

On the Impact of Recent 5G/6G BS Power Models on Energy Efficiency Studies

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Abstract—Energy efficiency is a central objective in 5G and emerging 6G networks, where base stations (BSs) dominate overall power consumption. While numerous studies propose energy-saving mechanisms, the impact of the underlying BS power model on their evaluation is often overlooked. In this paper, we compare the standardized 3GPP TR 38.864 model and the analytical AAU-based model proposed by Piovesan *et al.* under a unified framework and identical operating conditions. Considering both static and dynamic scenarios with radio-domain adaptations and sleep modes, we show that modeling assumptions significantly influence energy-efficiency results. In particular, our results show that the analytical model predicts up to 30% higher energy-saving gains due to differences in how power consumption scales with system resources. These findings highlight that energy-efficiency evaluations are highly sensitive to the chosen power model, and that conclusions drawn from a single model may not generalize.

Index Terms—5G/6G Networks, Energy Efficiency, Base Station Power Models, Sleep Modes, Energy-Saving Mechanisms, Performance Evaluation.

I. INTRODUCTION

Improving Energy Efficiency (EE) has become one of the main design goals in the deployment of 5G and 6G networks. Base Stations (BSs) are the dominant contributors to overall network power consumption, especially during low-traffic periods when many hardware components operate below full load [1]. Early frameworks such as the EARTH model [2] and, some years later, the GreenTouch/IMEC model [3] provided the first empirical formulations linking power consumption to traffic load and radio configuration. These models paved the way for numerous studies on energy-efficient resource allocation [1], [4], [5] and many others. More recently, we proposed a comprehensive review of sleep-mode strategies for energy saving in next-generation radio access networks [6].

As part of ongoing standardization efforts, the Third Generation Partnership Project (3GPP) introduced the power consumption model defined in TR 38.864 (Release 18), which provides a detailed and standardized representation of BS operation through explicit active downlink/uplink states and three hierarchical sleep modes (micro, light, and deep). The specification defines normalized power levels for reference configurations and specifies transition times and energy parameters, enabling uniform and component-aware evaluations [7]. Since its publication, this model has served as a common foundation

for assessing energy-efficient radio access mechanisms. For example, Laselva *et al.* [8] employed it to investigate multi-domain adaptation strategies combining antenna and transmit-power control, while Borja *et al.* [9] analyzed advanced sleep modes based on discontinuous transmission and reception cycles. Elayoubi *et al.* [10] further extended its use to short-term sleep-mode management through a discrete-time queuing formulation for 5G BSs. Recently, the authors in [11] proposed a Q-learning framework based on the 3GPP TR 38.864 power model to jointly optimize multi-level sleep modes and antenna activation for energy-efficient BS operation.

In parallel, new analytical and data-driven approaches have been developed to refine the representation of base-station energy consumption. Among them, the analytical Active Antenna Unit (AAU) model proposed by Piovesan *et al.* [12] decomposes the total power into baseband, Radio Frequency (RF), and amplifier components, offering a more hardware-oriented view of energy behavior. Recent studies and surveys [6], [13] emphasize that such high-fidelity models are essential for the realistic evaluation and optimization of energy-saving mechanisms in next-generation Radio Access Networks (RANs).

Recent surveys and Reinforcement Learning (RL) studies [6], [13] further highlight the growing importance of accurate and scalable power models for realistic evaluation of energy-saving mechanisms in next-generation RANs.

Despite extensive research on energy-efficient RAN design, the impact of power-model structure on the interpretation of energy-efficiency results remains largely unexplored. As shown in recent studies [8], [9], [10], the 3GPP TR 38.864 model is widely used as a standard reference for evaluating energy efficiency. However, analytical formulations, such as the AAU-based model proposed by Piovesan *et al.* [12], also offer a detailed hardware representation that may lead to different energy-efficiency outcomes. This raises a fundamental question: to what extent are reported energy-efficiency gains intrinsic to the proposed techniques, and to what extent are they influenced by the adopted power consumption model? In this paper, we address this question by conducting a controlled comparative analysis of representative BS power models under a unified evaluation framework, enabling the isolation of intrinsic model-induced effects.

We summarize the main contributions of this paper as

follows:

- We isolate and quantify the impact of power-model structure on energy-efficiency evaluation, showing that model choice induces systematic biases in estimated gains.
- We develop a unified evaluation framework capturing both static operating conditions and dynamic traffic-driven behavior, allowing us to demonstrate that the observed model-dependent bias persists across fundamentally different system regimes.
- We observe that analytical and standardized models can lead to significantly different conclusions (up to 25–30% gap), highlighting the non-neutrality of power-model selection in energy-efficiency studies.

The remainder of this paper is organized as follows. Section II details the two power consumption models and their key differences. Section III presents the study environment. Section IV reports the comparative analysis and simulation results. Section V concludes and outlines future work.

II. POWER CONSUMPTION MODELS

This section presents the two BS power consumption models considered in this study and highlights their fundamental structural differences, which are expected to lead to distinct energy-efficiency behaviors.

A. 3GPP TR 38.864 Power Model

The standardized 3GPP TR 38.864 model provides a unified framework to represent the power consumption of 5G BSs, later extended to 6G studies. It captures the dependence of energy consumption on radio configuration parameters and operating states, including active transmission and multi-level sleep modes. The model decomposes the instantaneous power into a *static* component, independent of the radio load, and a *dynamic* component that scales with the current configuration and traffic activity. Additional *sleep-state* terms account for reduced-power operation during idle periods.

In the active downlink state, the total power is expressed as:

$$P^{DL} = P_{\text{static}}^{DL} + P_{\text{dynamic}}^{DL}, \quad (1)$$

where P_{static}^{DL} includes load-independent contributions such as site cooling, control signaling, and baseband overheads, while P_{dynamic}^{DL} depends on antenna usage, bandwidth, and transmit power.

The dynamic term is divided into two parts: an *antenna-dependent* portion and a *joint* portion that scales with both bandwidth and transmit power:

$$P_{\text{dynamic}}^{DL} = s_a \left(P_{\text{dyn,ante}}^{DL} + \frac{s_f s_p}{\eta(s_f, s_p)} P_{\text{dyn,joint}}^{DL} \right), \quad (2)$$

where s_a , s_f , and s_p denote the antenna, frequency, and power domain scaling factors, respectively, and $\eta(s_f, s_p)$ is the power-amplifier efficiency. The parameter A defines the split between antenna-dependent and joint components, such that $P_{\text{dyn,ante}}^{DL} = A \cdot (P_{\text{active}}^{DL} - P_{\text{static}}^{DL})$ and $P_{\text{dyn,joint}}^{DL} = (1 - A) \cdot (P_{\text{active}}^{DL} - P_{\text{static}}^{DL})$. This formulation implies that

only a fraction of the dynamic power is jointly scaled by the bandwidth and transmit-power factors (s_f and s_p), whereas the remaining fraction depends solely on the antenna scaling factor (s_a).

To compute the average BS power, the active power is weighted by the activity fraction s_t and combined with the power values of the three sleep states:

$$P_{\text{avg}}^{DL} = s_t P^{DL} + s_{SM1} P_{\text{micro}} + s_{SM2} P_{\text{light}} + s_{SM3} P_{\text{deep}}, \quad (3)$$

with $s_{SM1} + s_{SM2} + s_{SM3} = 1 - s_t$.

The 3GPP specification defines multiple reference configurations and BS categories [7]. In this work, we consider a Category 2 BS representative of macro deployments. This formulation introduces partially non-scalable components, which limits the sensitivity of total power consumption to resource adaptation and generally leads to conservative energy-saving estimates.

B. Analytical AAU-Based Model

The analytical model proposed by Piovesan *et al.* [12] offers a hardware-driven representation of 5G AAU power consumption. Unlike the 3GPP TR 38.864 model, it decomposes the total BS power into distinct hardware blocks corresponding to the internal components of an AAU offering a more detailed and physically interpretable view of energy behavior. The model was derived from extensive measurements on thousands of commercial units and refined using a neural-network-based fitting process.

The total AAU power is expressed as a sum of hardware-dependent components:

$$P_{\text{AAU}} = P_0 + P_{\text{BB}} + \underbrace{\sum_{t=1}^T M_{\text{av},t} D_{\text{Tran},t}}_{P_{\text{Tran}}} + \underbrace{M_{\text{ac}} D_{\text{PA}}}_{P_{\text{PA}}} + \underbrace{\frac{1}{\eta} \sum_{c=1}^C P_{\text{TX},c}}_{P_{\text{out}}}, \quad (4)$$

where P_0 denotes the baseline circuitry that remains always active, P_{BB} the baseband processing power, P_{Tran} the power consumed by the transceiver chains, P_{PA} the static power of the multi-carrier power amplifiers (MCPAs), and P_{out} the RF output power required for data transmission. Here, $M_{\text{av},t}$ and M_{ac} denote the numbers of active transceiver and amplifier chains, respectively, while $D_{\text{Tran},t}$ and D_{PA} represent the corresponding normalized power coefficients. $P_{\text{TX},c}$ denotes the transmit power of component carrier c , and η denotes the power-amplifier efficiency.

Each component reflects a specific hardware function within the AAU, enabling a direct mapping between power consumption and hardware activity. In particular, P_{Tran} and P_{PA} depend on the number of active RF chains, while P_{out} is proportional to the transmitted power and amplifier efficiency. This formulation allows low-power states to be modeled as partial deactivations of hardware components. For instance,

during *symbol shutdown*, the MCPAs are temporarily disabled, reducing P_{PA} and P_{out} ; in *carrier shutdown*, the transceivers and amplifiers of selected component carriers are switched off, leaving only $P_0 + P_{\text{BB}}$; and in *deep dormancy*, the baseband section is also turned off, leaving only the baseline circuitry (P_0) active. This hardware-driven representation enables the model to capture the impact of advanced energy-saving mechanisms with high fidelity.

To instantiate the analytical model with realistic values, the model parameters were obtained in [12] by fitting Eq. 4 to synthetic data generated by an artificial neural network trained on measurements from 7,760 commercial AAUs. The resulting parameters are expressed as normalized coefficients with respect to a reference AAU configuration. In particular, $P_0 = 0.22$ and $P_{\text{BB}} = 0.16$, while the transceiver and amplifier coefficients are $D_{\text{Tran}} = 1.47 \times 10^{-3}$ and $D_{\text{PA}} = 3.81 \times 10^{-3}$, with a power amplifier efficiency $\eta = 0.4$. These values correspond to a reference configuration with 64 RF chains and two component carriers. In practice, these normalized coefficients are scaled according to the number of active RF chains, component carriers, and transmit power to obtain the total power in watts. This formulation achieves a balance between realism and tractability, as it provides a compact analytical expression while preserving a clear physical interpretation of hardware behavior.

To enable a direct comparison with the 3GPP TR 38.864 model, we map the hardware-based formulation to the radio-domain scaling factors s_a , s_f , and s_p . Under this mapping, the transceiver and amplifier components scale with the number of active RF chains (s_a), while the RF output power is approximated as scaling with both bandwidth and transmit power ($P_{\text{out}} \propto s_f s_p$). In contrast, P_0 and P_{BB} remain constant, representing always-on circuitry and baseband processing. Under this simplified mapping, the AAU power consumption can be expressed as:

$$P_{\text{AAU}}(s_a, s_f, s_p) = P_0 + P_{\text{BB}} + s_a P_{\text{Tran}} + s_a P_{\text{PA}} + s_f s_p P_{\text{out}}. \quad (5)$$

Unlike the 3GPP formulation in Eq. (2), all scalable terms in Eq. (5) are directly linked to hardware activity, leading to a stronger dependence of total power consumption on resource utilization.

C. Key Structural Differences

The two models differ fundamentally in how power scales with radio-domain parameters, leading to different interpretations of energy-efficiency gains. Indeed, in the 3GPP TR 38.864 formulation (Eq. 2), only part of the dynamic term varies with transmit power and bandwidth, while the remaining components remain fixed. As a result, reductions in the scaling factors lead to limited changes in total power, yielding more conservative energy-saving estimates. Conversely, in the analytical AAU-based model by Piovesan *et al.* (Eq. 4), most hardware blocks, such as transceivers, power amplifiers, and RF output, are directly coupled to the active configuration

TABLE I
MAIN VARIABLES USED IN THE BS POWER MODELS.

Symbol	Description
s_a	Antenna-domain scaling factor
s_f	Bandwidth-domain scaling factor
s_p	Transmit-power scaling factor
A	Fraction of antenna-dependent dynamic power
s_t	Active-time fraction
$s_{SM1}, s_{SM2}, s_{SM3}$	Sleep-state occupancy fractions
P_{static}^{DL}	Static BS power consumption
P_{dynamic}^{DL}	Dynamic BS power consumption
$P_{\text{dyn,ante}}^{DL}$	Antenna-dependent dynamic power
$P_{\text{dyn,joint}}^{DL}$	Joint dynamic power component
P_0	Baseline circuitry power
P_{BB}	Baseband processing power
P_{Tran}	Transceiver-chain power
P_{PA}	Power amplifier power
P_{out}	RF output power
$M_{\text{av},t}$	Number of active transceiver chains
M_{ac}	Number of active amplifier chains
$D_{\text{Tran},t}$	Normalized transceiver power coefficient
D_{PA}	Normalized amplifier power coefficient
$P_{\text{TX},c}$	Transmit power of component carrier c
η	Power-amplifier efficiency

parameters (s_a, s_f, s_p). This formulation provides stronger sensitivity to resource adaptation and thus predicts higher potential savings.

Overall, the 3GPP model provides a standardized system-level representation suitable for comparative evaluations, whereas the Piovesan model offers a hardware-oriented formulation with greater sensitivity to resource adaptation. These structural differences translate into distinct EE behaviors and can significantly influence the estimated gains of energy-saving mechanisms. Table II summarizes the main differences between the two models and their implications for energy-efficiency evaluation.

III. SYSTEM MODEL

The comparative analysis is conducted in a controlled single-cell downlink scenario, where a 5G BS serves multiple users uniformly distributed within its coverage area. A single-cell setup is intentionally adopted to isolate structural power-model effects and ensure that observed differences arise from the power-model formulation rather than inter-cell interference or coordination mechanisms. The setup represents a typical macro-cell deployment in the FR1 band, with a system bandwidth of 100 MHz at 3.5 GHz carrier frequency. The base station operates with up to $N_{\text{tx,total}} = 64$ transmit chains and a maximum total radiated power of 320 W when fully active [12], [8]. Fifty users are randomly deployed within an annular region bounded by the radii R_{min} and R_{max} around the BS, as shown in Fig. 1, to avoid placing users too close to the BS. Traffic arrivals follow a Poisson process with independent rates per user.

Energy-aware operation is modeled through three radio adaptation factors: (i) antenna scaling s_a , representing the fraction of active transmit chains; (ii) bandwidth scaling s_f ,

TABLE II
SUMMARY OF KEY DIFFERENCES BETWEEN THE TWO BS POWER MODELS AND THEIR IMPACT ON ENERGY-EFFICIENCY EVALUATION.

Aspect	3GPP TR 38.864	Piovesan Analytical Model	Impact on EE Evaluation
Model type	Standardized, empirical	Analytical, hardware-driven	Different modeling philosophies may lead to different estimates of achievable energy savings.
Structure	Static + dynamic terms	Component-based (BB, RF, PA, output)	Hardware-level decomposition captures adaptation effects more explicitly.
Power scaling source	Empirical scaling factors	Physical hardware components	Power reductions are more directly linked to resource adaptation.
Adaptation mechanism	Radio-domain scaling (s_a, s_f, s_p)	RF chains, amplifiers, and output power	Adaptation actions have stronger impact on power consumption.
Scaling behavior	Partial (only joint term scales)	Linear with (s_a, s_f, s_p)	Typically yields larger predicted energy-saving gains.
Sleep-state modeling	State-based (SM1/SM2/SM3)	Component-based (hardware shutdown)	Can increase sensitivity to low-load operation and sleep opportunities.
Calibration	Generic 3GPP reference sets	Fitted from real measurements	Provides greater hardware realism but less standardization.
Granularity	System-level abstraction	Hardware-level representation	Suitable for detailed optimization studies.
Use case	Standardization, comparability	Fine-grained analysis, optimization	May provide an upper bound on achievable energy savings.

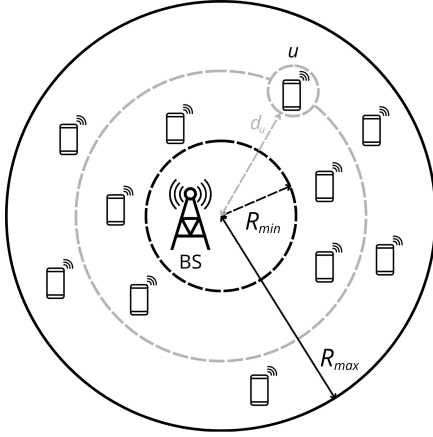


Fig. 1. Single-cell scenario with users uniformly distributed in the annulus $[R_{\min}, R_{\max}]$.

corresponding to the fraction of occupied resource blocks; and (iii) transmit power scaling s_p , defining the ratio between the actual and nominal transmit power. These parameters jointly influence both the achievable rate and the instantaneous power consumption, while their impact differs across the two power models due to their distinct scaling structures. This makes them central to the comparative analysis of energy–latency trade-offs and to revealing model-dependent behavior.

To emulate low-load traffic conditions, the AAU includes a multi-level sleep-state controller with four operating modes: ACTIVE, MICRO, LIGHT, and DEEP. When the transmission queue remains empty for longer than predefined inactivity thresholds τ_{MICRO} , τ_{LIGHT} , and τ_{DEEP} , the BS transitions sequentially toward deeper sleep levels, reducing its steady power consumption. Each state is characterized by a constant power level and a wake-up delay during which no packets are

TABLE III
SLEEP-MODE PARAMETERS FOR THE BS STATE MACHINE.

State	Power [W]	Wake-up time [ms]	Inactivity threshold [ms]
ACTIVE	32.0	–	–
MICRO (SM1)	5.5	2	2
LIGHT (SM2)	2.1	10	10
DEEP (SM3)	1.0	50	50

transmitted, as summarized in Table III. As in prior work [8], [14], we neglect wake-up energy. This assumption allows isolating the impact of steady-state power modeling and sleep-state transitions without introducing additional dependencies on hardware-specific transients, which are beyond the scope of this comparative study. For simplicity and consistency with common modeling practices in the literature [5], the inactivity thresholds and wake-up times are set to equal values for each sleep mode. While this simplified setup enables a clear isolation of model-induced effects, extending the analysis to multi-cell and interference-limited scenarios remains an important direction for future work.

Both the standardized 3GPP TR 38.864 model and the analytical AAU-based formulation by Piovesan *et al.* [12] are instantiated under this common configuration. At the fully active operating point ($s_a = s_f = s_p = 1$), the two models are calibrated to yield the same total power, ensuring that any observed differences arise solely from their structural formulation rather than parameter mismatches. Indeed, to evaluate their response under varying operating conditions, the system performs a parametric sweep over the scaling factors (s_a, s_f, s_p), which respectively control the fraction of active antenna chains, the occupied bandwidth portion, and the transmit power ratio. Each variation reflects a different radio-domain adaptation strategy (antenna muting, bandwidth reduction, or transmit-power scaling) and directly influences both the instantaneous power consumption and achievable data

rate, as later analyzed in Section IV.

We define the following performance metrics used to evaluate the impact of the considered adaptation strategies.

1) **Achievable rate:**

$$R(s_a, s_f, s_p) = s_t \cdot s_f \cdot L(s_a) \log_2(1 + \text{SNR}(s_a, s_f, s_p)), \quad (6)$$

where s_t is the active-time fraction and $L(s_a)$ the number of spatial layers associated with the antenna activation ratio. The $\text{SNR}(\cdot)$ denotes the received signal-to-noise ratio, which depends on the transmit power, bandwidth, and channel attenuation. It is computed from the link budget as follows:

$$\text{SNR}_{\text{dB}}(s_a, s_f, s_p) = P_{\text{tx,dBm}}(s_a, s_p) + G_{\text{AE}} + G_{\text{UE}} - PL(d) - X_\sigma - N_{\text{dBm}}(s_f), \quad (7)$$

where the total transmit power is expressed as:

$$P_{\text{tx}}(s_a, s_p) = s_a s_p N_{\text{tx,total}} P_{\text{TX,chain}}, \quad (8)$$

and the receiver noise power over the occupied bandwidth is given by

$$N_{\text{dBm}}(s_f) = -174 + 10 \log_{10}(s_f B) + NF. \quad (9)$$

Here, $PL(d)$ denotes the path loss at distance d . $X_\sigma \sim \mathcal{N}(0, \sigma_{\text{sh}}^2)$ denotes the log-normal shadowing component, with σ_{sh} being the shadowing standard deviation. G_{AE} and G_{UE} are the BS and UE antenna gains, respectively, and NF is the receiver noise figure. The linear SNR used in the achievable-rate expression is obtained as

$$\text{SNR}(s_a, s_f, s_p) = 10^{\frac{\text{SNR}_{\text{dB}}(s_a, s_f, s_p)}{10}}. \quad (10)$$

2) **Latency:**

$$T_{\text{tx}}(s_a, s_f, s_p) = \frac{N_{\text{bits}}}{R(s_a, s_f, s_p)}, \quad (11)$$

where N_{bits} denotes the packet size requested by the user. The relative latency on the other hand increases with respect to the fully active baseline as follows:

$$\Delta T_{\%} = 100 \times \left(\frac{T_{\text{tx}}(s_a, s_f, s_p)}{T_{\text{tx}}(s_a = 1, s_f = 1, s_p = 1)} - 1 \right). \quad (12)$$

3) **Energy per bit:**

$$E_{\text{bit}}(s_a, s_f, s_p) = \frac{P_{\text{active}}(s_a, s_f, s_p) T_{\text{tx}}(s_a, s_f, s_p)}{N_{\text{bits}}}. \quad (13)$$

4) **Normalized Energy Saving (NES):**

$$\Delta E_{\%} = 100 \times \left(1 - \frac{E_{\text{bit}}(s_a, s_f, s_p)}{E_{\text{bit}}(s_a = 1, s_f = 1, s_p = 1)} \right), \quad (14)$$

where the trade-off between $\Delta E_{\%}$ and $\Delta T_{\%}$ quantifies the efficiency of each adaptation, with Pareto-optimal configurations located near the top-left of the NES–latency plane.

TABLE IV
MAIN PARAMETERS USED IN THE SYSTEM-LEVEL STUDY.

Parameter	Symbol / Unit	Value
Carrier frequency	f_c [GHz]	3.5
System bandwidth	B [MHz]	100
Total TX chains	$N_{\text{tx,total}}$	64
TX power per chain	$P_{\text{TX,chain}}$ [W]	5.0
Antenna gain (BS / UE)	$G_{\text{AE}}/G_{\text{UE}}$ [dBi]	8 / 5
Receiver noise figure	NF [dB]	7.0
Shadowing std. dev.	σ_{sh} [dB]	8.0
Number of users	K	50
User distance	$[R_{\text{min}}, R_{\text{max}}]$ [m]	[0.125 500]
Traffic model	—	Poisson arrivals
Packet size	N_{bits} [kB]	50
Packet arrival rate per user	λ_a [pkt/s]	1
Slot duration	Δt [ms]	0.5
Simulation time	T_{sim} [s]	100

IV. PERFORMANCE EVALUATION

To assess how structural differences between power models affect system-level behavior, we conduct a comparative evaluation using a unified simulation framework. The objective is to quantify how model assumptions influence the performance metrics defined in Section III, including energy efficiency, latency, and sleep-state utilization. The main simulation parameters are listed in Table IV, defining the common configuration adopted for both models.

A. Static Comparison: NES–Latency Trade-off

Figures 2 and 3 show the normalized energy saving (NES) versus excess latency for antenna (s_a), transmit-power (s_p), and bandwidth (s_f) scaling, computed according to equations (12) and (14). The parameters s_a and s_p are varied over the vector $[1.0, 0.75, 0.5, 0.25, 0.125]$, while s_f is sampled with finer granularity at smaller values to capture its non-linear behavior. In all cases, both models exhibit the expected energy–performance trade-off: reducing resources decreases power consumption, but increases transmission delay. However, the Piovesan model consistently yields higher NES gains at the same latency cost, confirming the analytical interpretation discussed in Section II. The largest gap occurs for power scaling (s_p), where Piovesan model’s total power decreases almost linearly with s_p , while the 3GPP model retains a non-scaling portion of dynamic power. For antenna scaling (s_a), both show monotonic savings, but Piovesan achieves steeper gains thanks to explicit scaling of the transceiver and amplifier terms. In contrast, bandwidth scaling (s_f) produces an apparent degradation of the NES, as reducing bandwidth inherently lowers the number of transmitted bits per second, increasing the transmission time and thus the computed energy per bit. This effect stems from the definition of the metric shown in equations (13) and (14) rather than from the model behavior. The Piovesan model consistently predicts higher energy-saving gains, since its RF output term scales linearly with s_f , partially offsetting the throughput loss. This behavior highlights that metric definition plays a critical role in interpreting energy-efficiency results, particularly under bandwidth adaptation.

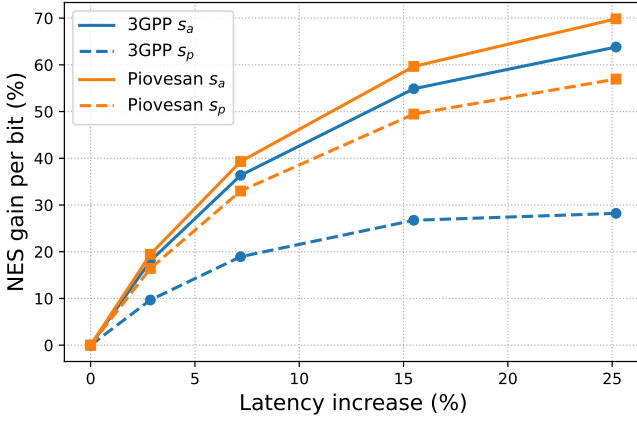


Fig. 2. Normalized energy saving vs. latency increase for antenna and transmit-power adaptations (s_a , s_p).

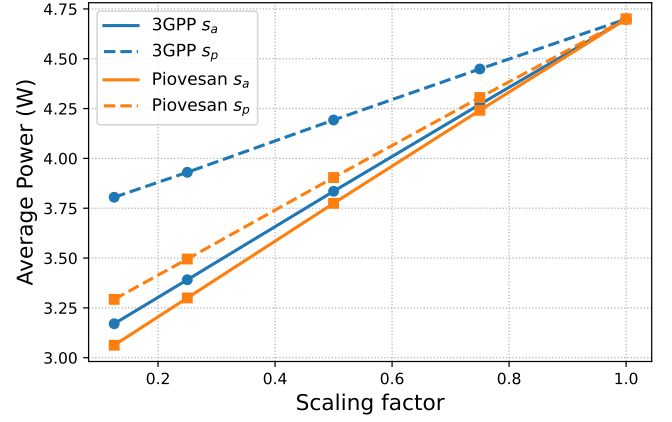


Fig. 4. Average BS power versus antenna and transmit-power scaling factors s_a and s_p .

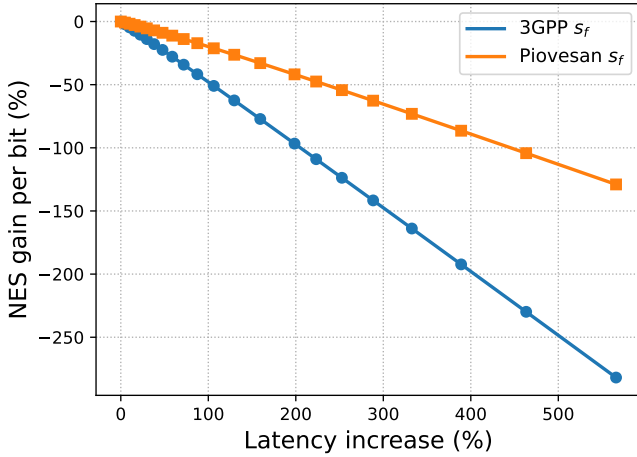


Fig. 3. Normalized energy saving vs. latency increase for bandwidth scaling factor s_f . When the bandwidth share is reduced (i.e., as the scaling factor s_f decreases), both latency and energy consumption increase, resulting in negative energy savings.

B. Dynamic Results: Traffic and Sleep States

The dynamic analysis extends the study to non-stationary traffic, where packet arrivals follow a Poisson process and the BS can enter the MICRO, LIGHT, or DEEP sleep states depending on queue occupancy and inactivity thresholds. Figures 4 and 5 report the resulting average power levels across different scaling factors.

For all configurations, the Piovesan model predicts lower total and active power than the 3GPP formulation, along with higher sleep-state utilization. This stems from its hardware-level granularity: in the Piovesan model, the transceiver and amplifier terms scale proportionally to the number of active RF chains and output power, producing stronger energy sensitivity. An exception to the overall linear trend can be observed in Fig. 5, which reports the average power versus bandwidth scaling (s_f). In this case, the corresponding active power trend shown in Fig. 6 is included to highlight the different

behavior observed for frequency adaptation. While the active power decreases almost linearly with s_f , since both models scale proportionally with the occupied bandwidth, the average power curve flattens and slightly rises for small s_f values ($s_f \leq 0.25$). This deviation arises from the interaction between traffic dynamics and sleep-state control: as s_f decreases, the transmission rate drops, causing longer queue occupancy and an increased active-time fraction s_t . As a result, the BS remains active for a larger portion of time, reducing its opportunity to enter low-power states and raising the average power despite the lower instantaneous consumption.

For the antenna (s_a) and transmit-power (s_p) adaptations, the relationship between average and active power remains consistent across both models, exhibiting a nearly linear dependence on the scaling factor. The Piovesan formulation continues to show lower absolute power levels and stronger sensitivity to scaling, while the 3GPP model retains non-scalable dynamic terms, leading to a more conservative estimation. These results further indicate that model structure not only affects instantaneous power scaling but also interacts with traffic dynamics and sleep-state behavior, reinforcing the observed model-dependent bias.

C. Physical Interpretation and Discussion

Across both analyses, the results quantitatively confirm the trends predicted by the analytical reasoning of Section II. The 3GPP TR 38.864 model keeps part of its power consumption fixed regardless of adaptation depth, leading to conservative energy-saving estimates. In contrast, the Piovesan model proportionally scales all major components (baseband, transceivers, amplifiers, and RF output) with the active configuration, yielding a steeper NES–latency curve and higher sensitivity to parameter variations. From a system-design perspective, this implies that the Piovesan model provides an upper bound on achievable energy savings, physically interpretable and suitable for short-term analyses, whereas the 3GPP model remains more appropriate for standardized large-scale evaluations. These findings confirm that the choice of

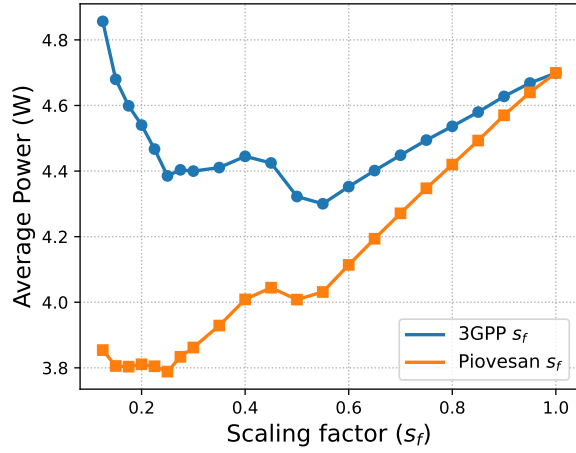


Fig. 5. Average BS power versus bandwidth scaling factor s_f .

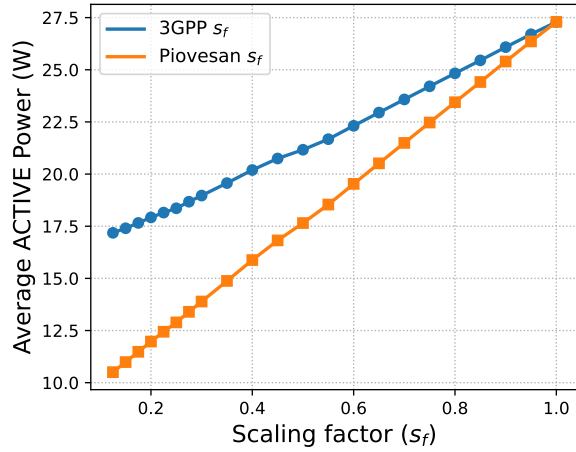


Fig. 6. Average active power versus bandwidth scaling factor s_f .

power model is not neutral and must be explicitly considered when evaluating energy-efficiency mechanisms in 5G/6G networks.

V. CONCLUSION AND FUTURE WORK

This paper investigated the impact of BS power-model selection on energy-efficiency evaluation in 5G/6G radio access networks by comparing the standardized 3GPP TR 38.864 model and the analytical AAU-based model proposed by Piovesan et al. [12]. Using a unified simulation framework, we showed that structurally different models lead to significantly different energy-saving estimates and energy-latency trade-offs, even under identical operating conditions. In particular, the Piovesan model consistently predicts higher gains (up to 30%) due to its stronger coupling between power consumption and hardware activity, whereas the 3GPP model yields more conservative estimates because of partially non-scalable components. These results demonstrate that the choice of power model is not neutral and directly influences the perceived

effectiveness of energy-saving strategies, implying that conclusions from energy-efficiency studies must be interpreted with respect to the underlying modeling assumptions. While the simplified single-cell setup enables clear isolation of structural effects, future work will extend the analysis to multi-cell and interference-limited scenarios.

ACKNOWLEDGMENT

This work has benefited from a government grant managed by the Agence Nationale de la Recherche under the France 2030 program, reference "ANR-22-PEFT-0008".

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