An Economic Viability Analysis on Energy-Saving Solutions for Wireless Access Networks

Sibel Tombaz[a,1,*], Ki Won Sung[a], Sang-wook Han[a], Jens Zander[a]

[a] KTH Royal Institute of Technology, Wireless@KTH, Stockholm, Sweden

Abstract

As the energy bill for mobile operators rises with the continuing traffic growth, energy efficiency problems attract an increasing attention in the telecommunication industry. However, the investment for the implementation of any energy-saving solution could be so costly that it may not achieve the total cost reduction. Therefore, the economic viability of the proposed solutions is of substantial importance for the operators in the process of investment decisions. In this paper, we present a methodology for assessing the economic viability of energy-saving solutions. We conduct two case studies using the proposed methodology, and analyze the cost-benefit tradeoff for: i) hardware upgrade enabling dynamic sleep mode operation at the base stations (BSs), ii) energy efficient network deployment minimizing the network energy consumption. Simulation results show that the hardware upgrade can save up to 60 percent of energy consumption particularly when the high data rate requirement forces low network resource utilization. Consequently, the solution is shown to be increasingly cost effective as the unit energy cost increases. Network deployment optimized for energy efficiency is shown to bring about further energy savings, but it demands denser deployment of BSs. Thus, it is not deemed as economically viable considering today's cost values.

Keywords: Energy efficiency, power consumption, economic viability, network planning, greenfield network deployment, achievable daily energy savings, cell DTX, traffic profile, total cost of investment.

1. Introduction

In recent years, with the explosive growth of mobile traffic, the energy consumption of wireless access networks has experienced a significant increase. Currently, information and communications technology (ICT) is responsible for 3 percent of worldwide electricity consumption, out of which wireless access networks contribute approximately 10 percent with 60 billion kWh per year [1, 2, 3]. This situation poses a big challenge for mobile operators since the rising energy consumption together with growing energy prices directly leads to an increase in their operational expenditures (OPEX). In fact, operators' cost figures show that nowadays the energy cost of running a network constitutes almost 50 percent of overall OPEX [4, 5].

A multitude of models and approaches have been recently proposed to increase the energy efficiency of these networks at all levels, including hardware design, network management, network deployment, and resource allocation [6, 7, 8, 9]. A remaining issue is that most of these solutions require a new investment for the operators due to the need of hardware and software upgrade, or the deployment of new sites, etc. Therefore it is a non-trivial question if the proposed solutions, reducing the energy cost, can provide sufficient economic gain such that they provide return on investment. To the best of our knowledge, there is no study addressing this issue and analyzing the total cost of investment of the solutions. Considering the fact that the motivation of reducing the energy consumption of wireless access networks is driven not only by environmental concerns, but mainly by economic reasons, it is essential to assess the economic viability in order to identify whether or not the additional expenditures required for energy efficient solutions are compensated by the energy savings.

In this paper, we aim to answer the following question: *Under which circumstances an operator achieves a total cost reduction from an energy-saving solution?*. For this, we propose a methodology for assessing economic viability of energy-saving solutions for wireless access systems. It incorporates the net present value (NPV) of a given solution over the network lifetime in order to compare the energy saving benefit with the increment in overall expenditures with respect to the existing network where the solution is not implemented. Our methodology builds upon widely accepted economic models [10, 11], and it is easy to apply to a variety of energy-saving solutions.

With the aid of the proposed methodology, we conduct two case studies and analyze the cost-benefit tradeoff of two popular energy-saving solutions, i.e., hardware upgrade and energy efficient deployment. We demonstrate in detail how our methodology can be utilized to assess the economic viability of a general energy-saving solution with these examples. Furthermore, the case studies give us insights into the important parameters to be

*Corresponding author

Email addresses: sibel.tombaz@ericsson.com (Sibel Tombaz), sungkw@kth.se (Ki Won Sung), swhan@kth.se (Sang-wook Han), jenz@kth.se (Jens Zander)

[1] Sibel Tombaz is currently working at Ericsson Research as an Experienced Researcher.

considered for the network-level energy efficiency analysis.

For the case of the hardware upgrade solution, we assume that an operator decides to upgrade the existing BS transceivers in order to enable dynamic sleep mode operations, also called cell discontinuous transmission (DTX), in its network [7, 8, 12]. However, this fast traffic adaptability feature comes at the expense of increased CAPEX due to the necessity of a new hardware. In order to analyze this tradeoff between reduced energy cost and increased CAPEX, we first identify the annual energy savings with cell DTX considering the daily variation of the traffic and accordingly the variation of the cell loads in the network. Then, we analyze the break-even cost of the hardware upgrade below which the incremental increase in CAPEX is compensated by the reduced energy cost, and thus the solution provides total cost savings for the operator.

As for the energy efficient deployment solution, we assume that a greenfield operator deploys the network guaranteeing the minimum network energy consumption. Then, it is compared to the traditional CAPEX-optimized planning which requires the deployment of a minimum number of BSs to meet the network coverage and capacity requirements. In order to analyze this tradeoff between energy- and CAPEX-optimized planning, we first propose a simple algorithm to identify the optimum network deployment solutions taking into consideration the traffic-dependent cell load variations which directly impact perceived user data rate and annual energy consumption, based on our previous work [12]. We note that the solution approach adopted in this paper for defining the energy-optimized network deployment significantly differs from the ones in the literature that are mostly based on busy hour traffic conditions and full buffer traffic model assumptions [3, 13, 14]. Finally, based on the defined deployment solutions with respect to the considered objectives, and the proposed viability assessment methodology, we obtain the break-even cost of energy above which the energy oriented design presents total cost savings during the network lifetime.

2. A Method for Analyzing Economic Viability of Energy Efficient Solutions

Assume that a mobile operator aims at finding solutions for minimizing the total network energy consumption while providing the required capacity. The resulted energy efficient solution might be a maintenance strategy such as to upgrade hardware and/or software, or to apply an traffic adaptive resource allocation scheme etc., for a given deployment. Moreover, the operator might also be interested in identifying greenfield deployment strategies that provide the minimum energy consumption in case of the rolling out the new technology in their network. However, it should be noted that even though these solutions will reduce operators' energy expenses, they might be obtained with an increase in the total cost due to required capital expenditures. In this regard, it is essential to analyze the total cost of investment of the solutions solely aimed at energy minimization considering the fact that operators' energy interest is driven mainly by economic reasons.

In this section, we first introduce a detailed total cost of investment model, and then present our economic viability analysis methodology.

2.1. Total Cost of Investment Model

In this paper, a simple linear cost model is considered which is widely adopted in cost analyses of wireless access networks [10, 11]. Based on this model, total cost of investment for the whole wireless infrastructure can be approximated as

$$C_{tot} = c\,N_{BS}, \quad [€] \tag{1}$$

where c is the cost per base station including CAPEX, such as installation, radio equipment, and OPEX such as energy, site rentals, maintenance, etc. N_{BS} denotes the number of base stations needed to provide the desired service level in the network.

In order to incorporate the time aspect into the cost analysis, we need to capture two main points. The first point is that in the case of postponing the investment in the radio network, one can earn interest by depositing the money into a bank. This implies the fact that future costs are worth less [15]. Second, the price of the equipment will decrease over the years. To this purpose, we define the cost of a BS (c) by applying a discount rate, and express it in terms of its NPV as below:

$$c = \sum_{n=1}^{N} \frac{c_n}{(1+d)^{n-1}}. \quad [€/\text{unit}] \tag{2}$$

where d is the discount rate, c_n and N are the total cost in year n and the network lifetime respectively. Here, price erosion can be included into the model by letting c_n diminish over the years. Note that c_n includes both the capital (c_n^{capex}) and the operational (c_n^{opex}) expenditures during the year under examination.

Under the assumption that capital expenditures occurs at the beginning of the deployment, the total cost of investment of deploying N_{BS} BSs during N years can be written as

$$C_{tot} = N_{BS}\left(c^{capex} + \sum_{n=1}^{N} \frac{c_n^{opex}}{(1+d)^{n-1}}\right). \quad [€] \tag{3}$$

Here c^{capex} denotes the capital expenditures of deploying a BS in the first year, i.e., n=1.

For simplicity, we assume that all operational costs of a BS, excluding energy cost, i.e., c^o, are constant during the network lifetime, N years. Under this assumption, total OPEX of a BS in year n can be written as below:

$$c_n^{opex} = c^o + c_n^{energy}, \quad [€/\text{unit}] \tag{4}$$

where c_n^{energy} is the total energy cost per BS in year n.

Let $\mathbb{E}_n[C_{energy}]$ denote the average annual energy cost of the considered wireless access network with N_{BS} BSs in year n. Then, the total cost of investment presented in Eq. (3) can be expressed in detail as below:

$$C_{tot} = N_{BS}\left(c^{capex} + \sum_{n=1}^{N} \frac{c^o}{(1+d)^{n-1}} \right) + \sum_{n=1}^{N} \frac{\mathbb{E}_n[C_{energy}]}{(1+d)^{n-1}}. \quad [€] \tag{5}$$

Here, the average annual energy cost of a network in year $n \in N$, i.e., ($\mathbb{E}_n[C_{energy}]$), depends on the average annual energy consumption (E_n) in kWh and the unit energy cost (e_n) in €/kWh and is given by

$$\mathbb{E}_n[C_{energy}] = e_n \times E_n(N_{BS}). \quad [€] \tag{6}$$

Based on the given relationships, total cost of investment will have the following dependence on number of BSs:

$$C_{tot} = N_{BS}\left(c^{capex} + c^o \times \frac{(1+d)^N - 1}{d(1+d)^N} \right) + \sum_{n=1}^{N} \frac{e_n \times E_n(N_{BS})}{(1+d)^{n-1}}. \quad [€] \tag{7}$$

Note that we made several assumptions on capital and operational expenditures based on real-world scenarios in order to increase the applicability of the total cost of investment model for general use. However, these assumptions are not valid for all scenarios. For example, we might expect a case where a mobile operator progressively pays the capital expenditures over the years, instead of making one-time investment. Furthermore, operators may have different deal regarding electricity prices throughout the years. Therefore, we encourage the readers to revise the model if the assumptions are not applicable for their scenarios.

2.2. Methodology for Economic Viability Analysis

We define economic viability as the operator's ability to raise enough income from energy-saving solutions to cover the required investment costs, and to make a profit during the network lifetime.

Let i and C^i_{tot} denote a candidate solution to reduce the total network energy consumption and the total cost of implementing the i^{th} solution, respectively. Then, in order to identify whether or not the additional capital investments required for the i^{th} solution can be compensated by reduced energy cost, we make the following relative comparison:

$$\frac{C^i_{tot}}{C^{ref}_{tot}} = \frac{c^i\, N^i_{BS}}{c^{ref}\, N^{ref}_{BS}} \leqslant 1 \tag{8}$$

Here, C^{ref}_{tot} denote the total cost of investment for the basic reference system with N^{ref}_{BS} BSs; each costs c^{ref}.

According to this, an operator will get total cost benefit from the chosen energy oriented solution if the ratio $\frac{C^i_{tot}}{C^{ref}_{tot}}$ is less than one. In order to compare the OPEX term, consisting of annual savings related to energy consumption, with the CAPEX term, consisting mostly of a one time expenditure, total cost of investment analysis will be performed over the network lifetime using the model introduced in the previous section.

Based on Eq.(7) and Eq.(8), we observe that economic viability of i^{th} solution is highly dependent on important parameters such as unit cost values, e.g., c^{capex}, e_n, discounting factor, d, number of BSs required in each system, i.e., N^i_{BS} and N^{ref}_{BS}, as well as the time dependency of annual energy consumption, unit cost values and the BS density.

In order to enhance the practicality of the proposed methodology and maintain simplicity, we make the following assumptions. Firstly, we restrict the economic viability analysis to the BSs considered in the first year for both systems, i.e., N^{ref}_{BS} and N^i_{BS}. This means that despite the fact that the number of BSs in the network changes over the years with respect to annual traffic growth, the viability comparison in Eq.(8) is made based on the same number of BSs over the network lifetime, N. Respectively, we assume that average loads of the considered BSs stay constant over network lifetime. This can represent a reasonable expectation that the mobile operator maintains the same design strategy over the years resulting in steady resource utilization in each BS despite the increasing BS density in the network. Regarding the time dependency of unit cost values, we assume that the annual increase in unit energy cost equals to the discount rate, i.e., $e_n = e_{n-1}\,(1+d)$. Finally, we ignore the indirect cost saving through energy consumption reduction in our analysis. An example of this can be the reduction in BS unit CAPEX due to the reduced need for battery backup in case of lowering the energy consumption of the site.

Note that the considered assumptions are made to encourage the widespread usage of this methodology by minimizing the complexity of the expressions. However, these will not make an impact on the validity of the proposed methodology since it is applicable for different set of assumptions with a simple modification.

2.3. Case Studies

We carry out two case studies to analyze the economic viability using the methodology explained above. More specifically, we aim at identifying whether or not the investment for the implementation of the considered two energy-saving solutions can be compensated by the reduced energy cost. Here we will use the traditional minimum-CAPEX solution as the reference scenario. The details of the considered energy efficient solutions and the related viability approaches are introduced below.

2.3.1. Hardware Upgrade

Here we assume that an incumbent operator aims at reducing its energy consumption through a hardware upgrade. In this respect, it is decided to change the existing BS transceivers so as to enable a short-term sleep mechanism at the BS, also called cell DTX [7, 8, 12]. Cell DTX, or micro sleep, is a new hardware feature enabling the deactivation of some components of a BS during the empty TTIs, and thus significantly lowers the idle power consumption when there is no traffic. This solution enables node-level power consumption adaptation in accordance with traffic variation in a very short time scale (millisecond level) without necessitating any network level cooperation schemes. However, it comes at the expense of increased expenditures.

Let Δc denote the additional capital expenditures required for the hardware upgrade per BS. On the other hand E_n^{ref} and E_n are the annual energy consumption (in year n) of the reference network, i.e., BSs does not have cell DTX capability, and the upgraded network, i.e., cell DTX is enabled, respectively. Note that in this scenario, number of BSs in the reference system and the improved system are the same. Moreover, we assume that the BS reconfiguration to reduce the energy consumption occurs at the beginning of first year.

Under these assumptions and using the total cost of investment model in Eq.(7), we can define the condition where the total cost of investment of the proposed solution is lower compared to the current static deployment without cell DTX using (8) as

$$\sum_{n=1}^{N} \frac{e_n \times (E_n^{ref} - E_n)}{(1+d)^{n-1}} > N_{BS} \times \Delta c. \tag{9}$$

Here, the left hand side (LHS) denotes the total energy cost saving during N years by upgrading the hardware in the first year, whereas the right hand side (RHS) shows the incremental increase in capital expenditures to achieve this energy saving.

In this scenario, we aim to analyze the break-even cost of the new hardware Δc^b, defined as the point where the energy cost saving with hardware upgrade is equal to the required capital expenditures. Consequently, for all hardware cost values below the break-even cost, the considered solution will bring total cost savings.

2.3.2. *Energy Efficient Deployment*

As a second scenario, we consider a greenfield operator that builds a network from scratch. We assume that the initial idea is to conduct the deployment for minimum energy consumption which is shown to require higher capital investments compared to the traditional CAPEX-minimum deployment in our previous study [12]. Therefore, in this paper, we aim to answer "*How expensive the energy must be so that energy-oriented design will result in lower net present value during network lifetime?*"

Despite the fact that BS types can be arbitrary, in this paper we consider deployments with same type of BSs ensuring a tractable analysis. Let N_{BS}^{e} and N_{BS}^{c} denote the number of base stations required to provide the desired service level with minimum energy consumption and minimum capital expenditures respectively, i.e., $N_{BS}^{e} \geq N_{BS}^{c}$. On the other hand E_n^{ref} and E_n are the respective annual energy consumption of these deployment solutions in year n, i.e., $E_n \leq E_n^{ref}$.
Then, based on Eq. (7) and Eq. (8) , the energy efficient network deployment will be more cost-effective compared to the CAPEX-minimum deployment if the following condition is fulfilled:

$$\sum_{n=1}^{N} \frac{e_n \times (E_n^{ref} - E_n)}{(1+d)^{n-1}} > \Bigg[(N_{BS}^{e} - N_{BS}^{c}) \times \left(c^{capex} + c^{o} \, \frac{(1+d)^N - 1}{d(1+d)^N} \right) \Bigg] \tag{10}$$

Here, the LHS denotes the total energy cost saving during N years due to energy-oriented network planning, whereas the RHS shows the resulted increase in both capital and energy-independent operational expenditures.

3. System Model

This section introduces the system model and assumptions underlying the approaches followed in this paper in order to conduct the economic viability analysis.

3.1. *Network Layout*

We consider an OFDM network with M number of BSs covering a compact region $\mathcal{R}$ (km^2). We assume the network to be modeled as a hexagonal grid with density $\rho_{BS} = \frac{1}{3\sqrt{3}\,R^2/2}$ where each site is equipped with one omni-directional antenna. Here R denotes the cell range. Within the area, users are uniformly distributed with density ρ_u (users/km^2).

3.2. *Traffic Model*

In order to provide a realistic analysis of the energy efficiency in wireless access networks, it is essential to know the area traffic demand variation in the network. In this respect, the long-term large-scale traffic model presented in [16] has a significant importance which is defined based on real traffic measurements of the downlink traffic in Europe and the mobile traffic forecast in [17]. Based on this model, the daily generated traffic $\mathcal{T}(t)$ over a given area is written as below:

$$\mathcal{T}(t) = \rho_u \, \alpha(t) \, \bar{r} \quad [\text{Mbps/km}^2]. \tag{11}$$

Here $\alpha(t)$ represents a typical daily traffic variation in terms of percentage of active users in different time intervals t, whereas $\bar{r}$ denotes the average data rate demand per user.

In this paper, we consider two different user types, i.e., heavy and ordinary users, which differ based on users' monthly data usage. Consequently, a heavy user is assumed to utilize the network significantly more compared to an ordinary user. Based on the data traffic model in [16], we assume that $\varrho\%$ of the users are classified as heavy users.

Let Ω^{heavy} and $\Omega^{ordinary}$ denote the hourly data demand per heavy and ordinary user respectively given in MB/hour. Then average offered throughput per user will be:

$$\bar{r} = \tau \, \frac{\varrho \, \Omega^{heavy} + (100 - \varrho) \, \Omega^{ordinary}}{100} \quad [\text{Mbps}]. \tag{12}$$

where $\tau = \frac{8}{3600}$. Note that under these assumptions, average area throughput $\mathcal{T}(t)$ (Mbps/km^2) during a certain hour $t \in [1, 24]$ is generated by $N_{act}^{t} = \rho_u \times \alpha(t) \times \mathcal{R}$ number of active users, each requesting $\bar{r}$ Mbps in a given network area $\mathcal{R}$.

3.3. Network Coverage

We define network coverage $\mathcal{A}$ as the fraction of the area where the received power is above a given level, P_{min}.

Let user i be connected to BS b_i and the set $\beta_k = \{i : b_i = k\}$ contain the users connected to base station k. P_k is the power spectral density per minimum resource unit in scheduling in cell k. Consider a time instant where the link gain between base station k and user i is stationary and given by g_{ik}. Then, the coverage of cell k can be mathematically written as below:

$$\mathcal{A}_k := \frac{1}{|\mathcal{R}|} \int_{\mathcal{R}} r\, \mathbb{P}[g_{ik} P_k \geq P_{min}] d_r d\phi. \tag{13}$$

where $\mathcal{A} = \bigcup_{k=1}^{M} \mathcal{A}_k$.

3.4. Radio Link Performance

3.4.1. Propagation Model

Received power at a terminal is affected by multiplication of three components which are; distance dependent path loss, shadowing and multipath. When we neglect the effect of multipath and shadowing, link gain between base station k and user i can be written as below:

$$g_{ik}[\text{dB}] = G[\text{dB}] - PL_{ik}[\text{dB}] \tag{14}$$

In this paper, we use COST-231 Hata propagation model to calculate the mean path loss given below:

$$\begin{aligned} PL_{ik}[\text{dB}] = 46.3 + 33.9\, log(f_c) - 13.28\, log(h_b) - a(h_m) \\ + [44.9 - 6.55\, log(h_b)] log(d_{ik}) + c_m. \end{aligned} \tag{15}$$

where f_c represents the operating frequency in MHz, d_{ik} denotes the distance between the BS k and user i, h_b and h_r are the antenna height of base station and receiver height respectively. Here the parameter c_m is equal to 3 for urban areas and $a(h_m)$ is the mobile station antenna height correction factor, i.e., $a(h_m) = [1.1\, log(f_c) - 0.7]h_m - [1.56\, log(f_c) - 0.8]$.

3.4.2. Radio Link Quality

We define the average SINR of a user $i \in \beta_k$ that is served by BS k is defined as

$$\gamma_i(\boldsymbol{\eta}) = \frac{g_{ib_i} P_j}{\sum_{k \neq j}^{M} \eta_k\, g_{ik} P_k + \sigma^2} \tag{16}$$

where σ^2 is the noise power and $\eta_k \in [0,1]$ denotes the load of BS k in the network. The entire network load is given by a vector $\boldsymbol{\eta}=(\eta_1, \eta_2, ..., \eta_M)$, where $\eta_k \in [0, \eta^{max}]$, $\forall\, k$. Here $\eta^{max} \leq 1$ denotes the maximum allowed load for each cell.

The load or cell resource utilization is defined as the fraction of time-frequency resources that are scheduled for data transmission in a given cell. It also represents the probability of BS k is transmitting. Therefore in (16), $\sum_{k \neq j}^{M} \eta_k\, g_{ik} P_k$ denotes the time averaged interference power.

The corresponding achievable data rate of user i per resource block (RB), which is the minimum time-frequency scheduling unit, is modelled based on Shannon capacity considering average SINR, i.e.,

$$r_i(\gamma_i(\boldsymbol{\eta})) = W_{RB} \min \left[\xi_1 \log_2(1 + \xi_2 \gamma_i(\boldsymbol{\eta})),\ \nu_{max} \right], \tag{17}$$

where W_{RB} bandwidth of a RB and ν_{max} reflects the maximum sustainable link spectral efficiency in practice by the highest modulation and coding scheme. According to [18], the model parameters ξ_1 and ξ_2 are defined as the bandwidth efficiency coefficient and SINR gap respectively.

3.4.3. User-Perceived Throughput

In this paper, we consider user-perceived throughput as user QoS metric given by the product of the achievable data rate and the idle time of serving BSs. Considering the user $i \in \beta_k$, served by BS k, it can mathematically be written as below:

$$\begin{aligned} c_i(\gamma_i(\boldsymbol{\eta})) = (1 - \eta_k)\, N_{RB}\, r_i(\gamma_i(\boldsymbol{\eta})) \\ = N_{RB}\, W_{RB}\, (1 - \eta_k) \min \left[\zeta_1 \log_2(1 + \zeta_2 \gamma_i(\boldsymbol{\eta})), \nu_{max} \right]. \end{aligned} \tag{18}$$

Here N_{RB} denotes the maximum number of RBs in frequency space depending on available bandwidth W.

Note that user-perceived throughput is monotonically decreasing in η_k. Therefore, reducing the cell load significantly improves the user QoS in the network.

3.5. Cell Load

As defined in the previous subsection, cell load describes the fraction of time-frequency resources allocated for transmission, where zero load corresponds to no active user in the cell. On the other hand, full load describes the case where all resources available are provided to one or more users in the cell.

Let N denote the total number of resource units in a considered observation period of frequency-time domain, then based on the definition, load of cell k can be written as

$$\eta_k = \frac{1}{N} \sum_{i \in \beta_k} \phi_i^k, \quad \forall\, k \in M. \tag{19}$$

Here ϕ_i^k represents the required resource consumption of cell k to serve user $i \in \beta_k$ under the assumption that the demand of user i is $\Omega_i \in \{\Omega^{heavy}, \Omega^{ordinary}\}$ which is given by

$$\phi_i^k = \frac{\Omega_i}{r_i(\gamma_i(\boldsymbol{\eta}))} \tag{20}$$

By these definition, we have the following equations,

$$\eta_k = \sum_{i \in \beta_k} \phi_i^k = \sum_{i \in \beta_k} \frac{\Omega_i}{N r_i(\gamma_i(\boldsymbol{\eta}))}, \tag{21}$$

$$= \sum_{i \in \beta_k} \frac{\Omega_i}{N r_i\left(\frac{g_{ik} P_k}{\sum_{j \neq k}^{M} \eta_j\, g_{ij} P_j + \sigma^2}\right)}. \tag{22}$$

It is observed from (22) that the load of cell k is a function of the load levels of the other cells in the network. It is due to the fact that load of interfering BSs has a direct impact on the SINR of the users for a cell k. This coupling relation creates the *"feasible load problem"* [19] in which the objective is to find a load vector $\boldsymbol{\eta}$ that balances the resource utilization with the interference-dependent resource demand in all cells which can be written mathematically as below:

$$T\,\eta_k = \sum_{i\in\beta_k} \frac{\Omega_i}{r_i(\frac{g_{ik}P_k}{\sum_{j\neq k}^{M}\eta_j\, g_{ij}P_j+\sigma^2})} \tag{23}$$

In order to define the feasible load levels $\boldsymbol{\eta}^t$ of the cells for a given area traffic demand during an observation period t, different techniques are recently proposed in literature [19]-[20]. These techniques provides simple and tractable iterative algorithms to find feasible load levels for a given deployment and traffic variation compare to intractable flow level models.

Here we adopt the iterative time static simulation methodology proposed in [19] that solves (23). This algorithm uses as input the parameters related to daily area traffic demand variation $\mathcal{T}$ Mbps/km^2, such as the user density ρ_u, the active users percentages in different hours, i.e., $\alpha(t),\ t\in\ [1,\,24]$, the amount of data delivered to each heavy and ordinary users $\boldsymbol{\Omega}\in\{\Omega^{heavy},\Omega^{ordinary}\}$, together with initial load vector $\boldsymbol{\eta}_0$ and accuracy parameter ϵ, and returns feasible load vector during the given hour $\boldsymbol{\eta}^t$. The details of the algorithm used in the numerical evaluations is provided in Appendix A.

3.6. Energy Consumption Model

In this paper, we assume that a cell can be either in *active* state, i.e., there is at least one user requesting a service, or in *idle* state, i.e., there is no active user. Based on the linear model proposed in [3], a cell consumes a considerable amount of power even when there is no user in the cell, i.e, P_0. However, with hardware improvement a cell can be put into DTX mode during *idle* state which decreases the baseline power consumption to $P_s = \delta\,P_0$, where $0\leq\delta<1$. Based on these assumptions, average energy consumption per unit time (or average power consumption) of cell k with the load of $\eta_k\in\boldsymbol{\eta}$ can be written as below [12]:

$$\mathcal{E}_k = \zeta\,P_k\,\eta_k + (1-\delta)P_0\eta_k + \delta P_0 \tag{24}$$

Here, as we mentioned, P_k denotes the power spectral density per minimum resource unit in scheduling in cell k, whereas ζ represents the portion of the transmit power dependent power consumption due to feeder losses and power amplifier.

Note that $\delta = 1$ represents the case where the BS does not have the DTX capability and therefore consumes $\mathcal{E}_k = \zeta\,P_k\,\eta_k + P_0$. In this case, cell load only impacts the transmission related power consumption, i.e., $\zeta\,P_k$.

3.7. Annual Energy Saving With Cell DTX

Let E_n represents the annual energy consumption of a network with M BSs covering $\mathcal{A} = M\times 3\sqrt{3}R^2/2\,\text{km}^2$ in year n. Under the assumption that area traffic demand $\mathcal{T}$ and its variation $\alpha(t)$ are constant throughout year under exam, E_n will have the following dependence on hourly energy consumption of the network at the t^{th} hour , $\mathcal{E}^t = \sum_{k=1}^{M}\mathcal{E}_k^t,\ t\in\ [1,\,24]$:

$$\begin{aligned} E_n &= 365\times\sum_{t=1}^{24}\sum_{k=1}^{M}\mathcal{E}_k^t, \qquad (25)\\ &= 365\times\sum_{t=1}^{24}\sum_{k=1}^{M}\zeta\,P_k\,\eta_k^t + (1-\delta)P_0\eta_k^t + \delta P_0. \end{aligned}$$

Here $\mathcal{E}_k^t$ denotes the average energy consumption of the BS k during the observation hour t introduced in Eq. (24) which is calculated based on the defined feasible load vector $\boldsymbol{\eta^t} = (\eta_1^t,\eta_2^t,....,\eta_M^t)$, during the hour under consideration.

Let $\mathcal{S}^n(M,\delta)$ denote the achievable daily energy saving in year n by upgrading the existing BSs' transceivers so as to enable cell DTX in a given network with M BSs. Then, we have the following formula,

$$\mathcal{S}^n(M,\delta) = E_n|_{\delta=1} - E_n|_{\delta<1}. \tag{26}$$

Here $E_n|_{\delta=1}$ denotes the daily energy consumption of the network with the old hardwares lack of the DTX capability. On the other hand, $E_n|_{\delta<1}$ represents the daily energy consumption of the same network when the cells gain fast power consumption adaptation capability in accordance with traffic with the hardware upgrade.

Based on the given definitions, the saving is expressed in detail:

$$\begin{aligned} \mathcal{S}^n(M,\delta) &= 365\times\sum_{t=1}^{24}\sum_{k=1}^{M}\Big(\mathcal{E}_k^t|_{\delta=1} - \mathcal{E}_k^t|_{\delta<1}\Big),\\ &= 365\times\sum_{t=1}^{24}\sum_{k=1}^{M}P_0\,(1-\delta)\,(1-\eta_k^t). \qquad (27) \end{aligned}$$

As can be seen in Eq. (27), the saving is highly dependent on cell DTX performance represented with δ and the load of the BSs in the network. As mentioned before, δ denotes the fraction of the baseline power that is reduced during an idle state due to cell DTX. On the other hand, cell load represents the average resource utilization determining the deactivation time of each cell for a given traffic demand.

4. Viability of Hardware Upgrade

The viability condition of hardware upgrade has been introduced in Section 2.2 as

$$\sum_{n=1}^{N}\frac{e_n\times(E_n^{ref}-E_n)}{(1+d)^{n-1}} > N_{BS}\times\Delta c. \tag{28}$$

This condition indicates that in order to identify the circumstances under which upgrading the hardware with cell DTX capability is economically preferable, we need to calculate the achievable energy savings with cell DTX throughout the network lifetime, N. To this end, the mathematical derivation introduced in Eq. (27), indicating the annual energy saving with cell DTX, and the aforementioned assumptions in Section 2.2 are of great importance.

As we indicated before, we assume that average loads of the considered M BSs stay constant over network lifetime. Moreover, the annual increase in unit energy cost is assumed to be equal to discount rate, i.e., $e_n = e_{n-1}(1+d)$. Under these assumptions, Eq. (28) can be expressed as below:

$$\sum_{n=1}^{N} \frac{e_n \times \mathcal{S}^n(M,\delta)}{(1+d)^{n-1}} > M \times \Delta c. \quad (29)$$

Based on the given relationships, the viability condition for hardware upgrade can be formulated in detail as follows:

$$\sum_{n=1}^{N} \frac{e_{n-1}(1+d)}{(1+d)^{n-1}} \times \left(365 \times \sum_{t=1}^{24}\sum_{k=1}^{M} P_0\,(1-\delta)\,(1-\eta_k^t)\right) > M \times \Delta c. \quad (30)$$

It can be observed in Eq. (30) that the break-even cost of the new hardware Δc^b, the point where the energy cost saving with hardware upgrade equals to required capital expenditures, is highly dependent on unit energy cost e_n, and the cell DTX performance of the hardware δ. Therefore, we identify the break-even cost for various e_n and δ values by means of system level simulations and present the results in Section 6.

5. Viability of Energy Efficient Deployment

The viability condition of energy efficient deployment has been introduced in Section 2.2 and formulated in Eq. (10). This condition indicates that in order to identify the circumstances under which the energy-oriented design results in lower total cost of investment compared to CAPEX-oriented deployment, we need to identify the network deployments based on two different objectives, namely, minimizing total energy consumption and minimizing the initial capital investments.

In this section, we first introduce the greenfield deployment problems for the considered objectives and provide an solution approach. Finally, we explain in detail how the provided solutions can be used to analyze the viability of energy efficient deployment.

5.1. Energy-Optimized Network Planning

Despite the fact that energy efficient network deployment is mostly determined based only on the busy hour energy consumption, in this paper we consider the objective of minimizing the annual energy consumption which is more relevant for achieving truly energy efficient networks. The basis of this novel approach has been presented in our previous work [12].

This problem can be formulated as

$$\underset{M}{\textbf{Minimize}} \quad E_n = 365 \times \sum_{t=1}^{24} \mathcal{E}^t, \quad (31a)$$

$$\textbf{subject to} \quad F_{\chi\%}\big[\boldsymbol{c}(\boldsymbol{\eta}^{bh})\big] \geq r_{min}, \quad (31b)$$

$$g_{ik}P_k \geq P_{min}, \quad \forall\, k \quad (31c)$$

where $F_{\chi\%}[.]$ denotes the χ percentile of the cumulative distribution function (CDF) of the random variable in the blanket. Here, the first condition ensures that χ percentile perceived user data rate at busy hour, i.e., $c^{\chi\%} = F_{\chi\%}\big[\boldsymbol{c}(\boldsymbol{\eta}^{bh})\big]$, is higher than r_{min} Mbps, and the second condition ensures full network coverage, which means that the received power of user i in a cell k is above a given threshold, P_{min}.

For simplicity, we assume that the number of BSs (M) in the network is constant, whereas network coverage $\mathcal{A} = M \times 3\sqrt{3}R^2/2$ is changing based on the control variable, i.e., cell range R. With this respect, the problem of energy-optimized planning equals to optimizing cell range that minimizes the daily average area power consumption $\mathbb{E}_t[\mathcal{P}^t_{area}(R)]$ under the same service requirements. Below, the objective function is expressed in detail:

$$\mathbb{E}_t[\mathcal{P}^t_{area}(R)] = \frac{1}{|t|}\sum_{t=1}^{24} \frac{\sum_{k=1}^{M} \zeta\, P_k\, \eta_k^t + (1-\delta)P_0\eta_k^t + \delta P_0}{\mathcal{A}(R)} \quad (32)$$

Here, we choose P_k as the minimum transmit power required to ensure full coverage, i.e., $P_k : g_{ik}P_k = P_{min}$. This also represents the optimum transmit power for interference limited systems considering that energy consumption is strictly increasing with P_k.

Further, we will introduce the key property of the objective function as follows.

Property (Unimodality): Based on the given relationships, daily average area power consumption will have the following dependence on cell range:

$$\mathbb{E}_t[\mathcal{P}^t_{area}(R)] \approx f_1(R^{x+c_2-2}) + f_2(R^{x-2}) + f_3(R^{-2})$$

Here $f_1(.)$, $f_2(.)$ and $f_3(.)$ denote the relationship between each term of $\mathbb{E}_t[\mathcal{P}^t_{area}(R)]$ with R. It is clearly observed that $\mathbb{E}_t[\mathcal{P}^t_{area}(R)]$ is a unimodal function since, while $f_1(R^{x+c_2-2}) + f_2(R^{x-2})$ is monotonically increasing with R, $f_3(R^{-2})$ is monotonically decreasing. Therefore, there always exists a non-null and finite cell range (R^{EE}_{opt}) that minimizes $\mathbb{E}_t[\mathcal{P}^t_{area}(R)], \forall\, \delta \in [0,1]$.

The proof of this property is provided in Appendix B.

5.2. CAPEX-Optimized Network Planning

In this subsection, we will introduce the network planning problem aiming to minimize the initial capital expenditures under certain coverage and QoS constraints. As mentioned earlier, this traditional deployment strategy will be used as the reference scenario in order to determine whether or not additional capital investments required for energy-minimum design is compensated by reduced energy cost.

Due to the linear relationship between the capital expenditures and the total number of BSs in the network introduced in Section 2.1, the CAPEX minimization problem is exactly equivalent to finding the maximum cell range R^{capex}_{opt} that meets the introduced user QoS and coverage requirement in (31b)-(31c) respectively.

Considering the fact that with full network coverage is verified by the chosen transmit power, i.e., $P_k : g_{ik}P_k = P_{min}$, the total capital expenditures only depends on the QoS requirement. Therefore we can simplify the problem as

$$R_{opt}^{capex} = \underset{R \in \boldsymbol{R}}{\textbf{argmax}} \Big[R : F_{\chi\%}\big[\boldsymbol{c}(\boldsymbol{\eta}^{bh})\big] \geq r_{min} \Big] \tag{33}$$

Here, $\boldsymbol{R}$ indicates the considered cell ranges varies between R_{min} and R_{max}, i.e., $\boldsymbol{R} = [R_{min}, R_{max}]$, whereas R_{opt}^{capex} is the optimum cell range ensuring that χ percentile perceived user data rate at busy hour is higher than r_{min} Mbps.

5.3. Solution Proposal

We observe that it is difficult to formulate a closed form expression for the objective functions introduced in (31) and (33) due to the coupling relationship between cell load $\eta_k^t(\boldsymbol{\eta^t})$ $\forall t \in [1, 24]$ and cell range R which directly impacts the perceived user data rate and the daily energy consumption. For this reason, we propose a simple algorithm to optimize the cell range enabling minimum annual energy consumption or minimum capital expenditures. A detail description of the algorithm used in the numerical evaluations is provided in Appendix C. Here we provide a short summary as follows.

The algorithm takes as input 1) daily area traffic demand variation $\mathcal{T}(t)$ Mbps/km^2, 2) system requirements such as coverage and QoS constraints i.e., r_{min} and P_{min}, 3) the set of feasible cell ranges $\boldsymbol{R} = [R_{min}, R_{max}]$.

- The algorithm starts with an initial cell range R_{min} and defines the minimum transmit power satisfying the coverage requirement, i.e., $P_k : g_{ik}P_k = P_{min}$.
- For each hour $t \in [1, 24]$, the algorithm determines the feasible load vector $\boldsymbol{\eta}^t = (\eta_1^t, \eta_2^t, ..., \eta_M^t)$ by using Algorithm 1 that solves (23) and returns hourly energy consumption $\mathcal{E}_k^t$, $\forall k \in M$, and the CDF of the perceived user data rates $F_{\chi\%}\big[\boldsymbol{c}(\boldsymbol{\eta}^t)\big]$.
- The algorithm iterates through the set of feasible cell ranges and computes area power consumption $\mathbb{E}_t[\mathcal{P}_{area}^t(R)]$ and perceived user data rate distribution for busy hour $F_{\chi\%}\big[\boldsymbol{c}(\boldsymbol{\eta}^{bh})\big]$.
- Finally, the algorithm searches over feasible cell ranges and determines R_{opt}^{EE} and R_{opt}^{capex} which minimize the daily average area power consumption for a given δ and the initial capital expenditures respectively.

5.4. Viability Analysis of Energy-Optimized Network Planning

As aforementioned in the previous subsections, energy- and CAPEX-optimized network planning are completed by finding the optimum cell size by assuming that the number of BSs are constant, M. This indicates that the proposed solution provides the optimized BS densities, i.e., $\rho_{opt}^{EE} = \frac{2\,M}{3\sqrt{3}(R_{opt}^{EE})^2}$ and $\rho_{opt}^{capex} = \frac{2\,M}{3\sqrt{3}(R_{opt}^{capex})^2}$, instead of optimum number of BSs for each deployment objective. Therefore, we update the viability condition for energy efficient deployment presented in Eq. (10) as below:

$$\sum_{n=1}^{N} \frac{e_n\, N_h \times \Big(\mathbb{E}_t[\mathcal{P}_{area}^t(R_{opt}^{capex})] - \mathbb{E}_t[\mathcal{P}_{area}^t(R_{opt}^{EE})]\Big)}{(1+d)^{n-1}}$$
$$> \bigg[(\rho_{opt}^{EE} - \rho_{opt}^{capex}) \times \Big(c^{capex} + c^{o}\frac{(1+d)^N - 1}{d(1+d)^N}\Big)\bigg]. \tag{34}$$

Here, N_h is the total number of hours per year, i.e., $N_h = 8760$. On the other hand, $\mathbb{E}_t[\mathcal{P}_{area}^t(R_{opt}^{capex})]$ and $\mathbb{E}_t[\mathcal{P}_{area}^t(R_{opt}^{EE})]$ are the daily averaged area power consumption (Watt/km^2), for CAPEX- and energy-optimized deployments, respectively. As a result, the LHS denotes the total energy cost saving per km^2 during N years due to energy-oriented network planning, whereas the RHS shows the resulted increase in both capital and energy-independent operational expenditures per km^2.

It can be observed in Eq. (35) that the economic viability of energy efficient deployment is highly dependent on unit cost values, i.e., c_{capex}, c_o, e_n, and the discounting factor, d. Moreover, the annual energy savings throughout the network lifetime is dependent on the variation in the utilization of the BSs. In order to incorporate these aspects, we made several assumptions as summarized in Section 2.2. Firstly, we assume that the BSs, deployed in the beginning of the first year based on the chosen network deployment objective, will have a steady resource utilization throughout the network lifetime despite the increasing BS density in the network. This can represent a reasonable expectation that the mobile operator will maintain the same design strategy over the years. As a result, the annual energy savings through energy efficient deployment will be the same during N years compared to CAPEX-optimized network deployment.

Moreover, in order to investigate the circumstances under which energy-oriented network planning is more cost-efficient in the long run, we identify the break-even cost of electricity for various c^{capex} and c^o values by means of system level simulations and present the results in Section 6.

6. Simulation Results

In this section, we present the simulation results which consists of two main parts. First, we focus purely on introduced energy efficient solutions, and present the achievable energy savings for i) Case 1: Hardware upgrade enabling DTX in the BSs in a given deployment; ii) Case 2: Energy efficient network deployment for minimum energy consumption. Note that energy efficient network deployment is achieved for two sub-cases: i) Case 2.1: $\delta \in [0, 1)$ (Cell DTX is incorporated with clean-slate network deployment); ii) Case 2.2: $\delta = 1$ (Cell DTX is not in the planning phase, but it is in operation). Second, with the help of obtained technical results, we will conduct an economic viability analysis in order to define the circumstances under which

Table 1: Simulation Assumptions

Deployment and Traffic Specific Parameters	
Cell range	R ∈ [100-800] m
Number of BSs/Number of cells	M=19 / 19
Deployment area	$\mathcal{A} = M\,3\sqrt{3}/2\,R^2$ km^2
User density	$\rho_u = 1000$ users/km^2
Data demand per heavy user per month	Ω^{heavy}=21 GB/month
Traffic per ordinary user per month	$\Omega^{ordinary}$=3.5 GB/month
Fraction of heavy users in the system	ϱ=20%
Daily traffic profile	$\alpha(t)$, $t \in [1, 24]$ [3]
Radio Link Performance Specific Parameters	
Carrier frequency	f_c=2GHz
Bandwidth	W=10 MHz
Number of RBs	N_{RB}=50
Antenna gain	G=15 dBi
Thermal noise	N_0=-174 dBm/Hz
Antenna height	h_b=25 m
Receiver height	h_m=1.5 m
Min received power	P_{min}=-70 dBm
Max spectral efficiency	ν_{max}=5 bps/Hz
Bandwidth efficiency coefficient	ξ_1=0.83
SINR gap	ξ_2=1
Power Consumption Parameters	
Power slope	ζ=4.7
Baseline power consumption	P_0=130 W
Cell DTX performance	δ ∈ [0,1]

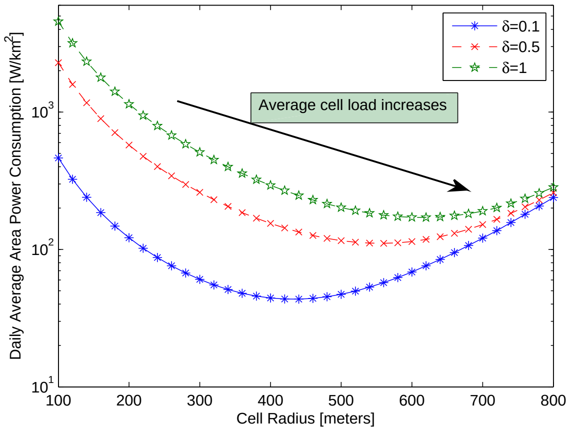


Figure 1: The relationship between annual energy consumption per area, cell range and δ.

Table 2: Energy savings with hardware upgrade ($\bar{\eta} = 0.11$)

Cell DTX Performance	δ=0.1	δ=0.3	δ=0.5	δ=0.8
Daily Average Area Power Cons. [W/km^2]	68.6	91.5	114.2	148.5
Annual Energy Cons.per Area [KWh/km^2]	600.9	801.5	1000.4	1300.9
Annual Energy Saving [%]	60%	46.6%	33.3%	13.3%

resulted energy savings from considered solutions compensate the increase in capital expenditures.

6.1. Simulation Scenario

We consider a LTE-like network with a regular hexagonal layout consisting of $M = 19$ sites adopting a wrap around technique where the cell radius varies between 100 and 800 meters. We assume deployments with macro type BSs with one omnidirectional antenna. Users are randomly distributed over the network area with a density of ρ_u=1000 (users/km^2). It corresponds to a population density of 3500 (people/km^2) under the assumption that the operator of interest has 30% market share and overall service penetration is 95%. In order to provide realistic traffic analysis, we consider the scenario defined as the most relevant for Europe in 2015 with the daily traffic variation presented in [3]. In this model, 20% of the users are classified as heavy users, each consuming 21 GB per month whereas an ordinary user demands for 3.5 GB per month.

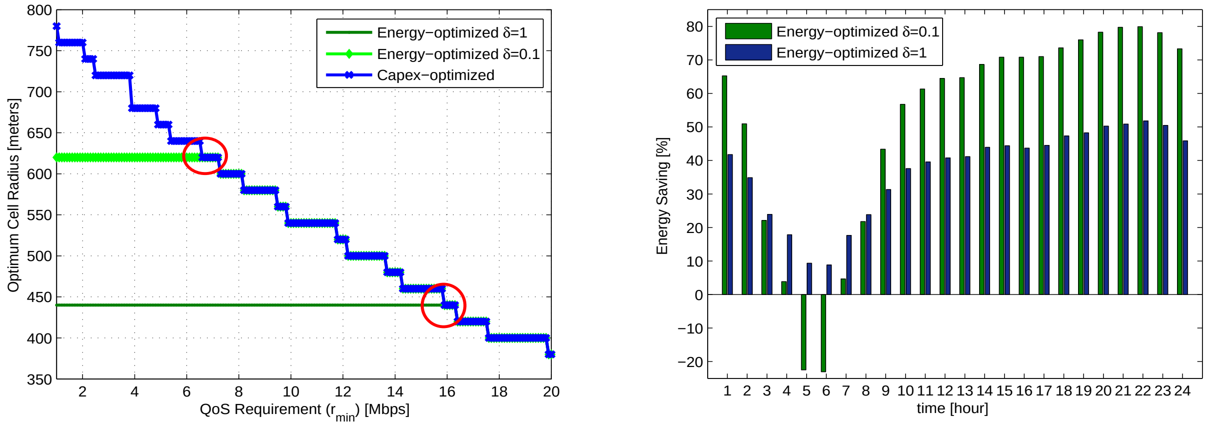
Here, COST-231 Hata path loss model for an urban area is utilized based on 3GPP specifications [21] with 8 dB user noise figure, and ξ_1=0.83 and ξ_2=1 are considered as the modified LTE capacity parameters [18]. For the proposed algorithm, we set $\nu_{max} = 5$ bps/Hz, p_{min}=-70 dBm, $\eta^{max} = 1$, ζ=4.7, P_0=130 W. The detailed assumptions on system and power consumption parameters are listed in Table 1.

6.2. Analysis on Achievable Energy Savings

Firstly we illustrate the relationship between daily average area power consumption $\mathbb{E}_t[\mathcal{P}^t_{area}(R)]$ and the cell range in Fig. 1 for the considered daily traffic variation $\mathcal{T}(t)$ for various δ values. Note that here increasing cell ranges represent higher average load levels in the network ($\bar{\eta}^t = \mathbb{E}_k[\eta^t_k]$, $k = 1, 2, ..., M = 19$) due to the fact the number of active users in a cell increase with R^2. Moreover, with the resulting higher probability of receiving interference from the neighbor cells, the average resource utilization further increases. Therefore, for the considered cell ranges, i.e., 100 meters to 800 meters, the average cell load at busy hour varies between 10^{-3} and 0.9 resulting in a growth rate of more than R^2.

Based on the given descriptions, the results in Fig. 1 can be interpreted in two aspects. First, it shows that significant energy savings are achievable by upgrading the hardware that enables cell DTX feature in a given deployment (given R) in which the savings are inversely proportional to δ. Also, it is evident that the current situation of the network, i.e., how loaded the cells are, significantly impacts the achievable energy savings which reduces as the network becomes highly loaded.

In order to indicate the potential energy savings through cell DTX, we consider a network deployment with R=600 meters, where the daily average resource utilization is 11% (busy hour load is 23%). This scenario represents a good illustration of the existing networks where the average load of a mature 3G network is shown to be 12.2% in [22]. Based on this assumption, the daily average area power consumption of the baseline network, i.e., BSs are without cell DTX capability $\delta = 1$, is defined from Fig.1 as $\mathbb{E}_t[\mathcal{P}^t_{area}(R)]|_{\delta=1}$=171.3 Watts/km^2. Thus, the annual energy consumption per area can be calculated as $E_{area} = \frac{365}{\mathcal{A}} \times \sum_{t=1}^{24} \mathcal{E}^t = N_h \times \mathbb{E}_t[\mathcal{P}^t_{area}(R)] = 8760 \times 171.3 = 1500.6$ kWh/km^2. Accordingly, using the results from Fig.1, we present the annaul energy consumption per area and the achievable energy savings in percentage in Table 2, for various δ values.



(a) Impact of QoS requirement on optimum network planning.

(b) Energy saving through energy-optimized deployment during a day.

Figure 2: Optimized network deployments and resulted energy savings.

The results show that up to 60 percent energy saving is achievable with cell DTX when δ=0.1, representing the case where a significant part of the BS components can be switched off and be activated upon request in milliseconds level. However, the achievable energy savings reduces to 13 percent when the cell DTX performance is insufficient, i.e., the reduction in baseline power consumption is only 20 percent when there is no traffic in the cell, i.e., δ=0.8.

Secondly, Fig. 1 illustrates what has been mathematically proved in Section 5.1, that is in the case of greenfield deployment, there always exists a non-null and finite cell range minimizing the daily average area power consumption regardless of power consumption parameters. This simply occurs because of the tradeoff between the reduced power consumption in small cells due to lower load levels and the additional baseline power consumption due to the increase in the number of BSs in the network. Furthermore, we observe that when cell DTX is incorporated at the planning stage, i.e., δ¡1, higher number of BSs tend to be preferred which also brings additional energy savings. This is mainly because network planning with cell DTX takes into consideration that lower cell load levels creating longer deactivation periods can be efficiently exploited by cell DTX.

Based on the illustrated relationships between the daily average area power consumption, the cell range and the cell DTX capability, in Fig. 2 we present the optimized network deployment solutions based on different objectives, and the obtained annual energy savings with energy-optimized network deployment compared to the CAPEX-minimum deployment strategy. Fig. 2a depicts the optimum cell ranges, i.e., R_{opt}^{EE} (for δ=1 and δ=0.1) and R_{opt}^{capex}, as a function of various QoS requirements. We observe that the optimum network planning significantly depends on the QoS constraint, i.e., busy hour perceived throughput for the worst 5th percentile of users. Due to the fact that user throughput is monotonically decreasing with the load, higher requirements for r_{min} favor for smaller cell sizes in order to reduce the average resource utilization.

It is also shown that if the objective is that of obtaining the minimum energy solution, the optimum design requires denser deployment for all δ values compared to minimum-capex solution, which, as a consequence, increases the installation cost. However, we observe that the tradeoff between lower capital investment and the reduced energy cost is only valid for low and medium level QoS requirements. A very high QoS constraint inactivates the network planning objective and indicates a unique solution for both energy and CAPEX-optimized planning.

On the other hand, Fig. 2b illustrates the annual energy savings through energy-optimized greenfield network planning solutions for a moderate QoS target, r_{min}=3 Mbps which is defined as the minimum requirement to enable consistent user experience in [23]. Note that the obtained optimum cell ranges for energy optimized planning ($R_{opt}^{EE}(\delta)$) in this scenario are 440 meters and 620 meters for δ=0.1 and δ=1, respectively. On the other hand, CAPEX-optimized solution indicates R_{opt}^{capex}=720 meters in order to satisfy the given QoS requirement with minimum capital expenditures. It should be noted that, for the greenfield network deployment scenario, we assume that all the BSs have DTX capability regardless of the considered network planning objective. Consequently, unlike Case 1, i.e., hardware upgrade, δ=1 represents the case, where cell DTX is not incorporated into the network planning stage, however, it is in operation. Therefore, the savings in Fig. 2b is calculated based on the assumption that all the BSs in the network can reduce their baseline power consumption by 90 percent when there is no traffic regardless of the assumptions made at the planning stage. This ensures that the presented energy savings in Fig. 2b only originate from energy-oriented network planning.

The results show that energy efficient network deployment solutions bring striking energy savings compared to CAPEX-minimum deployment. Especially when the network is designed by taking into account BSs' fast traffic adaptation capabilities (δ=0.1), up to 70 percent energy savings can be obtained at busy hour by deploying slightly faster than the actual requirement warrants. It is interesting to observe that the energy-optimum deployment does not always bring energy saving throughout a day as shown in Fig. 2b. In the least busy hours, this approach comes with a higher energy consumption since the incremental increase in load-independent baseline power consumption due to densification can not be compensated by the energy savings arising from longer deactivation periods. Table 3 summarizes the results obtained through energy efficient network deployments with δ=0.1 and δ=1. It clearly shows that energy-optimized deployment can lead to 37 and 51.4 percent average annual energy savings at the cost of deploying 35 and 160 percent more BSs in the network, respectively. We can conclude that with energy efficiency oriented network planning, the installation costs grow while the total energy consumption decreases.

Table 3: Energy savings through energy-optimized network planning

Network Planning Objective	Base Station Density (1/km^2)	Annual Energy Cons. per Area (kWh/km^2)	Energy Saving (%)
CAPEX-optimized	0.74	1201	-
Energy-optimized $\delta = 1$	1.00	648.9	37 %
Energy-optimized $\delta = 0.1$	1.98	380.6	51.4 %

We would like to note that the presented energy saving results with hardware upgrade and energy-optimized network planning would be affected by large number of parameters, such as number of sites, system bandwidth, carrier frequency, antenna gain, transmit power, traffic density at busy hour, traffic variation during the day, etc. However, we focus on few important parameters which characterize each example for clearer illustration of our proposed methodology. The impact of various parameters remains as an interesting further study.

6.3. *Economic Viability Analysis*

Based on the obtained energy savings from the considered solutions solely aiming at energy minimization, in this section we perform an economic viability analysis based on the methodology introduced in Section 4 and Section 5, in order to answer "*Under which circumstances an operator will get a total cost saving from the considered energy efficient solutions?*". To this end, we identify the circumstances under which Eq. (30) and (35) are satisfied based on the stated assumptions.

For numerical evaluations, we assume that unit installation cost of a BS is c^{capex}=15 K€, whereas annual operational costs excluding energy is c^{o}=7.5 K€ [24]. Moreover, the lifetime of the networks is assumed to be $N = 15$ years.

We first present the results for the existing deployment with an average load of $\bar{\eta} = 0.11$ in which the achievable energy savings through hardware upgrade is given in Table 2. With this respect, Fig. 3 shows the break-even cost of the hardware upgrade enabling cell DTX with respect to its unit CAPEX, i.e., $\Delta c^{b}/c^{capex}$. Here the break-even cost is illustrated as a function of two important parameters that impact the achievable energy cost saving with cell DTX, i.e., unit electricity price, e_n in €/kWh and the cell DTX performance represented by δ. Results reveal that the break-even cost of hardware upgrade is an

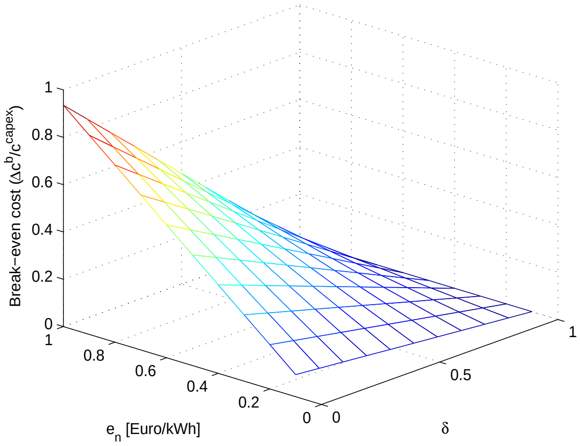


Figure 3: Break-even cost for hardware upgrade in existing deployment ($\bar{\eta} = 0.11$).

increasing function of the unit energy cost. Thus, upgrading the existing BS transceivers' is *increasingly cost effective* as the unit energy cost increases. It may come as no surprise that higher δ values, resulting in lower energy savings, indicates that hardware upgrade might not bring total cost saving for the operators. This is mainly because the energy cost reduction with cell DTX is insufficient despite the fact that the network is lightly loaded.

Considering todays' electricity prices and highly capable hardware ($\delta = 0.1$), we can conclude that the resulted energy cost saving via hardware upgrade can compensate the incremental increase in CAPEX when the price Δc is below the break-even cost of 8% and 42% (of a BS CAPEX) for the countries in low (e_n=0.1 €/kWh) and high (e_n=0.5 €/kWh) electricity price zones respectively. If we look from a different angle, we can also conclude that for a country with 0.2 €/kWh unit electricity cost, and a hardware upgrade cost of 22% of the CAPEX, there is no actual benefit of hardware upgrade if δ is equal to or higher than 0.3. We believe thay the presented viability results have a substantial importance for the operators in the process of investment decisions.

In case of energy efficient deployment, we perform the economic viability analysis based on the assumptions introduced in Section 5. The optimum network deployments, achieving minimum energy consumption or minimum capital expenditures, are determined for a given perceived data rate requirement of r_{min}=3 Mbps for the worst 5th percentile of the users. Note that, here we consider a constant CAPEX per BS despite the fact that small cells with lower capital expenditures, e.g., micro or pico, can be utilized as the cell range is reduced. The main reason behind this assumption is that the considered cell ranges are typically covered by the same type of BS. In other ranges (e.g., applicable for rural areas), different parameters should be considered, which will be analyzed in a future work.

With these assumptions in mind, we first show the discounted total cost of investment results for a limited operation time of N=15 years in Fig. 4. Here we illustrate the achievable energy

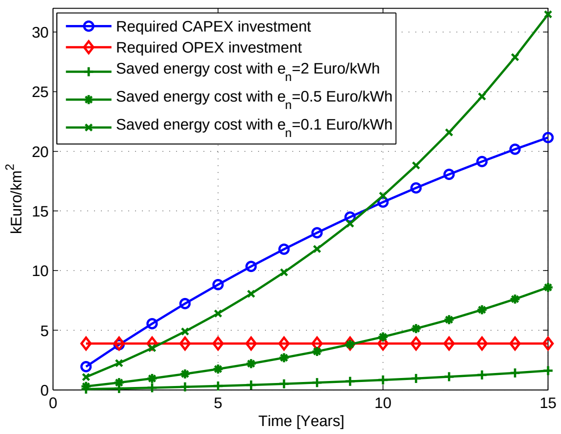


Figure 4: Annual variation of saved energy csot and the incremental increase in OPEX and CAPEX (δ=1, r_{min}=3 Mbps).

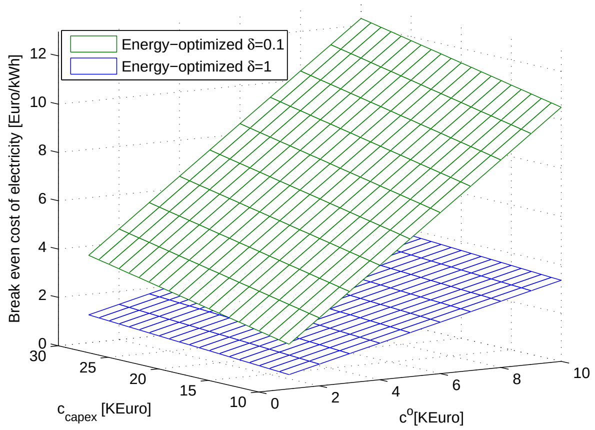


Figure 5: The break-even cost of electricity vs. unit cost values.

cost savings through energy-oriented deployment for δ=1 and its consequences in terms of the required increase in CAPEX and OPEX, compared to CAPEX-optimized planning. The results are presented as a function of the operation year $n \in N$ for various unit electricity cost in €/kWh. As aforementioned, we assume that the capital expenditures occur at the beginning of the first year, and thus it is independent of the network lifetime. Based on this scenario, Fig. 4 shows that the energy-oriented design (δ=1), enabling 37% saving per year, leads to a significant cost saving over the network lifetime especially for the countries with higher electricity cost. However, it is observed that despite the fact that the energy cost saving possibly can offset the incremental increase in capital expenditures, i.e., 3882 Euro/km^2, it is inadequate to compensate the annual increase in OPEX arising due to denser network deployment. The compensation during network lifetime might only be feasible if there is some hidden benefits of energy saving for the operators, e.g., marketing, spectrum cost reduction, etc.

Finally Fig. 5 illustrates the break-even electricity costs for energy-optimized deployment considering the cases of δ=1 and δ=0.1 as a function of unit capital and operational expenditures. The results indicate how expensive energy must be so that energy-oriented deployments result in the same net present value as the traditional minimum-CAPEX solution. We observe that energy-optimized network planning, which incorporates cell DTX already in the planning stage, i.e., δ=0.1, is decreasingly cost effective as the unit CAPEX and OPEX increase, despite the fact that the solution enables 51.4 percent annual energy saving compared to CAPEX-optimized solution. This mainly arises from the fact that the energy-optimized solution with δ=0.1 indicates significant densification, i.e., 160 percent more BSs, in order to increase the deactivation periods of the BSs that is efficiently exploited by cell DTX. However, we observe that even though the energy-oriented network deployment, ignoring BSs' capability at the planning stage, i.e., δ=1, results in lower energy saving, it is more cost effective approach compared to the case of δ=0.1, due to the need for less densification.

We can conclude that energy-optimized network planning, which favors deploying slightly faster than the actual requirement warrants, brings significant energy savings. However, if the cost savings are restricted to the direct saving due to reduced energy consumption, the achieved savings are not sufficient to compensate the increase in other expenditures.

We would like to note that the this economic viability analysis is valid for the considered scenario and thus the break-even cost will be different for different setups. We believe that the detailed analysis on the impact of system parameters threshold point of δ and e_n would provide direct guidance on decision making for the operators, which will the scope of our future study.

7. Conclusions

In this paper, we presented a novel methodology to assess the economic viability of the technical solutions for energy efficient wireless access networks. We demonstrated the usability of the proposed methodology by performing cost-benefit analysis for two different energy efficient solutions applicable to existing and greenfield deployment scenarios.

Regarding the hardware upgrade solution, we considered dynamic sleep mode operation of BSs, namely cell DTX. Based on the load-dependent performance evaluation, we have quantified the achievable energy saving of the hardware upgrade with the cell DTX feature. Then, we derived the break-even cost of the new hardware below which the increment in CAPEX is compensated by the reduced energy cost. It is shown that up to 60 percent of cost saving is achievable with the cell DTX by taking advantage of low resource utilization in the current networks due to the high data rate requirements. Consequently, the resulted energy cost saving via hardware upgrade can compensate the required investment, and thus brings the total cost saving, when the additional hardware cost for each BS is lower than 8% of unit CAPEX in the countries with energy cost of 0.1 €/kWh.

Regarding the greenfield network deployment scenario, we identified the network planning that enables minimum annual energy consumption without degrading perceived user QoS by using BSs with cell DTX capability. To this end, we proposed a simple algorithm to obtain the optimum BS density considering the average load levels in the network varying with the daily traffic fluctuations. We have shown that the optimal topology from the deployment cost point of view does not match with the network density which is optimal for the energy consumption. Consequently, if the energy-awareness is incorporated at the initial deployment phase, a significant energy saving is feasible over CAPEX-minimized network planning. However, it comes at the expense of increased BS density. In that respect, our viability analysis illustrates that, unless the operators acquire additional cost benefits besides the direct electricity consumption, the energy-optimal deployment strategy is not viable under today's cost values.

Appendix A
Defining Feasible Load Levels

In order to define the feasible load levels of the cells for a given area traffic demand during an observation period t, an iterative time static simulation approach is adapted in this paper that solves (23).

Algorithm 1 Calculate feasible load vector at time t $\boldsymbol{\eta}^t$

Require: $\alpha(t)$, $\mathcal{A}$, $\boldsymbol{\Omega}$, ρ_u, M, δ, ϵ, $\boldsymbol{\eta}_0$,
1: Calculate active user at time t, N_{act}^t
2: Define the set $\beta_k = i : b_i = k, \forall k \in M$
3: Initialize load vector, $\boldsymbol{\eta}_0$
4: **repeat**
5: Compute $\boldsymbol{\eta^{new}} = (\eta_1^{new}, \eta_2^{new}, ..., \eta_M^{new})$ from (22)
6: **if** $\boldsymbol{\eta^{new}} - \boldsymbol{\eta}^t > \epsilon$ **then**
7: $\boldsymbol{\eta}^t \leftarrow \mathbf{updateLoad}(\boldsymbol{\eta^{new}})$
8: **else**
9: $\mathbf{return}\quad \boldsymbol{\eta}^t \leftarrow \boldsymbol{\eta^{new}}$
10: **end if**
11: **until** $\boldsymbol{\eta^{new}} - \boldsymbol{\eta}^t < \epsilon$

Appendix B
Proof of Unimodality

In order to present the dependence of the objective function on the cell edge, we first provide the functional relationship between η_k^t and R in the following corollary.

Corollary 1 *The feasible load level of each cell η_k^t, $\forall\, k$, $\forall\, t \in$ [1, 24] is increasing with R^x, where $x > 2$.*

Proof of Corollary 1: Under the constant user density assumption, number of active users in a cell during a given hour t is increasing with R^2. On the other hand, user's data rate $r_i(\gamma_i(\boldsymbol{\eta}))$, $\forall\, i \in \beta_k$ is decreasing with R due to higher interference level. Therefore, the feasible load level of each cell $\eta_k^t = \sum_{i \in \beta_k} \phi_i^k = \sum_{i \in \beta_k} \frac{\Omega_i}{Tr_i(\gamma_i(\boldsymbol{\eta^t}))}$ will increase with R^x, $x > 2$. □

Regarding P_k, as mentioned, we we choose its value as the minimum transmit power required to ensure full coverage, i.e., $P_k : g_{ik} P_k = P_{min}$. Therefore, based on the general form of the path loss model, i.e., $g_{ik}^{dB} = 10\, log_{10}(c_1) + 10\, c_2\, log_{10}(d_{ik})$, the functional relationship between transmit power and cell range will be $P_k(R) = \frac{P_{min}}{c_1} R^{c_2}$. Here c_1 and c_2 denote the model parameters.

Based on the introduced relationships, daily average area power consumption will have the following dependence on cell range:

$$
\begin{aligned}
&\mathbb{E}_t[\mathcal{P}_{area}^t(R)] \\
&= \frac{1}{|t|} \sum_{t=1}^{24} \frac{\sum_{k=1}^{M} \zeta\, P_k(R)\, \eta_k^t(R) + (1-\delta) P_0 \eta_k^t(R) + \delta P_0}{\mathcal{A}(R)} \\
&\approx f_1(R^{x+c_2-2}) +\; f_2(R^{x-2}) +\; f_3(R^{-2}).
\end{aligned}
\tag{35}
$$

This proves that under the stated assumptions, the objective function of energy-optimized network planning problem is a unimodal function, and thus there is always non-null and finite cell range that minimizes annual energy consumption. □

Appendix C
Defining Optimal Network Planning

Algorithm 2 first defines the minimum transmit power that satisfies the coverage requirement for each cell range $R \in \boldsymbol{R}$. Then, for each hour t, feasible load vector $\boldsymbol{\eta}^t$ at time t is determined by using Algorithm 1 that solves (23). The determined feasible load vector $\boldsymbol{\eta}^t$ is then used to calculate the average area power consumption $\mathcal{P}_{area}^t(R)$ and CDF of the perceived user data rates $F[\boldsymbol{c}(\boldsymbol{\eta}^t(R))]$ during that hour t. We finally determine the daily average area power consumption $\mathbb{E}_t[\mathcal{P}_{area}^t(R)]$ and χ percentile user data rate at busy hour $c^{\chi\%}$ for a given $R \in \boldsymbol{R}$.

The search over cell ranges aims at finding the optimum cell range R_{opt}^{EE} that minimizes the daily average area power consumption for a given δ. This overall search algorithm increasing R by a step size $\triangle$ will be stopped if the objective value are increasing $\mathbb{E}_t[\mathcal{P}_{area}^t(R)] > \mathbb{E}_t[\mathcal{P}_{area}^t(R-\triangle)]$ or χ percentile user data rate at busy hour, i.e., $c^{\chi\%} = F_{\chi\%}\left[\bar{c}(\boldsymbol{\eta}^{bh})\right]$, is less than r_{min} Mbps. This is due to the fact that while $\mathbb{E}_t[\mathcal{P}_{area}^t(R)]$ has a convex relation with R, $c^{\chi\%}$ is non-increasing function of R.

On the other hand, the search that aims at finding the optimum cell range R_{opt}^{cost} that minimizes the total initial capital investments will only consider the defined performance requirement regardless of the energy consumption and it will stop when $c^{\chi\%}$, is less than r_{min} Mbps. This will indicate maximum cell range that satisfies the user QoS requirement.

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Algorithm 2 Calculate the cell ranges R_{opt}^{EE} and R_{opt}^{cost} that optimizes (31) and (33)

Require: $\alpha(t),\ \boldsymbol{\Omega},\ \rho_u,\ r_{min},\ P_{min},\ \boldsymbol{R} = [R_{min}, R_{max}]$

for all $R = R_{min}$ to R_{max} **do**
  Compute $P_k(R) = \frac{P_{min}}{c_1} R^{c_2}$ for all k
  Compute $\mathcal{A}(R) = M \times 3\sqrt{(3)}/2$
  for all $t \in [1, 24]$ **do**
    Calculate active user at time t, $N_{act}^t(R)$
    Using N_{act}^t, find $\eta_k^t(R)$ for all k from **Algorithm 1**
    Compute $r_i(\gamma_i(\boldsymbol{\eta}^t(R)))$ for all i
    Compute $\mathcal{P}_{area}^t(R)$ and $F[\boldsymbol{c}(\boldsymbol{\eta}^t(R))]$
  end for
  Compute $\mathbb{E}_t[\mathcal{P}_{area}^t(R)]$ and $F_{\chi\%}\left[\boldsymbol{c}(\boldsymbol{\eta}^{bh})\right]$
  if $\mathbb{E}_t[\mathcal{P}_{area}^t(R)] < \mathbb{E}_t[\mathcal{P}_{area}^t(R - \triangle)]$ and $F_{\chi\%}\left[\bar{c}(\boldsymbol{\eta}^{bh})\right] \geq r_{min}$ **then**
    Update $R = R + \triangle$
  else
    Return $R_{opt}^{EE} = R$
  end if
  if $F_{\chi\%}\left[\bar{c}(\boldsymbol{\eta}^{bh})\right] \geq r_{min}$ **then**
    Update $R = R + \triangle$
  else
    Return $R_{opt}^{cost} = R$
  end if
end for

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