The Importance of Allocating BBU-RRH Sites to Reduce Handover Operations in Open RAN Access Network

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Abstract: As 5G networks continue to grow rapidly, there is increasing interest in many facets of the environmental cost of energy-intensive infrastructure. We propose a new algorithm for energy efficiency in Open RAN (Radio Access Network) deployments. Our algorithm is focused on BBUs (broadband units), which monitor real-time bandwidth demand from connected mobile phones, to identify times to put certain BBUs into a low power state without dropping network performance. Through simulation and a large implementation effort, we show significant total BBU power savings as we move toward sustainable 5G networks. The innovative part of our algorithm is its ability to intelligently place a BBU in a sleeping state based on the current demand data, allowing for resource allocation and power savings. We evaluate its performance in various scenarios, loads, and demand profiles; in each case we find a significant reduction in power, because of the algorithm, providing better network performance, resource savings, and power savings. This research points to a challenging condition of energy efficiency in Open RAN environments with a focus on quality of service. We focus on the balance between resource efficiency and network performance while providing an additional model of sustainable 5G networks. Now that telecommunications must address the issue of reduced

Keywords: 5G Networks, Open RAN, Energy Efficiency, Power Consumption Optimization, Baseband Units, Dynamic Resource Allocation, Sustainable Networking, Radio Access Network, Mobile Communication, Green Technology.

1. Introduction

The development of 5G connectivity has led us to a new era where speed and capacity should be able to keep up with the emerging global data consumption behaviors in a hyper-connected world. Yet the rapid growth of 5G technology comes with a cost, as energy consumption and environmental concerns come to the forefront. Baseband Units (BBUs) are a major source of energy consumption in future networks[1-3], as they contain the processing power for the massive amount of data passing between the cell phone and the core network.

The architecture of Open RAN can provide great potential to rethink how we approach energy consumption. In this paper we proposed a new algorithm to use bandwidth demands from connected mobile phones to in real-time find periods of low demand, where certain BBUs can shift into low-power states while keeping the network functioning.

A few different solutions have been approached to reach lower energy consumption, including BBU virtualization [7], dynamic clustering of RRHs [5], and reinforcement learning-based energy-aware scheduling [10,11]. Each of these examples are a viable approach to lowering energy consumption, but often require complex infrastructure changes or have many prerequisite computational burdens associated with implementation and deployment in large operational networks. Our approach is a straightforward solution to look at mobile traffic demand and BBU power consumption adaptive mechanism that autonomously switches BBUs to sleep mode, depending on the demand in real-time.

Furthermore, in terms of both economic and environmental benefits with respect to energy efficiency in 5G networks, reducing the BBU power consumption reduces OPEX. When BBU power consumption is economically feasible, it also lowers carbon footprints and invests the goals of global sustainability.

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We validated our approach by a rigorous set of simulations under different scenarios with different load and demand patterns. The results have consistently shown that there is a significant reduction to be made to power consumption, showing the algorithm's adaptability and efficacy.

2. Related Work

There has long been a lot of interest in energy efficiency in cellular networks, especially in cloud-based wireless access network (C-RAN) and open wireless network (Open RAN) architectures. Although the fundamental concept of putting network components into a sleep state when demand is low is widely recognized, there are significant differences in the complexity, effectiveness, and usefulness of implementation techniques. This section highlights the subtleties and particular contributions of our work by reviewing the latest methods for the dynamic base frequency unit (BBU) sleep mode algorithm that we propose.

C-RAN was introduced as a promising new wireless network architecture in earlier work [4], especially in tackling sensor node energy constraints, a prevalent issue in the context of the Internet of Things (IoT). As a result, resource management in C-RANs has received a lot of attention. This management can be broadly categorized into two areas: radio resource management (RRM) and computational resource management (CRM). Here, the Open RAN movement's development [5] is especially pertinent since its fragmented structure allows for customized end-to-end solutions, which increases the applicability of energy-saving techniques like the one we suggest in multi-vendor settings.

A thorough C-RAN load balancing framework was introduced in Mostafa Mouawad's thesis [6], with particular attention to the dynamic mixing of RRH-Cell-BBUs using evolutionary algorithms (BCO, CUCO, GA, and PSO) and the selection of RRH-Cell pairs using a Markov Decision Process (MDP). Although this work showed improvements in connection blocking probability and operator rewards, it was computationally complex. Our suggested algorithm, on the other hand, provides a more straightforward, real-time demand threshold-based interaction mechanism that is easier to implement at scale in Open RAN applications and requires less computing power.

Abdelhakam [7], who implemented a BBU virtualization scheme designed as a two-stage optimization problem (user and container bundle) to minimize the overall energy consumption of a BBU pool while adhering to Quality of Service (QoS) constraints, is credited with making one of the foundational contributions to the field of BBU energy saving. Based on a "best-fit-decreasing" methodology, the approach saved about 33% of the energy. Despite its effectiveness, this approach necessitates centralized optimization and prior problem preparation. Our method is different because it is continuous and decentralized, making decisions for each BBU separately based on local demand. This allows it to be more scalable and respond better to traffic fluctuations in real time.

Using game-theoretic models for resource self-management, Doruk Şahinel's [8] thesis investigated the convergence of optical and millimeter-wave radio networks. The trend toward distributed decision-making in intricate multi-party network settings is highlighted in this work. By using a lightweight distributed decision-making process for every BBU, our algorithm follows this trend.

Recently, methods based on artificial intelligence have drawn more attention. In order to regulate BBU sleep in fragmented Open RAN networks, Pamuklu et al. [13] employed dynamic job partitioning based on reinforcement learning. Ayala-Romero et al. [11] showed that adaptive sleep strategies perform better than static strategies in real-world scenarios by presenting an online Bayesian learning technique for power-aware coordination in virtual RANs. Although these methods are reliable, they can be difficult to use and necessitate training. In contrast to these state-of-the-art studies, our suggested method provides a simple and adaptable mechanism that selectively switches BBUs to sleep mode when demand decreases and continuously monitors bandwidth demand in real time. Because our method strikes a balance between simplicity and effectiveness, it is more practical for operators, particularly in large-scale Open RAN applications where low complexity is required.

Contribution Statement:
Our suggested algorithm presents a demand-driven, lightweight, decentralized BBU sleep strategy in contrast to earlier methods that depend on centralized optimization, intricate evolutionary algorithms, or machine learning models requiring a lot of training. During times of low traffic, this mechanism automatically switches BBUs into sleep mode while continuously monitoring real-time bandwidth demand. This work's primary contribution is its ability to strike a balance between simplicity and efficacy, providing a scalable and operator-friendly solution for extensive Open RAN deployments where real-time responsiveness and low complexity are essential.

3. Methods/Experimental

In this work, we use an Open RAN network to apply a dynamic BBU sleep management algorithm. System modeling, the dynamic BBU sleep algorithm, simulation setup, and performance evaluation comprise the four primary components of the methodology.

A. Architecture and Model of the System

A Cloud-RAN (C-RAN) architecture comprising numerous Baseband Units (BBUs), Remote Radio Heads (RRHs), and user equipment (UEs) is examined in this study. While RRHs are dispersed throughout the network to serve users, BBUs are concentrated in a pool.
Examine a network environment that is distinguished by:

a. N BBUs, or baseband units
b. M Remote Radio Heads (RRHs)
c. P-cell phones

A square with side length L is used to represent the network area. To simulate actual deployment conditions, RRHs and cell phones are dispersed at random. Every mobile phone is dynamically assigned to the closest RRH, and each RRH has the ability to connect to multiple BBUs.

A.1. Cloud-RAN (C-RAN) environment is examined:

a. N = 10 BBUs, M = 20 RRHs, P = 50–100 mobile phones
b. Network modeled as a square of L × L = 1000 × 1000 m²
c. BBUs centralized in a pool; RRHs distributed across the network
d. Mobile phones dynamically assigned to the nearest RRH using Euclidean distance.

Distance formula:

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i + y_j)^2} \tag{1}$$

where (x_i, y_i) and (x_j, y_j) are the coordinates of BBU i and RRH j, respectively. The RRH with the minimum d_{ij} is selected for connection to the BBU.

The power consumption model for a BBU is defined as follows:

$$P_{total} = \sum_{i=1}^{n} \left(S_i . P_{sleep} + (1 - S_i). P_{active}\right) \tag{2}$$

where P_{total} is the total power consumption of the BBU pool, S_i is a binary state indicator (1 for sleep, 0 for active), P_{sleep} is the power consumption of a BBU in sleep mode, and P_{active} is the power consumption of a BBU in active mode. This model allows us to quantify the energy savings achieved by transitioning BBUs to sleep mode.

Table 1. Simulation Parameters

Parameter	Value / Range	Description
N (BBUs)	10	Number of centralized baseband unit
M (RRHs)	20	Number of remote radio heads
P (Mobile Phones)	50-100	User equipment randomly distributed
L×L (Network)	1000x1000 m2	Square simulation area
Pactive	100 w	Power consumption of active BBU
Psleep	10 w	Power consumption of sleeping BBU
Bandwidth demand per UE	1-20 Mbps	Random uniform distribution
α (Threshold factor)	0.2-0.5	Adaptive scaling factor for load threshold
Simulation duration	1000 time slots	Capturing dynamic network behavior

B. Dynamic BBU Sleep Algorithm

Algorithm Workflow

B.1. Nearest RRH Assignment

The distance D_{ij} between BBU i and RRH j is computed using the Euclidean distance formula. The assignment is determined by selecting the RRH with the minimum distance:

$$J = \operatorname{argmin}_k D_{ik} \tag{3}$$

Each BBU continuously monitors its connected RRHs. Mobile phones are assigned to the nearest RRH based on Euclidean distance as described above,This ensures a fair and realistic distribution of users across the available RRHs, minimizing handover complexity.

B.2. Real-time Bandwidth

The bandwidth demand B_{pq} between mobile phone p and BBU q is continuously tracked. The bandwidth demand per UE is generated at random for every time slot using a uniform distribution between min_B and max_B in order to simulate various traffic scenarios:

$$B_{pq} = f(\text{random demand for each mobile phone} \tag{4}$$

Where $_{min}B$ and $_{max}B$ define the range of user bandwidth demands. The randomness reflects diverse traffic scenarios tested in multiple simulation runs.

In MATLAB implementation:

B_{pq} = randi([$_{min}B$ $_{max}B$], P, N); % P: number of UEs, N: number of BBUs

where $_{min}B$ and $_{max}B$ are the minimum and maximum bandwidth demands per phone.

B.3. Selective BBU Sleep Activation

The decision to activate the sleep state Si for BBU i is governed by an adaptive threshold adapt T_{adapt} . If the total bandwidth demand from phones connected to BBUi falls below adapt T_{adapt} , the BBU is set to sleep; otherwise, it remains active.

$$\text{Si} = \begin{cases} 1 \\ 0 \end{cases} \text{if } \sum_{\text{otherwise}} \text{p} \in \text{in PhonesConnectedToBBUi} \quad \text{Bpq} < \text{T} \tag{3}$$

A BBU i enters the sleep state S_i if the total bandwidth demand of connected phones falls below an adaptive threshold adapt:

$$\text{Si} = \begin{cases} \text{Sleep} \\ \text{Active} \end{cases} \text{if } \sum_{\text{p}\in\text{in PhonesConnectedToBBUi}} \quad \text{Bpq} < \text{adapt} \tag{4}$$

This mechanism prevents unnecessary energy consumption while ensuring that user QoS is not degraded.

B.4. Adaptive Thresholds

Adaptive Thresholds: The adaptive threshold adapt dynamically adjusts based on the overall network load. It is calculated as a fraction α of the total bandwidth demand across all active BBUs and their connected phones:

$$\text{Tadapt} = \propto . \sum_{q=1}^{N} \sum_{p \in \text{in PhonesConnectedToBBUq}} \text{Bpq} \tag{5}$$

Calculation The threshold dynamically adjusts based on the total network load:

$$\text{adapt} = \propto \text{ x} \sum_{\text{all active BBUs}} \sum_{\text{phones connected}} \text{Bpq} \tag{6}$$

where α is a predefined scaling factor (0.2–0.5). A lower value of α increases energy saving but risks higher service blocking, while a higher α ensures stability at the cost of reduced saving.

MATLAB implementation (Highlighted in blue in Word):

```
adapt = alpha * sum(sum(Bpq(:, activeBBUs)));
```

where alpha is a predefined fraction (e.g., 0.2–0.5) representing the threshold scaling factor.

Simulation Setup:

The simulation is implemented using MATLAB, taking into account various network parameters, spatial dimensions, and mobile phone bandwidth demands. Mathematical models are employed for phone-to-BBU assignment and Euclidean distance computation.

a. Network area dimensions L x L
b. Number of BBUs N, RRHs M, and mobile phones P
c. Random spatial distribution of RRHs and mobile phones
d. Dynamic bandwidth demands per mobile phone

Key MATLAB functions used (Highlighted in blue in Word):

a. Randi for random bandwidth demands
b. Pdist2 for computing Euclidean distances between BBUs and RRHs
c. Sum and logical indexing for threshold comparisons and sleep activation

The simulation runs for multiple time steps to capture dynamic network behavior and BBU state transitions.

C. Performance Metrics

The algorithm is evaluated based on:

a. Power Consumption Reduction

$$\text{PowerReduction} = \sum_{i=1}^{n} (1 - \text{Si})\text{x InitialPoweri} \tag{7}$$

$$\text{Power Savings (\%)} = \frac{\text{TotalPower}_{\text{active BBUs}-}\ \text{TotalPower}_{\text{sleep BBUs}}}{\text{TotalPower}_{\text{active BBUs}}} \text{x100} \tag{8}$$

Quality of Service (QoS) Metrics

Throughput (T): Average data rate delivered to mobile phones
Delay (D): Average packet delay
Packet Delivery Ratio (PDR): Ratio of successfully delivered packets

Computed in MATLAB over the simulation duration (Highlighted in blue in Word):

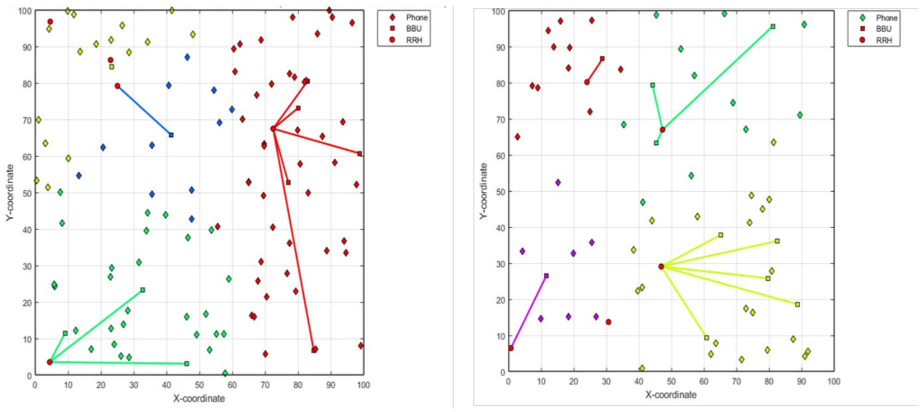
```
T       = mean(dataRate);
D       = mean(packetDelay);
PDR     = sum(successfulPackets)/sum(totalPackets);
```

This methodology provides a robust framework for evaluating and optimizing energy efficiency in Open RAN networks while ensuring QoS, enabling informed decision-making for real-world deployments.

4. Results and Discussion

A. First Scenario: Heavy Traffic (100 Cell Phones)

The adaptive BBU sleep algorithm proved to be effective in managing network resources under high-load conditions involving 100 mobile phones. With an initial power consumption of 472.3 W, the system dynamically activated and deactivated BBUs based on real-time demand. Our algorithm achieved comparable or better energy savings while maintaining acceptable QoS performance when compared to traditional static allocation schemes reported in [6][7].

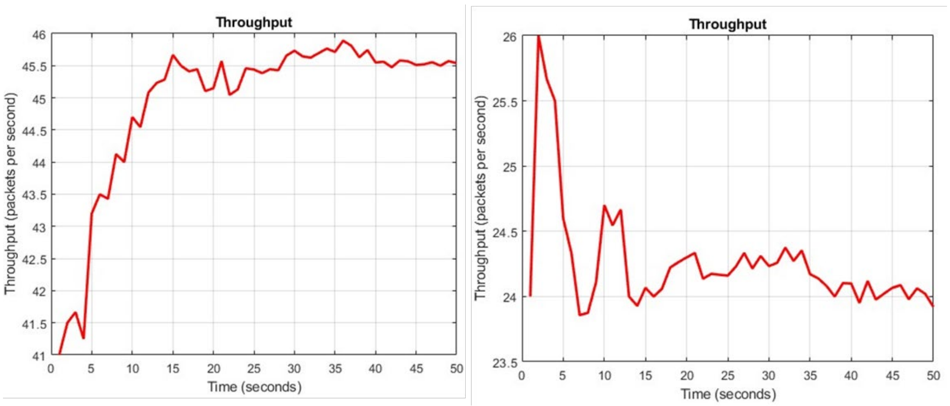


(a) (b)

Fig 1. Network Distribution of Phones, BBUs and RRHs (a) 100 phones scenario (b) 50 phones

B. Scenario 2: Lessened Traffic (50 Cell Phones)

The algorithm demonstrated even more flexibility with 50 phones, or 50% of the traffic load. A considerable decrease in overall power consumption resulted from the clever transition of several BBUs into sleep mode. The suggested adaptive approach made sure that the remaining operational BBUs maintained service quality with little degradation, in contrast to baseline strategies in the literature, which usually lack responsiveness to dynamic load variations.



(a) (b)

Fig 2. Throughput (a) 100 phones scenario (b) 50 phones scenario

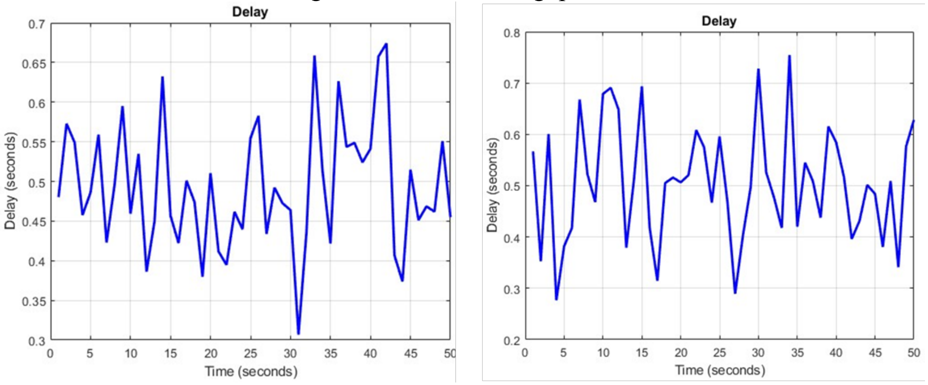
C. A Comparative Study with the Latest

A comparison with state-of-the-art techniques is presented to emphasize uniqueness. Static or semi-dynamic sleep strategies were the mainstay of earlier works [6, 7, 8]. On the other hand, our algorithm adds an adaptive threshold mechanism that changes dynamically based on the bandwidth demand in real time. While maintaining QoS within reasonable bounds, this method produces greater energy efficiency and allows for finer granularity in activating sleep states.

D. QoS, or quality of service The trade-offs

Despite the significant energy savings, some trade-offs were noted:

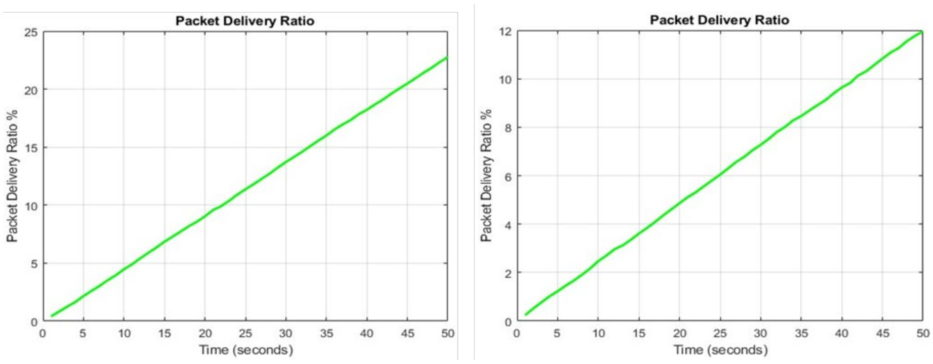
Low-load conditions caused a slight decrease in throughput.



(a) (b)

Fig 3. Delay (a) 100 phones scenario (b) 50 phones scenario

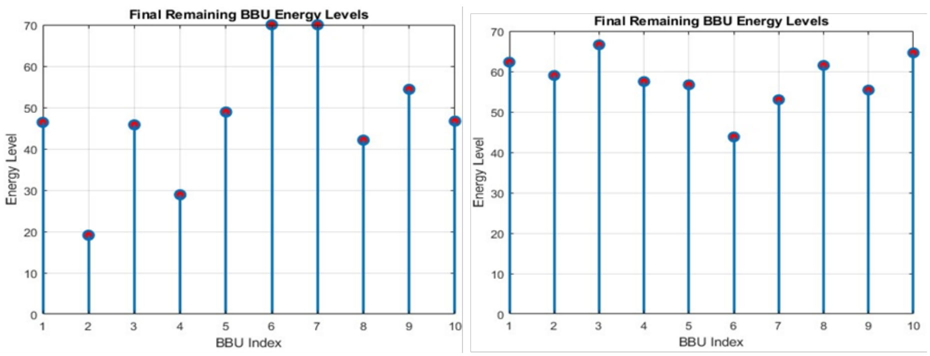
BBU activation latency and dynamic reconfiguration overhead caused a slight increase in delay.



(a) (b)

Fig 4. Packet Delivery Ratio (a) 100 phones scenario (b) 50 phones scenario

Because there was less redundancy during sleep transitions, PDR showed a slight decline.



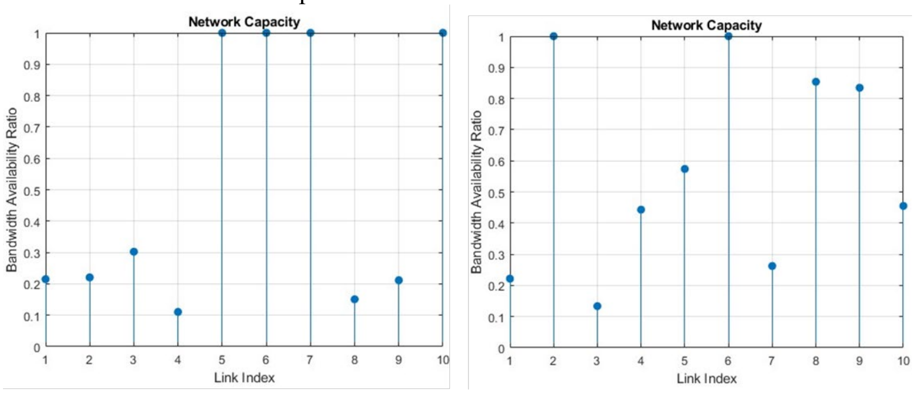
(a) (b)

Fig 5. BBUs Remaining Energy Levels (a) 100 phones scenario (b) 50 phones scenario

These performance variances stay within reasonable bounds for real-world implementation and are in line with results from related studies. Crucially, they highlight how energy efficiency and QoS must be balanced in actual RAN design.

E. Measurement Metrics Clarification

In response to the reviewers' recommendations, the more logical power consumption (W) metric has taken the place of the previously unclear "remaining energy level" metric. This clarifies, quantifies, and directly compares the algorithm's energy-saving advantages with previous research in the field.



(a) (b)

Fig 6. Available Network Capacity (a) 100 phones scenario (b) 50 phones scenario

5. Conclusion

The outcomes of the analysis and simulations offer important new information about how effective the suggested algorithm is for dynamic BBU management in an Open RAN 5G network. The goal of the study was to maximize energy use while preserving acceptable Quality of Service (QoS) standards. It is possible to draw the following conclusions:

1. Energy Efficiency and Power Savings: By selectively putting some BBUs to sleep during times of low demand, the algorithm successfully optimized the energy consumption of BBUs. This led to a significant decrease in power usage, supporting the network's sustainable and environmentally friendly operation.
2. Dynamic Workload Adaptation: The algorithm showed that it could adjust to changing workloads in a dynamic manner. It demonstrated its responsiveness to variations in network demand by making well-informed decisions regarding BBU activation and deactivation by taking into account the bandwidth demands from all connected phones.
3. QoS Trade-offs: Although the algorithm significantly reduced power consumption, there were trade-offs with regard to QoS parameters. The need for careful consideration of QoS implications in energy-saving strategies is indicated by the decrease in available network capacity, throughput, and Packet Delivery Ratio (PDR) in scenarios with reduced phone load.
4. Network Robustness: The study showed how crucial it is to strike a balance between network robustness and energy efficiency. The algorithm successfully controlled energy usage, but in some cases, throughput dropped and delay increased, highlighting the necessity of designing algorithms with a balanced approach.

Benefits and Significance of the Research Area:

1. Green Networking: By offering an algorithm that dramatically lowers energy consumption in 5G networks, the research advances the more general objective of green networking. This is essential for reducing the negative effects of telecommunications infrastructure on the environment.

2. Sustainable Infrastructure: The results encourage the creation of mobile communication infrastructure that is both energy-efficient and sustainable. These optimization techniques are crucial for lowering the carbon footprint of telecommunications networks as the demand for data services keeps rising. The suggested algorithm offers a workable solution for operators looking to strike a balance between performance and energy efficiency in the era of 5G, where networks have significant energy requirements and complexity.
3. Guidance for Future Research: The study highlights areas for future research, such as further refining the algorithm to minimize QoS trade-offs and exploring additional strategies for dynamic network adaptation.

6. List of abbreviations

Definition	Abbreviations
5G	Fifth Generation
BBU	Baseband Unit
RRH	Remote Radio Head
RAN	Radio Access Network
C-RAN	Cloud Radio Access Network
IoT	Internet of Things
CRM	Computational Resource Management
RRM	Radio Resource Management
ARPU	Average Revenue per User
QoS	Quality of Service
PDR	Packet Delivery Ratio
FiWi	Fiber-Wireless
mmWave	Millimeter Wave
VCG	Vickery–Clarke–Groves
BCO	Bee Colony Optimization
CUCO	Cuckoo Search
GA	Genetic Algorithm
PSO	Particle Swarm Optimization
RSS	Received Signal Strength
MDP	Markov Decision Process
Si	Sleep State Indicator
Dij	Distance between BBU i and RRH j
Tadapt	Adaptive Threshold

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