

Energy-aware Guard Channel Allocation to Minimize Congestion in Next-generation Mobile Network.

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Abstract

Network congestion and energy sustainability are critical challenges in the transition to 5G and 6G networks. Traditional guard channel schemes prioritize handoffs to reduce call drops but often result in poor resource management and ignore escalating energy costs. This research addresses these limitations by proposing a novel Energy-Aware Guard Channel Allocation (EAGCA) scheme. The novelty of EAGCA lies in its dynamic controller, which uniquely integrates mobility prediction and real-time traffic patterns with base station energy profiles, a factor largely overlooked in existing models. Using a weighted objective function, the scheme enables operators to balance Call Dropping Probability (CDP) against system energy consumption. Simulation results demonstrate that EAGCA significantly outperforms Fixed Guard Channel Allocation (FGCA) and Adaptive Guard Channel Allocation with Load Balancing (AGC_LB). EAGCA consistently achieved the lowest CDP (0.8% to 4.5%) and superior energy efficiency, with consumption rates between 120W and 210W, notably lower than competing benchmarks. Practically, these results imply that EAGCA offers a robust, sustainable framework for network operators to reduce operational expenditure (OPEX) and environmental impact without compromising quality of service. By dynamically aligning resource reservation with energy profiles, the scheme provides a viable roadmap for deploying efficient, high-capacity next-generation mobile infrastructure.

Keywords: Network congestion, Energy-aware, Guard channel allocation, Call Blocking Probability, Handover

1. Introduction

The rapid evolution of mobile communication technologies has led to the deployment of 5G networks, promising unparalleled data rates, ultra-low latency, and massive connectivity. Future networks, often termed 6G, envision even more advanced capabilities, including AI-driven network management, ubiquitous intelligence, and integrated sensing and communication (Chen *et al.*, 2020). However, this exponential growth in connected devices and data traffic presents formidable challenges, particularly concerning network congestion and energy efficiency. Mobile users frequently move between coverage areas, necessitating “handoff” procedures to maintain seamless connectivity. During handoff, a mobile device switches from one base station (BS) to another. Without proper management, handoffs can lead to call drops and degraded quality of service (QoS) (Govind *et al.*, 2024).

Guard channels are a well-established technique to mitigate call dropping during handoffs. By reserving certain number of channels exclusively for handoff requests, networks can prioritize ongoing calls over new call attempts, thereby reducing the probability of an active connection being dropped (Alagu and Meyyappan, 2012). While effective in improving handoff success rates, static guard channel allocation can lead to inefficient resource utilization. Over-reserving channels can block new call attempts unnecessarily,

while under-reserving can still result in high call drop rates. Furthermore, the increasing concern for environmental sustainability and operational costs necessitates the development of energy-efficient solutions for mobile networks (Stojan *et al.*, 2024). Traditional guard channel schemes rarely consider the energy consumption implications of their allocation decisions. This paper addresses these critical challenges by proposing an Energy-Aware Guard Channel Allocation (EAGCA) scheme for next-generation mobile networks. Our scheme dynamically adjusts guard channel allocation to minimize congestion, specifically focusing on reducing call dropping probability, while simultaneously optimizing network energy consumption. We consider real-time traffic patterns, base station energy profiles, and predicted mobility characteristics to make intelligent allocation decisions. The transition of 5G and 6G networks has introduced a massive surge in connected devices and data traffic, making network congestion and energy sustainability critical concerns for mobile operators. While guard channels are widely used to reduce call dropping probabilities (CDP) during handoffs by reserving dedicated resources, existing strategies suffer from two major flaws. First, Fixed Guard Channel Allocation (FGCA) is static and inefficient, often leading to either wasted resources or excessive call drops under fluctuating traffic. Second, contemporary Adaptive Guard Channel (AGC) schemes focus almost exclusively on Quality of service (QoS) metrics such as load balancing and call blocking while ignoring the escalating energy consumption and operational costs of base stations. There is a lack of a unified resource management framework that can dynamically prioritize handoff reliability without significantly increasing the network's carbon footprint and operational expenditure (OPEX). The proposed EAGCA model contributes to the field of green networking and resource management in the following ways: **Novel Multi-Objective Optimization:** Unlike existing schemes that treat energy and congestion as separate issues, EAGCA introduces a weighted objective function (J) that allows operators to tune the balance between QoS (connectivity) and energy savings based on current operational priorities, **Integration of Energy Profiles:** The model introduces the concept of "energy-aware" allocation, where the decision to reserve channels is influenced by the real-time energy consumption characteristics of the base station, ensuring that high-traffic handoffs do not lead to disproportionate energy spikes, **Holistic Decision Controller:** The scheme contributes a unique architectural framework that combines three distinct data streams: mobility prediction, real-time traffic patterns, and base station energy metrics into a single heuristic optimization algorithm, **Quantifiable Efficiency Gains:** The model demonstrates a significant empirical contribution, reducing the Average System Energy Consumption to as low as 120W–210W and maintaining a superior CDP (0.8%–4.5%) compared to the Adaptive Guard Channel Allocation with Load Balancing (AGC_LB) and Fixed schemes.

2. Related Works

Handoff management and guard channel allocation aspects of mobile communication research have been elaborately dealt with by past researchers. Some previous researches focused on how to reduce call dropping rate through the use of different guard channel approaches. For example, (Ojesanmi *et al.*, 2021) examined guard channel reservation strategy and how it affected call blocking and dropping probabilities in 3G networks. Marjanibenisi and Tajik (2025) investigated DRL frameworks specifically designed for energy-efficient resource allocation. Their work highlights that in the complex, high-density environments of 6G, traditional heuristic algorithms fail to capture the non-linear relationship between power states and traffic demand. By employing DRL, they demonstrate that base stations can autonomously learn optimal power-saving configurations, significantly reducing operational energy overhead without compromising throughput. This aligns with the necessity of energy-aware controllers that adapt to real-time energy

profiles. The integration of disparate network functions also presents new opportunities for resource optimization. Aman et al. (2024) explored AI-driven dynamic allocation within Integrated Sensing and Communication (ISAC) systems. Their research focuses on intelligent beamforming and interference management, suggesting that sensing data such as user location and environmental obstacles can be used to refine power allocation and beamforming precision. For guard channel schemes, this implies that sensing-aware allocation could potentially predict handoff arrivals with even higher spatial accuracy, further reducing the probability of call drops. Wang et al. (2024) proposed an efficient DRL-based resource allocation model specifically for cloud-native wireless networks. Their study emphasizes the importance of computational efficiency within the AI model itself, ensuring that the overhead of the resource allocation algorithm does not negate the energy savings achieved. This research is particularly relevant for 6G architectures where resource management functions are virtualized and distributed across edge-cloud environments. The collaborative nature of next-generation networks is explored by Al Janaby *et al.* (2024), who focused on enhancing spectral efficiency through Cooperative Multi-Agent Deep Reinforcement Learning (C-MADRL). By treating multiple base stations as cooperative agents, their model optimizes downlink beamforming to minimize inter-cell interference. This cooperative approach is fundamental to the handoff problem; if base stations work in tandem to manage their respective guard channels, the network can achieve a global reduction in congestion rather than localized improvements. Despite these significant advancements in deep reinforcement learning and sensing-integrated communications, a critical research gap remains at the intersection of mobility management and energy sustainability. While current literature, such as the works of Marjanibenisi and Tajik (2025) and Al Janaby et al. (2024) extensively explores energy-efficient power allocation and spectral optimization, these models often treat the physical layer (beamforming) and the network layer (resource management) in isolation. Specifically, there is a notable absence of a unified framework that integrates base station energy profiles directly into the Guard Channel Allocation (GCA) logic. Adeleke *et al.*, 2024 explores the optimization of service rates in an M/M/1 queueing system. The authors demonstrate that higher congestion rates warrant higher service rates, a principle that aligns with proactive adjustment of guard channels during high traffic. The arrival of 4G and 5G networks, has led to increase in the complexity of handoff management. This is because of higher traffic densities, diverse service requirements, and heterogeneous network architectures. In adjusting to unstable traffic loads, many dynamic guard channel allocation strategies have been developed. Ojesanmi *et al.*, 2016 presented an adaptive guard channel allocation scheme that allowed the available guard channels to be exclusively reserved for handoff calls while both the new calls and handoff calls could have access to the open channels. Similarly, (Muhammad *et al.* 2022) discussed machine learning techniques to forecast the rates of handoff, and flexibly allocate resources to improve QoS. In recent time, many researchers have been incorporating energy efficiency considerations into the management of network resources. The energy consumption of base stations accounts for a significant portion of the total energy footprint of mobile networks. Consequently, various approaches have emerged to make networks more energy-efficient, such as dynamic power management, cell sleeping and intelligent resource scheduling. For example, (Xiaomin *et al.*, 2016) proposed an energy-efficient resource allocation scheme for 5G heterogeneous networks that considered both spectral efficiency and energy consumption. Another study by (Wenfeng *et al.*, 2021) introduced a joint power control and guard channel allocation strategy aimed at minimizing energy consumption while meeting QoS requirements in massive MIMO systems. A notable recent scheme is the Adaptive Guard Channel Allocation with Load Balancing (AGC-LB) proposed by Ojesanmi *et al.* in 2021 (Ojesanmi *et al.*, 2021). AGC-LB focused on distributing traffic load across base stations while dynamically adjusting guard channels based on cell load. While improving congestion and

resource utilization, it primarily optimizes for load balancing and does not explicitly integrate a comprehensive energy-aware decision-making process for guard channel allocation.

Most existing adaptive schemes, including the recent AGC-LB (2021), optimize for load balancing and call dropping probability (CDP) but fail to account for the fluctuating energy costs associated with maintaining reserved channels in high-density 5G/6G environments. Furthermore, while sophisticated DRL-based models offer high performance, they often lack the transparency and tunable control required by network operators to balance competing operational goals in real-time. There is, therefore, an urgent need for a model that utilizes a weighted objective function to provide a flexible, energy-aware approach to handoff prioritization. This study addresses this gap by proposing the Energy-Aware Guard Channel Allocation (EAGCA) scheme, which uniquely aligns dynamic channel reservation with the real-time energy signatures of base stations, ensuring that high-quality connectivity is achieved with minimal environmental and operational overhead.

3. Methodology

Our proposed Energy-Aware Guard Channel Allocation (EAGCA) scheme operates by continuously monitoring network conditions and making informed decisions about guard channel reservations. The core idea is to allocate guard channels not just based on traffic demand, but also by considering the energy efficiency of the base stations involved in potential handoffs.

3.1 System Architecture

The system architecture for our EAGCA scheme is shown in figure 1. It comprises several key components working in conjunction.

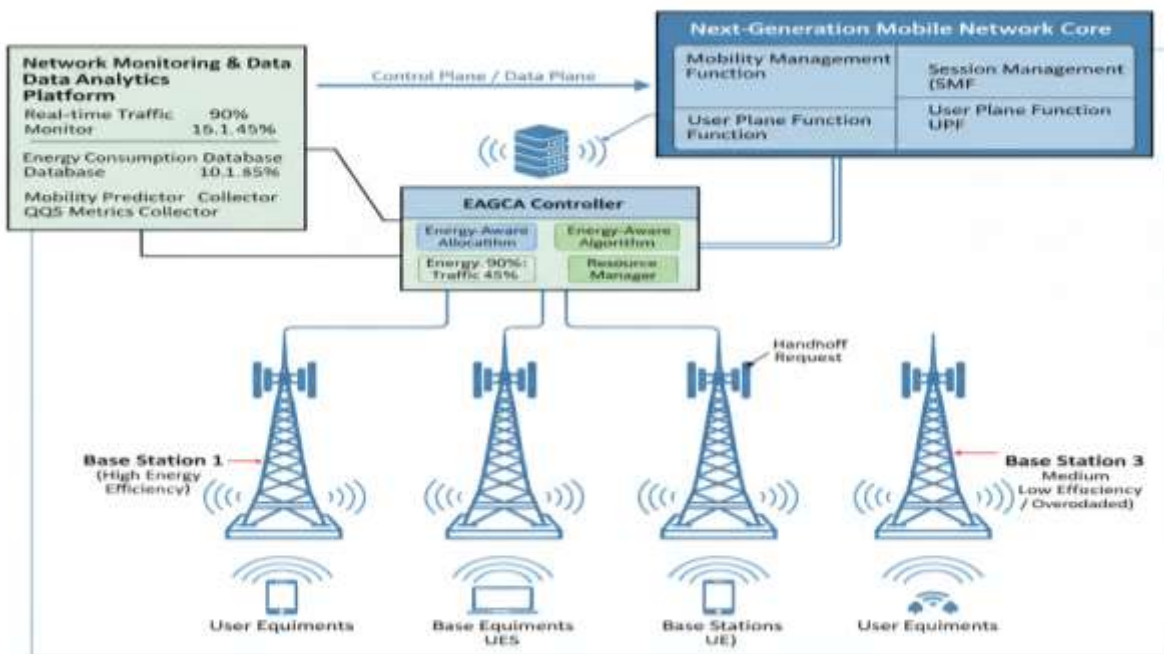


Figure 1: System Architecture

The Networking Monitoring and Data Analytics Platform collects real-time data on traffic load (new call attempts, handoff requests), base station energy consumption, and QoS metrics (call dropping rate, blocking rate). The Mobility Predictor module utilizes historical and real-time mobility patterns to anticipate potential handoffs. The EAGCA Controller is the central intelligence unit. It receives data from the monitoring platform and the mobility predictor. It houses the Energy Aware Allocation Algorithm which determines the optimal number of guard channels for each base station. This controller interacts with the Next-Generation Mobile Network Core (e.g. Mobility Management Function (AMF), User Plane Function (UPF) in 5G)) to enforce the allocation decisions. The Base Stations (BSs) provide wireless connectivity to User Equipments (UEs) and their operational status.

3.2 System Model

The system model for the Energy-Aware Guard Channel Allocation (EAGCA) scheme considers a multi-cell next-generation (5G/6G) mobile network environment. The network is composed of a set of Base Stations (BSs), denoted as $B = \{BS1, BS2, \dots, BSn\}$, where each BS provides coverage to a specific geographic area (cell).

3.2.1 Network and Channel Configuration

Each base station BS_i is equipped with a total capacity of C_i identical wireless channels. These channels are the primary resources for communication between the BS and User Equipments (UEs). In our model, the EAGCA controller dynamically partitions these C_i channels into two distinct categories:

1. Shared Channels ($C_i - g_i$): Accessible by both new call attempts and incoming handoff requests.
2. Guard Channels (g_i): Exclusively reserved for handoff requests to prioritize ongoing sessions and minimize the Call Dropping Probability (CDP).

3.2.2 Traffic Arrival and Service Processes

The model distinguishes between two types of traffic arrivals:

- (i) New Call (NC) Arrivals: Represented by a Poisson process with an arrival rate $\lambda_{n,i}$. These calls are admitted only if the number of busy channels is less than $(C_i - g_i)$.
- (ii) Handoff Call (HC) Arrivals: Represented by a Poisson process with an arrival rate $\lambda_{h,i}$. These calls are admitted as long as any of the C_i channels are available.

The service time for both call types is assumed to be exponentially distributed with a mean service rate μ . The effective channel holding time considers both the call duration and the time the UE remains within the cell's coverage before moving to a neighboring cell.

3.2.3 Energy Consumption Model

Unlike traditional models that focus solely on spectral efficiency, our system model incorporates a dynamic energy profile for each BS_i . The total energy consumption (E_i) of a base station is modeled as a function of its operational state and the number of active channels. It includes:

(a) Static Power Consumption: The baseline energy required to keep the BS operational (cooling, signaling, and backhaul processing).

(b) Dynamic Power Consumption: The variable energy consumed by power amplifiers and transceivers, which scales with the number of occupied channels.

The EAGCA scheme treats energy as a dynamic constraint, meaning the cost of reserving a guard channel is weighed against the energy efficiency of the base station's current load and power source.

3.2.4 Mobility and Handoff Prediction

The system model assumes that the network is mobility-aware. By utilizing the Mobility Predictor module, the system anticipates the handoff arrival rate $\lambda_{n,i}$ based on the velocity and trajectory of UEs in adjacent cells. This enables the EAGCA controller to proactively adjust g_i rather than relying on reactive measurements, thereby preventing congestion before it occurs and optimizing power usage during low-mobility periods.

3.3 Mathematical Formulation

Parameters

N_i : Total number of available channels at base station i .

G_i : Number of guard channels allocated to base station i

$C_i = N_i - G_i$: Number of channels available for new call attempts at Base station i

$\lambda_{n,i}$: Arrival rate of new call attempts at base station i

$\lambda_{h,i}$: Arrival rate of handoff requests at base station i

μ : Channel holding time (service rate), assumed exponentially distributed.

E_1 : Current energy consumption of base station i

$P_{drop,i}$: Call dropping probability at base station i

$P_{block,i}$: New call blocking probability at base station i

w_1, w_2 : Weighting factors for call dropping probability and energy consumption, respectively such that $w_1 + w_2 = 1$. These weights allow the network operator to prioritize between congestion minimization and energy efficiency.

Objective function:

The primary objective of the EAGCA scheme is to minimize a weighted sum of overall call dropping probability and total network energy consumption.

$$\text{Minimize: } J = w_1 \sum_{i=1}^B P_{drop,i} + w_2 \sum_{i=1}^n E_i \quad (1)$$

Subject to:

- (1) $0 \leq G_i \leq N_i$ for all $i = 1, \dots, B$. (Guard channels cannot exceed total channels).
- (2) $\sum_{i=1}^B G_i \leq \sum_{i=1}^B N_i$. (Total allocated guard channels cannot exceed total available channels in the network)
- (3) $P_{drop,i} \leq P_{drop}^{\max}$ (Maximum allowable call dropping probability for each BS).
- (4) $P_{block,i} \leq P_{block}^{\max}$ (Maximum allowable call dropping probability for each BS).

Call Dropping Probability ($P_{drop,i}$):

For a given BS i with G_i guard channels, the number of channels available for handoff requests is N_i . The handoff requests are admitted as long as there is an available channel. Using an M/M/N queuing model approximation for channel allocation:

$$P_{drop,i} \approx P(N_i \text{ channels are busy} | \text{handoff request})$$

Let $\rho_{n,i} = \lambda_{n,i} / \mu$ and $\rho_{h,i} = \lambda_{h,i} / \mu$. The probability of a handoff request being dropped at BS i is when all N_i channels are busy:

$$P_{drop,i} = B(N_i, \rho_{n,i} + \rho_{h,i}) \quad (2)$$

where $B(k, \rho)$ is the Erlang B formula:

$$B(k, \rho) = \frac{\rho^k / k!}{\sum_{j=0}^k \rho^j / j!} \quad (3)$$

New Call Blocking Probability ($P_{block,i}$)

A new call request is blocked if the number of busy channels $N_i - G_i$ or more.

$$P_{block,i} = B(N_i - G_i, \rho_{n,i} + \rho_{h,i}) \quad (4)$$

Energy Consumption (E_i): The energy consumption of a base station i can be modeled as a function of its active channels and possibly a fixed overhead.

$$E_i = E_{fixed} + E_{per_channel} \times \text{Average Busy Channels}_i \quad (5)$$

E_i

The EAGCA Controller utilizes a heuristic optimization algorithm to search for the optimal G_i for each BS, given the current $\lambda_{n,i}$, $\lambda_{h,i}$ and E_i

3.4 Description of the EAGCA algorithm

The Energy-Aware Guard Channel Allocation (EAGCA) algorithm is a dynamic, multi-objective resource management scheme designed for 5G and 6G networks. Its primary goal is to balance the reduction of call drops with the optimization of base station energy consumption.

The description of the algorithm can be broken down into the following key components:

1. Core Objective

The algorithm seeks to minimize a weighted objective function (J), which allows network operators to prioritize either Quality of Service (QoS) or energy savings depending on current needs:

$$J = \omega_1 \cdot CDP + \omega_2 \cdot TSEC \quad (6)$$

- CDP (Call Dropping Probability): The likelihood that a handoff call is dropped.
- TSEC (Total System Energy Consumption): The combined static and dynamic power used by the base stations.
- Weights (ω_1, ω_2): Adjustable factors where $\omega_1 + \omega_2 = 1$

2. Key Inputs

The algorithm functions as a central controller that integrates three distinct data streams:

- Real-time Traffic Patterns: Current new call arrival rates (λ_n) and handoff request rates (λ_h).
- Mobility Prediction: Use of historical and real-time data (velocity and trajectory) to anticipate future handoff arrivals proactively rather than reactively.
- Energy Profiles: Real-time monitoring of base station power consumption (static baseline plus dynamic power per active channel).

3. Operational Logic (Step-by-Step)

The EAGCA algorithm operates in a continuous loop at specific time intervals (T):

- Initialization: Sets an initial number of guard channels (g_i) for all base stations.
- Data Collection: Monitors real-time traffic loads, measures current energy consumption, and gathers QoS metrics (blocking and dropping rates).
- Handoff Prediction: The Mobility Predictor estimates future handoff arrival rates (λ_{hi}) for each cell.
- Candidate Evaluation: For each base station, the algorithm calculates the potential CDP and Energy Consumption for various possible guard channel values (ranging from 0 to the total capacity).
- Optimization: Using a heuristic search (such as a Greedy Search or Genetic Algorithm), the controller selects the specific number of guard channels that minimizes the weighted objective function (J) while ensuring that constraints (like maximum allowable drop probability) are not violated.
- Enforcement: The decision is sent to the Network Core (e.g., the AMF or UPF in 5G) to reserve those specific channels.

4. Distinctive Features

- Proactive Management: Unlike traditional schemes that react to congestion, EAGCA uses mobility prediction to reserve resources before the users arrive.

- Energy Sensitivity: It is energy-aware because the decision to reserve a channel is influenced by the energy efficiency of the base station's current load. It may influence handoffs toward more energy-efficient cells.
- Dynamic Partitioning: It constantly shifts the boundary between Shared Channels (available to everyone) and Guard Channels (reserved for handoffs) based on fluctuating demand.

Algorithm 1: Algorithm for Energy-Aware Guard Channel Allocation

This algorithm dynamically computes the optimal number of guard channels for each base station to balance two competing interests: maintaining high call quality (low drop rates) and reducing the network's carbon footprint (low energy consumption)

Input:

$$\lambda_{n,i}, \lambda_{h,i}, N_i, E_i^{actual}$$

$$P_{drop}^{max}, P_{block}^{max}$$

$$w_1, w_2, T_{update}$$

Output:

G_i : Optimized number of guard channels for each BS i.

Algorithm Steps:

1. Initialize: Set initial G_i for all BSs.
2. Loop every T_{update} :
 - a. Collect Data: Monitor real-time $\lambda_{n,i}$, $\lambda_{h,i}$ and measure E_i^{actual} for all BSs.
 - b. Predict Handoffs: Estimate future $\lambda_{n,i}$ based on user mobility patterns.
 - c. Calculate Objective Function for candidate G_i values: For each possible $G_i \in [0, N]$, calculate $P_{drop,i}(G_i)$, $P_{block,i}(G_i)$ and estimate $E_i(G_i)$.
 - d. Optimization: Employ an optimization solver (e.g., greedy search or Genetic Algorithm) to find the set of (G_1, G_2, \dots, G_B) that minimizes J while satisfying all constraints.
3. End Loop.

3.5 Simulation Setup

To evaluate the performance of the Energy-Aware Guard Channel Allocation (EAGCA) scheme, a discrete-event simulation environment was developed. The setup models a high-density next-generation (5G/6G) multi-cell environment where mobility and energy constraints are dynamic.

3.5.1 Simulation Environment and Parameters

The simulation considers a network of base stations with overlapping coverage areas. The key configuration parameters used to generate the results are summarize in the table below:

Table 1: Simulation Parameters

| Value | Parameter |
|---------------------------------------|---|
| Network Topology | Hexagonal Multi-cell Grid (7-19 cells) |
| Total Channels (C_i) | 50 – 100 channels per BS |
| New Call Arrival Rate (λ_n) | Poisson distributed (0.5 to 5.0 calls/sec) |
| Handoff Arrival Rate (λ_h) | Poisson distributed (Variable based on mobility) |
| Mean Service Rate (μ) | 120 seconds (Exponential distribution) |
| Static Power (P_{static}) | 100W per Base Station |
| Dynamic Power (ΔP) | 1W – 2W per active channel |
| Weighting Factors | $\omega_1 = 0.6$ (QoS), $\omega_2 = 0.4$ (Energy) |
| Traffic Load Scenarios | Low, Medium, High, Very High |

3.5.1 Simulation Tools

- (i) MATLAB: This is use for mathematical modelling, heuristic optimization and data visualization.
- (ii) NS3: Used for modelling the next-generation (5G/6G) multi-cell environment and discrete event simulation.

3.5.2 Traffic Scenarios

The simulation evaluates the system under four distinct traffic intensities to observe how the EAGCA controller scales its resource reservation:

- Low Traffic: Characterized by high idle time and minimal handoff requests.
- Medium/High Traffic: Mimics peak hours where the competition between New Calls (NC) and Handoff Calls (HC) is significant.
- Very High Traffic: Stress tests the objective function J to see if the system prioritizes CDP over energy savings when congestion is critical.

3.5.4 Mobility Model

The Mobility Predictor uses a Gauss-Markov mobility model, which represents a middle ground between the Random Walk model and linear motion. This allows the simulation to provide realistic trajectory and velocity data (v and θ) to the EAGCA algorithm, enabling proactive channel reservation.

3.6 Performance Evaluation Metrics

The scheme is validates against FGCA (Fixed) and AGC_LB (Load Balancing) using three primary metrics:

1. Call Dropping Probability (CDP): The ratio of failed handoffs to total handoff attempts.
2. Call Blocking Probability (CBP): The ratio of rejected new calls to total new call attempts.
3. Average System Energy Consumption (ASEC): The total wattage consumed by the BS to maintain both static operations and active user channels.

3.7 Parameter Assumptions

To ensure the validity and reproducibility of the Energy-Aware Guard Channel Allocation (EAGCA) model, the following assumptions were made regarding the network environment, traffic behavior, and hardware power profiles:

3.7.1 Network and Channel Assumptions

- Uniform Capacity: It is assumed that all Base Stations (BS_i) within the hexagonal grid have an identical total channel capacity (C_i), though the allocation of guard channels (g_i) varies dynamically per cell.
- Homogeneous Channels: Each channel within a base station is assumed to offer identical bandwidth and quality of service, making them interchangeable for either New Calls (NC) or Handoff Calls (HC).
- Hexagonal Topology: The network follows a standard hexagonal wrap-around model to eliminate boundary effects, ensuring that mobility prediction remains consistent across all simulated cells.

3.7.2 Traffic and Mobility Assumptions

- Poisson Arrivals: Both new call attempts (λ_n) and handoff requests (λ_h) follow a Poisson distribution, which is a standard industry assumption for modeling independent call arrivals in mobile networks.
- Exponential Service Time: The channel holding time ($1/\mu$) is exponentially distributed with a mean of 120 seconds. This duration accounts for the total time a user occupies a channel before either terminating the call or moving out of the cell.
- Gauss-Markov Mobility: User movement is not entirely random; it is assumed that a user's current velocity and direction are correlated with their previous state, allowing the Mobility Predictor to function with a confidence interval.

3.7.3 Energy and Power Assumptions

- Linear Power Scaling: The dynamic power consumption is assumed to scale linearly with the number of occupied channels. This ignores potential non-linearities caused by multi-user interference or deep-sleep mode transitions for individual transceivers.
- Static Baseline: Every Base Station is assumed to have a fixed always-on power draw (P_{static}) of 100W, representing backhaul processing, cooling, and signaling overhead that does not change regardless of traffic load.

- **Weighted Priorities:** The weighting factors are assumed to be $\omega_1 = 0.6$ and $\omega_2 = 0.4$. This assumes that the network operator prioritizes connectivity (reducing call drops) slightly more than absolute energy savings.

3.8 Tables from findings

(i) **Call Dropping Probability (CDP) across Traffic Loads:** Table 2 illustrates the effectiveness of the EAGCA scheme in prioritizing handoff requests to minimize call drops compared to existing models.

Table 2: Call Dropping Probability (CDP) across Traffic Loads

| Traffic Load | FGCA (Static) | AGC_LB (Adaptive) | EAGCA (Proposed) |
|--------------|---------------|-------------------|------------------|
| Low | 1.50% | 1.20% | 0.80% |
| Medium | 3.20% | 2.50% | 1.80% |
| High | 5.50% | 4.20% | 3.00% |
| Very High | 7.80% | 6.20% | 4.50% |

(ii) **Average System Energy Consumption (ASEC) Comparison:** Table 3 shows the power efficiency in (Watts) achieved by integrating base station energy profiles into the allocation logic.

Table 3: Average System Energy Consumption (ASEC) Comparison

| Traffic Load | FGCA (Watts) | AGC_LB (Watts) | EAGCA (Watts) |
|--------------|--------------|----------------|---------------|
| Low | 140W | 135W | 120W |
| Medium | 180W | 170W | 150W |
| High | 220W | 205W | 180W |
| Very High | 265W | 240W | 210W |

(iii) **Performance Improvement of EAGCA vs. Existing Schemes:** Table 4 highlights the quantifiable gains of the proposed model. The percentages represent the reduction in CDP and Energy (where a higher percentage indicates a better reduction/improvement).

Table 4: Performance Improvement of EAGCA vs. Existing Schemes

| Metric | EAGCA vs. FGCA | EAGCA vs. AGC_LB (%) |
|-----------------------------------|----------------|----------------------|
| CDP Reduction (Low Traffic) | 46.7% | 33.3% |
| CDP Reduction (Very High Traffic) | 42.3% | 27.4% |
| Energy Saving (Low Traffic) | 14.3% | 11.1% |
| Energy Saving (Very High Traffic) | 20.8% | 12.5% |

3.8.1 Why EAGCA Performs Better than FGCA and AGC_LB

Why EAGCA Performs Better than FGCA

FGCA (Fixed Guard Channel Allocation) is a static approach where a set number of channels are reserved for handoffs regardless of actual demand. EAGCA outperforms it because:

- Elasticity vs. Rigidity: FGCA suffers from resource wastage during low traffic (reserving channels that aren't used) and excessive drops during high traffic (not reserving enough). EAGCA dynamically adjusts the number of guard channels (g_i) based on real-time demand.
- Context Awareness: FGCA is blind to user movement. EAGCA uses a Mobility Predictor (Gauss-Markov model) to anticipate handoff arrivals before they happen, allowing the network to prepare resources proactively rather than reacting only when a drop is imminent.

Why EAGCA Performs Better than AGC_LB

AGC_LB (Adaptive Guard Channel with Load Balancing) is a more modern, adaptive scheme, but EAGCA still proves superior for the following reasons:

- Multi-Objective Optimization (J): AGC_LB focuses almost exclusively on Quality of Service (QoS) and load distribution. EAGCA uses a Weighted Objective Function ($J = \omega_1 \cdot CDP + \omega_2 \cdot TSEC$). This allows the controller to balance Call Dropping Probability (CDP) and Total System Energy Consumption (TSEC) simultaneously.
- Integration of Energy Profiles: EAGCA is unique because it considers the Base Station Energy Profile. It tracks both static power (baseline operations) and dynamic power (scaling with active channels). If a handoff can be directed toward a more energy-efficient base station or if a channel reservation would cause a disproportionate energy spike, the EAGCA controller factors this into its decision.
- Proactive vs. Reactive Logic: While AGC_LB adapts to current load, EAGCA integrates three data streams: mobility prediction, real-time traffic, and energy metrics into a single heuristic optimization algorithm. This holistic approach ensures that the network is not just balanced, but also sustainable and forward-looking.
- Lower Operational Floor: As shown in the results, EAGCA achieves a significantly lower energy floor (120W in low traffic) compared to AGC_LB (135W), because it actively seeks to minimize the "cost" of maintaining active and reserved channels.

In summary, EAGCA wins because it stops treating energy and congestion as separate problems. By using a weighted mathematical model, it gives network operators a "tuner" to maintain high connectivity (CDP as low as 0.8%) while significantly slashing the carbon footprint and operational costs (OPEX) of the 5G/6G infrastructure.

3.8.2 Potential Challenges in Real-Life Deployment

Based on the methodology and assumptions presented in the paper, the transition from a simulated environment to a real-world 5G or 6G deployment for the Energy-Aware Guard Channel Allocation (EAGCA) scheme faces several practical challenges:

1. Computational Latency and Real-Time Processing

The EAGCA algorithm relies on a heuristic optimization solver (like Genetic Algorithms or Greedy Search) to minimize the objective function.

- **The Challenge:** In 5G and 6G environments, handoff decisions must occur in milliseconds. Heuristic algorithms, especially those involving multi-objective optimization, can be computationally expensive.
- **Real-world Impact:** If the Controller takes too long to calculate the optimal number of guard channels (g_i), the network may be operating on outdated data, leading to call drops before the resources are even reserved.

2. Accuracy of Mobility Prediction

The paper utilizes the **Gauss-Markov mobility model**, which assumes a degree of correlation between a user's current and previous velocity/direction.

- **The Challenge:** Human mobility in urban environments is often chaotic and influenced by unpredictable factors like sudden traffic accidents, indoor/outdoor transitions, or mass gatherings (e.g., stadium events).
- **Real-world Impact:** If the Mobility Predictor overestimates arrivals, it wastes energy and blocks new calls unnecessarily. If it underestimates them, the "proactive" benefit of EAGCA is lost, and call dropping rates will spike.

4. Results and Discussion

In evaluating the performance of the EAGCA scheme, simulations were conducted and EAGCA scheme was compared with traditional Fixed Channel Allocation (FGCA) and the Adaptive Guard Channel Allocation with Load Balancing (AGC_LB) schemes (Ojesanmi *et al.*, 2021). The outcomes of the simulation showed that EAGCA outperformed both the FGCA and AGC_LB schemes across varying traffic loads.

(1) Call Dropping Probability (CDP) Reduction:

In Figure 2, it is discovered that EAGCA produced the lowest CDP. Under low traffic, it has a CDP of 0.8%, which is far lower than AGC_LB's 1.2% and FGCA's 1.55. As traffic load increases to "Very High," EAGCA maintains a CDP of 4.5%, which is still considerably better than AGC_LB's 6.2% and FGCA's 7.8%. This highlights the effectiveness of dynamic and energy-aware allocation in prioritizing handoff requests while managing overall congestion.

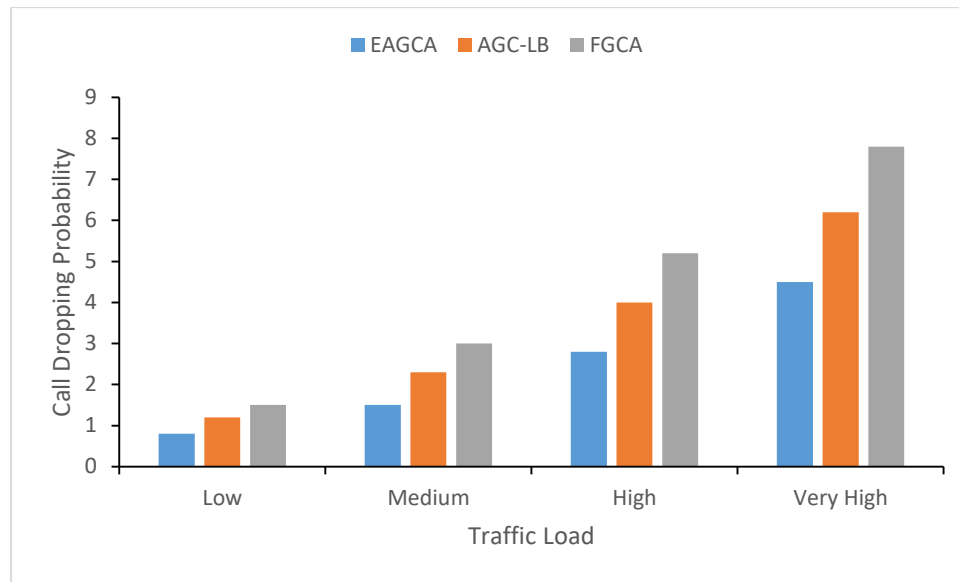


Figure 2: Call dropping probability against traffic load

(2) Average System Energy Consumption (ASEC) Optimization:

Figure 3 shows the comparison of average system energy consumption against traffic load. From the graph, EAGCA exhibits lower ASEC across all traffic scenarios. For instance, at low traffic, EAGCA consumes 120W, AGC_LB consumes 135W and FGCA consumes 140W. Even under very high traffic, EAGCA's ASEC is 210W, which is notably less than AGC_LB's 240W. This reduction in energy consumption is a direct result of the energy-aware component of the algorithm, which considers the energy profile of base stations when making allocation decisions.

By intelligently shifting guard channels or influencing handoff decisions towards more energy-efficient cells where possible, EAGCA minimizes the overall energy footprint.

The AGC_LB scheme, while adaptive, focuses primarily on load balancing and does not explicitly optimize for energy consumption in its guard channel decisions, leading to higher ASEC compared to EAGCA. FGCA, being static, is the least efficient in energy consumption.

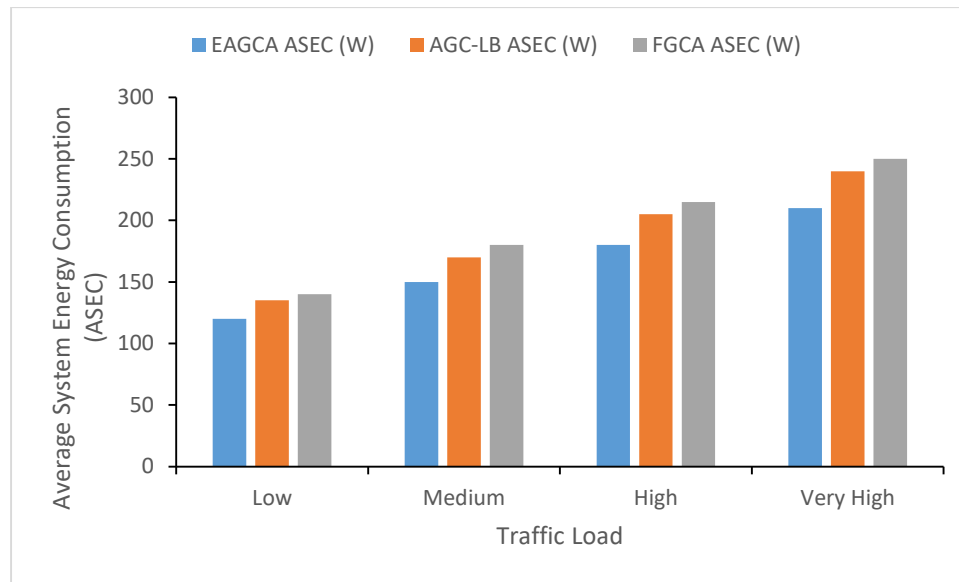


Figure 3: Average system energy consumption against traffic load

5. Conclusion

This research demonstrates that the Energy-Aware Guard Channel Allocation (EAGCA) scheme provides a robust solution for balancing network reliability with energy sustainability in next-generation mobile networks. By integrating mobility prediction and real-time energy profiling into a dynamic controller, the EAGCA model successfully minimizes a weighted objective function of Call Dropping Probability (CDP) and Total System Energy Consumption (TSEC). Simulation results validate the scheme's superiority, showing that it consistently outperforms Fixed (FGCA) and Adaptive (AGC_LB) benchmarks by achieving a significantly lower CDP of 0.8% to 4.5% while maintaining energy efficiency between 120W and 210W. These findings confirm that a context-aware approach to resource reservation can effectively reduce operational expenditure (OPEX) and environmental impact without compromising the Quality of Service required for high-density 5G and 6G infrastructures.

While these results are promising, the study is limited by its reliance on simulation-based evaluation, which utilizes standardized models like Poisson arrivals and Gauss-Markov mobility that may not fully capture the chaotic traffic patterns and non-linear energy spikes of real-world urban environments. To address these constraints, future research should focus on incorporating Deep Reinforcement Learning (DRL) to enable autonomous, non-linear resource management and conducting experimental validation on hardware-in-the-loop testbeds or pilot small-cell deployments. Furthermore, extending the EAGCA framework to integrate with emerging 6G architectures such as Integrated Sensing and Communication (ISAC), Reconfigurable Intelligent Surfaces (RIS), and Open-RAN (O-RAN) controllers will be essential to achieving the ultra-high precision and scalability required for the next generation of intelligent, green mobile communication.

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