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An Analytical Energy Performance Evaluation Methodology for 5G Base Stations

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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 combine radio resource adaptation with SMs and propose a dynamic Q-learning based algorithm to adapt a BS's resources according to the traffic demand and reduce its 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 studies the impact of these on the EC of a BS under varying traffic loads. We also consider the benefits of a lean carrier design, spatial multiplexing, massive MIMO, and bandwidth adaptation on the EC of a BS. 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

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 of a BS 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 advantages offered by 5G in terms of flexible signaling periodicity and 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 while 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 features of 5G that could lead to a lower BS EC.

- *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 take one of the following durations: [5, 10, 20, 40, 80, 160] ms [11]–[13]. This flexible periodicity results 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 implement multi-user beamforming to serve multiple users simultaneously. The higher spatial multiplexing gain obtained helps in improving 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 interfering BSs, i.e., $\phi_c = 6$. The BS serves a

total number of active UEs N in time T which are assumed to be uniformly distributed in the cell of radius D_o and have a requirement of Ω MB. The hourly traffic demand ξ is then given by,

$$\xi = N * \Omega \quad (1)$$

If Γ_p represents the peak traffic demand in a deployment areas, then the maximum number of active UEs N_{max} at any point over 24 hrs is given by [7],

$$N_{max} = \frac{\Gamma_p}{\Omega} \quad (2)$$

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:

$$r_k = B_i N_k \log_2 \left(1 + \frac{\mathcal{S}_{k,i}}{\mathcal{I}_k + \mathcal{N}_k} \right) \quad (3)$$

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:

$$\mathcal{S}_{k,i} = \frac{c}{(D_{ik})^\alpha} \frac{|\mathbf{H}_{ik} \mathbf{W}_{ik}|^2}{\|\mathbf{W}_{ik}\|^2} \frac{p_i M_i}{K_c} (M_i - K_c) \quad (4)$$

$$\mathcal{I}_k = \sum_{j=1}^{\phi_c} \frac{c \eta_j}{(D_{jk})^\alpha} \frac{|\mathbf{H}_{jk} \mathbf{W}_{jk}|^2}{\|\mathbf{W}_{jk}\|^2} \frac{p_j M_j}{K_c} (M_j - K_c) \quad (5)$$

$$\mathcal{N}_k = \sigma^2 \|\mathbf{W}_{jk}\|^2 \quad (6)$$

In (4), $\mathcal{S}_{k,i}$ 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 obtained by using larger antenna arrays at the BS [10] contributes to the increase in the signal power received at the UEs and is given by the factor $(M_i - K_c)$. This is the maximum gain that can be obtained considering a zero-forcing (ZF) precoder at the transmitter [10]. D_{ik} and D_{jk} represent the distance 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,

$$R = \sum_{k=1}^{K_c} r_k = \sum_{k=1}^{K_c} B_i N_k \log_2 \left(1 + \frac{\mathcal{S}_{k,i}}{\mathcal{I}_k + \mathcal{N}_k} \right) \quad (7)$$

A. Base station activity factor

The fraction of the total amount of 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,

$$\eta = \frac{\sum_{k=1}^N \frac{\Omega_k}{r_k}}{T} \quad (8)$$

Taking into account the rate experienced by each UE as given in Eq.(3), the activity of the BS can be expressed as,

$$\eta_i = \frac{1}{TK_c} \left[\sum_{k=1}^N \frac{\Omega_k}{B_i N_k \log_2 \left(1 + \frac{S_{ik}}{I_k + N_k} \right)} \right] \quad (9)$$

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]:

$$G_{upperbound} = \left(\sqrt{M_i} + \sqrt{N_k} \right)^2 \quad (10)$$

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

$$\eta_i = \frac{1}{TK_c} \left[\sum_{k=1}^N \frac{\Omega_k}{\max[r_k, r_{max}(M_i, N_k)]} \right] \quad (11)$$

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 BS power model quantifies the variation in the PC of a BS with the load. An accurate power model helps us to analyze the impact of various components on the overall EC of the BS. Furthermore, a model is dependent on the BS type and hence, 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 can be divided into two parts: i) load-dependent PC, and ii) load-independent PC and is expressed as:

$$P_{total} = P_{load-dependent} + P_{load-independent} \quad (12)$$

The load-dependent PC is further divided into the baseband (BB) and PA's PC. The BB PC varies with B_k , 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 of the BS can be expressed as:

$$P_{load-dependent} = P_{baseband} + P_{PA}(p) \quad (13)$$

$$P_{baseband}(M_i, K_c, B_k) = \left[AR_c + \frac{M_i B_k}{L_{bs}} \left(2 + \frac{1}{T_c} \right) \right] K_c + \left(\frac{3B_k M_i}{L_{bs}} \right) K_c^2 + \left(\frac{B_k}{3T_c L_{bs}} \right) K_c^3 \quad (14)$$

$$P_{PA}(p) = M_i \left[\frac{1}{(1+\epsilon)\eta} (p + \epsilon P_{max,PA}) \right] \quad (15)$$

$$P_{load-independent} = P_{syn} + M_i P_{bs} + P_{fixed} \quad (16)$$

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

A. Base station sleep modes

SMs help in reducing the PC of a BS during the idle period by deactivating various hardware resources. In this work, the SMs have been categorized into 4 levels based on the minimum sleep duration and the activation/deactivation time of the hardware resources. The SM characteristics are obtained from [23].

Deeper sleep levels (SM2, SM3 and SM4) reduce the BS's PC by a large amount as more hardware resources are deactivated. However, due to the increased burstiness in the traffic during the peak hours, it might be difficult to switch down to deeper sleep levels that have long transition times. The sleep deltas (*or power consumption reduction factors*) for the various sleep levels used in this work are presented in Table I. Due to 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 PC model of the BS taking into account the various SMs is expressed as:

$$P_{BS}^{5G} = N_s * \begin{cases} P_{total} & \text{if } p > 0 \\ P_B & \text{if } p = 0 \text{ without sleep} \\ \delta_1 P_B & \text{if } p = 0, 72\mu s \leq T_{sleep} < 1ms \\ \delta_2 P_B & \text{if } p = 0, 1ms \leq T_{sleep} < 10ms \\ \delta_3 P_B & \text{if } p = 0, T_{sleep} \geq 10ms \end{cases} \quad (17)$$

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

$$P_B = M_i \left[\frac{1}{(1+\epsilon)\eta} (\epsilon P_{max,PA}) \right] + P_{syn} + M_i P_{bs} + P_{fixed} \quad (18)$$

The EC of the BS during the period T also depends on the transition time to the opted SM T_{ac,δ_i} that the BS switches down to during the idle period and is given by:

$$E_i = \eta_i T N_s P_{total} + \left(\sum_{i=1}^3 S_i \delta_i P_B' \right) (T' - T_{ac,\delta_i}) \quad (19)$$

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

$$E_{total} = E_i \beta A_r \quad (20)$$

TABLE I
POWER CONSUMPTION MODEL PARAMETERS AND THEIR VALUES

Variable	Definition	Value(s)
Power consumption modeling		
R_c	Average UE data rate	
B_k	Bandwidth per UE, k	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	3.5 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 the formula (??) and takes into account the daily traffic variation profile as given in [3]. This variation is assumed to be the same across all deployment areas. According to [3], the percentage of active UEs 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. 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 $R(t)$ using the formula:

$$R(t) = \frac{\rho}{N_{op}} \alpha(t) \sum_a r_a \lambda_a \quad (21)$$

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 the number of operators is assumed to be 1 i.e., $N_{op} = 1$. 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

From Sections III-A and IV, we understood mathematically the impact of bandwidth (BW) on the activity factor and the instantaneous PC of a BS. In Fig.1, we analyzed the impact of BW on the activity factor of a 64T BS deployed in an scenario with a peak traffic demand of 2000 $Mbps/km^2$. We found that by varying the total BW from 5 to 100 MHz, the activity factor of the BS reduces by approximately 26x times. The decrease is due to the increased throughput experienced by the UEs. However, as seen in Fig.2, the total BW used has a significant impact on the instantaneous PC of

a BS. These results highlight the importance of identifying the total BW 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

SMs reduce the EC of the BS during the inactive periods by turning off various hardware resources. Here, we analyzed the impact of having deep SMs on the EC of the BS over 24 hours (see Fig.3). We consider a SDU (2020) scenario with a peak traffic demand of 1200 Mbps/km^2 . We found that deep SMs additionally reduce the EC by up to 57% 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.

We also found that SMs had a varying level of impact on the ES obtained (see Fig.4). For example, we compared the ES obtained by deploying two different types of BSs 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 area in the year 2025. Our results show that by having deep SMs, a reduction of 20% in the daily EC of a 4T BS was obtained. This is much lower when compared to the 56% drop in EC observed by deploying a 64T BS in the same area. The higher reduction in the EC of a 64T BS is due to one main reason, i.e., the higher array and spatial multiplexing gain of a 64T BS improves the spectral efficiency and lowers the BS's activity factor. This enables the BS to switch down to

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

deeper SMs and conserve more energy during the long idle periods.

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

A plot of the EC of the two BS types in three different deployment scenarios (see Fig.5) shows that the peak traffic demand has a direct impact on the overall EC of a BS. In rural scenarios, we find that a 64T BS is energy-inefficient and a power-hungry BS. This is due to the 100x times lower traffic demands in these scenarios as compared to a SDU scenario. Furthermore, the higher idle mode PC of a 64T BS as compared to a 4T BS also results in its higher overall EC. In SDU scenarios, the higher spectral efficiencies and array gains obtained by 64T BSs could help in serving high traffic demands efficiently. As a result, the UEs are served at a faster rate, thereby gaining long idle periods during which the BS can switch down to deeper sleep levels. In such a scenario, we find that a 64T BS consumes up to 60% less energy as compared to a 4T BS. This trend is contrasting in rural scenarios where a 64T BS consumes 60% more energy during the peak hours as compared to a 4T BS during the same period due to the very low traffic demands. These results indicate the importance of identifying the right kind of BS for a deployment scenario based on the peak traffic demands.

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.

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 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.

REFERENCES

- [1] J. Navarro-Ortiz *et al.*, "A Survey on 5G Usage Scenarios and Traffic Models," *IEEE Communications Surveys Tutorials*, vol. 22, no. 2, pp. 905–929, 2020.
- [2] E. Oh *et al.*, "Dynamic Base Station Switching-On/Off Strategies for Green Cellular Networks," *IEEE Transactions on Wireless Communications*, vol. 12, no. 5, pp. 2126–2136, 2013.
- [3] G. Auer *et al.*, "How much energy is needed to run a wireless network?" *IEEE Wireless Communications*, vol. 18, no. 5, pp. 40–49, October 2011.
- [4] M. Masoudi *et al.*, "Green Mobile Networks for 5G and Beyond," *IEEE Access*, vol. 7, pp. 107 270–107 299, 2019.
- [5] A. Krendzel and P. Ginzboorg, "From the rigid hierarchical to flexible flow-based 5G architecture: Dimensioning issues," in *2015 6th International Conference on the Network of the Future (NOF)*, 2015, pp. 1–6.
- [6] R. Bassoli *et al.*, "Analytical energy-efficient planning of 5G cloud radio access network," in *2017 IEEE International Conference on Communications (ICC)*, 2017, pp. 1–4.
- [7] EARTH Project, 2010–2011. <https://cordis.europa.eu/docs/projects/cnect/3/247733/080/deliverables/001-EARTHWP2D23v2.pdf>.
- [8] M. Olsson *et al.*, "Energy performance evaluation revisited: Methodology, models and results," in *2016 IEEE 12th International Conference on Wireless Computing, Networking and Communications (WiMob)*, Oct 2016, pp. 1–7.
- [9] M. M. A. Hossain *et al.*, "Energy Saving Game for Massive MIMO: Coping With Daily Load Variation," *IEEE Transactions on Vehicular Technology*, vol. 67, no. 3, pp. 2301–2313, March 2018.
- [10] —, "Energy-Efficient Load-Adaptive Massive MIMO," in *2015 IEEE Globecom Workshops (GC Wkshps)*, Dec 2015, pp. 1–6.
- [11] F. E. Salem *et al.*, "Advanced Sleep Modes and Their Impact on Flow-Level Performance of 5G Networks," in *2017 IEEE 86th Vehicular Technology Conference (VTC-Fall)*, 2017, pp. 1–7.
- [12] —, "Optimal Policies of Advanced Sleep Modes for Energy-Efficient 5G networks," in *2019 IEEE 18th International Symposium on Network Computing and Applications (NCA)*, 2019, pp. 1–7.
- [13] F. E. Salem *et al.*, "Reinforcement learning approach for Advanced Sleep Modes management in 5G networks," in *VTC-FALL 2018 : 88th Vehicular Technology Conference*. Chicago, United States: IEEE Computer Society, Aug. 2018, pp. 1 – 5. [Online]. Available: <https://hal.archives-ouvertes.fr/hal-02100053>
- [14] M. Masoudi *et al.*, "Reinforcement learning for traffic-adaptive sleep mode management in 5G networks," in *2020 IEEE 31st Annual International Symposium on Personal, Indoor and Mobile Radio Communications*. IEEE, 2020, pp. 1–6.
- [15] S. K. G. Peesapati *et al.*, "Q-Learning Based Radio Resource Adaptation for Improved Energy Performance of 5G Base Stations," in *2021 IEEE 32nd Annual International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC) (IEEE PIMRC 2021)*, Helsinki, Finland, Sep. 2021.
- [16] S. Tombaz *et al.*, "Energy performance of 5G-NX radio access at country level," *2016 IEEE 12th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob)*, pp. 1–6, 2016.
- [17] "Spatial Multiplexing - an overview — ScienceDirect Topics," <https://www.sciencedirect.com/topics/computer-science/spatial-multiplexing>.
- [18] "Designing for the future: the 5G NR physical layer - Ericsson," <https://www.ericsson.com/en/reports-and-papers/ericsson-technology-review/articles/designing-for-the-future-the-5g-nr-physical-layer>.
- [19] (2019) MIMO - Rohde Schwarz. https://cdn.rohde-schwarz.com/pws/dl_downloads/dl_application/application_notes/1sp18/1SP18_10e.pdf.
- [20] G. Andersson *et al.*, "Energy efficient heterogeneous network deployment with cell DTX," in *2016 IEEE International Conference on Communications (ICC)*, May 2016, pp. 1–6.
- [21] "Three design principles of 5g new radio - ericsson," <https://www.ericsson.com/en/blog/2017/8/three-design-principles-of-5g-new-radio>.
- [22] J. B. Andersen, "Array gain and capacity for known random channels with multiple element arrays at both ends," *IEEE Journal on Selected Areas in Communications*, vol. 18, no. 11, pp. 2172–2178, 2000.
- [23] B. Debaillie *et al.*, "A Flexible and Future-Proof Power Model for Cellular Base Stations," in *2015 IEEE 81st Vehicular Technology Conference (VTC Spring)*, May 2015, pp. 1–7.
- [24] "Ericsson mobility report - June 2020," <https://www.ericsson.com/49da93/assets/local/mobility-report/documents/2020/june2020-ericsson-mobility-report.pdf>.