicator. For convenience, the total SINR around a cell (in dB) is first defined as

$$\begin{aligned}\Gamma_c(i)&=\overline{\Gamma}(i)+\sum_{j\in N(i)}\overline{\Gamma}(j)\\&=\overline{S}(i)-\overline{I}(i)+\sum_{j\in N(i)}\left(\overline{S}(j)-\overline{I}(j)\right),\end{aligned} \tag{6}$$

where $\overline{S}(i)$ and $\overline{I}(i)$ are the average desired signal and interference levels (in logarithmic units) received in cell i, respectively.

In (6), averages correspond to the aggregation of all users in a cell. In most network planning tools, potential users are represented by locations. In a real scenario, each location has a different probability of a user demanding service from it, which is given by the spatial traffic distribution. This can be taken into account by multiplying the values of each variable in a location by a weight function representing traffic probability in that location as

$$\begin{aligned}\Gamma_c(i)=&\sum_{(x,y)\in A(i)}p_u(x,y)\left(S(x,y)-I(x,y)\right)\\&+\sum_{j\in N(i)}\sum_{(x,y)\in A(j)}p_u(x,y)\left(S(x,y)-I(x,y)\right),\end{aligned} \tag{7}$$

where $A(i)$ is the service area of cell i (i.e., locations served by cell i), $p_u(x,y)$ is the probability that a user generates traffic from location (x,y), and $S(x,y)$ and $I(x,y)$ are the received signal level from the serving cell and total interference level from neighbor cells for a UE located at (x,y), respectively. Obviously,

$$\sum_{(x,y)\in A(i)}p_u(x,y)=1\quad\forall i. \tag{8}$$

From (3) and (7), it follows that the sensitivity of Γ_t to changes in $P_{TX}(i)$ is the same as that of Γ_c, that is,

$$\beta(i)=\frac{\partial\Gamma_t(i)}{\partial P_{TX}(i)}\approx\frac{\partial\Gamma_c(i)}{\partial P_{TX}(i)}. \tag{9}$$

For simplicity, the partial derivative in (9) is broken down in four addends as

$$\beta(i)\approx F_1-F_2+F_3-F_4, \tag{10}$$

where

$$\begin{aligned}F_1&=\frac{\partial\overline{S}(i)}{\partial P_{TX}(i)},\\F_2&=\frac{\partial\overline{I}(i)}{\partial P_{TX}(i)},\\F_3&=\frac{\partial\left(\sum_{j\in N(i)}\overline{S}(j)\right)}{\partial P_{TX}(i)},\\F_4&=\frac{\partial\left(\sum_{j\in N(i)}\overline{I}(j)\right)}{\partial P_{TX}(i)}.\end{aligned} \tag{11}$$

F_1 reflects the impact of $P_{TX}(i)$ on the desired signal level in the modified cell (i.e., that received by users in cell i from cell i). F_2 does the same for the total interference received by users in cell i from neighbor cells, F_3 for the desired signal received by users in neighbor cells j, $j\neq i$, and F_4 for the interference received by users in neighbors j. All these factors are calculated as follows.

Source Desired Signal Term, F_1. The signal level received from a cell i in location (x,y) is calculated as

$$P_{RX}(i,x,y)=P_{TX}(i)-\mathrm{PL}(i,x,y), \tag{12}$$

where $\mathrm{PL}(i,x,y)$ is the path loss (including antenna gains) between cell i and location (x,y). In particular, the desired signal level in a location is

$$S(x,y)=P_{RX}(i,x,y),\quad(x,y)\in A(i). \tag{13}$$

Note that the spatial traffic distribution, $p_u(x,y)$, does not depend on power settings. Then, from (7), (12), and (13), it is deduced that the impact of changing $P_{TX}(i)$ on the desired signal level received by users in cell i is

$$\begin{aligned}F_1&=\frac{\partial\left(\sum_{(x,y)\in A(i)}p_u(x,y)S(x,y)\right)}{\partial P_{TX}(i)}\\&=\sum_{(x,y)\in A(i)}p_u(x,y)\frac{\partial P_{TX}(i)}{\partial P_{TX}(i)}=\sum_{(x,y)\in A(i)}p_u(x,y)\\&=1.\end{aligned} \tag{14}$$

Source Interference Term, F_2. The interference received in location (x,y) in cell i from any other cell $j\neq i$ is calculated as

$$I(x,y)=10\cdot\log_{10}\left(\sum_{j\in N(i)}p_{rx}(j,x,y)\,l(j)+n_0\right), \tag{15}$$

where $p_{rx}(j,x,y)$ is the power received at (x,y) from interfering cell j (in natural units), n_0 is the thermal noise (in natural units), and $l(j)$ is the load of cell j (dimensionless).

The average load of a cell i is estimated by the sum of the traffic load generated by each location (x, y) served by cell i as

$$l(i) = \sum_{(x,y)\in A(i)} l(x,y) = \frac{\sum_{(x,y)\in A(i)} \left(t(x,y)/\mathrm{se}(x,y)\right)}{N_{\mathrm{prb}}(i)}, \tag{16}$$

where $t(x, y)$ is the average traffic generated by location (x, y) (in bps), $\mathrm{se}(x, y)$ is the spectral efficiency obtained by users at location (x, y) (in bps per PRB), and $N_{\mathrm{prb}}(i)$ is the number of PRBs in cell i, given by the system bandwidth. In this work, spectral efficiency is estimated from SINR by the truncated Shannon bound formula [34]

$$\mathrm{se}(x,y) = \begin{cases} 0 & \gamma(x,y) < \gamma_{\min}, \\ \alpha_{\mathrm{IL}} \log_2(1+\gamma(x,y)) & \gamma_{\min} \le \gamma(x,y) \le \gamma_{\max}, \\ \mathrm{se}_{\max} & \gamma_{\max} < \gamma(x,y), \end{cases} \tag{17}$$

where $\mathrm{se}_{\max}$ is the maximum spectral efficiency that can be obtained in a location, $\gamma(x, y)$ is the SINR in a location (in linear units), $\gamma_{\min}$ and $\gamma_{\max}$ are SINR values corresponding to 0 and $\mathrm{se}_{\min}$, respectively, and α_{IL} is an attenuation factor representing implementation losses.

Thus, the impact of changing the power of a cell on the total interference level received by that cell is

$$F_2 = \frac{\partial \bar{I}(i)}{\partial P_{TX}(i)} = \sum_{(x,y)\in A(i)} p_u(x,y) \frac{\partial I(x,y)}{\partial P_{TX}(i)} = \sum_{(x,y)\in A(i)} \left[\frac{10}{\ln 10} \frac{p_u(x,y)}{\sum_{j\in N(i)} p_{rx}(j,x,y)\, l(j) + n_0} \cdot \sum_{j\in N(i)} p_{rx}(j,x,y) \frac{\partial l(j)}{\partial P_{TX}(i)} \right]. \tag{18}$$

In (18), it is observed that changing the transmit power of a cell only affects the received interference level in the same cell through changes in the load of neighbor cells.

As traffic demand does not depend on link quality, it is deduced from (16) that the sensitivity of neighbor load to changes in $P_{TX}(i)$ is

$$\frac{\partial l(j)}{\partial P_{TX}(i)} = \frac{\sum_{(x,y)\in A(j)} t(x,y) \left(\partial\left(1/\mathrm{se}(x,y)\right)/\partial P_{TX}(i)\right)}{N_{\mathrm{prb}}(j)}. \tag{19}$$

From (17), it is deduced that the slope of the spectral efficiency with respect to the transmit power is nonzero only in those locations where $\gamma_{\min} \le \gamma(x, y) \le \gamma_{\max}$, so that

$$\begin{aligned} \frac{\partial l(j)}{\partial P_{TX}(i)} &= -\frac{1}{N_{\mathrm{prb}}(j)} \cdot \sum_{\substack{(x,y)\in A(j),\\ \gamma(x,y)\in[\gamma_{\min},\gamma_{\max}]}} \left(t(x,y) \frac{1}{\alpha_{\mathrm{IL}} \left[\log_2(1+\gamma(x,y))\right]^2} \cdot \frac{1}{1+\gamma(x,y)} \frac{1}{\ln 2} \frac{\partial\left[10^{\Gamma(x,y)/10}\right]}{\partial P_{TX}(i)} \right) \\ &= -\sum_{\substack{(x,y)\in A(j),\\ \gamma(x,y)\in[\gamma_{\min},\gamma_{\max}]}} l(x,y) \cdot \frac{\gamma(x,y)}{(1+\gamma(x,y))\ln(1+\gamma(x,y))} \frac{\ln 10}{10} \cdot \frac{\partial(-I(x,y))}{\partial P_{TX}(i)}. \end{aligned} \tag{20}$$

To compute the derivative of $\Gamma(x, y)$ in (20), it has been considered that only the received interference, $I(x, y)$, changes with $P_{TX}(i)$. For tractability, additional side effects have not been considered. In addition, it is assumed that the sum of contributions to the change in load from all locations (x, y) in a cell can be approximated by the change in load experienced when all the traffic in the cell is generated in a single location with the average link performance of the cell. This consideration assumes that the change in the average cell performance is representative of the changes in all points in the cell. Thus, (20) can be approximated by

$$\frac{\partial l(j)}{\partial P_{TX}(i)} \approx l(j) \frac{\bar{\gamma}(j)}{(1+\bar{\gamma}(j))\ln(1+\bar{\gamma}(j))} \frac{\ln 10}{10} \frac{\partial\left(\bar{I}(j)\right)}{\partial P_{TX}(i)}, \tag{21}$$

where $\bar{\gamma}(j)$ and $\bar{I}(j)$ are, respectively, the traffic-weighted average SINR (in linear units) and interference level (in logarithmic units) for all locations in cell j. Then,

$$\frac{\partial \bar{I}(j)}{\partial P_{TX}(i)} = \sum_{(x,y)\in A(j)} p_u(x,y) \frac{\partial I(x,y)}{\partial P_{TX}(i)} = \sum_{(x,y)\in A(j)} \left[\frac{10}{\ln 10} \frac{p_u(x,y)}{\sum_{m\in N(j)} p_{rx}(m,x,y)\, l(m) + n_0} \cdot \sum_{m\in N(j)} \frac{\partial\left(p_{rx}(m,x,y)\, l(m)\right)}{\partial P_{TX}(i)} \right]. \tag{22}$$

Note that any change of transmit power in a cell affects signal quality, spectral efficiency, and, ultimately, the load of the

cell whose power is modified. Such a change in cell load cause changes in the interference generated on neighbor cells, which also change their signal quality, spectral efficiency, and load. For tractability, it is assumed here that the only cell changing load is the cell changing transmit power. This is true if the change in transmit power is small enough. It has been checked with simulations in a typical scenario that neighbors' load changes less than 7% (in relative terms) if the change of transmit power is less than 1 dB. If the change of cell load in neighbors is negligible,

$$\frac{\partial l(m)}{\partial P_{TX}(i)} \approx 0 \quad \forall m \neq i. \tag{23}$$

Thus, (22) can be rewritten as

$$\frac{\partial \overline{I}(j)}{\partial P_{TX}(i)} \approx \sum_{(x,y)\in A(j)} \left[\frac{10}{\ln 10} \cdot \frac{p_u(x,y)}{\sum_{m\in N(j)} p_{rx}(m,x,y)\, l(m) + n_0} \cdot \left(\frac{\partial p_{rx}(i,x,y)}{\partial P_{TX}(i)} l(i) + p_{rx}(i,x,y) \frac{\partial l(i)}{\partial P_{TX}(i)} \right) \right]. \tag{24}$$

The two partial derivatives in (24) show how the interference in neighbors changes with the change of transmit power and load in the modified cell. These terms can be calculated as

$$\frac{\partial p_{rx}(i,x,y)}{\partial P_{TX}(i)} = \frac{\ln 10}{10} p_{rx}(i,x,y), \text{ and} \tag{25}$$

$$\frac{\partial l(i)}{\partial P_{TX}(i)} = -\frac{\ln 10}{10} l(i) \frac{\overline{\gamma}(i)}{(1+\overline{\gamma}(i))\ln(1+\overline{\gamma}(i))}. \tag{26}$$

From (21), (24), (25), and (26), it is obtained that

$$F_2 \approx \sum_{(x,y)\in A(i)} \left[\frac{p_u(x,y)}{\sum_{j\in N(i)} p_{rx}(j,x,y)\, l(j) + n_0} \cdot \sum_{j\in N(i)} \left(p_{rx}(j,x,y)\, l(j) \frac{\overline{\gamma}(j)}{(1+\overline{\gamma}(j))\ln(1+\overline{\gamma}(j))} \cdot \sum_{(x,y)\in A(j)} \left[\frac{p_u(x,y)}{\sum_{m\in N(j)} p_{rx}(m,x,y)\, l(m) + n_0} \cdot \left(p_{rx}(i,x,y)\, l(i) - p_{rx}(i,x,y)\, l(i) \frac{\overline{\gamma}(i)}{(1+\overline{\gamma}(i))\ln(1+\overline{\gamma}(i))} \right) \right] \right) \right]. \tag{27}$$

By grouping terms, F_2 can be rewritten as

$$F_2 \approx [1 - f(\overline{\gamma}(i))] \sum_{j\in N(i)} \left[\overline{ic}(j,i)\, f(\overline{\gamma}(j))\, \overline{ic}(i,j) \right], \tag{28}$$

where

$$f(\overline{\gamma}(i)) = \frac{\overline{\gamma}(i)}{(1+\overline{\gamma}(i))\ln(1+\overline{\gamma}(i))}, \tag{29}$$

and $\overline{ic}(j,i)$ is the average ratio of interference in cell i due to neighbor j, defined as

$$\overline{ic}(j,i) = \sum_{(x,y)\in A(i)} \frac{p_u(x,y)\, p_{rx}(j,x,y)\, l(j)}{\sum_{k\in N(i)} p_{rx}(k,x,y)\, l(k) + n_0}, \tag{30}$$

Neighbor Desired Signal Term, F_3. From (7) and (11),

$$F_3 = \frac{\partial \left(\sum_{j\in N(i)} \overline{S}(j) \right)}{\partial P_{TX}(i)} = \frac{\partial \left(\sum_{j\in N(i)} \sum_{(x,y)\in A(j)} p_u(x,y)\, P_{RX}(j,x,y) \right)}{\partial P_{TX}(i)}. \tag{31}$$

As neither $p_u(x,y)$ nor $P_{RX}(j,x,y)$ depends on $P_{TX}(i)$, $F_3 = 0$.

Neighbor Interference Term, F_4. Similarly to F_2, the change in neighbor interference can be expressed as

$$F_4 = \frac{\partial \left(\sum_{j\in N(i)} \overline{I}(j) \right)}{\partial P_{TX}(i)} = \sum_{j\in N(i)} \sum_{(x,y)\in A(j)} p_u(x,y) \frac{\partial I(x,y)}{\partial P_{TX}(i)}. \tag{32}$$

Note that $N(j)$ includes cell i as an interferer of cell j. Then, the partial derivative in (32) must be separated in two groups of cells: the interfering cell i and the rest of interfering cells $m \neq i$. Thus,

$$\frac{\partial I(x,y)}{\partial P_{TX}(i)} = \frac{10}{\ln 10} \frac{1}{\sum_{m\in N(j)} p_{rx}(m,x,y)\, l(m) + n_0} \cdot \left[\frac{\partial \left(\sum_{m\in N(j), m\neq i} p_{rx}(m,x,y)\, l(m) \right)}{\partial P_{TX}(i)} + \frac{\partial \left(p_{rx}(i,x,y)\, l(i) \right)}{\partial P_{TX}(i)} \right]. \tag{33}$$

Following the same steps as for F_2, it is obtained that

$$F_4 \approx [1 - f(\overline{\gamma}(i))] \sum_{j \in N(i)} \left[\overline{ic}(i,j) + \sum_{m \in N(j), m \neq i} \overline{ic}(m,j) f(\overline{\gamma}(m)) \overline{ic}(i,m) \right]. \quad (34)$$

Two terms can be identified in (34). The first term reflects the change of interference in cell j, caused by the load variation in cell i due to the change in spectral efficiency from the new transmit power of cell i. The second term reflects the change of the interference received by cell j, caused by the load variation in the rest of interferers of cell j, which also modify their load due to change of interference from cell i.

4. Self-Planning Algorithm

In this section, a heuristic method to find the best change in DL transmit power on a cell basis is presented. The aim of the method is to adjust the transmit power of each cell in the system so as to improve the total system SINR, Γ_t. The method makes use of a classical gradient ascent algorithm to find the best tradeoff between the SINR of a cell and its neighbors, based on the above-described indicator, $\beta(i)$, reflecting whether increasing the transmit power of a particular base station increases (or decreases) the total system SINR.

The gradient ascent algorithm is designed as a set of simple proportional controllers (one per cell), which iteratively compute changes in the DL transmit power based on the value of the β indicator. Specifically, the output of one of these controllers is the change in DL transmit power (in dB), $\Delta P_{TX}(i)$, computed as

$$\Delta P_{TX}(i) = \begin{cases} -1 & \beta(i) \leq \beta_{\min}, \\ 0 & \beta_{\min} < \beta(i) < \beta_{\max}, \\ 1 & \beta(i) \geq \beta_{\max}, \end{cases} \quad (35)$$

where $\beta_{\min}$ and $\beta_{\max}$ are thresholds for triggering $P_{TX}(i)$ modifications, introduced to keep the number of network changes to a minimum. In this work, both thresholds are symmetrical; that is, $\beta_{\max} = -\beta_{\min}$.

The proposed algorithm works as an iterative process, starting from an initial power value, $P_{TX}(i)$, which is later modified at every iteration (referred to as optimization loop). Every loop starts with the collection of network statistics, from which β is computed for all cells in the scenario. The collection period must be large enough (e.g., one day) to improve the robustness of the algorithm. Then, (35) is used to compute power changes, $\Delta P_{TX}^{(l)}(i)$, where l is the loop number. Finally, the new values of $P_{TX}(i)$ for the next loop are calculated as

$$P_{TX}^{(l+1)}(i) = P_{TX}^{(l)}(i) + \Delta P_{TX}^{(l)}(i). \quad (36)$$

An output range $[P_{TX_{\min}}(i), P_{TX_{\max}}(i)]$ is defined. $P_{TX_{\max}}$ is usually fixed by operators to the maximum value supported by the equipment, as network coverage is thus maximized. Such a maximum value may be hardware (i.e., power amplifier) or software (i.e., license) limited. Note that $P_{TX_{\max}}$ is not necessarily the same in all cells, since the DL power amplifier and/or the licensed power may be different between cells. In contrast, $P_{TX_{\min}}$ is defined as a safety brake for the tuning process to prevent coverage issues. In this work, $P_{TX_{\min}}$ is set to 10 dB less than $P_{TX_{\max}}$ for each cell to avoid excessive transmit power reduction.

5. Performance Assessment

The self-planning algorithm is validated with a static system-level LTE simulator implementing a live scenario adjusted with real measurements. The assessment methodology is first described and results are presented later.

5.1. Assessment Methodology. This section describes the simulation scenario and the experiments carried out to assess the proposed indicator and self-planning method.

5.1.1. Simulation Scenario. A DL static system-level LTE simulator implementing a real macrocellular scenario has been developed in MATLAB [30]. The simulator is designed to make the most of available network statistics to model a live macrocellular scenario. For this purpose, the simulator includes the following features:

(a) Initialization of cell load distribution across the scenario with PRB utilization figures obtained from counters in the network management system of a live LTE network.

(b) Adjustment of spatial user distribution within a cell by distance rings, so that the probability of a user being in a distance ring is derived from Timing Advance (TA) distributions [35].

(c) Tuning of propagation model parameters according to live RSRP measurements statistics.

Table 1 summarizes the main scenario parameters. The simulated area comprises 129 cells distributed in 44 sites with an average Inter-Site Distance (ISD) of 0.8 km. This scenario, with a relatively low ISD, is representative of an interference-limited scenario in a dense urban area. The geographical area under analysis is divided into a regular grid of points, representing potential user locations. Received signal level at each point from base stations is computed by a macrocellular propagation model including log-normal slow fading (i.e., Winner II C2 model [33]). For this purpose, user locations are classified into Line Of Sight (LOS) or Non-Line of Sight (NLOS) conditions based on real geolocated data of buildings and antenna positions in the scenario. Grid resolution is 40 meters. Cell service areas are computed by combining path losses and antenna gains, so that the serving cell is that providing the maximum pilot signal level for each point. Likewise, neighbor cells are defined as those providing

Table 1: Simulation scenario.

Number of sites	44
Number of cells	129
Avg. intersite distance [m]	815
Carrier frequency [MHz]	734
System bandwidth [MHz]	10
Number of PRBs	50
UE height [m]	1.5
BS antenna height [m]	[3, 54]
Initial cell transmit power [dBm]	[46.5, 47.4]
Maximum antenna gain [dB]	15
Antenna tilt angle [°]	[0, 13]
Propagation model	Winner II C2 [33] with $X = 14$ for NLOS users
Grid resolution [m]	40
Spatial traffic distribution	Distance based on TA measurements
PRB utilization ratio [%]	[5, 70]

the largest signal levels in the service area of a cell. Then, interference level at every point is computed by adding the interference from all neighbor cells. Finally, β is calculated on a cell basis and the self-planning algorithm is executed to obtain new P_{TX} values for the next optimization loop. PRB utilization ratios are updated at every new loop by estimating the impact of $P_{TX}(i)$ changes on the radio link spectral efficiency at every cell. The reader is referred to [30] for a more detailed explanation of the simulation tool.

5.1.2. Validation of β Indicator. A sensitivity test is first carried out to check the accuracy of indicator β, reflecting the impact of changing the power of a cell on the total system SINR. For this purpose, the default power plan configured by the operator is modified by increasing the power of a single cell by 1 dB, so a new power plan is obtained. This process is repeated for every cell in the scenario, so 129 new power plans are constructed. Then, the difference in the total system SINR, $\Delta\Gamma_t(i)$, from each individual power change is computed by subtracting the values with the default and the new power plan. Such differences should coincide with the values of β for the different cells, $\beta(i)$, estimated from network performance data obtained with the default plan as in (9).

It should be pointed out that the simulation tool can accurately model cell coupling effects. For instance, SINR in neighbor j is modified when the power of a cell i is modified. As a consequence, spectral efficiency in cell j changes, and so does its PRB utilization ratio. This load change in cell j causes interference changes in both cell i and other neighboring cells. Thus, the initial power change in cell i is propagated across the network. Likewise, the simulator updates cell service areas with the new power setting. However, these side effects cannot be taken into account by the analytical approach used to derive β. On the contrary, the definition of β only considers first-order effects of changing power settings. For a fair comparison, and only for this experiment, PRB utilization of neighbor cells j that do not change power is kept unaltered in the simulations, that is, only the modified cell i changes its PRB utilization. Likewise, cell service areas in the simulator are not recalculated when power settings are modified.

5.1.3. Algorithm Assessment. Three power planning methods are compared. A first method is the DL transmit power plan originally implemented by the operator, denoted as operator solution (OS). OS is the baseline against which all other methods are compared. In OS plan, DL transmit power is set to the maximum value in all cells. This is due to the fact that DL transmit power is often configured when the site is launched and remains unchanged when new sites are deployed in the surroundings, which may generate useless cell overlapping and high intercell interference.

A second method is the iterative self-planning algorithm for DL transmit power proposed here, denoted as SINR-PWR. This method is initialized with the OS plan and 30 optimization loops are simulated. It is checked a posteriori that this number of loops is enough to reach equilibrium.

A third method is the iterative self-planning algorithm for remote electrical tilt (RET) based on trace files described in [30], denoted as TF-RET (for Trace-based Fuzzy). TF-RET adjusts antenna tilt values instead of base station transmit power. For this purpose, three performance indicators are obtained from connection traces to detect cell overshooting, useless cell overlapping, and cell-edge coverage problems. Then, downtilting is performed in those cells generating overshooting and/or useless overlapping, and without coverage problems. As in [30], this method is also initialized with the OS plan and 20 optimization loops are simulated. It is checked a posteriori that this number of loops is enough to reach equilibrium.

For brevity, the analysis of SINR-PWR and TF-RET is restricted to the solution obtained in the last iteration.

Two figures of merit are used to assess power planning algorithms:

(i) Overall average DL SINR, $\overline{\text{SINR}_{\text{avg}}}$, as a measure of network connection quality and spectral efficiency,

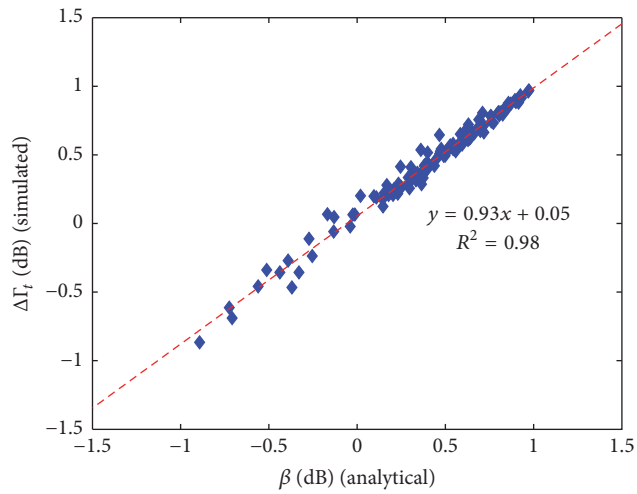

Figure 1: Analytical and simulated change of total DL SINR.

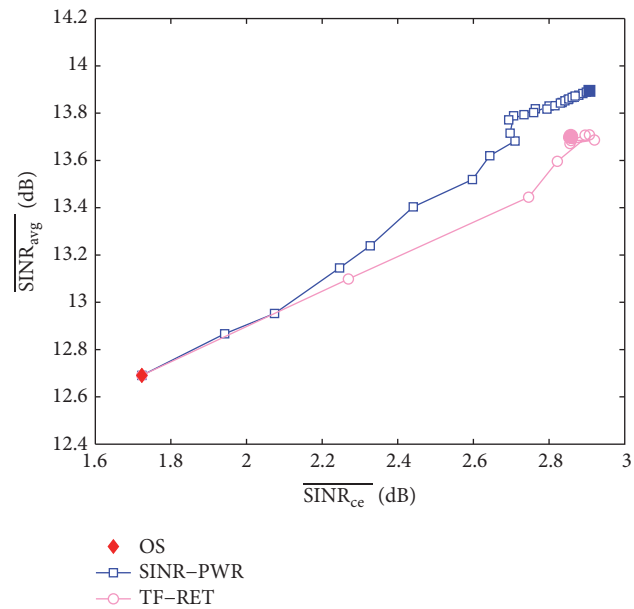

Figure 2: Performance comparison.

calculated as the arithmetic mean of the average DL SINR in each cell, $\overline{\Gamma}(i)$, and

(ii) Overall cell-edge DL SINR, $\overline{\text{SINR}_{\text{ce}}}$, as a measure of network coverage, calculated as the arithmetic mean of the 5th-percentile DL SINR in each cell, $\Gamma_{\text{ce}}(i)$.

In practice, any change in power settings through optimization loops might cause that some locations in the scenario do not receive enough signal level for establishing a connection, or, conversely, some locations initially not served by any cell could reach enough signal level to start a connection in a later optimization loop. These changes in the coverage area would have an influence on the total traffic carried by the network. For a fair comparison, both SINR indicators are computed in the same set of locations along iterations (i.e., the evaluated geographical area is always the same).

5.2. Results. The validation of the β indicator is first presented and the assessment of power planning algorithms is discussed later.

5.2.1. Validation of β Indicator. Figure 1 shows the accuracy of the proposed indicator by comparing estimates obtained with the formulas against results obtained with the simulator. Each point in the figure corresponds to one of the new 129 power plans built by increasing the transmit power of a cell by 1 dB. The x- and y-axes represent the values of β and $\Delta\Gamma_t$, respectively. It is observed that both indicators are strongly correlated, since the coefficient of determination, R^2, is 0.98, and the value of the regression slope is close to 1. This similarity between simulated and analytical values proves the validity of the β indicator.

Moreover, it is observed that the impact of increasing the transmit power of a cell greatly varies from cell to cell. In some cells (up and right points in Figure 1), the 1-dB transmit power increase is directly translated into a 1-dB increase in the total system SINR denoting an isolated cells scenario. In contrast, in other cells (left and down points in the figure), the same transmit power change leads to a decrease in the total system SINR, denoting a tightly coupled cell scenario. This result justifies the need for adjusting transmit power on a cell-by-cell basis.

5.2.2. Algorithm Assessment. Figure 2 compares the results of the different algorithms. The overall cell-edge and cell-average SINR metrics are shown on the x- and y-axes, respectively. Points in the upper right part of the figure show better performance. The OS configuration method used as a reference is represented by a single dot (diamond). Self-planning methods (i.e., SINR-PWR and TF-RET) are represented by a curve of multiple dots showing the performance of intermediate network parameters settings reached across optimization loops. For clarity, the last value in these iterative methods is highlighted with a filled marker. Both SINR-PWR and TF-RET curves start with the OS network configuration, and their performance is thus the same in the first iteration. Thereafter, SINR-PWR and TF-RET improve both average and cell-edge SINR along iterations.

Table 2 compares the performance of the iterative methods, SINR-PWR and TF-RET, at the end of the optimization process against the initial solution, OS. Table 2 also presents the overall average and cell-edge DL user throughput, $\overline{\text{UeTH}_{\text{avg}}}$ and $\overline{\text{UeTH}_{\text{ce}}}$, respectively, calculated as the arithmetic mean of the individual cell values (average and cell-edge DL user throughput, resp.). DL user throughput in each user location is computed from SINR values by the bounded Shannon formula [34] with attenuation factor, $\alpha_{\text{imp}} = 0.6$, assuming that the whole system bandwidth is available to the user (i.e., 50 PRB · 180 kHz/PRB = 9 MHz). In addition, other important indicators are also included, such as the average received pilot signal level from the serving cell, $\overline{\text{RSRP}}$, average DL interference level, $\overline{I}$, average deviation of

Table 2: Method performance at the end of the adjusting process.

	OS	SINR-PWR	TF-RET
$\overline{\text{SINR}_{\text{avg}}}$ [dB]	12.69	13.90	13.70
$\overline{\text{SINR}_{\text{ce}}}$ [dB]	1.72	2.91	2.86
$\overline{\text{UeTH}_{\text{avg}}}$ [Mbps]	23.36	25.36	25.02
$\overline{\text{UeTH}_{\text{ce}}}$ [Mbps]	7.44	8.74	8.70
$\overline{\text{RSRP}}$ [dBm]	−88.44	−89.90	−88.17
$\overline{I}$ [dBm]	−101.13	−103.80	−101.88
$\overline{\Delta P_{TX}}$ [dB]	—	−1.80	—
$\overline{\Delta\alpha}[^\circ]$	—	—	0.50
Number of modified cells	—	48	65

transmit power and tilt angle from initial settings, $\overline{\Delta P_{TX}}$ and $\overline{\Delta\alpha}$, and the number of modified cells.

In Table 2, it is observed that both methods outperform the current operator solution. Specifically, SINR-PWR improves $\overline{\text{SINR}_{\text{avg}}}$ by 1.21 dB and $\overline{\text{SINR}_{\text{ce}}}$ by 1.19 dB when compared to OS, whereas TF-RET improves those indicators by only 1.01 and 1.14 dB, respectively. It is also observed that SINR-PWR outperforms TF-RET, since a better performance is achieved for both indicators at the end of the optimization process (i.e., 13.90 against 13.70 dB for $\overline{\text{SINR}_{\text{avg}}}$, and 2.91 against 2.86 dB for $\overline{\text{SINR}_{\text{ce}}}$). SINR improvements are directly translated into a better user experience reflected in throughput indicators. Specifically, $\overline{\text{UeTH}_{\text{avg}}}$ and $\overline{\text{UeTH}_{\text{ce}}}$ indicators are increased by 8.6% and 17.5% in relative terms, respectively, with SINR-PWR algorithm. In contrast, TF-RET algorithm only achieves a 7.1% and 16.9% increase for those indicators. The reason for the better performance of SINR-PWR is the fact that SINR-PWR is based on an analytical approach that ensures a (local) maximum of system performance, whereas TF-RET is based on heuristic rules. Recall that the main goal of SINR-PWR is to improve the overall average SINR, regardless of the overall cell-edge SINR. Then, the fact that SINR-PWR also improves $\overline{\text{SINR}_{\text{ce}}}$, and more than TF-RET, is a positive side effect that proves the robustness of the proposed method.

A close inspection of Table 2 shows that SINR-PWR obtains its results by decreasing both $\overline{\text{RSRP}}$ and $\overline{I}$ values (−1.46 and −2.67 dB, resp.). Such a reduction, typical of an interference-limited scenario, is done without deteriorating the overall SINR cell-edge performance, which is also improved. In contrast, TF-RET maintains $\overline{\text{RSRP}}$ and $\overline{I}$ values. As an additional advantage, SINR-PWR modifies fewer cells than TF-RET (i.e., 48 power changes versus 65 up/downtilts).

5.3. Implementation Issues. The time complexity of SINR-PWR algorithm is $\mathcal{O}(N_c)$, where N_c is the number of cells in the analyzed area. The method is designed as a control algorithm and therefore has a low computational complexity. Specifically, the total execution time of 30 optimization loops in the considered scenario with 129 cells, in a computer with a clock frequency of 3.47 GHz and 12 GB of RAM, is 1980 seconds (66 seconds per loop on average). Most of this time is spent on simulating the scenario to obtain network performance indicators, and only 0.085 seconds per loop is spent on the computation of the proposed indicator (i.e., less than 0.13% of the loop execution time).

Moreover, by computing the β indicator analytically, instead of deriving it by perturbation analysis, the number of parameter plans to be simulated is reduced by N_c times. Note that the β indicator can be calculated analytically by simulating a single parameter plan, whereas a perturbation analysis needs changing the power setting of one cell at a time and simulating a new parameter plan per cell.

6. Conclusions

In this work, a novel self-planning algorithm has been presented for adjusting the transmit power of LTE base stations on a cell basis to improve both network coverage and overall spectral efficiency. The algorithm is designed as a set of independent controllers that decide whether to increase or decrease the transmit power of a cell based on a new indicator showing the expected impact of that change on the total system DL SINR. The proposed self-planning algorithm has been tested in a static system-level simulator modeling a live dense urban interference-limited LTE scenario. Results have shown that the proposed method can improve both cell-average and cell-edge SINR values by more than 1 dB when compared with the solution currently implemented in the network.

During the tests, the proposed method has been compared with a state-of-the-art self-planning method based on adjusting antenna tilts. A priori, tilting is a more powerful technique, as it can improve both the modified cell (with higher desired signal level) and its neighbors (with less interference). However, the proposed power-based method outperforms the tilt-based method. The reason for that superiority is the fact that the power-based method is designed to reach the optimal power plan, based on the analysis of optimality conditions. Thus, the proposed approach ensures that network performance is always improved after every change of power settings. In contrast, the tilt-based method is based on a heuristic approach, in the absence of an analytic expression of the optimality conditions of antenna tilting. Moreover, unlike antenna tilting, power adjustment is still valid for cells with omnidirectional or multiband antennas.

Unlike other self-planning approaches, the proposed method is designed as a control algorithm. Due to its low computational complexity, the method can be adapted to be used as a self-optimization algorithm, provided that the β indicators are computed from network performance measurements available in connection traces. For this purpose, periodic RSRP measurements should be activated in all sites. This data should be processed periodically in a centralized node to obtain the new transmit power settings by the algorithm. Alternatively, each base station might exchange performance measurements with its neighbors to derive the associated β indicator in a distributed fashion.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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