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Energy Modelling of Mobile Network Components

Riya Asthana[1]
[1]Jamnabai Narsee International School, Mumbai, India

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***Abstract*: The substantial rise in global data traffic has significantly increased energy consumption in mobile networks, leading to higher operational costs and environmental concerns. This paper presents a detailed energy modeling approach for critical mobile network components. By developing mathematical models for computing, processing, and memory resources, this study identifies a considerable energy proportionality gap in core computing, where servers maintain a baseline power consumption of 40-60% even during idle periods. Further, comparative analysis reveals that the RAN is the most demanding energy user, accounting for 70-85% of total network power. The results demonstrate that while load reduction offers minor gains, implementing advanced deep sleep states in base stations can reduce power consumption by up to 85%. Strategic energy management must target the major power consumption of the RAN and the high idle power of core resources to achieve meaningful sustainability benefits.**

Keywords: Mobile Network, Energy Modeling, Radio Access Network, Core Network, Computing resources, Processing resources, Memory resources

1. Introduction

The proliferation of mobile devices and networks has led to an exponential surge in data traffic worldwide. Driven by the rapid growth of new, evolving technologies and network infrastructures, this rise in energy consumption is contributing to a substantial carbon footprint and raising serious environmental concerns for network operators. Additionally, it is forcing them to increase their functioning capacity by means of newer and bigger architectures, which also significantly raises running costs. Among the various contributors to this energy demand, mobile network components occupy a particularly extensive role in the total power consumption. To optimize power utilization and reduce operative expenses, it is crucial to model the energy consumption and the behavior of these components with accuracy and precision.

2. Components of Mobile Network

A. The Core Network

The core network, as its name suggests, is the central backbone of all mobile networks. It integrates a range of functions such as the authentication and security of subscribers’ data, management of data traffic, interconnection between end users and external packet data networks, and records usage for billing.

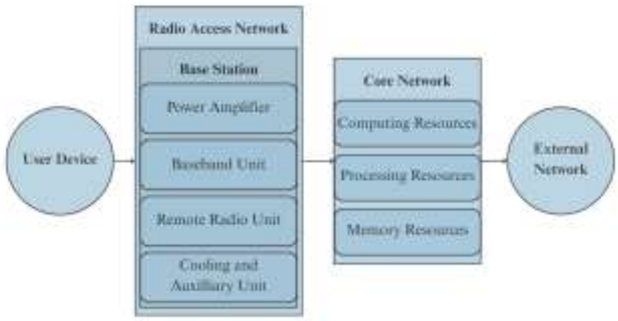

Fig. 1. Components of the Mobile network

It serves as the control and data-processing hub of mobile communication systems. As a consequence of the gradation from hardware-centric designs to cloud-based and virtualized architectures, the energy depletion of the core has remarkably increased. Bellin et al. (2025) states that "deployment choices, such as virtualization framework and 5GC software, can significantly impact on the power consumption of the network" [1], and essentially highlights the fact that the energy consumption of the core network is not driven solely by its functions, but also by the underlying computing, processing, and memory resources that support it.

1) Computing Resources

Computing resources in the core are the processing elements, typically CPU cores and GPUs deployed in data centers, that are responsible for running virtualized network functions (VNFs) required for control-plane and user-plane services. These resources are workload-dependent - reaching near peak utilization during high traffic periods, while even at idle periods they sustain substantial baseline power usage as the servers are kept powered on. For instance, even at a low load, they consume often 40-60% of peak power usage which is a major cause of inefficiencies in energy proportionality [2]. Since core functions have now become software based, precise energy modelling of CPU/GPU utilization, I/O bandwidth, and memory employment is critical for energy-efficient development, dynamic scaling, and maintaining sufficient processing capacity without excessive idle power consumption.

2) Processing Resources

Processing resources refer to central processors (CPUs), accelerators (GPUs, FPGAs), and specialized network processors (NPUs, DPUs) and hold the analytical and storage capabilities of the core network. They are vital components that not only manage, process, and route all traffic, but also execute the packet forwarding, encryption/decryption, deep packet inspection and protocol stack functions. These details are power-intensive and can account for a massive share of the system's energy usage. The power consumption is highly traffic-dependent, and during peak load, these resources draw close to maximum power. However, this energy use is often not linear to the load, and even during low traffic, they consume a baseline power due to leakage currents, background tasks, and virtualization overheads. As Ge et al. (2017). report, "Simulation results reveal that more than 50% of the energy is consumed by the computation power at 5G small cell BS's. Moreover, the computation power of 5G small cell BS can approach 800 watt when the massive MIMO (e.g., 128 antennas) is deployed to transmit high volume traffic." [3]. This illustrates the significant role of processing resources in dense deployments, where the power may account for over 50% of the total consumption.

3) Memory Resources

Memory resources are responsible for storing and processing massive amounts of data, and signaling traffic from the vast amount of users. In depth, they maintain user session states, control-plane databases, and temporary data buffers. The power utilized by these resources is proportional to the quantity of data being accessed and processed. They consume less energy than CPUs or accelerators, however, the CPU uses different data all the time as it runs functions, thus, the memory only makes up a minor fraction of the total power usage and is overshadowed by the huge power exhaustion by the CPUs. Nevertheless, it cannot be neglected as continuous memory access is required for packet processing and state management, especially in virtualized network functions. A recent study by GreenNFV also displays that memory subsystems have a non-trivial impact on energy consumption in NFV workloads and that tuning last-level cache allocation can significantly improve the energy efficiency of virtualized network functions [4].

B. The Radio Access Network

A radio access network (RAN) refers to the interface that provides wireless connectivity between user devices and the core network, through modulation, error correction, and resource allocation functions. It ensures that devices can perform their usual functions requiring network coverage and stay connected as they move. The RAN dominates the network's total energy consumption, accounting for approximately 70-85% according to 5G Americas (2023), making it the most energy-intensive segment of mobile communication systems [5]. It is composed of multiple components such as base stations, baseband units, remote radio units, and supporting systems for cooling and power supply, amongst which base stations account for a majority of the overall consumption. This is due to the combined demands of power amplifiers, digital processing units, and active cooling systems. Therefore, the comprehension and energy profiling of RAN components and base stations in particular is necessary to build a reliable energy model.

1) Base Stations (BSs)

Base stations are the infrastructures that connect a user's device to the larger main network. They are the primary energy consumers in the RAN and their power usage varies by traffic load, deployment type, and type of technology. One of the key components is the power amplifier which often contributes to 50-65% of BS energy and wastes energy when there is low traffic due to inefficiency. Cooling and auxiliary systems can also add up to 10-15% of BS power [6].

Relationship between Operational States and Memory Consumption: Beyond the power consumption of individual components, there is a vital relationship between the operational state of a base station and its total consumption. The following graph compares relative power levels across different modes based on industry standards to illustrate the energy saving potential of modern 5G hardware.

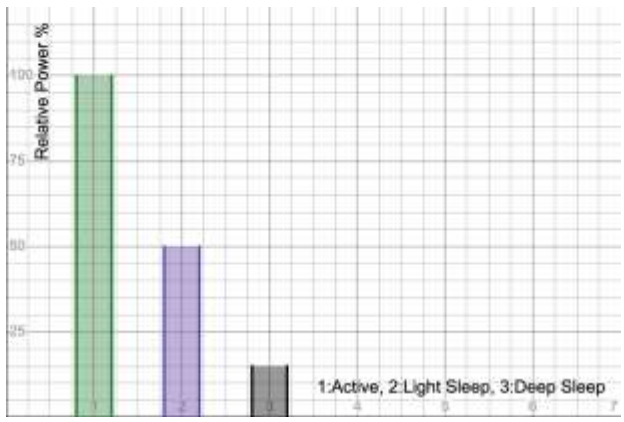

Fig. 2: Base Station Power Consumption by Operational Mode

Analysis of states in the above graph:

1. Active Mode (100%): Represents peak traffic and full operational capacity where all subsystems are active [1][5].
2. Light Sleep (50%): Used during short idle gaps as power is significantly reduced by deactivating the power amplifier.
3. Deep Sleep (15%): The most efficient state where most of the hardware is powered down. However, this requires a longer reactivation time to return to an active state [7].

Baseband units are responsible for signal processing and use less energy than power amplifiers, but not negligible. Collectively, these units contribute to a vast amount of energy wastage. Many strategies have been proposed for more efficient energy usage, such as sleep modes for transceivers during low load and dynamic cell on/off switching depending on traffic [7].

3. Energy Modelling

To create an accurate energy model for the mobile communication network, it is necessary to build mathematical models for each individual network component derived from the correlation between their workload traffic and the amount of power they consume. Such models are increasingly vital, as stated by Buzzi et al. (2016), "energy efficiency has now become a key pillar in the design of communication networks" [8].

A. Energy modelling for core components

The three principal resources of mobile networks, i.e. computing, processing, and memory, exploit varied amounts of energy based on their utilization, load, and deployment choices [1]. Thus, discrete energy profiles aggregated together can provide an explicit idea of the power consumption of the core network. This focused approach allows us to separately analyze the behavior of each component, the effect of various specific energy optimization techniques, and consistently aligns with other works in recent literature that emphasize the role of each independent resource in the overall power consumption.

1) Model 1: Computing Resources

Computing resources mainly use CPUs to run functions in the core network. Their energy consumption relies on the amount of traffic they incur. They are highly inefficient as even when they are idle, they consume a lot of energy, and at maximum traffic they reach peak usage. Energy consumption for computing resources can be modeled as the sum of a fixed, baseline power that is used when idle, and a variable power that changes along with the workload. To demonstrate this behaviour, the following formula can be constructed:

$$P_{CPU}(t) = P_{CPU,idle} + (P_{CPU,peak} - P_{CPU,idle}) \cdot U_{CPU}(t)$$

Eqn. 1: Model for calculation of energy consumption by CPU in core network

Here, $P_{CPU}(t)$ is the instantaneous power utilization of the CPU, $P_{CPU,idle}$ is the baseline power consumed during idle periods, $P_{CPU,peak}$ is the peak power usage as peak traffic, and $U_{CPU}(t)$ is the amount of time the CPU was being utilized.

To predict the behavior of the proposed model, a linear power model was using normalized values of power. Based on prior studies, a peak power of 30,000 mW was used as the upper bound, and the idle power was set at 15,000 mW, reflecting the 50% baseline consumption typical in virtualized environments [1].

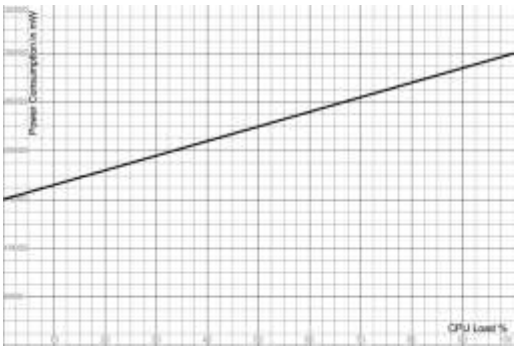

Fig. 3: Base Station Power Consumption by Operational Mode

The resulting graph illustrates a significant gap in energy proportionality - even at 0% load, the system draws 50% of its maximum power. This confirms that core software components maintain a high energy floor even when no user traffic is being processed due to background system tasks. This highlights the requirement of deep sleep states to bridge this efficiency gap. A similarly structured model appears in a comprehensive survey proposed by O'brien et al. (2017) [9]. For instance, if the CPU is at 50% utilization, the power consumption would be exactly halfway between baseline and peak power. This is why a graph of total power consumption against the percent CPU utilization would not start from origin, as shown in this image obtained from Bellin et al. (2024):

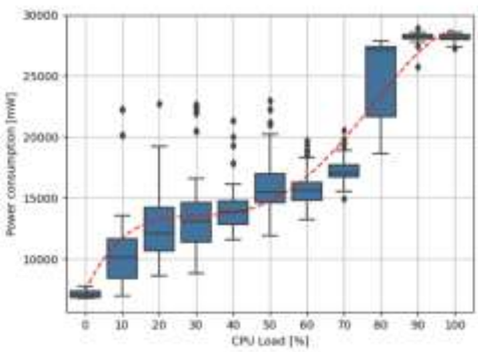

Fig. 4: Base Station Power Consumption by Operational Mode

This captures why computing resources are not efficient - even at 0% load, they consume a high amount of power.

2) *Model 2: Processing Resources*

Processing resources comprise of hardware components such as general-purpose CPUs, GPUs, field programmable gate arrays, network or data processing units, digital signal processors, and other accelerators. These technologies are designed to efficiently handle specific workloads, but energy consumption still varies with load. They typically operate in one of two behavioral patterns: **State-based behavior,** where energy utilization depends on the operating mode (example - idle, active, or sleep); **Throughput-proportional behavior,** where power increases approximately linearly with the processing throughput (example - in Gbps or GOPS) Depending on the behavior of these components, either of the following formulas can be used: fpr State-based model -

$$P_{proc}(t) = \sum_{s\in\{idle,active,sleep\}} P_s \cdot 1_{\{state(t)=s\}}$$

Eqn. 2: State-based model for calculation of energy consumption by processing resources

Here, $P_{proc}(t)$ is the instantaneous power utilization of the processing resources at time t , P_s indicates power consumption in state s, and $1_{\{state(t)=s\}}$ is an indicator function that equals 1 when the system is in that state.
This model is more suitable to use when hardware supports deep sleep and observably transitions between explicit power states [10]. For Throughput-proportional model -

$$P_{proc}(t) = P_{proc,idle} + \alpha \cdot T_{proc}(t)$$

Eqn. 3: Throughput-based model for calculation of energy consumption by processing resources

Here, $P_{proc,idle}$ represents the power consumption when idle, $T_{proc}(t)$ is the processing throughput at time t, and α stands for watts per unit of throughput and is the slope.
This model can be used when continuous throughput measurements are available and power changes more smoothly with processing load [11].

For both models, the total energy consumed during a time T is calculated by:

$$E_{proc} = \int_0^T P_{proc}(t)dt$$

Eqn. 4: Model for calculation of total energy consumption by processing resources

This demonstrates that power consumption of processing units depends not only on hardware, but also on the nature of the workload and the level of offloading.

3) *Model 2: Memory Resources*

Memory resources, mainly RAM/DRAM modules [12], work closely with CPUs, but their power usage is significantly smaller. Although, as previously mentioned, they cannot be ignored. Their energy consumption can be summed up by two parts: **Static baseline**, which is the power needed to ensure the memory stays active even when it is not in use; **Dynamic part**, which measures the number of read/write operations.
These two parts can be added to give a formula for the total energy consumption such as:

$$P_{mem(t)} = P_{mem,static} + E_{access} \cdot A_{mem}(t)$$

Eqn. 5: Model for calculation of energy consumption by memory resources

Here, $P_{mem(t)}$ is the instantaneous power at time t, $P_{mem,static}$ is the baseline power when memory is not in use, E_{access} is the average energy consumed per access, and $A_{mem}(t)$ is the number of accesses at time t. Practically, a single RAM/DRAM module may only consume 3-5W, while a CPU can consume over 100W of power. This shows that memory power consumption is overshadowed by CPU power consumption, but at a large scale and an enormous workload, it becomes a non-deniable contributor to the total energy consumption of the core network.

4) Energy model for total consumption of core network components

The instantaneous power consumption of the core network at time t is given by the following equation:

$$P_{core}(t) = P_{CPU}(t) + P_{proc}(t) + P_{mem}(t) + P_{aux}(t)$$

Eqn. 6: Model for calculation of instantaneous power consumption of core network

The total energy consumption over a time period T of the core network is given by E_{core}:

$$E_{core} = \int_0^T P_{core}(t)dt$$

Eqn. 7: Model for calculation of total power consumption of core network

B. Energy modelling for Radio Access Network

The power consumption of a base station can be modelled as the sum of its main subsystems.

1) Power Amplifiers

These play the largest role in energy consumption [5], and can be modelled as:

$$P_{PA,in}(t) = \frac{P_{out}(t)}{\eta(P_{out}(t))}$$

Eqn. 8: Model for power consumption of power amplifier

Here, η drops at low output power. This causes wastage of energy during light workloads.

2) Baseband Units

Baseband units are often expressed using a simple affine model as such:

$$P_{BBU}(t) = P_{BBU,idle} + (P_{BBU,peak} - P_{BBU,idle}) \cdot u(t)$$

Eqn. 9: Model for power consumption of baseband unit

Here, $u(t)$ represents the cell utilization at time t.

3) Other Components

Remote Radio Units energy consumption is approximated as per-antenna constant power, changing with the number of active antenna chains. Auxiliary Systems, responsible for the cooling and overhead power supply, can take up a non-insignificant portion of total energy consumption.

4) Energy model for total consumption of Radio Access Network

The total power utilization of base station can be acquired from the sum of all base station machines:

$$P_{BS}(t) = P_{PA}(t) + P_{BBU}(t) + P_{RRU}(t) + P_{aux}(t)$$

Eqn. 10: Model for total power consumption of base station

Further, the aggregate energy consumption for the RAN can be estimated by the following model:

$$E_{RAN}(t) = \sum_{i=1}^{N_{BS}} E_{BS,i}(t)$$

Eqn. 11: Model for total power consumption of radio access network

Here, N_{BS} is the number of base stations in the network.

C. Comparative Analysis of Network Segment Energy Distribution

In the following graph, the total energy consumption of a 5G network was analysed in order to determine the relative weight of each segment from sections 4.1 and 4.2. This relationship is critical for prioritizing system-wide energy optimization. Analysis of Distribution is as follows:

1. RAN: RAN is the most energy demanding segment, consuming approximately 70-85% of total network power [1]. This high consumption is driven by the vast number of distributed base stations and the continuous power requirements of their power amplifiers and cooling systems.
2. Core: The core network accounts for the remaining 15-30% of consumption. While its total demand is smaller than the RAN, its energy profile is more complex due to the inefficiency gap identified in section 4.1.1, where servers sustain 40-60% of peak power even when idle.
3. Strategic Implications: This 80/20 distribution relationship confirms that while the core network's efficiency is vital for cloud scaling, RAN-based strategies must be implemented to achieve impactful reductions in a network's carbon footprint, such as the advanced sleep modes discussed in section 3.1.1.

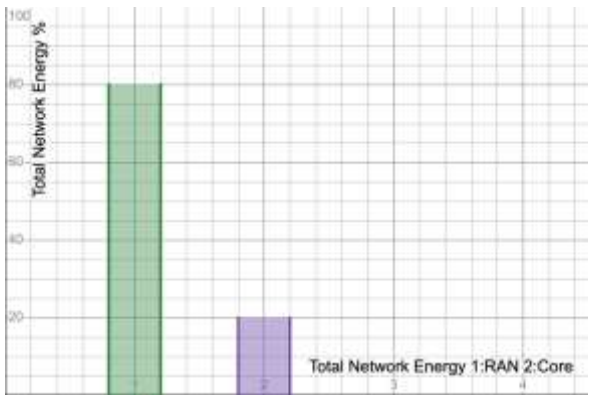

Fig. 5: Total Energy Consumption Split in 5G Networks

4. Results and discussions

This research has successfully modeled the energy behavior of critical energy network components, providing a baseline for network optimization. A key discovery of this analysis is the significant energy proportionality gap within core network computing resources. During idle periods, these components reveal substantial inefficiency, maintaining a power floor of 40-60% of their peak power regardless of the actual load. This suggests that current virtualization overheads prevent hardware from scaling down its energy use in line with data demand, representing a major target for cloud-native energy management. In contrast, the modeling of the radio access network subsystems reveals that hardware state management is much more productive than load reduction. While decreasing the load provides some gains, transitioning hardware components into deep sleep states holds the potential to reduce base station power consumption by up to 85%.

Finally, the comparative analysis of the entire network architecture confirms a clear systemic priority for energy reduction. Because the RAN accounts for the vast majority of the total energy, optimization efforts should be focused on this segment for reducing global carbon emissions. When viewed together, these results point towards a RAN-focused approach in sustainability strategies, where minimizing the core network's idle power and maximizing the base station's deep sleep states work together to eliminate system-wide energy wastage.

5. Conclusion

This paper proposed energy profiles for the key components of mobile networks, particularly computing, processing, memory resources, and base stations. Individual modelling of each separate component allowed the consideration of both static and dynamic behaviors. It highlighted inefficiencies in the machines, for instance, during low load time periods, where the analysis identified a persistent energy proportionality gap in core network resources. These findings also demonstrate that while the core network presents complexity, the RAN remains the dominant energy consumer, accounting for up to 85% of total network power. However, the models also show that implementing advanced sleep modes can reduce this consumption considerably. This approach better enables us to design an analysis of energy use and supports future efforts to eradicate energy wastage in mobile networks.

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