An Analytical Energy Performance Evaluation Methodology for 5G Base Stations

S. Krishna Gowtam Peesapati[1,2], Magnus Olsson[2], Meysam Masoudi[1], Sören Andersson[2], Cicek Cavdar[1]
[1]KTH Royal Institute of Technology, Sweden
[2]Huawei Technologies Sweden AB, Stockholm, Sweden
[1]Email: {svkgpe, cavdar, masoudi}@kth.se
[2]Email: {soren.andersson, magnus.olsson}@huawei.com

***Abstract*—The implementation of various base station (BS) energy saving (ES) features and the widely varying network traffic demand makes it imperative to quantitatively evaluate the energy consumption (EC) of 5G BSs. An accurate evaluation is essential to understand how to adapt a BS's resources to reduce its EC. On the other hand, modeling the variation in the power consumption (PC) of a BS with its resources considering the user equipment (UE) performance is mathematically rigorous. In this work, we present a novel analytical methodology to evaluate the EC of a 5G BS under varying traffic load. We mathematically formulate the impact of massive multiple-input and multiple-output (MIMO) arrays, vast spectral resources, and the spatial multiplexing ability of these systems on the UE performance and activity of the BS. Next, we present an updated power model to capture the PC variation of two BSs types: a 4T and a 64T BS. Our proposed analytical methodology simplifies the complex network EC evaluation. Using this methodology, we show that identifying the right BS type for a given deployment area can reduce the overall network EC by up to 60%. Furthermore, by implementing deep sleep modes (SMs) facilitated by 5G, one can gain considerable energy savings (ES), especially during the off peak hours of the day.**

***Index Terms*—Energy performance, energy efficiency, evaluation methodology, 5G, activity factor, massive MIMO, carrier aggregation, spatial multiplexing**

I. Introduction

The fifth-generation (5G) of mobile networks are designed to cater to 1000x times higher traffic demands while consuming the same or lower energy [1]. On the other hand, the roll-out of 5G over the existing technologies and the deployment of complex BSs in smaller cells could lead to a higher network EC. It could mean higher operational expenditure (OPEX) for the network operators and increased global carbon emissions [2]–[4]. Therefore, improving the energy efficiency (EE) of wireless networks has gained interest from industry and academia.

The next-generation 5G BSs are powered with advanced massive MIMO systems and vast spectral resources to serve the UEs efficiently. However, various studies [3]–[7] have shown that these resources are often under-utilized due to a large variation between the peak and non-peak hour traffic demands leading to an unnecessarily high BS and network EC. One promising approach to improve resource utilization and reduce network EC is by dynamically adapting the resources following the input traffic demand.

Evaluating the EC of a BS in a dynamic environment can be quite challenging as it depends intricately on the resources used and the SMs implemented. The EARTH project [7] had provided the initial impetus for an integrated solution to evaluate a network's EC by holistically analyzing the impact of the BS's components and different network-level deployment strategies on the ES obtained. However, the solution assumed slightly inefficient BSs deployed in an over-dimensioned baseline network for comparison [8]. In [8], the authors proposed updates to [7] by considering deployment and traffic models more suitable in a 5G time frame. By detailed system-level simulations and with rather simplistic BS power models, these works managed to evaluate a network's EC under varying loads.

Nevertheless, we need more detailed and accurate PC models as different resources have a different impact on a BS's PC [9]. In [9] and [10], the authors modeled the variation in the PC with the number of active antenna elements and bandwidth. Not considering the impact of SMs on the EC, the authors implement an adaptive massive MIMO system to maximize the downlink EE under varying load. On the other hand, the authors in [11]–[14] mainly focused on SM management under different traffic loads by assuming fixed BS resources. In [15], we combined radio resource adaptation with SMs and proposed a dynamic Q-learning based algorithm to adapt a BS's resources according to the traffic demand and reduce the overall EC. While the areas covering PC models and EC evaluation methodologies have seen some progress, the quest for a simplified, unified and analytical network-level EC evaluation methodology remains open.

In this work, we propose an analytical network-level EC evaluation methodology that connects resources used with SMs and analyzes its impact on the BS's EC under varying traffic loads. We also consider the benefits of a lean carrier design, spatial multiplexing, massive MIMO, and bandwidth adaptation on the EC. The main contributions of this work are summarized as follows.

- We present a novel power model which captures the impact of three BS parameters, namely: the bandwidth, the active array size, and the spatial multiplexing factor on the instantaneous PC of the BS. This model also takes into account the 5G BS's advanced SMs.
- We develop a new formulation for the BS's activity factor

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by considering the impact of the three BS parameters on the overall cell throughput, and the performance experienced by the UEs.

- Finally, by applying the proposed methodology, we analyze the impact of the increasing traffic demands on the EC over the next 10-years. We show the importance of identifying the appropriate BS type for a given deployment scenario to save energy and meet future traffic demands.

The rest of this paper is organized as follows. In Section II, the utilized features of 5G are presented. The system model is presented in Section III followed by the power consumption model and the traffic model in Sections IV and V, respectively. Simulation results and discussions are given in Section VI. Finally, the whole paper is concluded in Section VII.

II. 5G Features

The implementation of flexible signaling periodicity in 5G along with the use of larger antenna systems enable us to improve the EC of the BS under varying traffic load. Massive MIMO systems could improve the UE performance thereby allowing the BS to gain on long idle periods during which it could switch down to deeper sleep levels and conserve more energy. In this section, we will look at two main features that could lead to higher ES.

- *Lean Signaling Design:* Minimal signaling involves reducing any transmissions not related to the delivery of user data [16]. These include signals for synchronization, idle mode mobility, and system and control information. 5G does away with the mandatory cell-specific reference signals as in LTE and allows for a flexible periodicity for the transmission of the synchronization signals (SSs). The periodicity of the SS blocks in 5G can vary from 5-160 ms [11]–[13]. This flexibility could result in idle periods that are 25-800 times longer as compared to LTE under no load.
- *Massive MIMO beamforming and spatial multiplexing:* Larger antenna arrays at the BS can be used to implement UE specific beamforming. This technique improves the performance of the UEs as they receive more spatially focused transmission and reception beams [7], [17], [18]. Due to the additional beamforming gain, the UEs experience higher signal-to-interference-plus-noise ratio (SINR) resulting in increased data rates reducing the time required by the BS to serve them [19], [20]. By having larger arrays, it is also possible to beamform to multiple users simultaneously. The higher spatial multiplexing gain so obtained improves the overall cell throughput [21].

III. System model

In this work, we consider a network consisting of a homogeneous deployment of 3-sector cells. The serving BS i is surrounded by ϕ_c number of interferers. In this work, we consider six interferering BSs, i.e., $\phi_c = 6$. The BS serves a total of N active UEs in time T who are assumed to be uniformly distributed in the cell of radius D_o. Assuming a fixed average requirement of Ω MB per UE, the hourly traffic demand ξ can be expressed as,

$$\xi = N * \Omega \tag{1}$$

The variation in the number of active UEs during the day is assumed to follow the profile (Fig 5) in [7].

Considering the downlink (DL) scenario and assuming perfect channel state information (CSI) to be available at the transceivers, the achievable rate per UE k can be expressed as:

$$r_k = B_i N_k \log_2\left(1 + \frac{\mathcal{S}_{k,i}}{\mathcal{I}_k + \mathcal{N}_k}\right) \tag{2}$$

Here, r_k depends on the signal power $\mathcal{S}_{k,i}$ from the serving BS i, and the interference from the neighbouring BSs $\mathcal{I}_k$. Furthermore, $\mathcal{I}_k$ depends on the activity of the interferers η_j while r_k varies with the bandwidth B_i and the number of spatial multiplexing layers N_k. These parameters can be expressed as:

$$\mathcal{S}_{k,i} = \frac{c}{(D_{ik})^{\alpha}} \frac{|\mathbf{H_{ik}W_{ik}}|^2}{\|\mathbf{W_{ik}}\|^2} \frac{p_i M_i}{K_c} (M_i - N_k) \tag{3}$$

$$\mathcal{I}_k = \sum_{j=1}^{\phi_c} \frac{c\eta_j}{(D_{jk})^{\alpha}} \frac{|\mathbf{H_{jk}W_{jk}}|^2}{\|\mathbf{W_{jk}}\|^2} \frac{p_j M_j}{K_c} (M_j - N_k) \tag{4}$$

$$\mathcal{N}_k = \sigma^2 \|\mathbf{W_{jk}}\|^2 \tag{5}$$

In (3), $\mathcal{S}_{k,i}$ depends on the number of UEs served simultaneously K_c, power per power amplifier (PA) p_i, and the active array size M_i, and is given by $\frac{p_i M_i}{K_c}$. The array gain is obtained by using larger antenna arrays at the BS. It improves the signal power received at the UEs and is given by the factor $(M_i - N_k)$. This is also the maximum gain that can be obtained considering a zero-forcing precoder at the transmitter [10]. D_{ik} and D_{jk} are the distances of the UE from the serving and interfering BSs respectively. c captures the gains of the antennas at the BS and UE. The instantaneous cell throughput can then be written as,

$$R = \sum_{k=1}^{K_c} r_k = \sum_{k=1}^{K_c} B_i N_k \log_2\left(1 + \frac{\mathcal{S}_{k,i}}{\mathcal{I}_k + \mathcal{N}_k}\right) \tag{6}$$

A. Base station activity factor

The fraction of the total time T that a BS i remains active while serving the UEs is known as the activity factor [20]. Denoted by η, it is calculated as the fraction of the sum of the time to serve each UE with a requirement of Ω_k divided by the total time T and is expressed as,

$$\eta = \frac{\sum_{k=1}^{N} \frac{\Omega_k}{r_k}}{T} \tag{7}$$

Replacing r_k in (7) with (2), we get,

$$\eta_i = \frac{1}{TK_c}\left[\sum_{k=1}^{N} \frac{\Omega_k}{B_i N_k \log_2\left(1 + \frac{\mathcal{S}_{ik}}{\mathcal{I}_k + \mathcal{N}_k}\right)}\right] \tag{8}$$

The maximum spectral efficiency obtained with a given antenna array also depends on the number of antennas used at the UE N_k. The upper bound on this efficiency is given by [22]:

$$G_{upperbound} = \left(\sqrt{M_i} + \sqrt{N_k}\right)^2 \tag{9}$$

Taking into account the upper bounds on the spectral efficiency, the activity factor of the BS is now modified as,

$$\eta_i = \frac{1}{TK_c}\left[\sum_{k=1}^{N} \frac{\Omega_k}{max\left[r_k, r_{max}\left(M_i, N_k\right)\right]}\right] \tag{10}$$

where r_{max} is the maximum data rate that can be achieved by a UE with M_i transmit and N_k receive antennas. T represents the observation window over which we measure the activity of the BS. In this work, we set T to be equal to the periodicity of the SS block transmission. The observation window and the hourly input traffic demand determine the overall activity factor of the BS.

IV. Power consumption model

The power model quantifies the variation in the PC of a BS with the load. An accurate power model helps to analyze the impact of various components on the overall EC of the BS. A model is dependent on the BS type and therefore, it is necessary to ensure that the implemented model accurately models the BS under consideration [3]. Inspired by the works [3], [9], [11], [23], we propose a novel power model that takes into account the 5G features as mentioned in Section II.

The total PC of the BS consists of the i) load-dependent, and ii) load-independent parts and can be expressed as:

$$P_{total} = P_{load-dependent} + P_{load-independent} \tag{11}$$

The load-dependent PC is further divided into the baseband (BB) and PA's PC. The BB PC varies with B_i, K_c, and M_i [9]. Representing the normalized load experienced by the BS with p ($0 \leq p \leq 1$), the load-dependent PC can be expressed as:

$$P_{load-dependent} = P_{baseband} + P_{PA}\left(p\right) \tag{12}$$

$$P_{baseband}(M_i, K_c, B_i) = \left[AR_c + \frac{M_i B_i}{L_{bs}}\left(2 + \frac{1}{T_c}\right)\right] K_c + \left(\frac{3B_i M_i}{L_{bs}}\right) K_c^2 + \left(\frac{B_i}{3T_c L_{bs}}\right) K_c^3 \tag{13}$$

$$P_{PA}\left(p\right) = M_i\left[\frac{1}{\left(1+\epsilon\right)\eta}\left(p + \epsilon P_{max,PA}\right)\right] \tag{14}$$

$$P_{load-independent} = P_{syn} + M_i P_{bs} + P_{fixed} \tag{15}$$

The various parameters in the equations above are given in Table I.

A. Base station sleep modes

SMs reduce the PC of a BS during the idle period by deactivating various hardware resources. The SMs have been categorized into 4 levels based on the minimum sleep duration and the activation/deactivation time of the hardware resources.

Deeper sleep levels (SM2, SM3 and SM4) reduce the BS's PC by a large amount as more hardware resources are deactivated. However, the increased burstiness in the traffic demand during the peak hours makes it difficult to switch down to deeper sleep levels having long transition times. Also, with the maximum periodicity of the SSB transmission in 5G being 160 ms, it is not possible for the BS to switch down to SM4 with a transition time of 1s. We therefore restrict ourselves to the first three sleep levels. The sleep deltas and the corresponding transition times for the various sleep levels used in this work are presented in Table I and are obtained from [23]. The BS PC model taking into account the various SMs can be expressed as:

$$P_{BS}^{5G} = N_s * \begin{cases} P_{total} & \text{if } p > 0 \\ P_B & \text{if } p = 0 \textit{ without sleep} \\ \delta_1 P_B & \text{if } p = 0, 72\mu s \leq T_{sleep} < 1ms \\ \delta_2 P_B & \text{if } p = 0, 1ms \leq T_{sleep} < 10ms \\ \delta_3 P_B & \text{if } p = 0, T_{sleep} \geq 10ms \end{cases} \tag{16}$$

Here, N_s is the number of sectors and P_B is the no-load PC of the BS which is given as:

$$P_B = M_i\left[\frac{1}{\left(1+\epsilon\right)\eta}\left(\epsilon P_{max,PA}\right)\right] + P_{syn} + M_i P_{bs} + P_{fixed} \tag{17}$$

The BS's EC during the period T also depends on the transition time to the opted SM T_{ac,δ_i} and is given by:

$$E_i = \eta_i T N_s P_{total} + \left(\sum_{i=1}^{3} S_i \delta_i P_B\right)\left(T' - T_{ac,\delta_i}\right) \tag{18}$$

The overall network EC in an area A_r with a BS density β can then be computed as:

$$E_{total} = E_i \beta A_r \tag{19}$$

TABLE I
Power consumption model parameters and their values

Variable	Definition	Value(s)
	Power consumption modeling	
R_c	Average cell throughput	
B_i	Bandwidth per UE	40 MHz
A	Sum of encoding and decoding power consumption [9]	1W
L_{bs}	BS computational efficiency in (Gflops/W) [9]	12.8e9 (Gflops/W)
T_c	Channel coherence time in symbols [9]	5000 symbols
ϵ	Fixed constant (PA dependent) [9]	0.0082
η	Efficiency of the PA	0.25
$P_{max,PA}$	Maximum output power of the PA	3.125W
P_{fixed}	Baseline/No-load power consumption of the BS	
P_{syn}	BS local oscillator power consumption [9]	1W
P_{bs}	BS circuit power [9]	1W
δ_i	Sleep level deltas (SM1/SM2/SM3) [16]	0.84/0.69/0.5
N_s	Number of sectors	3
N_i	Receiver diversity	2/4
f_c	Carrier frequency	1.8 GHz

TABLE II
DEVICE CATEGORIES, THEIR MIXES AND THEIR CORRESPONDING GROWTH RATES

Device category	Device mix, %	Growth rate of:	
		Number of devices,%	Data traffic per device,%
Smartphones	94.00	0.92	26
Mobile PCs	3.50	0.92	11
Tablets	2.50	0.86	15

TABLE III
DATA TRAFFIC VOLUME IN GB/MONTH FOR DIFFERENT DEVICE TYPES FOR THE YEARS 2020, 2025, 2030 [8], [24]

Device category	Year		
	2020	2025	2030
Smartphone	9.39	30.00	95.28
Mobile PC	14.27	24.05	40.51
Tablet	7.36	14.80	29.78

V. TRAFFIC MODELING

Traffic modeling involves understanding the network level traffic variation over 24 hours in different deployment areas. It consists of two parts: i) Large-scale traffic modeling and ii) Long-term traffic modeling.

- *Large-scale traffic modeling* involves understanding the traffic variations in different deployment areas based on the geographical statistics of the country and the distribution of the population. Similar to the methodology followed in [7], [8], we consider six different deployment areas, namely: super dense urban (SDU), dense urban (DU), urban (U), suburban (SU), rural (R), and wilderness (W) classified based on their population densities.
- *Long-term traffic modeling* involves predicting the growth in the peak traffic demands in an area over the next few years. Assuming a device mix as given in Table II, and using the device growth statistics from [24], we follow the methodology in [3] to obtain an estimate of the peak data traffic demand in different deployment areas over a 10 year span (see Table IV). These estimates are based on the current statistics and could vary in the future.

The hourly traffic demand is calculated using Eq.(1) and takes into account the daily traffic variation profile used in [3]. This variation is assumed to be the same across all deployment areas. The percentage of active UEs $(\alpha(t))$ has been found to vary between 16% to 2.25% during the peak and off-peak hours respectively with an average of 9.64% during a day [3], [7]. The data volumes per subscriber expected over 10 years is as calculated from the data in [24] and presented in Table III. These values are then used to estimate the traffic demand per network operator $R(t)$ given by:

$$R(t) = \frac{\rho}{N_{op}} \alpha(t) \sum_{a} r_a \lambda_a \tag{20}$$

where ρ is the total traffic demand in a given area, N_{op} is the number of operators, r_a is the average data rate demand and λ_a is the ratio of subscribers of device type a. In this study, we assume $N_{op} = 1$. Using the above statistics, the estimated peak traffic demand in different deployment areas for the years 2020, 2025 and 2030 are calculated and presented in Table IV.

TABLE IV
PEAK TRAFFIC DEMAND IN DIFFERENT DEPLOYMENT AREAS FOR THE YEARS 2020, 2025, 2030

Area	Traffic demand $[Mbps/km^2]$		
	2020	2025	2030
Super dense urban	1201.81	3718.21	11595.21
Dense urban	180.00	557.73	1728.28
Urban	60.00	185.91	579.76
Sub urban	30.04	92.95	289.88
Rural	6.01	18.59	57.98
Wilderness	1.50	4.64	14.49

VI. ENERGY PERFORMANCE EVALUATION

In this section, we apply the new methodology to study network EC resulting from the deployment of two types of 5G BSs in different deployment scenarios. We then illustrate the importance of identifying the right BS for a deployment scenario by plotting the daily variation in the EC and activity of the two BSs considered. The network-level evaluation is implemented and executed in an internal network evaluation tool.

A. System setup

We consider a homogeneous 3-sector hexagonal network deployment consisting of a total of 7 BSs with the serving BS in the center surrounded by 6 interfering BSs. We evaluate the EC of two types of BSs: i) a 4T BS; and ii) a 64T BS; with different baseline PC that can be calculated from the values given in Table I. The frequency reuse factor is set to 1 and the total bandwidth B of the system is limited to 40 MHz. The observation window T is set to 20ms which is also the default periodicity of the SS block transmission. A uniform inter-site distance (ISD) of 1500 m is assumed across all deployment scenarios. For the parameters of the power model, we assume the sleep deltas to be 0.84 for SM1, 0.69 for SM2, and 0.5 for SM3 [16], the efficiency of the PA's η to be 0.25, the fixed PA dependent parameter ϵ to be 0.082 [9].

B. Results

- *Activity factor and power modeling analysis*

In Sections III-A and IV, we presented the mathematical relationship between a BS's configuration and its instantaneous PC. In Fig.1, we analyzed the impact of bandwidth on the activity factor of a 64T BS deployed in a scenario with a peak traffic demand of 2000 $Mbps/km^2$. As seen, by increasing the total bandwidth from 5 to 100 MHz, the activity factor of the BS could be reduced by approximately 26x times. This decrease is due to the increased throughput experienced by the UEs. However, as seen in Fig.2, the total bandwidth utilized has a significant impact on the BS's PC.

These results highlight the importance of identifying the total bandwidth that must be allocated to BS depending on the traffic demands to reduce its overall EC.

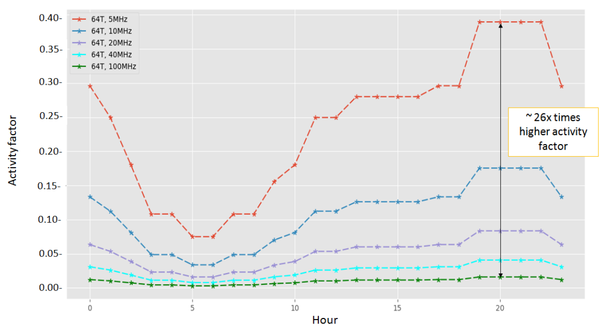

Fig. 1. Daily variation in the activity factor of a 64T BS with varying total bandwidth.

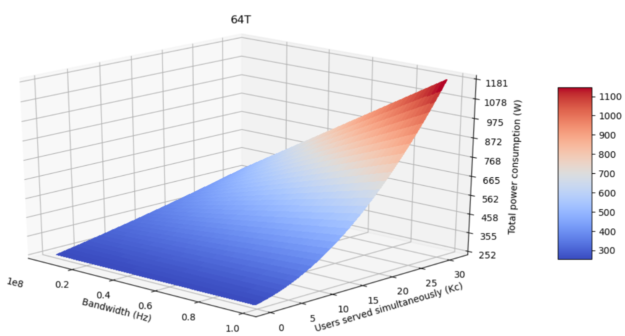

Fig. 2. Variation in the instantaneous power consumption of a 64T BS with bandwidth B and the spatial multiplexing factor K_c.

- *Impact of deep sleep modes on the EC of a BS*

In Fig.3, we analyzed the impact of having deep SMs on the EC of the BS over 24 hours. For this, we considered a SDU (2020) scenario with a peak traffic demand of 1200 $Mbps/km^2$. By activating deep SMs, we were able to achieve up to 57% higher ES during the off-peak hours of the day as compared to the scenario with no SMs. These savings are 40% higher as compared to symbol level SMs commonly implemented in LTE systems.

The impact of SMs varies with the type of BS. For example, in Fig.4 we compared the ES obtained by deploying the two different BS types in an area with a peak traffic demand of 4000 $Mbps/km^2$. This traffic demand is close to what we expect in a SDU scenario in the year 2025. Our results show that by having deep SMs, we obtained about 20% reduction in the daily EC of a 4T BS. This is comparatively lower to the 56% drop in EC observed by deploying a 64T BS in the same area. The higher ES obtained in a 64T BS is due to the higher array and spatial multiplexing gains which result in improved spectral efficiency and lowered BS's activity factor. These enable the BS to switch down to deeper SMs and conserve more energy during the longer idle periods.

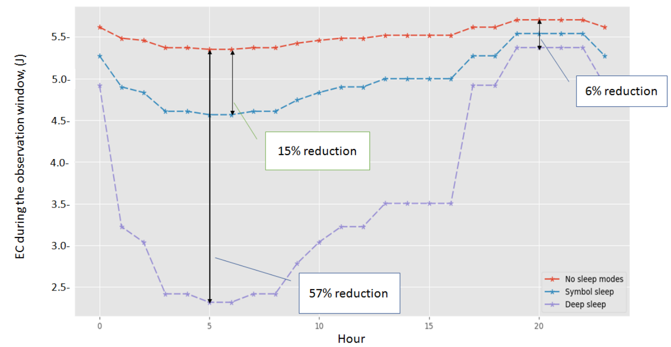

Fig. 3. Relative reduction in the EC of a BS with the activation of different sleep modes.

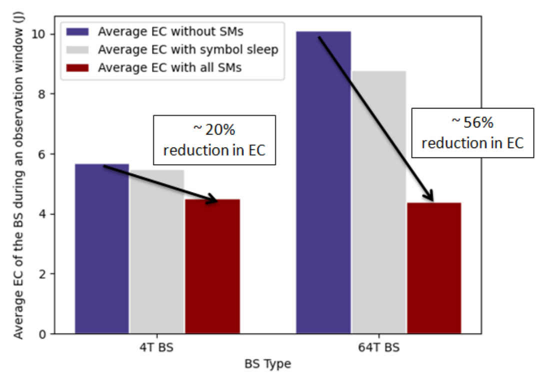

Fig. 4. Impact of deep sleep modes on the average EC of the two BS types in the same deployment scenario.

- *Variation in the EC of the two types of BSs in different deployment scenarios*

In Fig.5, we plot the EC variation of the two BS types in three different deployment scenarios. As seen, the peak traffic demand has a direct impact on the overall EC. In rural scenarios, we find that a 64T BS is energy-inefficient and power-hungry due to the very low (100x times lower) traffic demands in these scenarios as compared to a SDU scenario. Moreover, the higher idle mode PC of a 64T BS as compared to a 4T BS results in an increased overall EC. Whereas in SDU scenarios, the higher spectral efficiencies and array gains obtained by 64T BSs help in serving high traffic demands (UEs) at a faster rate, thereby allowing the BS to switch down to deeper sleep levels to conserve more energy. In such a scenario, we find that a 64T BS consumes up to 60% less energy as compared to a 4T BS. The dependency of the ES on the peak traffic demand highlights the importance of identifying the right type of BS for a deployment scenario.

VII. Conclusion

In this paper, we proposed a novel analytical methodology to simplify the evaluation of the EC of a massive MIMO BS in a network by taking into account the impact of its configuration on its activity factor and PC. By considering the possibility

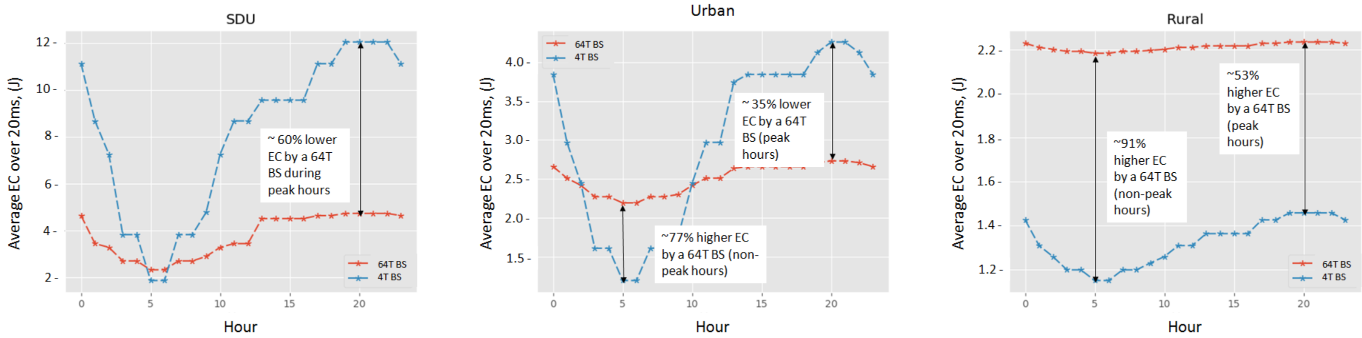

Fig. 5. Variation in the energy consumption of a 4T and 64T BS in three different deployment scenarios (SDU, urban and rural) in the year 2020.

to switch the BS down to deep SMs during the idle periods, we developed a rigorous and detailed mathematical process to evaluate the impact of BS configuration on the overall EC of the BS. Our evaluation results show that the type of BS deployed and its configuration can have a significant impact on the overall network EC in a deployment scenario. In future, one could extend our simplified evaluation methodology to improve a network's EC through BS resource adaptation. One could also study the impact of varying BS resources on the quality of service experienced by the UEs.

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