

MAC-SCH-Level Traffic Analysis for Energy Saving in 5G/Pre-6G gNBs

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Abstract—This paper presents an experimental study on real-time traffic characteristics in commercial 5G NR gNBs for energy-saving applications. Using a 4K YouTube streaming scenario with TTI-level data collection (0.5 ms granularity), we analyze traffic dynamics at the MAC level, revealing repetitive burst/idle patterns. By mapping idle intervals into advanced sleep modes (ASM), we show that up to 18% energy savings can be achieved compared to full-load operation. Unlike conventional approaches relying on long-term traffic statistics, our study emphasizes fine-grained, scheduler-level traffic analysis in real environments, providing practical insights for both Rel-15/16 deployments and future Pre-6G networks. This experimental evaluation forms a foundation for embedding AI-driven energy-saving control into commercial base stations.

Keywords— 5G, Pre-6G, MAC scheduling, traffic analysis, energy saving, advanced sleep mode.

I. INTRODUCTION

With the evolution of next-generation cellular networks, energy efficiency has become a critical challenge in the design and operation of radio access networks (RAN). Base stations account for the majority of network energy consumption, consuming significant power regardless of traffic load. Most existing approaches to network energy saving (NES) have focused on long-term traffic patterns or control-plane mechanisms such as radio resource control (RRC) and radio resource management (RRM), but these methods suffer from a lack of responsiveness and fine-grained control [1].

To address these limitations, Advanced Sleep Mode (ASM) has been recently discussed in open-RAN (O-RAN) and the third generation partnership project (3GPP) Release 18 (Rel-18) onwards [2]–[4]. ASM extends conventional DTX/DRX mechanisms and enables more fine-grained power control at the MAC scheduler (MAC-SCH) level, making it a key candidate for future energy-saving features in base stations. The proposed AI-based NES integration in this paper also operates at the MAC-SCH level, which highlights its technical similarity to ASM. However, the significance of this work lies not only in its relevance to pre-6G systems, but also in demonstrating a practical trial approach for applying AI and NES techniques to currently deployed Rel-15/16 commercial base stations.

II. SYSTEM ARCHITECTURE OF 5G/PRE-6G GNBS

The 5G NR networks used in this study is an commercialized system developed by the Intelligent RAN SW Research

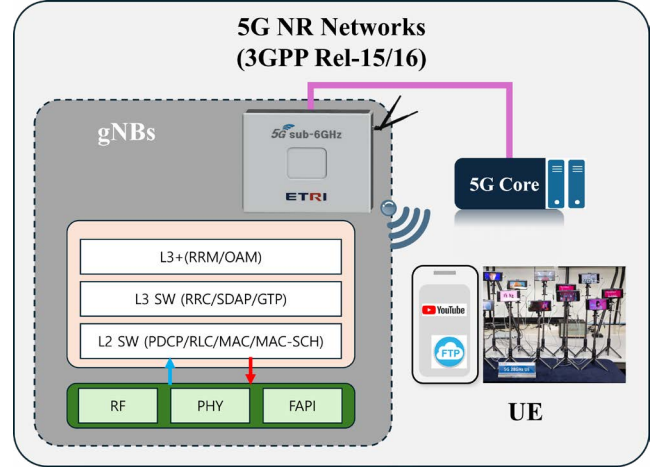


Fig. 1. Structure of 5G NR Networks

TABLE I. Specification of gNB and UE in the ETRI 5G Testbed [5]

Component	Description
gNB	5G NR Rel.15/16, n78 (3.5 GHz), TDD, 100 MHz BW 2×2 MIMO, 24 dBm/port Tx power Qualcomm. FSM10056 RRH NXP 20XX H/W platform
UE	Samsung Galaxy S20, Snapdragon X55 modem NSA mode, Band n78 support
Features	L2 logging interface (RLC, MAC, MAC-SCH Information)

Section of the Electronics and Telecommunications Research Institute (ETRI), South Korea, compliant with 3GPP Rel-15/16 standards and operating in the sub-6 GHz band [5]. Fig. 1 illustrates the basic interconnection between the gNB, 5G core, and user equipment (UE). The gNB consists of RF front-end, physical layer (PHY), and FAPI interface, along with higher protocol layers. The L2 software includes PDCP, RLC, MAC, and MAC-SCH modules, while the L3 software provides RRC, SDAP, and GTP functionalities. Furthermore, RRM and operations, administration, and maintenance (OAM) functions are supported at the L3+ level.

Table I summarizes the specifications of the ETRI 5G NR base station used in this experiment. Notably, the system is equipped with a Qualcomm FSM10056 chipset and standardized protocol stacks, enabling interoperability with commercial UEs such as the Samsung Galaxy S20. This architecture ensures operation at the level of commercial networks and provides a practical platform for verifying the applicability of the proposed AI-NES module.

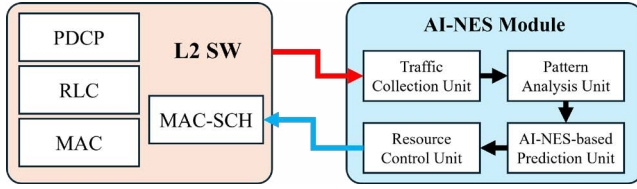


Fig. 2. The proposed AI-NES for Pre-6G Mobile Networks

III. AI-NES MODULE DESIGN AND INTEGRATION

The proposed AI-NES architecture directly interacts with the MAC-SCH module in the L2 layer of the 5G NR gNB, operating at the TTI level (approximately 0.5 ms). Fig. 2 illustrates the interaction between the L2 SW and the AI-NES module.

The AI-NES module consists of four functional blocks. The Traffic Collection Unit gathers real-time traffic information from the MAC-SCH, such as PRB utilization, RLC SDU size, and DL throughput. This information is processed by the Pattern Analysis Unit, which extracts features that reflect short-term traffic variability. The AI-NES-based Prediction Unit then applies machine learning or deep learning models to predict resource demand and usage patterns for the upcoming slot. Finally, the Resource Control Unit translates the prediction results into scheduling policies, which are fed back into the MAC-SCH to optimize resource allocation and reduce unnecessary power consumption.

Unlike conventional approaches that rely on long-term traffic statistics, the proposed method enables fine-grained, slot-level prediction and control. Moreover, the architecture can be integrated into commercial Rel-15/16 gNBs without significant modifications, thus allowing practical validation in real-world networks. It is worth noting that, although the proposed AI-NES framework includes all four functional units, in this study we implemented only the Traffic Collection and Pattern Analysis Units. These modules enable TTI-level traffic logging and statistical analysis, serving as the foundation for validating the feasibility of fine-grained data acquisition in commercial gNBs. The AI-based Prediction and Resource Control Units are left for future integration.

IV. TRAFFIC CHARACTERISTICS AND ENERGY-SAVING IMPLICATIONS

In this section, we focus on the implemented part of the proposed AI-NES framework, namely the Traffic Collection and Pattern Analysis Units. While the full architecture also includes prediction and control modules, in this study we limited our implementation to real-time data acquisition and statistical analysis. To this end, we conducted real-time traffic analysis by streaming a 2160p (4K) YouTube video for approximately 86 seconds using a commercial UE, while collecting TTI-level data from the gNB's L2 software. The first 4 seconds, corresponding to initialization and buffer filling, were discarded, and thus the analysis is based on the remaining 82 seconds of stable traffic. Fig. 3 illustrates six key indicators obtained from the measurements.

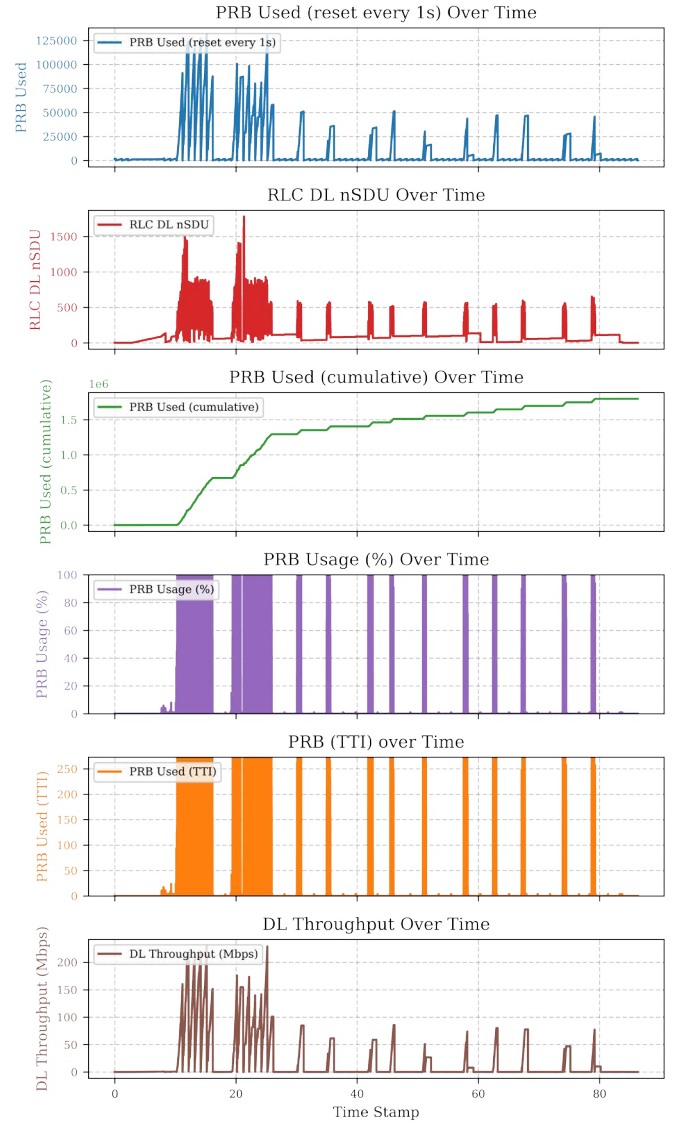


Fig. 3. Real time YouTube streaming traffic patterns analysis.

A. Measurement and Traffic Characteristics

First, PRB usage exhibits sharp increases during burst periods, followed by near-zero levels during idle periods. Second, RLC DL nSDU, collected from the RLC layer, shows bursts of SDUs arriving intensively within short intervals. Third, the cumulative PRB usage reflects the overall resource consumption, with steep increments observed in burst phases. Fourth, PRB usage ratio occasionally reaches 100%, indicating extremely high instantaneous load. Fifth, TTI-level PRB usage clearly demonstrates burst/idle patterns even within sub-millisecond time scales. Finally, DL throughput surges to several hundred Mbps during burst intervals but drops rapidly in idle intervals.

These results confirm that YouTube traffic inherently exhibits repetitive burst/idle patterns at very short timescales, which cannot be fully captured by long-term traffic models. The presence of such idle gaps highlights significant opportunities for energy saving when advanced sleep modes are employed in the gNB.

TABLE II. Estimated Power of FSM10056-Based 2×2 Small Cell (24 dBm/port) [8], [9]

Mode	Coefficient (α)	Power (W)
Full load	1.00	40.0
Micro sleep	0.675	33.5
Light sleep	0.55	31.0
Deep sleep	0.23	24.6

TABLE III. Energy Saving Evaluation Results

Metric	Baseline	ASM-enabled	Unit
Avg. Power	40.0	32.85	W
Energy Consumption	3280	2693.5	J (82 s)
Relative Reduction	–	18.0	%
Sleep Mode Distribution			
Mode	Baseline (%)	Proposed (%)	Duration (s)
Full load	100	17.1	14
Micro sleep	–	3.7	3
Light sleep	–	76.8	63
Transition	–	2.4	2

B. Power Model and Energy-Saving Results

We adopt a simplified power budget model for a commercial 2×2 indoor small cell with 24 dBm per-port output power. Based on typical vendor specifications, the full-load power consumption is approximately 40 W [6]–[8]. Using ASM coefficients reported in [9], the power of each mode is

$$P_{\text{mode}} = P_{\text{fixed}} + \alpha \cdot P_{\text{RU}}, \quad (1)$$

where P_{fixed} denotes baseband/synchronization/power-supply overhead (≈ 20 W), P_{RU} the radio-unit portion (≈ 20 W), and α the ASM factor ($\alpha = 1.0$ full-load; 0.675 micro; 0.55 light; 0.23 deep [9]). It is noted that P_{fixed} may vary depending on the hardware platform, implementation details, and deployment configuration, and the 20 W value adopted here represents a typical assumption for indoor small cells.

Given a measured profile of 82 s in total, where the gNB operated for 14 s in the Full-load state, 3 s in the ASM Micro-sleep state, 63 s in the ASM Light-sleep state, and 2 s in Transition, the average power $\bar{P}$ is derived from the time-weighted mean of each mode.

$$\bar{P} = \frac{\sum_i P_i t_i}{\sum_i t_i}, \quad (2)$$

and the consumed energy is

$$E = \sum_i P_i t_i. \quad (3)$$

For a conservative assumption where the transition interval is treated as full-load ($P_{\text{tr}} = 40$ W), inserting $P_{\text{full}} = 40$, $P_{\mu} = 33.5$, $P_{\ell} = 31.0$ W and $t_{\text{full}} = 14$, $t_{\mu} = 3$, $t_{\ell} = 63$, $t_{\text{tr}} = 2$ s into (2)–(3) yields

$$E = 40 \times 14 + 33.5 \times 3 + 31.0 \times 63 + 40 \times 2 = 2693.5 \text{ J},$$

$$\bar{P} = \frac{2693.5}{82} \approx 32.85 \text{ W},$$

which corresponds to an $\approx 18\%$ reduction compared to continuous full-load operation (40 W). This demonstrates that mapping burst/idle intervals to suitable ASM states, informed by TTI-level prediction, can provide tangible energy savings under practical traffic.

V. CONCLUSION AND FUTURE WORK

In this work, we demonstrated the feasibility of real-time traffic analysis for energy-saving opportunities in commercial 5G NR gNBs. By collecting TTI-level traces during 4K YouTube streaming, we observed clear burst/idle traffic patterns that provide a foundation for short-timescale power adaptation. Applying ASM to these idle intervals enabled an estimated 18% reduction in average power consumption for a 2×2 small cell. Unlike conventional approaches relying on long-term statistics, our framework highlights the potential of fine-grained, MAC-level control. Moreover, the proposed data collection structure serves as a preliminary step toward AI-NES integration, where intelligent prediction modules can guide ASM decisions in real time. As future work, we plan to embed AI models directly into gNB platforms to enable on-device inference and extend analysis to multi-user scenarios. These efforts will further strengthen the practicality of AI-driven energy saving in next-generation RANs.

ACKNOWLEDGEMENTS

This work was supported by Institute of Information & communications Technology Planning & Evaluation (IITP) grant funded by the Korea government(MSIT) (No.RS-2024-00395824, Development of Cloud virtualized RAN (vRAN) system supporting upper-midband)

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