Abstract

Energy is becoming a main concern nowadays due to the increasing demands on natural energy resources. Base stations (BSs) consume up to 80% of the total energy expenditure in a cellular network. In this paper, we propose and evaluate a green radio network planning (RNP) approach by jointly optimizing the number of active BSs and the BS on/off switching patterns based on the changing traffic conditions in the network in an effort to reduce the total energy consumption of the BSs. The problem is formulated as an integer optimization problem which proves to be NP-Complete and thus it can be efficiently solved for small to medium network sizes. For large network sizes, we propose a heuristic solution with close to optimal performance since the optimal solution becomes computationally complex. Planning is performed based on two approaches: a reactive and a proactive approach. In the proactive approach, planning will be performed starting with the lowest traffic demand until reaching the highest traffic demand whereas in the reactive approach, the reverse way is considered. Performance results are presented for various case studies and are complemented by testing the proposed approaches using commercial RNP tools. Results demonstrate considerable energy savings reaching up to 40% through dynamic adaptation of the number of simultaneously active BSs.

Index Terms

Radio network planning, Green radio network planning, LTE network, BS switching, Energy consumption
I. INTRODUCTION

Wireless technologies are continuously evolving in order to cope with the steadily increasing demands of end mobile stations (MSs) in terms of high bit rate multi-service capabilities. Therefore, wireless operators are continuously upgrading their networks to be inline with the technology advances. Radio network planning (RNP) is essential for operators to deploy wireless cellular networks in a cost-efficient manner [1].

The RNP process determines the locations and configurations of the base stations (BSs) that are needed to meet the network coverage and capacity requirements. One of the main objectives of the network operators while deploying a new network is to decrease the capital expenditure (CAPEX) and the operating expenditure (OPEX) of the network by deploying the minimum required number of BSs while meeting the coverage and capacity requirements. Thus, RNP is typically performed for the worst case scenario, i.e., at peak hour or for maximum load which determines the maximum required number of BSs [2]. Recently, in addition to decreasing the CAPEX of the network, there is an increased research interest in developing energy-aware RNP algorithms which decrease the overall network energy consumption in an effort to contribute to the reduction of carbon emission and the networks’ operational costs [3], [4]. For example, several international projects are launched to investigate energy-aware radio technologies such as energy aware radio and network technologies (EARTH) [5] and Greentouch [6]. Another example is the work presented in [7] where an energy-aware RNP approach is developed aiming at decreasing the emitted power in the network while taking demand uncertainties into account. However, the set of deployed BSs is active at all times even for low traffic states where some BSs could be turned off for further energy savings.

Energy is becoming a main concern especially that it constitutes up to 18% of the operational cost in European countries; this is due to the increase in energy prices. Nowadays, the energy demand of major network operators such as Vodafone is on the order of 3000 gigawatts (GW) per hour [8]. Mobile communications are increasingly contributing to global energy consumption and green house gas emissions which is very harmful to the environment since it traps heat inside the atmosphere. The global greenhouse gas emissions from Information and Communication Technology (ICT) are comparable with those of the aviation industry. Wireless communications constitute approximately 15% of ICT [8]. Emissions of CO$_2$ from the mobile network infrastructure was 64 MTons in 2002 and is expected to reach 178 MTons in 2020 [8]. Scientists believe that CO$_2$ emissions should be decreased by 70% to 80% to balance the
**CO₂ concentrations in the atmosphere** [5]. BSs consume the highest amount of energy in a mobile network. Moreover, the energy-efficiency of the BSs decreases significantly at off-peak hours since the power amplifiers (PAs) energy-efficiency degrades at lower output power [4]. Thus, power savings methods should focus on the access network level by trying to manipulate the BSs power consumption. This could be done by reducing the number of active elements (e.g., BSs) in the network for lower traffic states by switching some BSs off [3], [4]. The BS On/Off switching technique is currently under testing and development to be practically deployed in the near future. For example, one of the investigated techniques by the EARTH project was ‘The ON/OFF Scheme’ in which a heuristic BS ON/OFF switching scheme was proposed and validated using a real testbed measurement implemented by “Telecom Italia” [5].

Several network management algorithms for BS on/off switching in 4G LTE or OFDMA networks are proposed, in the literature, to reduce the network’s energy consumption while maintaining coverage and capacity requirements [9]–[21]. In these works, it is assumed that the network is already deployed and then based on traffic variation, some of the existing BSs are switched on or off while meeting the QoS constraints of the network. BS on/off switching to minimize the network’s energy consumption is an NP-hard problem that is very complex to model and solve. Thus, most of the works propose a heuristic solution for BS on/off switching [9], [12], [13], [15]–[17], [19]–[21]. For example, a distributed heuristic approach for dynamic BS switching is presented in [15] in which a BS decides to switch on or off based on a given traffic profile. In [17], a centralized heuristic solution is proposed in which the BSs are switched off based on the traffic variation and the distance of the MSs with respect to the BSs. In [21], the concept of cell zooming is presented which consists of adaptively adjusting the cell size according to the traffic load variations.

Optimized solutions for BS on/off have been limitedly investigated mainly due to the complexity of the problem [11], [14], [18]. In [14], the authors propose a nonlinear integer programming problem to decide on the set of active BSs for a given traffic state, however an exhaustive search is proposed to solve the problem as it is the only feasible alternative to solve the problem. In [18], a two-stage optimization problem is proposed to reduce the complexity of the problem; in the first stage, the maximum radius of the service areas of the BSs are calculated, then in the second stage, the minimal set of active required BSs is found. In [11], an efficient linear integer programming formulation is proposed to decide on the active set of BSs for a given traffic state, however, the interference of the BSs that affects the quality of service of the MSs is ignored. In general, modeling the SINR constraint of the MSs is challenging and non-trivial and
thus most of the previous works ignored interference [10]–[14], [17]–[19]. The optimization framework that jointly chooses the minimum set of BSs and allocates the users to the BSs while meeting their target SINR constraints taking interference into account have not been captured before. As a result, the optimal solution was never studied and analyzed.

The aim of the previous works is to propose a BS on/off switching scheme for an already existing network. To our knowledge, none of the existing works investigated the optimal BS on/off switching criteria as part of the RNP process for maximum energy savings.

A. Contributions

In this work, we develop optimal and heuristic solutions for LTE RNP taking into account green considerations. The objective is to jointly optimize BS location deployment and BS on/off switching patterns as part of the RNP process. The main contributions of this work are as follows: 1) formulating the green LTE RNP taking intercell interference into account as an integer linear programming (ILP) optimization problem and proving that it is NP-hard, 2) finding the optimal solution for small to medium network sizes, 3) proposing a heuristic solution, with close to optimal performance, for large network sizes where the optimal solution becomes computationally complex, 4) considering both reactive and proactive RNP approaches and comparing their performances for various traffic states, 5) evaluating CO$_2$ emissions reduction based on the proposed green RNP approach, and 6) testing the proposed approaches using commercial RNP tools to map the insights of our work and algorithms to real RNP scenarios. We have presented a preliminary heuristic proactive RNP approach in [22]. In this paper, we are presenting a more comprehensive model including the optimal solution, the reactive approach, complexity analysis along with more comprehensive results and analysis including simulations from a commercial RNP tool.

This paper is organized as follows; Section II presents the system model for green LTE RNP. The optimization problem formulation and the solution approaches are introduced in Sections III and IV. The results and analysis for the LTE RNP problem with green considerations are discussed in Section V. Finally, Section VI provides some concluding remarks.
II. System Model and Problem Definition

Given a candidate set, $B$, of possible BS locations and a traffic distribution at different time intervals, the aim is to choose the minimum set of BS locations from $B$ to meet coverage and capacity constraints while minimizing the energy consumption of the network. Moreover, based on the network’s traffic variations, the optimal BS on/off switching strategy should be determined. In this work, we minimize the number of active BSs that are necessary to meet the QoS requirements of the users; minimizing the number of required BSs while deploying a new network is a main concern to the cellular operators to reduce the CAPEX and OPEX of the network. Minimizing the number of active BSs reduces the energy consumption of the network as the energy consumption of the BS is significant in active mode even if it is not transmitting [23]. Then, as the traffic fluctuates, the minimal required number of active BSs is chosen by switching on/off the necessary BSs which reduces the overall energy consumption of the network compared to the case where all BSs are kept active for all traffic states. Each BS is assumed to be equipped with an omni-directional antenna that is placed at the cell center.

Nowadays, BSs are operated and deployed for the worst traffic peak estimates. However, traffic fluctuates with time, as shown in Figure 1 which presents a snapshot for the traffic variation in Beirut city at different times of the day. Traffic demands vary a lot during the day depending on the MSs’ behavior and their data needs. Figure 2 shows an example of the total traffic of a major operator per day [4], [15]. One can clearly see that the traffic degrades exponentially for all applications during specific periods of time and it could be 10 times lower during off-peak hours compared to peak hours. Operators can benefit from this decrease in traffic by turning selected BSs off and off-loading their traffic to neighboring BSs. By monitoring traffic loads, operators can switch off some of the BSs while maintaining coverage and capacity requirements.

In this paper, traffic conditions are taken into consideration and divided into multiple different states where each state $s$ represents a given range of traffic load in the network based on given statistics. For example, traffic variations are divided into three different traffic states ($s_1$, $s_2$, and $s_3$) in Figure 2.

The control center should monitor the traffic variations across a day over a period of time such as a week or a month. It definitely has data for much longer periods. Traffic variations are correlated; for example, the traffic around a university has a correlated behavior across the weekdays and another correlated behavior over the weekend. Using
Fig. 1. User density variation in Beirut.

![Image](image.png)

Fig. 2. Example quantized traffic variation.

this data, the control center can calculate the average traffic per hour and decide on traffic states. A traffic state can represent an interval of traffic such as those presented in Figure 2. But, how much to fine tune those intervals depends on the operators choice. So, once the traffic states are specified, the control center can run the BS on/off switching algorithms for each interval. Then, the BSs are switched on/off according to the detected traffic in the network.

A. Parameters and Variables

This section presents the main parameters and variables in the considered system model for LTE RNP. The input parameters are assumed to be the following:

- An area of interest defined by cartesian coordinates \((a_x, a_y)\) where \(a_x \in [a_{x,\text{min}}, \ldots, a_{x,\text{max}}]\) and \(a_y \in [a_{y,\text{min}}, \ldots, a_{y,\text{max}}]\)
on which the LTE network is to be deployed.

- A set of traffic states, \( S = \{s_1, \ldots, s_n\} \).
- A candidate set of BSs, \( i \in \{1, \ldots, N_B\} \), with cartesian coordinates \((x_i, y_i)\). \( N_B \) is the total number of input candidate BS locations.
- A set of MSs, \( k \in \{1, \ldots, K_s\} \), with cartesian coordinates \((u_k, v_k)\). \( K_s \) is the total number of MSs for a given traffic state \( s \).
- A maximum number of MSs, \( K_{BS} \), that can be served by each BS.
- A maximum BS transmit power, \( P_{BS} \).
- A target outage probability, \( \beta \).

The decision variables are:

- \( c_i \): a binary variable which indicates whether BS \( i \) is selected if \( c_i = 1 \), otherwise \( c_i = 0 \).
- \( t_{k,i} \): a binary variable which indicates whether MS \( k \) is served by BS \( i \) if \( t_{k,i} = 1 \), otherwise \( t_{k,i} = 0 \).

The output is the minimum set of optimized BSs locations that satisfy QoS requirements which is in our case the SINR requirements for the different traffic states.

In LTE, the downlink SINR over a given subcarrier assigned to MS \( k \) can be modeled as follows:

\[
\text{SINR}_k = \frac{P_{k,b(k)}}{\sigma^2 + I_k}
\]  

(1)

where \( P_{k,b(k)} \) is the received power for MS \( k \) by its serving BS \( b(k) \), \( \sigma^2 \) is the thermal noise power, and \( I_k \) is the intercell interference from neighboring BSs. We assume that all BSs are transmitting with maximum power \( P_{BS} \). Given that equal power allocation achieves near-optimal performance, we assume that the BS transmits with a power of \( \frac{P_{BS}}{K_{BS}} \) over a given subcarrier (e.g., [24]). Without loss of generality, we assume that each MS needs to be allocated one subcarrier in order to be served. The maximum number of subcarriers determines the maximum number of MSs that can be served by a BS. The received power at MS \( k \) from BS \( i \) can be expressed as:

\[
P_{k,i}(\text{dB}) = 10 \log_{10} \left( \frac{P_{BS}}{K_{BS}} \right) - L_{k,i}
\]  

(2)

where \( L_{k,i} \) is an estimate of the pathloss between MS \( k \) and BS \( i \). It can be modeled according to TR 25.942 as follows [25]:

\[
L_{k,i}(\text{dB}) = 128.1 + 37.6 \log_{10}(d_{k,i}) + h_{k,i}
\]  

(3)
where $d_{k,i}$ represents the Euclidean distance and $h_{k,i}$ is a random variable representing the channel gain (shadowing, fading) between BS $i$ and MS $k$. We assume $(h_{k,i})_{\text{dB}}$ to be a zero-mean Gaussian random variable with variance $\delta_{\text{dB}}^2$. Thus, $h_{k,i}$ follows a log-normal distribution which represents a slow fading (shadowing) channel model.

The interference term in (1) depends only on the intercell interference since the subcarriers are orthogonal per cell in an OFDMA-based network (assuming perfect orthogonality). For MS $k$ to be served, its downlink SINR needs to exceed a minimum threshold value $\text{SINR}_{\text{thr},k}$. The SINR expression can be written as follows:

$$\text{SINR}_k = \frac{P_{k,b(k)}}{\sigma^2 + \sum_{i=1, i \neq b(k)}^{N_B} c_i P_{k,i}} \geq \text{SINR}_{\text{thr},k}$$

(4)

where $c_i$ indicates whether BS $i$ is used or not. The term $\sum_{i=1, i \neq b(k)}^{N_B} c_i P_{k,i}$ represents the interference power received from neighboring BSs $i$ at MS $k$.

In this work, depending on the traffic demand which is represented in terms of active number of MSs and their required SINR thresholds, we choose the minimum number of BSs that guarantees capacity and coverage requirements. This, means that the chosen number of BSs is satisfying the SINR requirements of the MSs (which takes into account the receive power at the MS and intercell interference as shown by (4)). For example, whenever the active number of MSs decreases, this means that interference decreases and thus the BS can cover farther MSs, i.e., its coverage radius increases. Also, when interference decreases, it means higher SINR can be achieved and thus the capacity of the network increases. From this we can see that the coverage and capacity of a BS depends on the traffic demand (number of active MSs which directly affects interference).

### B. Approaches

In the reactive approach, the optimal set of BSs, at the highest traffic state, is chosen from $\mathcal{B}$ as shown in Figure 3. This set represents the largest set of BSs that can be active in the network for any traffic state. Then, as the traffic state decreases, several BSs can be turned off while meeting the capacity and coverage requirements.

In the proactive approach, the optimal set of BSs, at the lowest traffic state, is chosen from $\mathcal{B}$. This set of BSs can be used at any time, in the network, for all traffic states. Then, additional BSs are turned on incrementally from a traffic state to another as the traffic increases to meet the increasing capacity and coverage requirements.

In both cases, the optimal set of BSs that should be turned on/off at a given traffic state is determined. Thus, the operators can use these sets to optimally control the energy consumption of the network with the traffic variations.
This section presents the optimization problem formulation for LTE RNP taking intercell interference into account and analyzes its complexity. The RNP problem can be formulated as follows:

\[
\min_{c, t} \sum_{i=1}^{N_B} c_i \tag{5}
\]

subject to

\[
c_i P_{k,i} - \text{SINR}_{thr,k} \sum_{j=1, j \neq i}^{N_B} c_j P_{k,j} - \text{SINR}_{thr,k} \sigma^2 \geq \left(- \text{SINR}_{thr,k} \sum_{j=1, j \neq i}^{N_B} P_{k,j} - \text{SINR}_{thr,k} \sigma^2\right) \left(1 - t_{k,i}\right) \forall k, \forall i \tag{6}
\]

\[
t_{k,i} \leq c_i \quad \forall k, \forall i \tag{7}
\]

\[
\sum_{i=1}^{N_B} t_{k,i} \leq 1 \quad \forall k \tag{8}
\]

\[
\sum_{k=1}^{K_s} t_{k,i} \leq K_{BS} \quad \forall i \tag{9}
\]

\[
\sum_{k=1}^{K_s} \sum_{i=1}^{N_B} t_{k,i} \geq (1 - \beta) K_s \tag{10}
\]

\[
t_{k,i} \in \{0, 1\}, c_i \in \{0, 1\} \quad \forall k, \forall i \tag{11}
\]

This problem is an ILP problem. The objective (5) minimizes the number of selected BSs. Constraint (6) represents the quality of service of the MSs in the network. If \( t_{k,i} = 1 \), i.e., if MS \( k \) is served by BS \( i \), this means that \( c_i = 1 \) too; then, by plugging the values of \( t_{k,i} \) and \( c_i \) in constraint (6), it becomes equivalent to the SINR expression in (4).
which guarantees that the achieved SINR\(_k\) of MS \(k\) is greater than the required threshold SINR\(_{\text{thr},k}\). Moreover, if \(t_{k,i} = 0\), i.e., if MS \(k\) is not served by BS \(i\), then constraint (6) is feasible since the left hand side of (6) is always greater than or equal to its right side. As a result, constraint (6) is feasible for both served and non-served MSs in the network. Constraint (7) can allocate MS \(k\) to be served \((t_{k,i} = 1)\) by BS \(i\) only if BS \(i\) is selected to be on service in the network, i.e., \(c_i = 1\). Constraint (8) forces each MS \(k\) to be served by at most one BS. Constraint (9) guarantees that each BS \(i\) can serve at most \(K_{\text{BS}}\) MSs. Constraint (10) guarantees that the percentage of MSs in outage, i.e., unserved MSs \(k\) whose \(t_{k,i} = 0\) \(\forall i\), is lower than the target outage probability \(\beta\). Constraint (11) sets the selection variables \(c_i\) and \(t_{k,i}\) to be binary.

We can apply the same developed optimization problem for a resource block instead of a subcarrier assuming that the subcarriers within a resource block are undergoing the same channel conditions since they are allocated to the same user.

**Theorem 1:** Green LTE RNP subject to capacity and coverage constraints is NP-Complete.

**Proof:** To show that the formulated RNP problem is NP-complete, we will prove that a relaxed instance of it is similar to the Capacitated Facility Location Problem (CFLP) which is known to be NP-Hard.

The CFLP is defined as follows. Given a set of sites \(i \in \{1, \ldots, N_B\}\) and a set of customers \(k \in \{1, \ldots, K_s\}\) which are interested in being served plants from the set of sites. The cost of opening a site is \(f_i\) and the cost of assigning customer \(k\) to site \(i\) is \(r_{ki}\). The capacity of each site, or the amount of served plants, is limited to a maximum \(K_{\text{BS}}\). The problem is to find the set of sites that should be opened to satisfy the customers demands and site capacity constraints while minimizing the total cost of the system [26].

Now, consider a relaxed instance of the RNP problem where the SNR constraint (6) is relaxed. Moreover, let the outage probability \(\beta = 0\); this means that all MSs should be served. The relaxed RNP reduces to finding the set of BSs that should be chosen to serve the MSs given that the capacity of each BS is limited to serving \(K_{\text{BS}}\) MSs. The cost of turning any BS on is \(f_i = 1\) whereas the cost of serving MS \(k\) by BS \(i\) is \(r_{ki} = 0\). This problem is exactly similar to the CFLP which is NP-hard [26]. Thus, the more general RNP problem is NP-hard. We can easily show that any given solution can be verified in polynomial time, thus, the general RNP problem is NP-Complete.

ILP problems can be solved using standard ILP solving techniques such as linear programming (LP) based branch-and-bound, cutting plane algorithms, Lagrangian duality or a combination of the above. In this work, we will solve the
ILP problems to optimality using Branch-and-Cut which is a Branch-and-Bound algorithm at which cutting planes are generated at the node level; this solving technique has an acceptable computational time for small to medium network sizes [27]. For large network sizes with a high number of BSs and MSs, the optimal solution becomes computationally complex. As a result, we will propose heuristic algorithms with optimized performances verified by comparing the heuristic solutions with the optimal one for medium network sizes.

The complexity of ILP problems is, in the worst case, on the order of $O(2^n)$ where $n$ is the number of binary variables in the problem. So, it is obvious that if the number of BSs or MSs increases, the computational complexity of the optimal solution increases too.

Note that the optimal solution can be obtained for any given number of BSs and MSs, however the computational complexity and required memory increase as the number of BSs or MSs increases. RNP is an offline problem, thus the network operators are not concerned about the computational complexity of the problem that can take up to several days to compute the optimal solution. Moreover, network operators have powerful servers that enable them to compute the solution for large network sizes. Thus, there is no limit for the number of BSs and MSs after which the optimal solution cannot be computed, it depends on the specs of the used servers mainly the available memory space.

A. RNP with BS On/Off Switching

1) Proactive BS On/Off Switching: In the proactive approach, the optimal set of BSs, $B_{p,s_1}$, at the lowest traffic state $s_1$ is chosen from $B$ as shown in Figure 3. This set of BSs can be used at any time, in the network, for all traffic states. Then, as the traffic state increases, the additional optimized set of BSs that should be turned on, at traffic state $s_j$, should be chosen from $B - B_{p,s_{j-1}}$, where $j$ is an index varying between 1 and $n$. In this case, several BSs should be turned on incrementally from a traffic state to another as the traffic increases to meet the increasing capacity and coverage requirements. If a new set of BSs will be optimally determined for each traffic state without reusing those serving lower traffic states, the overall number of BSs will be higher. Thus, reusing existing BSs decreases the overall required number of BSs which reduces the CAPEX of the operator. The optimization formulation for this problem is equivalent to (5)-(11) with the additional constraint that all existing BSs from the lower traffic states should be reused to reduce the overall number of deployed BSs for all traffic states. This constraint can be modelled,
at traffic state \( s_j \), as follows:

\[
c_i = 1, \quad i \in \left\{ \bigcup_{s=s_1}^{s=s_j} B_{p,s} \right\}
\]  

(12)

2) Reactive BS On/Off Switching: In the reactive approach, the optimal set of BSs, \( B_{r,s_n} \), at the highest traffic state \( s_n \), is chosen from \( B \), as shown in Figure 3. Then, as the traffic state decreases, the optimal set of BSs, \( B_{r,s_j} \), at traffic state \( s_j \) is chosen from \( B_r \). In this case, several BSs can be turned off while meeting the capacity and coverage requirements. In this case, the optimization formulation presented in (5)-(11) is applied with input candidate set of BSs being \( B \). The obtained set, \( B_{r,s_n} \), represents the largest set of BSs that can be active in the network for any traffic state. For lower traffic states, some BSs from \( B_{r,s_n} \) can be turned off. To find the optimal set of BSs that should be kept on and turned off for traffic state \( s_j \), the optimization formulation (5)-(11) is applied with input candidate set of BSs being \( B_{r,s_n} \). The resulting output set includes the minimum set of BSs that are necessary to meet the coverage and capacity constraints of the optimization problem.

IV. SUB-OPTIMAL HEURISTIC ALGORITHMS

We have shown that the optimal RNP problem is NP-Complete and that a relaxed instance of it is at least as hard as the CFLP which is a well investigated problem in the literature. There exist several polynomial time approximation algorithms for restricted CFLP problems in which there are major assumptions on the considered system model; most of the works assume that the service costs obey the triangular inequality [28], [29]. This assumption is not applicable to our system model where the connection costs depend on pathloss and fading and thus the triangular inequality cannot be applied. To our knowledge, no work investigated an approximation algorithm for CFLP with general cost coefficients since the problem becomes very complex to approximate. Moreover, since our general RNP problem is harder than the CFLP problem as shown in Section III, we will present a heuristic polynomial time algorithm to solve the green LTE RNP problem for large network sizes where the optimal solution becomes computationally complex.

A. BS Elimination Algorithm

Given a candidate set of BSs locations, \( B \), out of which a subset should be chosen \( B_{sel} \), we propose a typical greedy solution that solves the problem iteratively by removing one BS at time that when eliminated maximizes the
Algorithm 1 BSs Elimination

**Input:** \( B ; s ; \{ x_i, y_i, i \in B \} ; \{ u_k, v_k, k = 1, ..., K_s \} ; F; I.\)

while true do

for \( i = 1 : |B| \{ \text{Try eliminating BS } i \} \) do

\( x_{\text{temp}} = \{ x_1, ..., x_{i-1}, x_{i+1}, ..., x_{|B|} \} \)

\( y_{\text{temp}} = \{ y_1, ..., y_{i-1}, y_{i+1}, ..., y_{|B|} \} \)

**Step 1.** Construct the new Voronoi tessellation corresponding to the BS locations and find the distance between each (BS, MS) pair

**Step 2.** Calculate the SINR expressions for each (BS, MS) pair as given in (4)

**Step 3.**

if the number of MSs in outage exceeds the target outage probability \{Eliminated BS causes outage\} then

\( i \in I \{ \text{Place BS } i \text{ in the infeasible set} \} \)

else

\( i \in F \{ \text{Place BS } i \text{ in the feasible set} \} \)

Calculate the total SINR which is the sum of the MSs’ SINR\(_k\) for the given BS configuration.

end if

end for

**Step 4.**

if \( F \neq \emptyset \{ \text{Some BSs can be eliminated. Remove BS } e \text{ that when eliminated results in the highest total SINR in the network according to Step 3.} \} \) then

\( x = \{ x_1, ..., x_{e-1}, x_{e+1}, ..., x_{|B|} \} \)

\( y = \{ y_1, ..., y_{e-1}, y_{e+1}, ..., y_{|B|} \} \)

\( |B| = |B| - 1 \)

\( B_{\text{sel}} = B - \{ e \} \)

else

break \{Converged: No BS can be eliminated without causing outage\}

end if

end while.

**Output:** \( B_{\text{sel}} \)

---

total SINR. A greedy algorithm solves the problem iteratively by including the next element of the solution, at each iteration, chosen in such a way that the best local improvement is achieved. In many problems, a greedy strategy does not in general produce an optimal solution, but nonetheless a greedy heuristic may yield locally optimal solutions that approximate a global optimal solution in a reasonable time.

Given a set of BSs, a MS distribution and a traffic state. Algorithm 1 outputs the set of BSs \( B_{\text{sel}} \) selected from the
candidate set $\mathcal{B}$ to meet the coverage and capacity requirements. Algorithm 1 is divided into four main steps to decide on which BSs to eliminate from the candidate set $\mathcal{B}$. The algorithm removes iteratively one BS at a time until no more BSs can be removed, i.e., the outage probability constraint will be violated. First, iteratively each BS is examined to be removed from the candidate set $\mathcal{B}$. Then, the Voronoi tessellations are constructed and the distance between all BSs and MSs is calculated after removing one of the BSs from the network. The set of BSs’ locations after trying to eliminate one of the BSs is $x_{\text{temp}}$ and $y_{\text{temp}}$. For the obtained BS configuration, the MS’s SINR expression is evaluated as given in (4). In Step 3, the outage probability is evaluated and compared to the target threshold. Based on the obtained result, the removed BSs are classified in one of two sets: $\mathcal{F}$ or $\mathcal{I}$. $\mathcal{F}$ represents the feasible set that contains the BS that can be eliminated without exceeding the target outage probability. $\mathcal{I}$ represents the infeasible set that contains the BSs that when eliminated result in an outage exceeding the target outage probability and as a result those BSs cannot be removed.

After performing these three steps for all the BSs, Step 4 removes the BS that when eliminated results in the highest total SINR compared to removing other BSs. The total SINR is calculated by summing the SINRs of all active MSs in the network. The same steps are repeated again until no more BSs could be further eliminated without exceeding the outage limit.

The computational complexity of the suboptimal heuristic solution mainly depends on the most computationally complex step of Algorithm 1 which is that of Step 2 that calculates the SINR value for each MS in the network. Initially, given $N_B$ BSs and $K_s$ MSs, Algorithm 1 iteratively removes one BS at a time and calculates the obtained SINR for each user which has a complexity of $O((N_B - 1)K_s)$. Repeating this step for the $N_B$ BSs requires $N_B O((N_B - 1)K_s)$ operations. At Step 4 of Algorithm 1, the BS that results in the highest total SINR value when removed is eliminated and the steps of the algorithm are repeated iteratively until no more BS can be removed without violating the outage probability constraint. Assume that $N_R$ BSs are removed, this implies that the worst case computational complexity of the solution is $N_B O((N_B - 1)K_s) + (N_B - 1) O((N_B - 2)K_s) + \ldots + (N_B - N_R) O((N_B - N_R - 1)K_s)$. Since $N_R$ is problem dependent, the worst case computational complexity of the heuristic solution can be approximated by $N_B^2 O((N_B - 1)K_s)$ which is obviously much less computationally complex than the optimal solution whose computational complexity is $O(2^{N_B K_s})$. 
Algorithm 2 Proactive LTE RNP Solution with Green Considerations

**Step 1.** Input: \( B; s_1; \{x_i, y_i, i \in B\}; \{u_k, v_k, k = 1, \ldots, K_s\}; \mathcal{F} = \emptyset; \mathcal{I} = \emptyset. \)

**Step 2.** Call Algorithm 1.

**Output:** The obtained output is \( B_{p,s_1}. \)

Let \( j = 1. \)

**while** \( s \neq s_n \) **do**

**Step 3.** Input: \( B; s_{j+1}; \{x_i, y_i, i \in B\}; \{u_k, v_k, k = 1, \ldots, K_s\}; \mathcal{F} = \emptyset; \mathcal{I} = \emptyset = B_{p,s_j} \{\text{place } B_{p,s_j} \text{ in the infeasible set } \mathcal{I} \text{ so that none of the existing BSs from lower traffic states can be removed}\}. \)

**Step 4.** Call Algorithm 1.

**Output:** The optimized set \( B_{p,s_{j+1}} \) for traffic state \( s_{j+1}. \)

\( j = j + 1. \)

**end while.**

B. Proactive BS On/Off Switching Algorithm

In the proactive approach, RNP is initially performed for the lowest traffic load as explained in details in Section III-A.1. As the traffic state increases, Algorithm 2 is responsible for turning on new BSs and finding their locations to meet the capacity and coverage requirements. It reuses Algorithm 1 with one additional constraint that all of the pre-existing BSs should appear in the final network plan. In Algorithm 2, two main tasks are applied: 1) the proper input data is specified and 2) Algorithm 1 is called to determine the output. First, Algorithm 1 is called for the lowest traffic state and assuming that all existing BSs are candidates to be chosen from. This determines the set of BSs, \( B_{p,s_1}, \) that cannot be removed when we adapt the network plan to the changing traffic conditions. As the traffic state increases, the set of BSs from lower traffic states are placed in the infeasible set of Algorithm 1 so that they cannot be removed and are forced to be reused in the higher traffic state. This determines the additional required BSs that will cover the increased number of MSs. These steps are repeated over and over until reaching the highest traffic state, \( s_n, \) in the network.

After calling Algorithm 2 that finds the proactive LTE RNP solution for all traffic states, the obtained set of BSs \( B_{p,s_n}, \) is the minimum set that satisfies the QoS requirements for all traffic states. However, for each traffic state \( s_i > s_1, \) not all the BSs in \( B_{p,s_i}, \) might be needed to be active. Thus, for each \( B_{p,s_i}, \) Algorithm 1 should be called to determine which set of BSs should be active for traffic state \( s_i \) without violating the outage probability constraint.
Algorithm 3 Reactive LTE RNP Solution with Green Considerations

Step 1. Input: $B \setminus s_n \setminus \{x_i, y_i, i \in B\} \setminus \{u_k, v_k, k = 1, \ldots, K_s\} \setminus F = \emptyset \setminus I = \emptyset$.

Step 2. Call Algorithm 1.

Output: The obtained output is $B_{r,s_n}$.

Let $j = n$.

while $s \neq s_1$ do

Step 3. Input: $B_{r,s_n} \setminus s_{j-1} \setminus \{x_i, y_i, i \in B_{r,s_n}\} \setminus \{u_k, v_k, k = 1, \ldots, K_s\} \setminus F = \emptyset \setminus I = \emptyset$.

Step 4. Call Algorithm 1.

Output: The optimized set $B_{r,s_{j-1}}$ for traffic state $s_{j-1}$.

$j = j - 1$.

end while.

C. Reactive BS On/Off Switching Algorithm

Algorithm 3 is proposed for the reactive approach. Its steps are similar to that of Algorithm 2, however with different inputs to the called algorithm (Algorithm 1) which change based on the reactive approach constraints. RNP is initially performed for the highest traffic load, $s_n$, as explained in details in Sections III-A.2 which gives the largest set of BSs, $B_{r,s_n}$, that can be active in the network. As the traffic state decreases, Algorithm 2 is responsible for turning off unwanted BSs from the obtained set, $B_{r,s_n}$, while still meeting the capacity and coverage requirements. It reuses Algorithm 1 with one additional constraint that the candidate set of BSs, to choose from for lower traffic states, is $B_{r,s_n}$ and not $B$. Algorithm 2 iteratively finds the optimized set of BSs for each traffic state starting from the highest to the lowest one.

V. RESULTS AND ANALYSIS

This section presents results and analysis for the proposed optimization framework, suboptimal heuristic algorithms and a complimentary experimental study for green LTE RNP. The developed algorithms can be applied to any MS distribution; in this work, results for uniform and non-uniform MS distributions are presented. For the non-uniform case, we choose Gaussian MS distribution which represents typical hot spots. Uniform vs. Gaussian MS distributions results in the highest difference in terms of the required number of BSs and energy savings which shows the effect of the MS distribution on the outcome. The general simulation parameters used throughout the different sections are presented in Table I. Without loss of generality, we assume that the SINR of all users is set to $-5$ dB.
<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P_{\text{BS}}$</td>
<td>20 W</td>
</tr>
<tr>
<td>$\sigma^2$</td>
<td>$5.97 \times 10^{-15}$ W</td>
</tr>
<tr>
<td>$K_{\text{BS}}$</td>
<td>50</td>
</tr>
<tr>
<td>$\beta$</td>
<td>0.05</td>
</tr>
<tr>
<td>SINR$_{\text{thr}}$</td>
<td>-5 dB</td>
</tr>
<tr>
<td>Transmitter and receiver gain</td>
<td>0 dBi</td>
</tr>
<tr>
<td>Carrier frequency</td>
<td>2000 MHz</td>
</tr>
</tbody>
</table>

In this work, we use simulations to obtain the results using MATLAB/CPLEX in Sections V.A-V.C and also using a commercial ICS telecom tool from ATDI in Section V.D.

### A. Optimal versus Sub-Optimal Solution Results

The optimal solution for LTE RNP is obtained by solving the optimization problem (5)-(11) presented in Section III. The problem is solved using the CPLEX solver which performs standard Branch-and-Cut techniques that are the most efficient in terms of performance for solving ILP problems [27]. The sub-optimal solution is also presented and compared with the optimal one to investigate its relative performance. Two different scenarios are presented and analyzed; both scenarios assume a uniform MS distribution and that the number of MSs to be served simultaneously is 196, however, the number and locations of BSs are different. In this section, the area dimensions are assumed to be $1000 \times 1000$ m.

Figure 4 and Figure 5 show the input BS locations, the optimal output BS locations and the sub-optimal BS locations assuming that there are 20 and 30 candidate input BS locations, respectively with different locations. For both scenarios, the optimal solution chose 4 BSs to serve the set of MSs however different locations are chosen since the input BS locations are different. Note that, a number lower than 4 BSs cannot be achieved since the total number of MSs is 196 and according to constraint (9) each BS cannot serve more than $K_{\text{BS}} = 50$ MSs. Thus, the optimal solution returned the smallest possible number of BSs that guarantee coverage and capacity requirements.

The suboptimal algorithm, chose 5 BSs in both cases which is higher than 4 since its search space is much smaller compared to the search space of the optimal solution as explained in Section III-A.2. The suboptimal solution becomes the only option for network operators for very large network sizes where the optimal solution becomes intractable due to the huge size of the obtained search space. The optimal solution has a lower SINR compared to the sub-optimal one but it has a lower number of BSs since the objective is to minimize the number of BSs while having SINR above threshold.
Fig. 4. Input and Output BS locations assuming initially 20 candidate BSs. MSs are represented by dots and BSs are represented by stars. The average SINR per user is 7.5652 dB for the optimal solution and 11.1742 dB for the sub-optimal solution.

Fig. 5. Input and Output BS locations assuming initially 30 candidate BSs. MSs are represented by dots and BSs are represented by stars. The average SINR per user is 10.75 dB for the optimal solution and 12 dB for the sub-optimal solution.

B. Sub-Optimal Solution Results

As discussed in the previous section, the optimal solution becomes computationally complex for large network sizes. This section presents suboptimal results for large network sizes where the area to be covered increased to 10 Km × 10 Km and the input number of active MSs and candidate set of BSs is much higher compared to the previous investigated scenarios which allows a comprehensive investigation for the various traffic states starting from low to highly condensed areas. Thus, results for the proactive and reactive approaches will be presented, analyzed and compared.

1) Proactive Approach Results: Results are reported for uniform and Gaussian MS distributions assuming a network with 600, 900, and 1200 MSs for three quantized traffic states $s_1$, $s_2$ and $s_3$, respectively. The aim is to jointly
determine the locations of the BSs to be deployed and the on/off switching patterns for the different traffic states as discussed in Algorithm 2.

Figure 6 shows the input and output BS locations for the various traffic states assuming uniform distribution. Applying Algorithm 2, RNP is initially performed for the lowest traffic state $s_1$ with 600 uniformly distributed MSs and for the input candidate set $B$ with $|B| = 70$ randomly located BSs. Results show that 80% of the BSs were eliminated, reaching 13 BSs out of 70 as shown in Figure 6(b). As the traffic state increases, new BSs should be turned on to meet the increasing demand for coverage and capacity. In the proactive approach and according to Algorithm 2, existing BSs from lower traffic states are all reused and new BSs are turned on as seen in Figures 6(c) and 6(d). Figure 6(c) shows the output set of BS for 900 MSs, it is obvious that the 13 pre-existing BSs from the lower traffic state are reused and 9 additional BSs represented by circles are added. The same idea is repeated for the highest traffic state where the number of MSs increased to 1200. In this case, 22 pre-existing BSs from the lower traffic states are reused and 11 additional BSs represented by squares are added as shown in Figure 6(d).
This work allows continuous network management based on the current traffic distribution in the network. If all BSs were transmitting at equal powers, 25% to 60% of the total power could be saved once the traffic load in the network decreases to lower states. Operators can proactively change the BS on/off switching patterns to anticipate changes in the network traffic conditions. For example, assume that Figure 6(c) was the current BS distribution in the network and assume that a higher number of active MSs was added to the current one triggering a higher state in the traffic load. Operators will then turn on new BSs, which are in this case, represented by the 11 squares in Figure 6(d) to meet the new MSs’ requirements. Whenever the number of active MSs drops down inducing a lower traffic state, operators can then switch off some of the BSs.

Similar steps are applied for Gaussian MS and BS distribution assuming a network with 600, 900, and 1200 MSs and an input candidate set of size $|B| = 110$. The results are illustrated in Figure 7. Similar conclusions to the uniform case can be deducted, however, when the density of the MSs increases, e.g., at the center of the area, then the density of deployed BSs increases too to meet the capacity and coverage constraints.

2) Reactive Approach Results: This section investigates reactive RNP for the network scenarios studied previously in proactive RNP. In the reactive approach, RNP is initially performed according to the highest traffic state which determines the largest possible set, $B_{r,s_3}$, that can be active at any time as shown in Figure 8(b). Then, as the traffic state decreases, the active set of BSs is chosen from $B_{r,s_3}$. The output results of Algorithm 2 for the lower traffic states $s_2$ and $s_1$ are shown in Figures 8(c) and 8(d), respectively. It is obvious that as the traffic state decreases, the required number of active BSs decreases while meeting coverage and capacity requirements. Moreover, all active BSs for traffic states $s_2$ and $s_1$ are existing BS locations already determined from traffic state $s_3$.

The Gaussian distribution is also investigated in the reactive approach using the same set of BSs and MSs of the investigated scenario of the proactive approach. We consider a network with 600, 900, and 1200 MSs and an input candidate set of size $|B| = 110$. The results are illustrated in Figure 9. Similar conclusions to the uniform case can be deducted.

3) Proactive versus Reactive Approach Comparison: For uniform and Gaussian MS distributions, results of the previous studied cases are summarized in Figure 10(a) and Figure 10(b), respectively. The two figures show the number of required BSs versus the traffic states for both proactive and reactive planning. There are important observations when comparing the results of the reactive and proactive approaches. In Figure 10(a), it is noticed that the required
number of active BSs for traffic state \( s_3 \) is 31 in the reactive approach whereas it was 33 in the proactive approach.

Whereas, the required number of active BS for traffic state \( s_1 \) is 15 in the reactive approach whereas it was 13 in the proactive approach. These results are logical since the obtained number of active BSs is the lowest for the traffic state for which RNP is initially performed starting from the input candidate set \( B \) with no other restrictions. In the proactive approach, higher traffic states are forced to reuse the BSs from lower traffic state. Whereas, in the reactive approach, lower traffic states are forced to reuse BSs from a smaller candidate set \( B_{r,s_3} \) compared to \( B \). These constraints and restrictions result in different output sets of BSs depending on whether the operator implements a reactive or a proactive approach in RNP.

Assuming we have three different traffic states \( S = \{s_1, s_2, s_3\} \) illustrated in Figure 2 that will be used depending on the current traffic for a specified period of time. The duration of a traffic state is denoted by \( T_{s_j} \). We assume the
Fig. 8. Reactive green LTE RNP for three different traffic states for uniform MS distribution. $|\mathcal{B}| = 70; |\mathcal{B}_{p,s_3}| = 31; |\mathcal{B}_{p,s_2}| = 23; |\mathcal{B}_{p,s_1}| = 15$. MSs are represented by dots, BSs are represented by stars.

Based on Figure 10(a) and the proposed schedule, adopting the proactive approach in RNP will allow considerable energy savings for the uniform MSs distributions. Operators will turn on 13 BSs for the lowest traffic state for 14 hours on average per day when using the proactive approach. As for the reactive approach, operators will have to turn 15 BSs for $s_1$. When initiating RNP from the lowest traffic state as in the proactive approach, better results are obtained since the algorithm selects the optimized locations of BSs from a larger initial set (70 BSs in our case). In the reactive approach, we start planning from the worst case scenario and thus, optimizing the location and number of BSs for the highest traffic state. When reaching $s_1$, the algorithm will have a smaller set of BSs to choose from. The candidate set is the set obtained from the previous traffic state $s_2$ (in our case 23). As for $s_2$ and for different
Fig. 9. Reactive green LTE RNP for three different traffic states for Gaussian MS distribution. $|\mathcal{B}| = 110; |\mathcal{B}_{p,s_3}| = 39; |\mathcal{B}_{p,s_2}| = 22; |\mathcal{B}_{p,s_1}| = 16$. MSs are represented by dots, BSs are represented by stars.

Fig. 10. Proactive versus reactive RNP.

scenarios, both approaches give similar or very close results. From a time dimension point of view, the number of BSs per day is $\frac{\sum_{j=1}^{N_{s_j}} N_{s_j} T_{s_j}}{\sum_{i=1}^{S} T_{s_j}}$ where $N_{s_j}$ is the current number of BSs for a given traffic state $s_j$ and $T_{s_j}$ is the duration of a traffic state $s_j$. For the proactive approach, 19 BSs are turned on during 24 hours. As for the reactive approach,
20 BSs are required during 24 hours. Optimizing the number and locations of BSs for the lowest traffic state will allow operators to save more energy compared to the reactive planning since the network remains for 14 hours in our schedule in the lowest traffic state.

For the Gaussian MSs distributions, MSs are concentrated in four hot spots. As the center of a hot spot is approached, MSs become more dense. This is why, more BSs are needed at the center of the hot spot to cover the higher number of MSs. For the lowest traffic state, results were the same. As for the highest traffic state, results were better for the reactive approach as expected. For $s_2$, less BSs were obtained in the reactive planning. This is related to the varying concentration of MSs in the network. For the reactive approach and for $s_2$, 39 BSs are available to choose from with no restrictions on keeping any of the BSs in the network. Whereas for the proactive approach, 16 out of the 110 BSs should remain in the network. Keeping these BSs fixed in the network, have required a higher number of BSs to cover the increased number of MSs and this is related to the distribution of MSs. From a time dimension point of view and for the proactive approach, on average 24 BSs are turned on during 24 hours. As for the reactive approach, on average 23 BSs are required during 24 hours.

As a summary, the proactive RNP is more energy efficient for lower traffic states whereas the reactive RNP is more energy efficient for higher traffic states. Depending on the distribution of the traffic states throughout the day, starting planning from the traffic state where the network remains most of the time will yield additional energy savings. Thus, based on the traffic distribution, the operator can decide whether to implement its network using a proactive or a reactive RNP approach.

C. CO$_2$ Emissions Analysis

BSs consume the highest amount of energy in a mobile network. Thus, turning on and off these components will lead to considerable energy savings and lower CO$_2$ emissions. The consumed energy could be converted to grams (gr) of CO$_2$ to investigate the carbon footprint of the network. We assume that electricity energy is derived from fuel oil where each 1 KWh represents 620 gr of CO$_2$ [30]. Based on Figure 2 which shows traffic variation for a normal day, BSs could be turned on and off illustrating different traffic states. We assume the time schedule for the various traffic states considered in the previous section, and that the maximum transmitting power of the BSs is 20 W. The total consumption of the BS is not only due to the transmitting power but also due to other components such as
the power amplifier, cooling system, signal processing, etc. The total power consumption of the BS is 140 W when transmitting with a maximum transmission power of 20 W [23]. The CO₂ expression for each traffic state can be written as follows:

\[
\text{CO}_2 \text{ emissions}[\text{Kg/day}] = \frac{N_s \times P_{BS}[\text{W}] \times T_s \times 620[\text{gr}]}{10^6}
\]  

(13)

The CO₂ emissions for each traffic state is calculated as follows:

1) Low traffic (0hr → 12hr and 22hr → 24hr): \( \frac{13 \times 140 \times 14 \times 620}{10^6} = 15.8 \text{ KgCO}_2/\text{day} \) are emitted.

2) Medium traffic (12hr → 14hr and 20hr → 22hr): \( \frac{22 \times 140 \times 4 \times 620}{10^6} = 7.638 \text{ KgCO}_2/\text{day} \) are emitted.

3) High traffic (14 hr → 20hr): \( \frac{33 \times 140 \times 6 \times 620}{10^6} = 17.186 \text{ KgCO}_2/\text{day} \) are emitted.

The total CO₂ emissions using green planning is \( 15.8 + 7.638 + 17.186 = 40.624 \text{ KgCO}_2/\text{day} \). As for the traditional planning, where all the 33 BSs are always on, \( \frac{33 \times 140 \times 24 \times 620}{10^6} = 68.745 \text{ KgCO}_2/\text{day} \) are emitted. Using green RNP, the energy consumed per day and CO₂ emissions are decreased by 40.5% compared to traditional planning as shown in Table II.

<table>
<thead>
<tr>
<th>Planning</th>
<th>Power consumed in KWh/day</th>
<th>CO₂ emissions in KgCO₂/day</th>
</tr>
</thead>
<tbody>
<tr>
<td>Traditional</td>
<td>110.088</td>
<td>68.745</td>
</tr>
<tr>
<td>Green</td>
<td>65.52</td>
<td>40.624</td>
</tr>
</tbody>
</table>

D. LTE Network Planning Lab Experiment with Green Considerations

In this section, we use the ICS telecom tool from ATDI [31] to perform coverage calculations and analysis for LTE networks. This tool will verify that the proposed algorithms can be applied in real case scenarios satisfying the QoS requirements and leading to significant energy savings. In order to relate the proposed RNP algorithms to real RNP scenarios, we consider the area of Beirut city. The parameters used for LTE RNP, in this experiment, are shown in Table III.

First, a cell pattern is generated for the whole network where the BSs are implemented at the cell centers. Then, the elimination procedure, proposed in Algorithm 1, is used to get the minimum required number of BSs to satisfy
TABLE III

SIMULATION PARAMETERS FOR ICS TELECOM.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Input area</td>
<td>Ras Beirut</td>
</tr>
<tr>
<td>BS nominal power</td>
<td>10 W</td>
</tr>
<tr>
<td>Transmitter and receiver gain</td>
<td>15 dBi</td>
</tr>
<tr>
<td>Carrier frequency</td>
<td>1900 MHz</td>
</tr>
<tr>
<td>Receiver sensitivity</td>
<td>-97 dBm</td>
</tr>
<tr>
<td>BS capacity</td>
<td>60 Mbits/s</td>
</tr>
</tbody>
</table>

After running the coverage calculations, ICS telecom will show the composite coverage of each sector. The colors depict the signal strength based on a color palette. Figure 11 shows the network after coverage calculations. The composite coverage of all sectors is shown in Figure 11(a). Figure 11(b) shows the best coverage display where each location is highlighted with the site color that covers it the most.

ICS telecom selects the minimum required number of BSs to achieve a certain coverage percentage. The achieved coverage, in the studied network, is 90%. Thus, none of the BSs can be removed. For a lower coverage percentage, some of the BSs can be turned off or deleted to reach a specific coverage target.
1) *Capacity Planning:* In order to analyze the traffic of the LTE network, we define a subscriber database that represents the location of MSs on the map. The MSs will be randomly distributed according to the traffic demand distribution. The traffic demands for the MSs is distributed as shown in Table IV. Note that the traffic demand presented by the required bit rate by the MSs can be mapped to the required SINR, as considered in Section II, that achieves the targeted bit rate.

<table>
<thead>
<tr>
<th>Traffic demand</th>
<th>Percentage of MSs</th>
</tr>
</thead>
<tbody>
<tr>
<td>5640 Kbits/s</td>
<td>10 %</td>
</tr>
<tr>
<td>4230 Kbits/s</td>
<td>15 %</td>
</tr>
<tr>
<td>2820 Kbits/s</td>
<td>10 %</td>
</tr>
<tr>
<td>2120 Kbits/s</td>
<td>15 %</td>
</tr>
<tr>
<td>1410 Kbits/s</td>
<td>50 %</td>
</tr>
</tbody>
</table>

After loading the simulation parameters, the parenting of MSs to BSs is performed by the simulation tool to check the connectivity of the MSs on the different LTE sectors. In order to investigate the performance of the proposed on/off switching approach, several traffic states are considered as shown in Table V.

<table>
<thead>
<tr>
<th>Traffic states</th>
<th>MSs per km²</th>
<th>Number of MSs</th>
</tr>
</thead>
<tbody>
<tr>
<td>$s_3$</td>
<td>70</td>
<td>1200</td>
</tr>
<tr>
<td>$s_2$</td>
<td>55</td>
<td>850</td>
</tr>
<tr>
<td>$s_1$</td>
<td>35</td>
<td>600</td>
</tr>
</tbody>
</table>

Simulation results show that for traffic state $s_3$, none of the BSs is turned off; in this case, 90% of the MSs is served. Whereas for lower traffic some of the BSs could be turned off as shown in Figure 12. BSs represented in forms of 3 arrows are activated whereas those represented by a + are deactivated. The small black squares represent
the served MSs whereas the grey ones represent the unserved MSs. The results are summarized in Table VI. The coverage percentage is the percentage of served MSs in the network after the BSs deactivation for each traffic state $s_j$.

**TABLE VI**

**GREEN PLANNING IN ICS TELECOM**

<table>
<thead>
<tr>
<th>Traffic states $s_3$</th>
<th>Number of BSs</th>
<th>Coverage percentage</th>
<th>Power consumed in KWh/day</th>
<th>CO$_2$ emissions in KgCO$_2$/day</th>
</tr>
</thead>
<tbody>
<tr>
<td>$s_3$</td>
<td>40</td>
<td>90%</td>
<td>17.91</td>
<td>11.11</td>
</tr>
<tr>
<td>$s_2$</td>
<td>33</td>
<td>91%</td>
<td>22.17</td>
<td>13.75</td>
</tr>
<tr>
<td>$s_1$</td>
<td>23</td>
<td>90%</td>
<td>36.06</td>
<td>22.36</td>
</tr>
</tbody>
</table>

The total CO$_2$ emissions using green planning is $11.11 + 13.75 + 22.36 = 47.22$ KgCO$_2$/day. As for the traditional planning, where all the 40 BSs are always on, 66.66 KgCO$_2$/day are emitted. Using green planning, CO$_2$ emissions and the total power consumed per day are decreased by 29.2% compared to traditional planning.

**VI. CONCLUSION**

In this work, we addressed the problem of LTE RNP with green considerations. The main objective was to jointly optimize BS locations and generate the BS on/off switching patterns based on the changing traffic conditions. By monitoring traffic loads, operators can switch off some of the BSs while maintaining coverage and capacity requirements. The problem was solved using reactive and proactive approaches for multiple MS distributions and scenarios. The proactive approach optimizes the locations and the number of BSs for the lowest traffic state where the network remains most of the time. As for the reactive approach, operators will try to adapt the network to the traffic variations after network deployment. In both approaches, energy consumption was reduced in the network. The optimal solution was obtained for small size networks. As for large size networks, heuristics were proposed to obtain sub-optimal solutions, however, with close to optimal performance. Moreover, we evaluated CO$_2$ emission reduction due to green RNP. We have also developed an experiment using ICS telecom tool to map the insights of the work and algorithms to real planning scenario and quantify gains in terms of the number of BSs and CO$_2$ emission reduction.
Fig. 12. Green planning for different traffic states. 40 BSs for $s_3$, 33 BSs for $s_2$, and 23 BSs for $s_1$.

ACKNOWLEDGMENT

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