



Performance Analysis of the Base Station in 5 G Networks by Considering Different Frequency Bands Using Stochastic Modelling

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Abstract

The potential advantages of 5 G networks, including faster data speeds and enhanced user experiences, are accompanied by a critical challenge—efficiently managing energy consumption in base stations. This study emphasizes the importance of maximizing energy efficiency in these stations to address this challenge. Base stations (BSs) are pivotal in providing coverage and capacity through the utilization of various frequency bands, which adapt to diverse communication requirements. The selection of a specific frequency band significantly influences network performance, data rates, coverage area, and signal propagation characteristics. Focusing on the essential task of conserving energy in 5 G base stations, this research underscores the significance of strategic frequency band selection for optimizing energy efficiency and network performance. To achieve this, stochastic models, including Markov and semi-Markov models, are introduced for base stations, aiding in frequency band selection based on system traffic considerations. Closed-form solutions for steady-state system size probabilities in these models are derived, and a sensitivity analysis is conducted to evaluate power consumption in different scenarios. The behavior of power consumption with respect to different distributions—exponential and hypo-exponential—is explored. This study underscores the importance of strategic frequency band selection for 5 G base stations in optimizing energy efficiency and meeting the evolving communication network's demands.

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1 Introduction

In response to a notable increase in demand, contemporary cellular networks have experienced a notable evolution, commencing in the late 1970s and progressing through subsequent iterations, ranging from second-generation (2G) to fourth-generation (4G). In the inaugural era, known as 1G, cellular networks had a channel capacity of 30 KHz and a data speed of 2.4 kbps, primarily catering to voice calls. However, the emergence of 2G in 1991 ushered in networks featuring bandwidths extending from 30 to 200 KHz, enabling users to send messages such as SMS and MMS, albeit at speeds reaching up to 64 kbps. To augment both bandwidth and data speed, significant strides were made in 2000 and 2008 with the advent of third-generation (3G) and 4G cellular networks. 3G networks provided bandwidths ranging from 5 to 20 MHz, whereas 4G networks boasted speeds of up to 100 Mbps for users, surpassing the 14 Mbps peak speed promised by 3G. This discrepancy in performance stems from the higher data rate inherent in 4G technology. Despite offering enhanced capacity and rapid data transfer rates, 4G networks exhibited slightly elevated latency.

Al-Falahy and Alani's paper [4] outlined the differences between 5G and earlier mobile network generations and listed a number of advancements. These improvements were intended to reduce latency, achieve multi-Gbps peak data speeds, increase dependability, and create a large-scale network architecture. In order to tackle these issues and fulfil the increasing need for connectivity, 5G cellular networks were unveiled in the beginning of 2019. Massive bandwidth capabilities, increased dependability, faster multi-Gbps peak data rates, and decreased latency were all promised by this next generation of networks. In addition to enhanced data rates and reduced latency, 5G networks significantly improve system dependability, which encompasses reliability, availability, and service continuity. This improvement is primarily driven by Ultra-Reliable Low-Latency Communication (URLLC), designed to achieve extremely high reliability (up to 99.999%) with minimal transmission delays. Furthermore, network densification through small-cell deployments provides redundancy and ensures seamless connectivity by enabling efficient handovers between base stations. Advanced technologies such as massive MIMO and beamforming enhance signal robustness and mitigate the effects of interference and fading. Moreover, network slicing allows the creation of virtual networks tailored to specific application requirements, ensuring guaranteed performance and reliability for critical services. The integration of edge computing reduces latency and enhances resilience by decentralizing processing tasks. Additionally, intelligent network management techniques, including self-organizing networks (SON) and AI-driven optimization, facilitate real-time fault detection and recovery, thereby further strengthening the dependability of 5G systems. The range of frequencies that a signal or communication channel covers determines its bandwidth.

Chih-Lin et al. [12] showed that the power consumption of 5G cellular networks, with a 100 MHz bandwidth, is five times greater than that of 4G networks. Bao et al. [8]

proposed a statistical-based decentralized demand response framework that enables large-scale 5G base stations to provide primary frequency support using adaptive droop control. The study integrates gNB dormancy and battery energy storage systems (BESSs) to achieve fast and accurate frequency regulation without compromising communication network performance. Al-Saegh et al. [5] proposed a rain-impairment-aware channel quality prediction model for HTS and 5G satellite-to-land links by integrating locally measured rainfall data with modified ITU-based algorithms. Their work primarily focuses on physical layer performance and reliability under environmental variations. However, channel quality variations significantly influence higher-level network operations, including traffic distribution, resource allocation, and frequency band selection in base stations. The present study complements their work by addressing the impact of such variations at the system level through stochastic modeling. Specifically, fluctuations in channel conditions can lead to dynamic adaptation of frequency bands and operational states of base stations, which are effectively captured in our proposed Markov and semi-Markov frameworks.

Because of the advanced technologies' high-power requirements, infrastructure densification, and increasing network complexity, the deployment of 5G networks presents substantial energy issues. Ensuring sustainable energy usage and addressing environmental effects are critical factors in determining the broad adoption of 5G technology. Research [16] examined how the excess capacity in 5G BS backup batteries, influenced by fluctuating energy demand, can be used as a flexible asset for power systems. This is because cellular base stations (BSs) rely on backup batteries to provide a constant power supply. Albert Ayang and colleagues [7] examined how much energy was used by each base station component. The research [9] investigated energy efficiency in 5G base stations using an N-policy and an M/G/1 queue model with numerous sleep modes.

Network design and deployment, switching-off strategies [11], radio resource management optimisation, component-level augmentation, and the utilization of renewable energy sources are some of the varied approaches that deal with the aforementioned problem at different scales. In order to maximize the UE's connection with a base station or access point and address energy efficiency concerns related to device-to-device communications in heterogeneous networks, a Q-learning technique combined with logarithmic cooling was suggested [13]. An improvement in energy efficiency of at least 10 to 100 times is one of the requirements for 5G networks and hence, Pervaiz et al. [14] suggested a tiered sleep technique to anticipate the BSs sleep time in order to improve energy efficiency. Assuming a high formation density for 5G base stations, the total power consumption might be twice as high as that of 4G base stations [12]. An MDP-based algorithm was created by Elsherif et al. [10] to handle base station ON/OFF switching in real-time and increase efficiency. Frequency bands are defined as certain radio frequency ranges that are used for signal transmission and reception between base stations and user equipment (UE) in the context of base station communication. These bands are set by regulatory organizations and standards organizations to guarantee efficient and interference-free wireless communication throughout the network.

To connect with UEs, base stations (BSs) use electromagnetic waves. Different frequency bands are assigned to different wireless technologies, such as 2G, 3G,

4G, and 5G. Each segment of these bands has a distinct frequency range and is further broken into smaller bands. By utilizing these many frequency bands, base stations can provide capacity and coverage while adjusting to the ever-changing needs of communication. The coverage area, data throughput, network performance, and signal propagation characteristics can all be greatly impacted by the frequency band selection.

As a result, frequency bands are essential to base station communication because they enable effective wireless communication within designated geographic regions. Among the designated frequency bands that are accessible for 5G are 2300 MHz, 2100 MHz, 1800 MHz, and 900 MHz. Network traffic concerns have a direct impact on frequency band selection. Many solutions have been explored to provide users with a desired quality of service while preserving base station energy, such as network traffic aggregation and base station reduction. An example of this extensive investigation of base station energy use is provided by [6]. In [1], base station availability was represented using a semi-Markov model that took component failures into account while examining energy efficiency in wireless sensor networks. Furthermore, the article [2] focused on applying the Q-learning method to improve base station energy efficiency, highlighting the complex balance between energy efficiency and Quality of Service (QoS). A stochastic model for energy-saving states was proposed in the paper [15], which used semi-Markov process and Markov process analyses to evaluate steady-state probabilities and improve energy efficiency. The authors [3] proposed stochastic modeling frameworks (Markov and semi-Markov models) to characterize the energy consumption behavior of 5G base stations under varying traffic conditions.

In line with the rising need for greater data rates, the model seeks to reduce energy usage in wireless networks. In order to determine an effective power-saving approach, it makes use of a variety of stochastic models to assess power consumption in base stations with multiple resource units spread across several frequency bands. In order to overcome power constraints, this work investigates stochastic models that use many remote units (RUs) within a single base station across various frequency bands. Redistributing users according to current traffic loads and moving to various frequency bands might help reduce power consumption. This research is new since it suggests a wireless network architecture designed to reduce base station power consumption. For this architecture, we have created a stochastic model to evaluate its viability. This model takes into account a broad range of stay durations in different states. To investigate power consumption in various settings, we have also investigated non-exponential distributions for sojourn periods in addition to conventional exponential distributions. It is vital to remember that different distributions can be taken into consideration and replaced to produce equivalent outcomes, even though a general distribution is assumed for clarity in state transition illustrations.

In order to do this, a stochastic model that makes use of semi-Markov processes (SMP) and continuous-time Markov chains (CTMC) is developed. State transitions in the CTMC have exponential distributions. On the other hand, mean sojourn periods in all states of the SMP, including deterministic and hypo-exponential situations, follow a generic distribution. The SMP dynamics are analyzed, and the system's steady-state probabilities are ascertained using a two-stage procedure. Our numerical results give

an overview of how different factors affect power usage and compare the outcomes of the stochastic model utilizing the MP and SMP.

The rest of the paper is structured as follows: Sect. 2 provides a model description outlining the proposed model. The subsequent subsections delve into the analysis of the proposed stochastic models—the CTMC model and SMP model, while Sect. 3 presents numerical results for these models. Lastly, Sect. 4 offers concluding remarks.

2 Model Description

The base station comprises of three sectors, each positioned at 120° angles from the antenna to ensure service provision across the entire 360° coverage area. Additionally, every sector encompasses five layers, representing five distinct frequency bands. These frequency bands include 2300 carrier A MHz, 2300 carrier B MHz, 2100 MHz, 1800 MHz, and 900 MHz.

Consider a base station equipped with different RUs utilizing distinct frequency bands to deliver services based on varying traffic activity. A model is proposed to manage the frequency bands required to handle the traffic load within the base station. However, the dynamic reallocation of frequency bands among users occurs based on the prevailing load and service demands.

The state space $S = \{A_1, A_2, A_3, A_4\}$ in this proposed model are delineated as follows:

- Full Service Mode (A_1): All layers are active to provide the services.
- Reduced Carrier A (A_2): All layers are active except for 2300 with carrier A.
- Selective Band Activation (A_3): All layers are active except for 2300 with carrier A and carrier B.
- Minimum Service Mode (A_4): Only 900 and 1800 layers are active.

The transition between these states is illustrated in the state transition diagram presented in Fig. 1. Here, $F_{i,j}$ is the cumulative distribution function of the sojourn time in state i before moving to state j , $i, j \in S$. We have considered two cases for the distributions of the sojourn time in different states. First, we have considered it to be exponential distributed and second, to be hypo-exponential distributed.

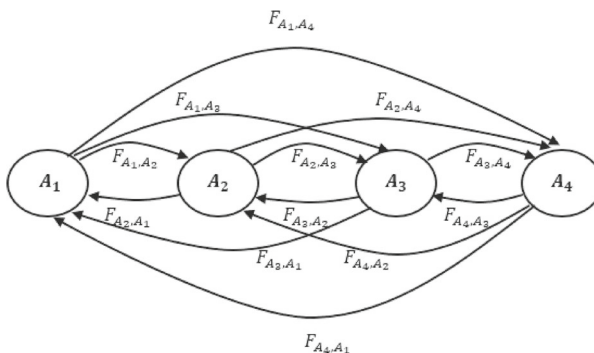


Fig. 1 State transition diagram for the proposed model

To bridge the gap between the theoretical stochastic abstractions used in this model and the complexities of practical 5 G deployments, it is important to note how physical-layer dynamics map to our state-space transitions. In real-world dense 5 G network environments, base stations experience highly dynamic channel state variations caused by user mobility, localization spikes, environmental fading, or rain impairments. Within our framework, these micro-level physical variations are effectively aggregated into macro-level system triggers that dictate the directional state transition rates $(\alpha_i, \beta_i, \gamma_i, \delta_i)$.

Furthermore, modern 5 G deployments carry strict Quality of Service and latency constraints managed by network slicing or URLLC protocols. Instead of utilizing a primitive binary approach that shuts down a base station sector completely during low-traffic epochs—which introduces severe wake-up delays and signaling overhead—our multi-layered configuration preserves backward compatibility and coverage safety. For instance, even in the lowest operational state (A_4), the essential coverage bands remain active to continuously handle control planes, low-rate user signaling, and basic synchronization, ensuring system functionality is never compromised.

2.1 Markov Model

In the realm of a discrete-time Markov chain, if we denote the system's state at time t_n as $X(t_n)$, we can express the transition probabilities as $P\{X(t_n + 1) = j \mid X(t_n) = i\}$, where i and j signify distinct system states. Given the presence of a general distribution governing the mean sojourn time of states and the adherence to Markov attributes during the time epochs T , it becomes suitable to represent the underlying as stochastic process. The state space for this foundational stochastic process is defined as $S = \{A_1, A_2, A_3, A_4\}$.

For a visual representation of state transitions within the proposed Markov model, please refer to Fig. 1. Furthermore, the cumulative distribution function (CDF) for the sojourn time in various states of the Markov model is detailed in Table 1.

Table 1 Distributions of sojourn times for different states of the proposed Markov model

CDF	Distribution	Mean
$F_{A_1, A_2}(t)$	Exponential	α_1
$F_{A_2, A_1}(t)$	Exponential	β_1
$F_{A_2, A_3}(t)$	Exponential	α_2
$F_{A_3, A_2}(t)$	Exponential	β_2
$F_{A_3, A_4}(t)$	Exponential	α_3
$F_{A_4, A_3}(t)$	Exponential	β_3
$F_{A_1, A_3}(t)$	Exponential	γ_1
$F_{A_3, A_1}(t)$	Exponential	δ_1
$F_{A_2, A_4}(t)$	Exponential	γ_2
$F_{A_4, A_2}(t)$	Exponential	δ_2
$F_{A_1, A_4}(t)$	Exponential	γ_3
$F_{A_4, A_1}(t)$	Exponential	δ_3

In this Section, the steady-state probabilities of the system are obtained using $\lim_{t \rightarrow \infty} P_{i,j}(t) = \pi_{i,j}$ and $\lim_{t \rightarrow \infty} P'_{i,j}(t) = 0$.

Hence, the steady-state equations are given by:

$$0 = -\alpha_1 \pi_{A_2} - \gamma_1 \pi_{A_3} - \gamma_3 \pi_{A_4} + (\beta_1 + \delta_1 + \delta_3) \pi_{A_1}, \quad (1)$$

$$0 = -\beta_1 \pi_{A_1} - \alpha_2 \pi_{A_3} - \gamma_2 \pi_{A_4} + (\beta_2 + \delta_2 + \alpha_1) \pi_{A_2}, \quad (2)$$

$$0 = -\beta_2 \pi_{A_2} - \alpha_3 \pi_{A_4} - \delta_1 \pi_{A_1} + (\gamma_1 + \alpha_2 + \beta_3) \pi_{A_3}, \quad (3)$$

$$0 = -\beta_3 \pi_{A_3} - \delta_2 \pi_{A_2} - \delta_3 \pi_{A_1} + (\gamma_2 + \alpha_3 + \gamma_3) \pi_{A_4}, \quad (4)$$

Solving these four equations, we obtain the steady-state probabilities for each state.

2.2 Semi-Markov Model

In this section, we delve into the examination of the model's steady state. We initiate the process by scrutinizing the system's underlying state dynamics, denoted as $X(t)$, $t \geq 0$. This depiction of the system's state at any given moment t is represented by the sequence of system states, labeled as $S = \{A_1, A_2, A_3, A_4\}$, which corresponds to specific time instances $T = \{t_0, t_1, t_2, \dots\}$. Together, this sequence and its associated time instances constitute an embedded discrete-time Markov chain, an analytical framework that delineates a series of events or states within a system. It functions based on the fundamental principle that the probability of transitioning to the subsequent state relies solely on the current state, devoid of any influence from preceding states. In the realm of a discrete-time Markov chain, if we denote the system's state at time t_n as $X(t_n)$, we can express the transition probabilities as $P\{X(t_n + 1) = j \mid X(t_n) = i\}$, where i and j signify distinct system states. Given the presence of a general distribution governing the mean sojourn time of states and the adherence to Markov attributes during the time epochs T , it becomes suitable to represent the underlying stochastic process using a Semi-Markov Process (SMP). Furthermore, the cumulative distribution function for the sojourn time in various states of the semi-Markov model is detailed in Table 2.

The CDF of the hypo-exponential distribution is given as follows

$$F(x) = 1 - \frac{\lambda_2}{\lambda_2 - \lambda_1} e^{-\lambda_1 x} + \frac{\lambda_1}{\lambda_2 - \lambda_1} e^{-\lambda_2 x}.$$

Therefore, consider the CDF of the transition of a system from one state to another state, given as:

$$\begin{aligned} F_{A_1, A_2}(x) &= 1 - \frac{\alpha_{12}}{\alpha_{12} - \alpha_{11}} e^{-\alpha_{11} x} + \frac{\alpha_{11}}{\alpha_{12} - \alpha_{11}} e^{-\alpha_{12} x}, \\ F_{A_2, A_3}(x) &= 1 - \frac{\alpha_{22}}{\alpha_{22} - \alpha_{21}} e^{-\alpha_{21} x} + \frac{\alpha_{21}}{\alpha_{22} - \alpha_{21}} e^{-\alpha_{22} x}, \\ F_{A_3, A_4}(x) &= 1 - \frac{\alpha_{32}}{\alpha_{32} - \alpha_{31}} e^{-\alpha_{31} x} + \frac{\alpha_{31}}{\alpha_{32} - \alpha_{31}} e^{-\alpha_{32} x}, \end{aligned}$$

Table 2 Distributions of sojourn times for different states of the proposed semi-Markov model

CDF	Distribution	Mean
$F_{A_1, A_2}(t)$	Hypo-exponential	$\frac{1}{\alpha_1}$
$F_{A_2, A_1}(t)$	Hypo-exponential	$\frac{1}{\beta_1}$
$F_{A_2, A_3}(t)$	Hypo-exponential	$\frac{1}{\alpha_2}$
$F_{A_3, A_2}(t)$	Hypo-exponential	$\frac{1}{\beta_2}$
$F_{A_3, A_4}(t)$	Hypo-exponential	$\frac{1}{\alpha_3}$
$F_{A_4, A_3}(t)$	Hypo-exponential	$\frac{1}{\beta_3}$
$F_{A_1, A_3}(t)$	Hypo-exponential	$\frac{1}{\gamma_1}$
$F_{A_3, A_1}(t)$	Hypo-exponential	$\frac{1}{\delta_1}$
$F_{A_2, A_4}(t)$	Hypo-exponential	$\frac{1}{\gamma_2}$
$F_{A_4, A_2}(t)$	Hypo-exponential	$\frac{1}{\delta_2}$
$F_{A_1, A_4}(t)$	Hypo-exponential	$\frac{1}{\gamma_3}$
$F_{A_4, A_1}(t)$	Hypo-exponential	$\frac{1}{\delta_3}$

$$F_{A_2, A_1}(x) = 1 - \frac{\beta_{12}}{\beta_{12} - \beta_{11}} e^{-\beta_{11}x} + \frac{\beta_{11}}{\beta_{12} - \beta_{11}} e^{-\beta_{12}x},$$

$$F_{A_3, A_2}(x) = 1 - \frac{\beta_{22}}{\beta_{22} - \beta_{21}} e^{-\beta_{21}x} + \frac{\beta_{21}}{\beta_{22} - \beta_{21}} e^{-\beta_{22}x},$$

$$F_{A_4, A_3}(x) = 1 - \frac{\beta_{32}}{\beta_{32} - \beta_{31}} e^{-\beta_{31}x} + \frac{\beta_{31}}{\beta_{32} - \beta_{31}} e^{-\beta_{32}x},$$

$$F_{A_1, A_3}(x) = 1 - \frac{\gamma_{12}}{\gamma_{12} - \gamma_{11}} e^{-\gamma_{11}x} + \frac{\gamma_{11}}{\gamma_{12} - \gamma_{11}} e^{-\gamma_{12}x},$$

$$F_{A_2, A_4}(x) = 1 - \frac{\gamma_{22}}{\gamma_{22} - \gamma_{21}} e^{-\gamma_{21}x} + \frac{\gamma_{21}}{\gamma_{22} - \gamma_{21}} e^{-\gamma_{22}x},$$

$$F_{A_1, A_4}(x) = 1 - \frac{\gamma_{32}}{\gamma_{32} - \gamma_{31}} e^{-\gamma_{31}x} + \frac{\gamma_{31}}{\gamma_{32} - \gamma_{31}} e^{-\gamma_{32}x},$$

$$F_{A_3, A_1}(x) = 1 - \frac{\delta_{12}}{\delta_{12} - \delta_{11}} e^{-\delta_{11}x} + \frac{\delta_{11}}{\delta_{12} - \delta_{11}} e^{-\delta_{12}x},$$

$$F_{A_4, A_2}(x) = 1 - \frac{\delta_{22}}{\delta_{22} - \delta_{21}} e^{-\delta_{21}x} + \frac{\delta_{21}}{\delta_{22} - \delta_{21}} e^{-\delta_{22}x},$$

$$F_{A_4, A_1}(x) = 1 - \frac{\delta_{32}}{\delta_{32} - \delta_{31}} e^{-\delta_{31}x} + \frac{\delta_{31}}{\delta_{32} - \delta_{31}} e^{-\delta_{32}x},$$

The parameters β_{ij} , γ_{ij} , δ_{ij} , and α_{ij} , $i = 1, 2, 3$ and $j = 1, 2$ are chosen such that

$$\frac{1}{\beta_i} = \frac{1}{\beta_{i1}} + \frac{1}{\beta_{i2}}, i = 1, 2, 3.$$

$$\frac{1}{\gamma_i} = \frac{1}{\gamma_{i1}} + \frac{1}{\gamma_{i2}}, i = 1, 2, 3.$$

$$\frac{1}{\delta_i} = \frac{1}{\delta_{i1}} + \frac{1}{\delta_{i2}}, i = 1, 2, 3.$$

$$\frac{1}{\alpha_i} = \frac{1}{\alpha_{i1}} + \frac{1}{\alpha_{i2}}, i = 1, 2, 3.$$

To calculate these probabilities, a two-stage approach is utilized, with a focus on the components of the kernel matrix $K(t)$. Here, $K_{m,n}(t)$ represents the probability that, given the system is in state m , it transitions to state n within time t . This matrix considers the underlying Markov renewal sequence of random variables $\{(Y_n, t_n), n \geq 0\}$, where $m, n \in S$. Alternatively, $K_{m,n}(t)$ can be interpreted as the likelihood of transitioning from state m to state n within time t . The cumulative distribution function $F_{m,n}$ governs this transition within the state space, with non-zero elements present in the kernel matrix as detailed below:

$$K_{m,n}(t) = P(X_1 = n, T_1 \leq t / X_0 = m).$$

$$K_{A_1, A_2}(t) = \int_0^t (1 - F_{A_1, A_3}(x)) (1 - F_{A_1, A_4}(x)) d(F_{A_1, A_2}(x)).$$

Similarly, all Kernel values can be obtained.

Using the two-stage technique for the semi-Markov model, we derive $K_{m,n}(\infty) = \lim_{t \rightarrow \infty} K_{m,n}(t)$, where $m, n \in S$. Here, the matrix $K(\infty)$, with its elements denoted as $K_{m,n}(\infty)$, signifies the one-step transition probabilities for the EMC (Embedded Markov Chain) of the SMP model. The row sum of the $K(\infty)$ matrix equals 1 for all rows. The steady-state probabilities for the states of EMC, represented by vector V and expressed as $(V_{A_1}, V_{A_2}, V_{A_3}, V_{A_4})$, can be calculated by solving:

$$V = VK(\infty), \sum_{m \in S} V_m = 1. \quad (5)$$

Let us assume T_m denotes the sojourn time in any state $m \in S$. Since the EMC obtained is irreducible, aperiodic, and positive recurrent, i.e., ergodic, hence, for this model, the steady-state probabilities for each state $m \in S$ of the semi-Markov model can be obtained as: Suppose T_m represents the duration spent in any state $m \in S$. Given that the EMC is irreducible, aperiodic, and positively recurrent and ergodic, the steady-state probabilities for each state $m \in S$ in the semi-Markov model can be derived as follows:

$$\pi_m = \frac{V_m E[T_m]}{\sum_{n \in S} V_n E[T_n]}, \quad m \in S, \quad (6)$$

where $E[T_m]$ denotes the expected sojourn time in any state $m \in S$, which can be obtained as given:

$$E[T_{A_1}] = \int_0^\infty (1 - F_{A_1, A_3}(t)) (1 - F_{A_1, A_4}(t)) (1 - F_{A_1, A_2}(t)) dt.$$

3 Numerical results

In this section, we unveil the numerical findings. Within the stochastic models outlined in this paper, transitions between states adhere to a general distribution, while the duration spent in each state is determined upon entry into that state. Consequently, power consumption correlates directly with the duration spent in various states, resulting in varying power consumption values across states. Consider the power consumption values given in Table 3 to obtain the results. The power consumption PC in the system is given by,

$$PC = PC_{A_1}\pi_{A_1} + PC_{A_2}\pi_{A_2} + PC_{A_3}\pi_{A_3} + PC_{A_4}\pi_{A_4},$$

where $PC_i, i \in S$ is power consumption in state i .

This experiment entails a comparative examination of analytical outcomes concerning power consumption in scenarios where states follow exponential and hypo-exponential distributions. Figure 2 depicts the behavior of power consumption concerning α_1 across both distributions. Specifically, the findings indicate that power consumption is approximately 8–9% higher in exponential scenarios than in the hypo-exponential case.

Figure 3 depicts the behavior of power consumption with respect to β_3 . The results exhibit that the value of power consumption is almost 2–3% more for the exponential case in comparison to the hypo-exponential.

Considering various distributions for modeling states aims to achieve a more realistic representation. The experiment highlights the significant impact of distribution choice on power consumption values, attributed to differing transition rates. Results underscore the influence of distribution type on analyzed metrics. Selection of distribution parameters depends on system requirements. Mismatch between system structure and chosen distribution may lead to inflated or underestimated metrics, emphasizing the importance of careful distribution selection for accurate performance assessment.

The static power consumption represents the baseline energy usage of a conventional, non-adaptive base station operating continuously in Full Service Mode (A_1). In this mode, all frequency bands and radio units remain active irrespective of traffic conditions. Based on Table 3, this corresponds to a constant maximum power consumption given by:

$$PC_{static} = PC_{A_1} = 250 \text{ W}$$

To quantify the effectiveness of the proposed stochastic model in reducing power usage, the percentage energy savings metric is defined relative to this static baseline:

$$EnergySavings(\%) = \frac{PC_{static} - PC}{PC_{static}} \times 100\%$$

Table 3 Power Consumption in different states [3]

State	A_1	A_2	A_3	A_4
Power Consumption	250 W	230 W	200 W	180 W

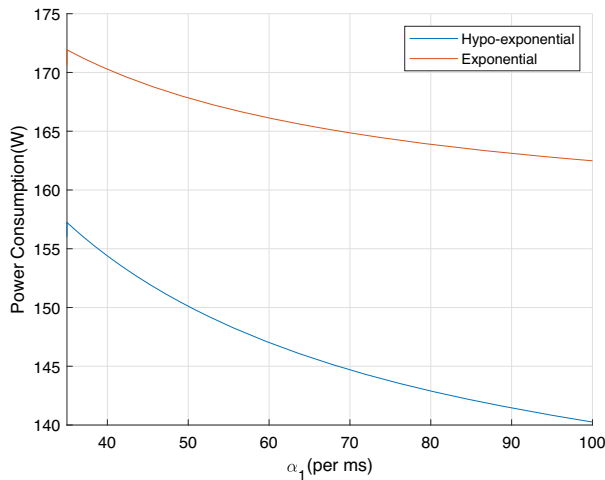


Fig. 2 Comparison of power consumption with varying parameters values α_1

where PC represents the average power consumption obtained from the steady-state probabilities of the proposed stochastic model.

This metric captures the relative reduction in energy consumption achieved by dynamically adapting the operational states of the base station based on traffic conditions. A higher energy savings value indicates more efficient utilization of low-power states, whereas lower values suggest a necessary transition to high-power modes due to heavier traffic conditions. The metric is evaluated under different parameter settings (e.g., varying α_1, β_3 and β_1) to analyze the impact of traffic dynamics on system efficiency.

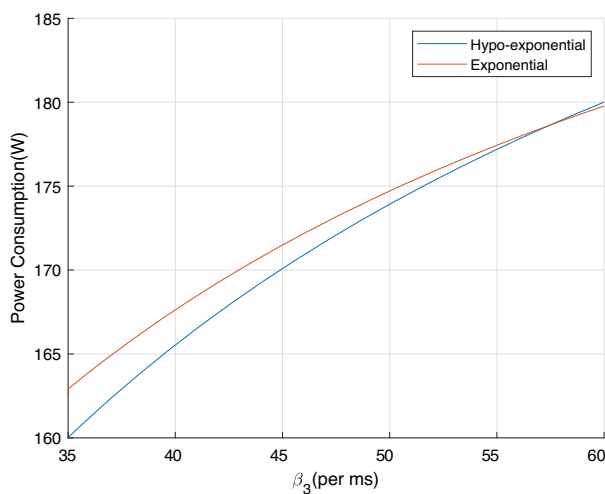


Fig. 3 Comparison of power consumption with varying parameters values β_3

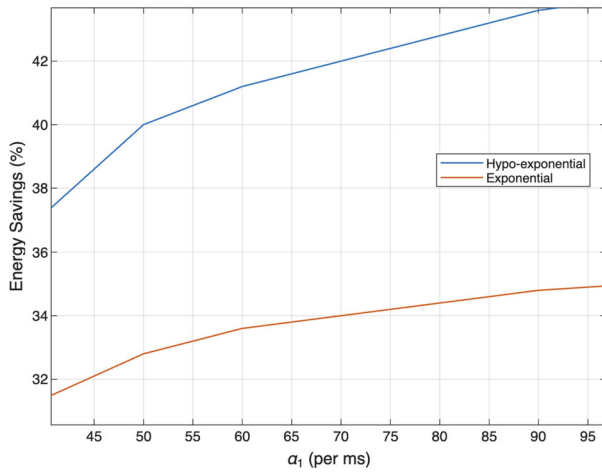


Fig. 4 Comparison of energy saving with varying parameters values α_1

To comprehensively validate the efficiency of our proposed framework and showcase performance improvements over existing deployments, the numerical analysis evaluates the system against two prominent network baselines:

- **Static “Always-On” Strategy:** The default non-adaptive benchmark described above, where power consumption remains fixed at 250 W, completely independent of actual traffic load.
- **Conventional Binary ON/OFF Strategy:** This represents standard network switching algorithms found in the literature, where intermediate power tiers are ignored. The system operates on a direct threshold trigger, toggling crudely between the absolute peak capacity state ($A_1 = 250$ W) and the deepest sleep/minimum tier state ($A_4 = 180$ W) depending on sudden load variations.

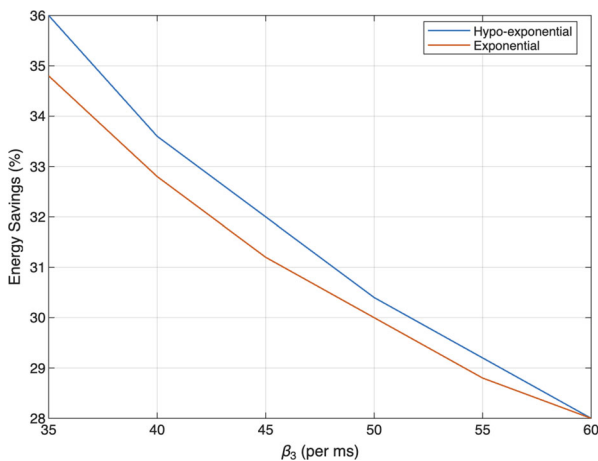


Fig. 5 Comparison of energy saving with varying parameters values β_3

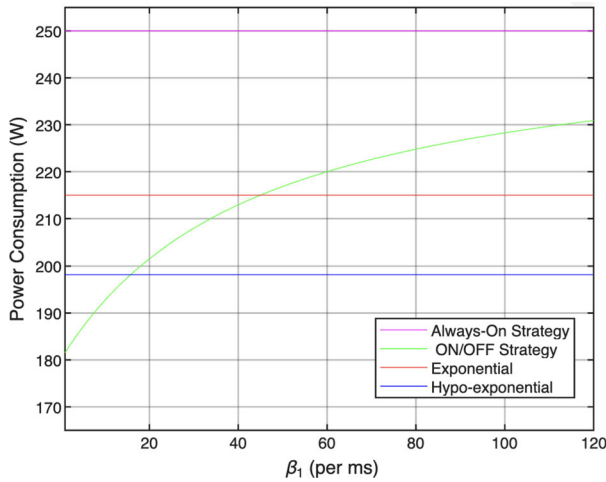


Fig. 6 Comparison of power consumption with varying parameters values β_1

Figure 4 depicts the behavior of energy saving (%) concerning α_1 across both the distributions. The findings indicate that energy saving is higher than in hypo-exponential scenarios than the exponential case.

Figure 5 depicts the behavior of energy saving (%) with respect to β_3 . The results exhibit that the value of energy saving is more for the hypo-exponential case in comparison to the exponential. The analysis shows that energy savings increase with higher values of transition parameter α_1 , as the system spends more time in lower-power states. Conversely, increasing β_3 reduces the achievable savings due to more frequent transitions toward higher power states.

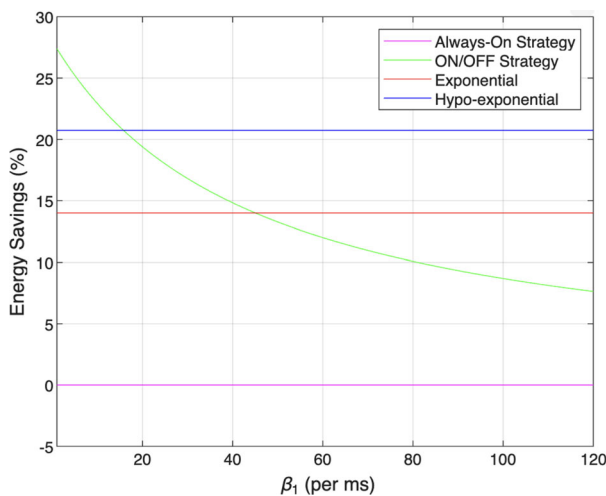


Fig. 7 Comparison of energy saving with varying parameters values β_1

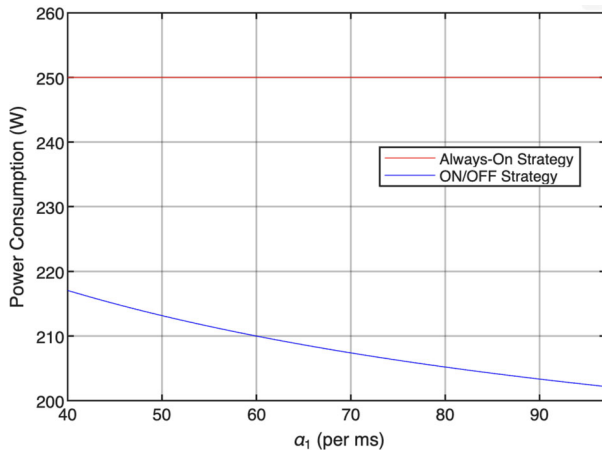


Fig. 8 Comparison of power consumption with varying parameters values α_1

Figures 6 and 7 analyze the effect of sweeping rate β_1 up to 120 per ms. For our proposed Markov and semi-Markov models, the trends remain completely flat and stable at 14% and 21% energy savings, respectively. This structural stability occurs because our multi-tier design isolates recovery impacts within the intermediate sub-bands.

In contrast, the Conventional Binary ON/OFF Strategy displays a sharp, highly sensitive non-linear curve. Its power consumption surges from 181W to 231W, causing its energy savings to plunge from 27.5% down to under 8%. Because binary strategies lack fallback sub-tiers, a high recovery demand forces the entire system matrix to lock into the full-power mode, highlighting the superior stability of our proposed architecture.

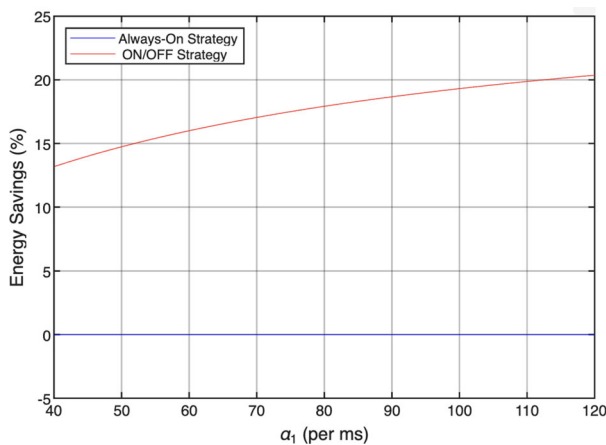


Fig. 9 Comparison of energy savings with varying parameters values α_1

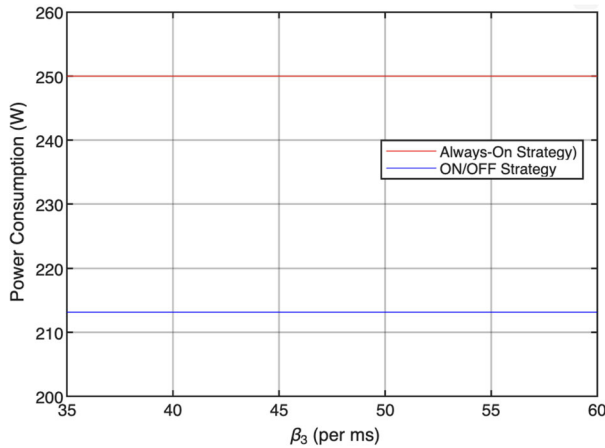


Fig. 10 Comparison of power consumption with varying parameters values β_3

Figures 8 and 9 illustrate the network metrics when sweeping the deactivation rate α_1 from 40 to 120 per ms. As α_1 increases, the Conventional Binary ON/OFF Strategy shows a distinct non-linear curve, where power consumption drops from 217W to 202W, and energy savings climb from 13% to over 20%. This occurs because accelerating early-stage deactivation routes the system out of the peak-power state much faster. Meanwhile, the Always-On baseline remains completely flat at 250W with no savings.

Figures 10 and 11 present an independence benchmark by sweeping the internal sub-band reactivation rate β_3 from 35 to 150 per ms. Across this entire axis, both the Always-On Strategy and the Conventional Binary ON/OFF Strategy trace perfectly flat, straight horizontal lines. The Always-On line is fixed at 250W (no savings), while the Binary baseline stays horizontal at 213W (14.8% savings).

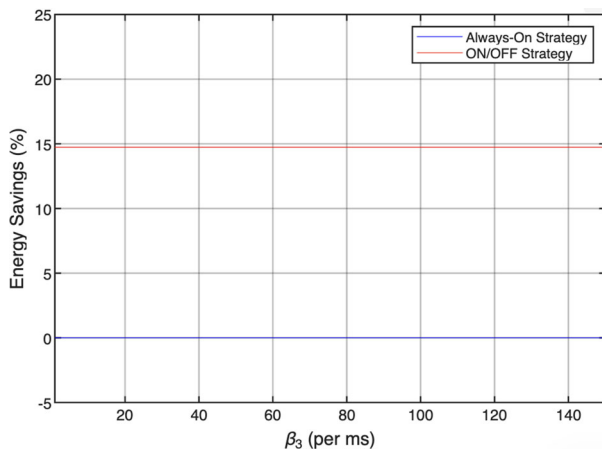


Fig. 11 Comparison of energy savings with varying parameters values β_3

This response mathematically validates the core thesis of our manuscript. Because conventional binary architectures lack sub-band granularity and only recognize a single macroscopic state change, they are fundamentally blind to micro-tier parameters like β_3 . This underscores the distinct edge of our proposed multi-state framework in enabling fine-grained cellular sleep control.

4 Conclusions and Future Works

This paper presented stochastic modeling approaches, specifically Markov and semi-Markov frameworks, employing multiple Radio Units operating across varied frequency bands to reduce base station power consumption through dynamic band switching. To quantify the effectiveness of the proposed multi-tier models, an energy savings metric was evaluated against a static always-on baseline operating continuously at full capacity (250W) and a conventional binary ON/OFF strategy. The sensitivity analysis demonstrated that accelerating early-stage carrier deactivation via the downward transition rate α_1 produces a clear non-linear trend, lowering power consumption and boosting energy savings past 20%. Conversely, varying the macro-recovery rate β_1 revealed the high vulnerability of conventional binary switching—causing its energy savings to plunge from 27.5% to under 8%—while our proposed multi-state models maintained stable energy savings due to the protective dampening of intermediate sub-states.

Furthermore, parameter sweeps over internal sub-band reactivation rates like β_3 yielded completely flat responses for traditional strategies, mathematically proving that legacy binary networks are fundamentally blind to micro-tier parameters. By incorporating exponential and hypo-exponential distributions for state sojourn times, the study provides a highly robust representation of energy conservation behavior. Overall, the proposed model achieves substantial energy savings reaching up to approximately 40–45% under favorable conditions, highlighting its effectiveness in improving energy efficiency while maintaining system functionality. Future work will extend this framework by evaluating these multi-tier state transitions under real-time, non-stationary traffic workloads to dynamically optimize the trade-off between energy conservation and network quality of service.

Future research can further extend this work by exploring a broader spectrum of sojourn time distributions beyond the exponential and hypo-exponential models considered here, such as Weibull, Erlang, or log-normal distributions, to better capture real-world variations in state durations. These extended models can provide deeper insights into non-memoryless behavior and its influence on system dynamics. Additionally, future studies could analyze the impact of these alternative distributions on key performance metrics, including system reliability, latency, throughput, and overall energy efficiency. Incorporating simulation-based validation alongside analytical modeling would also enhance the accuracy of predictions and bridge the gap between theoretical and practical implementations.

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Code Availability Code will be available on request to the corresponding author.

Declarations

Ethics Approval The authors provide ethics approval.

Consent to Participate Not applicable.

Consent for Publication The authors give consent for the publication in the journal.

Competing Interests The authors declare no competing interests.

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