

Energy Analysis for the Base Station: Analytical Approach

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Abstract—The growing prominence of wireless sensor networks underscores the necessity of continuous operation for these networks, chiefly dependent on the uninterrupted availability of base stations (BSs). However, this constant operation of BSs incurs substantial energy consumption. In response, this study employs a semi-Markov model to depict BS availability, accounting for failures in key components such as the baseband unit, remote unit, and software module. In the context of 5G cellular networks, energy-saving strategies for base stations (BSs) have become increasingly vital due to their substantial power consumption, a striking four-fold increase compared to 4G. By assigning reward rates based on component energy consumption, the analysis provides insights into expected energy usage within the model. This work not only presents a practical solution but also highlights the critical importance of achieving optimal energy usage in 5G BSs for the evolving wireless landscape.

Index Terms—Energy consumption, Remote Unit, Wireless Network, Reward Rate.

I. INTRODUCTION

Fifth-generation (5G) base stations (BSs) are pivotal components of the 5G wireless communication infrastructure, serving as essential links connecting user devices to the expansive 5G network, which promises high data speeds, minimal latency, and superior network reliability. The continuous and secure operation of these base stations is paramount to ensure uninterrupted service, especially in the face of escalating data traffic and energy efficiency concerns. Consequently, base station availability emerges as a critical factor, with network operators deploying redundancy and failover mechanisms to address potential outages and hardware issues. Furthermore, when designing 5G networks, ensuring base station reliability and availability takes center stage, crucial for superior performance and efficient energy management.

This focus on base station availability extends beyond practical network operations; it also represents a significant research challenge in the telecommunications field. As wireless communication becomes increasingly vital across various domains, improving base station availability aligns with the broader goal of delivering seamless connectivity and uninterrupted services to users in our interconnected world.

Existing literature extensively covers base station reliability, considering factors such as traffic demands and user requirements, as well as component failures and repairs. However,

there remains an unexplored gap in the literature regarding availability within this context, motivating our research initiative to introduce a comprehensive availability model encompassing these vital elements, offering a more holistic perspective on base station performance.

While sustaining continuous connectivity through uninterrupted base station operation is crucial, it raises concerns about sustainability and energy efficiency within the telecommunications sector. Enhancing the energy efficiency of these base stations is imperative, as operational efficiency significantly influences user satisfaction and overall network performance. Therefore, a comprehensive evaluation of base station throughput is necessary to ensure dependable and efficient network services while addressing energy-related challenges.

This paper provides an in-depth analysis centered on a stochastic availability model for base stations, dissecting their three essential components: the Baseband Unit (BBU), the Remote Unit (RU), and the software module. This proposed availability model undergoes rigorous examination as a semi-Markov process, leveraging probabilistic concepts to derive steady-state solutions. Furthermore, the study explores energy consumption within the system by assigning reward rates to each state of the semi-Markov model, aligning with the energy utilization of individual base station components.

In summary, this paper explores the critical role of 5G base stations in wireless communication, emphasizing uninterrupted service amidst growing data traffic and energy efficiency challenges. It introduces a comprehensive availability model that considers component failures and repairs, providing a holistic view of base station performance using a stochastic process, the semi-Markov process. The study also investigates base station energy consumption with the Markov reward model. Overall, this paper advances our understanding of base station availability and energy efficiency in the evolving landscape of wireless communication.

The primary objectives of 5G networks encompass achieving high-speed data rates, minimal latency, and sustained reliability. A study by Dharmaraja et al. [1] evaluated Vehicular Ad Hoc Networks' reliability, with a specific emphasis on hardware and communication channel availability. Stochastic modeling methods were applied in [2] to assess reliability and channel accessibility in LTE-Vehicular Ad-Hoc Networks

(LTE-V), proposing a hierarchical model to enhance network performance and reliability, particularly addressing hardware failures and channel unavailability. Another study [3] assessed mobile communication network reliability, investigating fault origins, and analyzing its architecture, communication infrastructure, and mobile communication technologies. Furthermore, Dharmaraja et al. [4] presented an analytical model for evaluating the reliability of Universal Mobile Telecommunication Systems networks, employing stochastic models such as Markov chains, semi-Markov processes, reliability block diagrams, and Markov reward models. While reliability relates to the capacity to withstand failures and repairs, availability pertains to maintaining continuous operational readiness for delivering uninterrupted services to users.

Base station availability hinges on the reliability of its components, encompassing hardware, software, and more. In their work, Albert Ayang et al. [5] analyzed energy consumption in each base station component. The availability and reliability of wireless networks were addressed in [6]. Shifting the focus from availability to the energy challenge of base stations, the study addressed energy efficiency in LTE-5G networks, striking a balance between energy conservation and optimizing throughput for peak system performance [7]. Energy consumption is a pivotal factor in wireless networks, with various authors exploring this dimension, such as investigating energy issues in User Equipment (UE) [8].

In wireless networks, base stations are essential for communication but consume significant energy. Consequently, extensive literature exists on the energy analysis of base stations. Furthermore, research initiatives [9] explored stochastic modeling techniques and energy efficiency mechanisms to enhance the energy efficiency of sleep strategies in 5G base stations, introducing novel models that consider system traffic patterns and assess power consumption. To achieve the desired quality of service and energy savings, studies like [10] focused on minimizing the number of base stations and aggregating network traffic. The energy used to operate base stations was analyzed in [11]. Additionally, research [9] systematically examined the energy efficiency of small cell base stations in 4G/5G networks and assessed energy consumption drivers and overall performance.

The paper's structure is organized as follows: Section II elucidates the proposed availability model, while Section III delves into the steady-state analysis of the model. Section IV addresses energy consumption in various states. The paper then progresses to Section V for numerical results, culminating in Section VI, where concluding remarks and future research directions are presented.

II. AVAILABILITY MODEL

In this section, we present our proposed availability model for the base station, which considers critical components that have a significant impact on the base station's availability and power consumption. These components encompass the base station hardware, software, and power supply, among others. We assume that power outages have a negligible probability

since the base station's power supply is crucial for its operation. Additionally, the availability of connections between the base station and the Evolved Packet Core Network (EPC), which is a fundamental network in wireless communication, is essential for base station functionality, and we assume that these links are always in working condition.

The hardware components include the baseband unit (BBU) and remote unit (RU), with their availability being pivotal for base station operation. The base station can accommodate up to three RUs. Furthermore, the availability model incorporates a software module, a redundant BBU that serves as a cold standby for the active BBU, and two statistically identical RUs.

Our proposed base station availability model is formulated as a continuous-time stochastic process denoted as $\{X(t), t \geq 0\}$, where $X(t)$ represents the system state at time t . The state depends on the availability of BBUs, RUs, and the base station's software module. The state space encompasses various states, denoted as $\Omega = \{U, B, S, R, BS, RS, BR, BRS, B_2, R_2, B_2S, B_2R, BR_2, B_2RS, BR_2S, R_2S, M_1, M_2, M_3, M_4\}$, with each state defined as follows:

- U: Upstate is the state with all the base station components in working condition.
- B: The state where the working BBU has failed and is under repair, and the base station works with the help of a redundant BBU.
- S: The state in which the software module of the base station has failed and is under repair.
- R: The state where one of the RUs has failed and is under repair, and the base station works with the help of another RU.
- BS: The state in which BBU and software module of the base station have failed and are under repair.
- RS: The state where the software module and one of the RUs have failed and are under repair.
- BR: The state where one of the RU and BBU have failed and are under repair.
- BRS: The state where BBU, software module, and one of the RUs have failed and are under repair.
- M_1, M_2, M_3, M_4 : The states where, after the failure of working BBU, manual change of BBU to redundant BBU takes place.
- B_2 : The state where both BBUs have failed and are under repair.
- R_2 : The state where both RUs have failed and are under repair.
- B_2S : The state where both BBUs and software components have failed and are under repair.
- R_2S : The state where both RUs and software components have failed and are under repair.
- B_2R : The state where both BBUs and one of the RUs have failed and are under repair.
- BR_2 : The state where both RUs and one of the RUs have failed and are under repair.
- BR_2S : The state where one of the BBUs, both the RUs and software module of the base station, have failed and

- B_2RS : The state where one of the RUs, both the BBUs and software module of the base station, have failed and are under repair.
- Downstate (D): The state where the system has failed and the repair of the failed components are going on.

- **Downstate (D):** The state where the system has failed and the repair of the failed components are going on.

The availability model for the base station is depicted in Figure 1. In this model, the failure and recovery times of components are modeled to follow exponential distributions. Additionally, the time it takes for manual switching from the active BBU to the redundant one is considered to be a deterministic duration denoted as T . Consider the failure rate and repair rate of

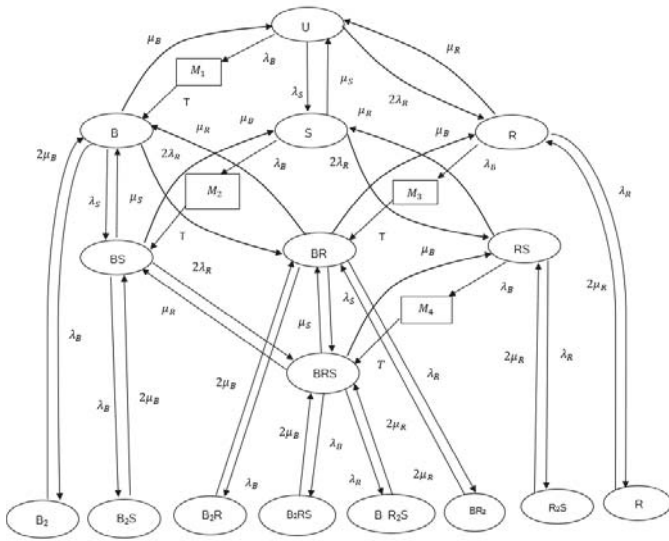


Fig. 1. State transition diagram for the availability model

the BBU, denoted as λ_B and μ_B , respectively. Similarly, the failure rates for the RU and software module are λ_R and λ_S , respectively, with corresponding repair rates of μ_R and μ_S . The manual switching time is represented as T .

Initially, the system is in the Upstate U , where all components are operational. If a fault occurs in the BBU, the system transitions to state M_1 at a rate of λ_B . In state M_1 , the BBU is manually changed to a redundant one within a deterministic time T , leading the system to enter state B . Automatic switching is not possible as the redundant BBU is in cold standby. In state B , the redundant BBU confirms the base station's availability, and the failed BBU is repaired at a rate of μ_B . If there is a fault in any of the RUs, the system transitions to state R at a rate of $2\lambda_R$. In state R , the failed RU is repaired at a rate of μ_R . If a fault occurs in the software module, the system transitions to state S at a rate of λ_S , and the failed component is repaired at a rate of μ_S .

Now, suppose the system is in state B . If a fault occurs in the redundant BBU, the system immediately moves to the downstate B_2 , where the repair of failed components begins. Faults in the software module or one of the RUs lead the system to transition to states BS and BR , respectively, with corresponding failure rates.

In the case of the system being in state R , if a fault occurs in another RU, the system immediately moves to the downstate R_2 , where the repair of failed components starts. A defect in the software module or BBU makes the system enter states RS and M_3 , respectively.

If the system is in state S , and there is a fault in the BBU or one of the RUs, the system transitions to state M_2 and RS , respectively.

Now, consider the system is in state BS , and there is a fault in the redundant BBU as well. The system immediately moves to the downstate B_2S . A fault in one of the RUs causes the system to transition to state BRS . Similarly, if the system is in state RS and enters the downstate R_2S and BRS , there is a fault in the other RU and BBU, respectively. The failure of the redundant BBU, software module, or other RU makes the system transition to downstates B_2R , BRS , and BR_2 from state BR . These transitions between states occur with the corresponding failure and repair rates.

Suppose the system is in state BRS , where the repair of all three base station components is ongoing. Again, before repairing the components, if there is a failure of the redundant BBU or other RU, the system moves to states B_2RS and BR_2S , respectively. In every state, repairing of failed components is taking place in this proposed model for the system to remain available. When the system is in one of the states $B_2, R_2, B_2S, B_2R, BR_2, B_2RS, BR_2S, R_2S$, it is considered in a downstate.

The transition from one state to another can be influenced by various factors, exhibiting random behavior. The distribution of transitions between states is determined by the failure and repair of the base station's components in the given model. Some states have sojourn times following non-exponential distributions, such as when a fault in the BBU necessitates manual switching. However, the time epochs in this model still possess the Markov property. Therefore, it is not a simple Markov model, and the failure of one component does not influence the failure of another component. Thus, this system can be appropriately modeled as a semi-Markov process (SMP). Figure 1 illustrates the state transition diagram of this proposed model, with ellipses representing sojourn times following exponential distributions and deterministic sojourn times indicated by rectangles.

III. STEADY STATE ANALYSIS

In this section, we present the steady-state analysis of the presented SMP. The state space of this model is represented as $\Omega = \{U, B, S, R, BS, RS, BR, BRS, B_2, R_2, B_2S, B_2R, BR_2, B_2RS, BR_2S, R_2S, M_1, M_2, M_3, M_4\}$. Let $K_{i,j}(t)$ denotes the elements of Kernel matrix $K(t)$, where $K_{i,j}(t)$ is the probability that the system just entered the state i , and in the next transition, it is going to enter the state j within time t [8]. The non-zero elements of the kernel matrix are given by

$$K_{U,M_1}(t) = \int_0^t (1 - F_{U,S}(x))(1 - F_{U,R}(x))dF_{U,M_1}(x),$$

where $F_{i,j}(x)$ is the cumulative distribution function (CDF) of transition from state i to state j , $i, j \in \Omega$ [2]. Define $K_{i,j}(\infty) = \lim_{t \rightarrow \infty} K_{i,j}(t)$, where $i, j \in \Omega$. Hence, matrix $K(\infty)$ with entries $K_{i,j}(\infty)$ gives the one-step transition probabilities for the model and row sum of $K(\infty)$ is 1. The steady state probabilities, $V = (V_U, V_R, \dots, V_{B_2RS})$ of the Embedded Markov Chain (EMC) can be obtained by solving

$$V = VK(\infty), \sum_{i \in \Omega} V_i = 1. \quad (1)$$

The steady-state probabilities of each state i of SMP can be obtained as [12]

$$\pi_i = \frac{V_i E[T_i]}{\sum_{j \in L} V_j E[T_j]}, i \in \Omega, \quad (2)$$

where, $E[T_i]$ denotes the expected sojourn time in state $i \in \Omega$. Let T_i denote the sojourn time in state $i \in \Omega$. The expected sojourn time in state U is obtained as

$$E[T_U] = \int_0^\infty (1 - F_{U,S}(t))(1 - F_{U,R}(t))(1 - F_{U,M_1}(t))dt.$$

IV. ENERGY CONSUMPTION MODEL

In this section, we delve into the analysis of energy consumption within the system, utilizing the steady-state probabilities obtained in Section III in conjunction with the reward rates associated with each state. These reward rates quantify the energy consumed in each corresponding state.

Remarkably, among the base station components, the RU equipment, which includes power amplifiers, transceivers, and cables, stands out as the most substantial energy consumer, accounting for approximately 65% of the total energy consumption. In contrast, the BBU contributes around 10% to the energy consumption, while the remaining base station components collectively consume approximately 25% of the energy, as detailed in [5]. It's crucial to note that the presence of a fault in any base station component leads to a reduction in energy consumption within the respective states, as the failed component no longer consumes power.

To illustrate, let r_i represent the reward rate associated with state $i \in \Omega$. Take, for instance, state M_1 , where the BBU experiences a failure, causing 10% of its energy consumption to go unused. Consequently, $r_{M_1} = 0.9$, indicating that 90% of the energy is effectively consumed in this state. Similarly, reward rates are assigned to the other states based on their corresponding energy utilization. Please refer to Table I for the specific reward rates assigned to each state. Let P represent the power consumption in the system. The expected steady state power consumption is given by the expected reward, i.e.,

$$E[P] = \sum_{i \in \Omega} r_i \pi_i, \quad (3)$$

where, r_i and π_i are the reward rate attached with the state i and steady-state probability of state i , respectively, $i \in \Omega$.

State	Reward rate	State	Reward rate
U	1	M_4	0.35
M_1	0.9	BRS	0.45
R	0.65	B_2	0.8
S	0.8	R_2	0.3
M_2	0.7	B_2S	0.6
M_3	0.55	B_2R	0.45
B	1	BR_2	0.3
BS	0.7	R_2S	0.1
BR	0.55	B_2RS	0.25
RS	0.45	BR_2S	0.1

TABLE I
REWARD RATES

V. DISCUSSION PART

In this section, we provide a numerical demonstration of the proposed model. We conduct a parameter analysis, varying different parameters, and visualize the resulting graphs to analyze their behaviors. We assume exponential distributions for the failure rates and repair rates of all components. Network parameter values are adopted from existing literature [1], [4], and these parameter values are summarized in Table II.

To obtain the steady-state results with the specified parameter

Parameter	Value (in hr^{-1})
λ_B	0.001
λ_R	0.01
λ_S	0.1
μ_B	3.5
μ_R	2.5
μ_S	1.5
T	0.5

TABLE II
PARAMETER VALUES

values, we first calculate the steady-state probabilities for each state of the EMC by solving Equation 1. Subsequently, leveraging the steady-state probabilities for each state of the EMC and their corresponding expected sojourn times, we derive the steady-state probabilities for each state of the SMP using Equation 2. The system's anticipated power consumption, as determined by Equation 3, exhibits a notable trend evident in Figures 2, 3, and 4.

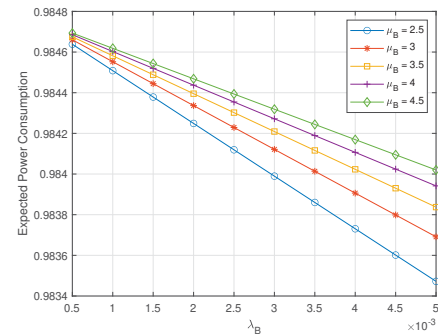


Fig. 2. Expected power consumption of system by varying the parameters λ_B and μ_B

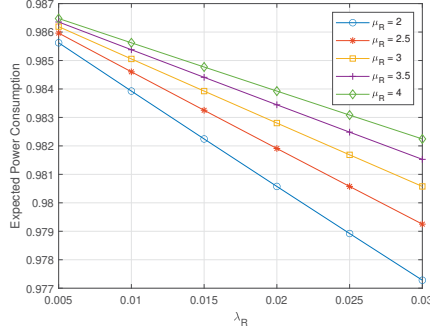


Fig. 3. Expected power consumption of system by varying the parameters λ_R and μ_R

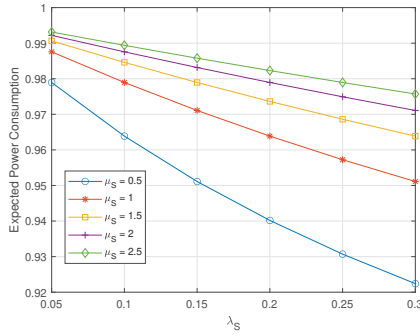


Fig. 4. Expected power consumption of system by varying the parameters λ_S and μ_S

As the failure rates of components increase, the expected power consumption of the system decreases. This correlation stems from the fact that heightened failure rates lead to a reduction in the system's upstate probability. Hence, the component's failure increases the power consumed by them decreases. Furthermore, these graphs highlight that the expected power consumption tends to be higher when the repair rates of the components are greater.

VI. CONCLUSION AND FUTURE WORK

This study employs a continuous-time stochastic model as a tool for evaluating base station availability. Within this framework, we scrutinize the individual components contributing to base station availability. Moreover, we delve into the realm of energy consumption within this specific context, examining how various components impact power utilization using the Markov reward model. Through a rigorous analysis, we derive solutions that reveal the probabilities associated with different states within the model. Looking forward, our research agenda includes expanding on this work to investigate energy harvesting within the various states defined by our model. These efforts hold significant importance in optimizing base station performance and enhancing energy management in wireless communication networks.

REFERENCES

- [1] S. Dharmaraja, R. Vinayak, and K. S. Trivedi, "Reliability and survivability of vehicular ad hoc networks: An analytical approach," *Reliability Engineering & System Safety*, vol. 153, pp. 28–38, 2016.
- [2] S. Gupta and V. Khaitan, "Reliability and survivability analysis of long-term evolution vehicular ad-hoc networks: an analytical approach," *Journal of Network and Systems Management*, vol. 29, pp. 1–34, 2021.
- [3] D. Davronbekov and U. K. Matyokubov, "The role of network components in improving the reliability and survivability of mobile communication networks," *Acta of Turin Polytechnic University in Tashkent*, vol. 10, no. 3, pp. 1–8, 2020.
- [4] S. Dharmaraja, V. Jindal, and U. Varshney, "Reliability and survivability analysis for umts networks: An analytical approach," *IEEE Transactions on Network and Service Management*, vol. 5, no. 3, pp. 132–142, 2008.
- [5] A. Ayang, P.-S. Ngohe-Ekam, B. Videme, and J. Temga, "Power consumption: base stations of telecommunication in sahel zone of cameroon: typology based on the power consumption model and energy savings," *Journal of Energy*, vol. 2016, 2016.
- [6] A. Taherkordi, M. A. Taleghan, I. F. I. C. o. A. R. Sharifi, Mohsen, and S. (ARES'06), "Achieving availability and reliability in wireless sensor networks applications," 2006, pp. 7–pp.
- [7] P. Kalita and D. Selvamuthu, "Stochastic modeling for energy efficiency in modified directional discontinuous reception for lte-5g networks," *International Journal of Communication Systems*, vol. 36, no. 6, p. e5434, 2023.
- [8] S. Dharmaraja, A. Aggarwal, and R. Sudhesh, "Analysis of energy saving in user equipment in lte-a using stochastic modelling," *Telecommunication Systems*, vol. 80, no. 1, pp. 123–140, 2022.
- [9] A. Aggarwal and D. Selvamuthu, "Energy optimization of a base station using q-learning algorithm, 2023 ieee, 17th international conference on telecommunications (contel)," in *2023 17th International Conference on Telecommunications (ConTEL)*, 2023, pp. 1–5.
- [10] P. González-Brevis, J. Gondzio, Y. Fan, H. V. Poor, J. Thompson, I. Krikidis, and P.-J. Chung, "Base station location optimization for minimal energy consumption in wireless networks, 2011 ieee 73rd vehicular technology conference (vtc spring)," 2011, pp. 1–5.
- [11] G. Auer, V. Giannini, C. Desset, I. Godor, P. Skillermark, M. Olsson, M. A. Imran, D. Sabella, M. J. Gonzalez, O. Blume *et al.*, "How much energy is needed to run a wireless network?" *IEEE wireless communications*, vol. 18, no. 5, pp. 40–49, 2011.
- [12] L. B. Castañeda, V. Arunachalam, and S. Dharmaraja, *Introduction to probability and stochastic processes with applications*. John Wiley & Sons, 2012.