Energy Efficiency Optimization in 5G and 6G Networks Using Machine Learning: A Comprehensive Review

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Abstract

Cellular technologies have evolved continuously from the 1st to the 5th generation (5G) to meet the exponentially growing needs for bandwidth, throughput, and latency. However, energy consumption has risen proportionally with each generation, driven by the need for new hardware to support additional applications. Notably, 5G, which already consumes four times more energy than 4G, is expected to cause a significant spike in energy consumption. This paper focuses on energy consumption at the base station and access network levels, which together account for approximately 80% of energy consumption in mobile networks. The application of machine learning techniques to improve energy efficiency in these components is explored. Specifically, efficient base station deployment strategies, adaptive operational modes, and access network technologies such as massive MIMO and millimeter waves, which employ machine learning to enhance energy efficiency, are reviewed in depth. The paper also proposes a framework combining efficient base station deployment methods with machine learning-based switching between different operational modes based on traffic load. Additionally, an adaptive beamforming methodology involving the identification of hotspots, user association, sub-channel, and power allocation in heterogeneous networks is discussed.

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Introduction

Evolution of Cellular Technologies

Historically, the main aim of mobile communication standards has been to gradually increase data rates. The advent of 5G technology represents a significant leap forward, designed not only to increase data rates but also to support a wide range of services and sustain the connectivity of the rapidly expanding Internet of Things (IoT) devices. According to Statista (2022), the number of IoT devices worldwide is projected to almost triple from 8.74 billion in 2020 to more than 25.4 billion by 2030. To meet these demands, 5G incorporates three primary service sets:

1. **Enhanced Mobile Broadband (eMBB)**: Designed to provide faster data rates of up to 10 Gbps, catering to high-bandwidth applications like video streaming and virtual reality.
2. **Ultra-Reliable Low-Latency Communication (URLLC)**: Critical for mission-critical services where negligible error rates and low latency are paramount, such as autonomous vehicles and industrial automation.
3. **Massive Machine Type Communications (mMTC)**: Developed to handle the high device density introduced by IoT, with a focus on energy efficiency.

Energy Consumption Challenges

The diverse requirements of 5G have led to a significant increase in energy consumption within the Information and Communications Technology (ICT) sector. Predictions by Fonseca et al. (2019) suggest that ICT could account for up to 30% of global power consumption by 2025. Base stations, which consume up to 80% of the total energy in cellular networks, are the most promising area for enhancing energy efficiency (Alsharif et al., 2017; Cai et al., 2016; Lahdekorpi et al., 2017). The introduction of small cells in 5G systems (Abrol and Jha, 2016; Alamu et al., 2020; Johnson, 2018; Meng et al., 2020) and the increased interest in massive MIMO (Anandharajan et al., 2019; Li et al., 2017; Perez et al., 2021; Rajoria et al., 2018) have further exacerbated the

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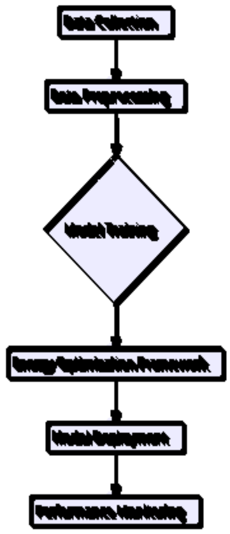
energy requirements, highlighting the urgent need for efficient resource and spectral management strategies.



5G Enabling Technologies

To leverage the capabilities of 5G, several enabling technologies have been adopted, including Software Defined Networking (SDN), Network Functions Virtualization (NFV), Cloud Radio Access Network (CRAN), millimeter waves, massive MIMO, and Heterogeneous Networks (HetNets). These technologies are applied at various levels of cellular networks, including the core, access, and edge networks. Machine learning-based energy-efficient schemes have been developed to optimize the use of these technologies (Mao et al., 2021; Salah et al., 2021).

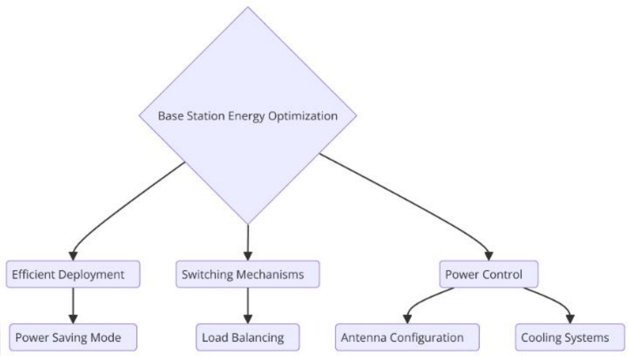
Energy Consumption Breakdown

Gruber et al. (2009) highlighted that base stations accounted for approximately 57% of a network's total power consumption. Han et al. (2011) further identified that power amplifiers contribute 50% to 80% of the base stations' energy consumption. Consequently, energy efficiency has emerged as a key capability of 5G, as established by the International Telecommunications Union (ITU) (Poirot et al., 2019).

Review of Existing Research

Energy Optimization at Base Station Level

The literature on energy optimization at the base station level predominantly focuses on three strategies: switch-off techniques, positioning and deployment strategies, and transmission power control. While most studies consider only two operational modes—on and off (Gao et al., 2020; Han et al., 2016; Hoffmann et al., 2021; Salem et al., 2019; Ye and Zhang, 2020)—El-Amine et al. (2019) introduced a Q-learning approach for adaptive sleep modes, offering a more nuanced approach that reduces energy consumption by up to 90% without compromising service quality.

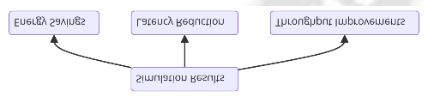


For base station deployment, Dai and Zhang (2020) proposed a network planning tool using received signal strength prediction. Although their simulation showed an 18.5% higher coverage rate compared to real-world deployment, energy consumption analysis was limited. Borah et al. (2019) suggested additional deployment scenarios, such as uniform or cluster-based deployments, resulting in increased energy efficiency of up to 6 kbps/watt for dense deployments.

Xiao et al. (2020) proposed a reinforcement learning-based power control mechanism (RLIC) to reduce downlink inter-cell interference, achieving a 12.6% improvement in average throughput compared to traditional solutions.

Energy Optimization at Access Network Level

At the access network level, energy optimization strategies have primarily focused on user association, subchannel, and power allocation. Zhang et al. (2020) addressed the user association problem using Lagrange dual decomposition, while semi-supervised learning and deep neural networks (DNN) were employed for subchannel and power allocation, respectively. The DNN scheme achieved energy efficiency levels varying between 4 × 10^11 and 6 × 10^12 bits/J.

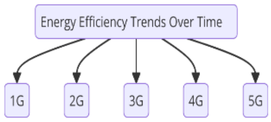


Giannopoulos et al. (2021a, 2021b) explored reducing energy consumption by controlling downlink channel transmission power and reconfiguring user association schemes. The T-DQN method they developed proved effective in dense macro-cell environments, offering an energy efficiency of 12 Mbps/W in a two-micro-cell scenario.

Sanguinetti et al. (2018) focused on downlink power allocation in massive MIMO networks, using deep neural networks to predict efficient power allocation profiles based on user device positions. The M-MSE scheme they proposed achieved a spectral efficiency of 4 bits/Hz, outperforming the MR precoding scheme.

Advantages and Disadvantages of Machine Learning

Machine learning offers several advantages over traditional big data processing methods, particularly in 5G/6G networks that require the processing of vast data volumes and quick adaptation to rapidly changing environments. Key benefits include:



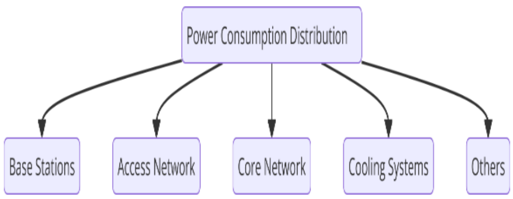
1. **Pattern Recognition**: Machine learning can easily identify trends and patterns by analyzing large volumes of data, making accurate predictions of future events.

2. **Autonomous Decision-Making**: Machine learning algorithms can make decisions and improve performance without human intervention, making them ideal for dynamic 5G/6G environments.

3. **Multi-Dimensional Data Handling**: Machine learning algorithms excel at handling multi-dimensional data, crucial for complex 5G/6G scenarios.

4. **Enhanced Learning Speed**: Machine learning algorithms significantly improve their performance over time, especially in large-scale problems.

However, machine learning also has drawbacks, such as the need for large, unbiased datasets for training and substantial computational resources for execution (Mughees et al., 2020; Qiu et al., 2016). Despite these challenges, machine learning remains the most viable strategy for optimizing 5G/6G networks.



Identified Research Gaps

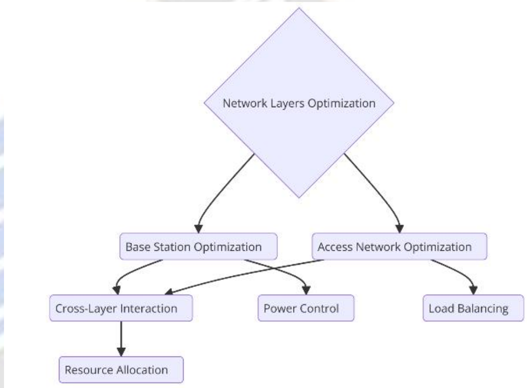
Several gaps exist in the current literature on energy optimization in 5G/6G networks. Most research at the base station level, such as Hoffmann et al. (2021) and Gao et al. (2020), considers only two operational modes, leading to increased latency. Furthermore, signaling bursts are not consistently factored into energy consumption calculations, and most simulation environments do not accurately represent 5G/6G scenarios, often focusing on single-cell environments (Donevski et al., 2019; Sanguinetti et al., 2018). Crucially, existing research is limited to optimizing a single network layer or a single aspect of base station operations, with no studies exploring the hybridization of optimization algorithms across base station and access network layers.

Proposed Frameworks for Energy Optimization

This paper proposes three novel frameworks for energy optimization at the base station and access network levels:

1. **Holistic Base Station Optimization**: This framework combines the approaches of Gao et al. (2020), Borah et al. (2019), and Xiao et al. (2020) to optimize base station deployment, switching mechanisms, and downlink power transmission based on traffic loads.

2. **Access Network Optimization**: Building on the work of Giannopoulos et al. (2021a, 2021b) and Ge and Lv (2018), this framework optimizes downlink channel transmission power, user association schemes, and adaptive antenna arrays based on traffic loads.



3. **Cross-Layer Optimization**: This framework integrates the Q-learning-based adaptive sleep modes proposed by El-Amine et al. (2019) with the deep learning-based radio resource management in NOMA networks proposed by Zhang et al

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