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Energy Efficiency Optimization and Low-Carbon Operation of 5G Base Stations Toward Carbon Neutrality

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Abstract. The large-scale rollout of 5G has sharply increased base station energy use, making it a major source of carbon emissions in communications. Against the background of China's dual-carbon targets, investigating low-carbon operation strategies for 5G base stations is of both theoretical significance and practical value. This paper analyzes the energy consumption composition and operational behavior of 5G base stations, establishes an energy consumption model based on traffic load, and proposes an integrated low-carbon operation framework that includes hardware energy optimization, software-driven consumption reduction, alternative energy adoption, and intelligent monitoring and control. On this basis, it investigates the principles and applicability of software-based energy-saving methods like symbol shutdown, channel shutdown, deep sleep, and carrier shutdown, as well as energy-side strategies such as coordination between base stations and smart grids, integration of solar and wind power, and optimized energy storage scheduling. Furthermore, an AI-based traffic prediction and dynamic energy saving scheduling algorithm is designed, together with a layered, coordinated intelligent management architecture. The results show that, by combining multidimensional technological coordination with intelligent management, 5G base stations can reduce overall energy consumption by 30%-45%, thereby providing technical support for the low-carbon transition of communication networks.

Keywords: 5G Base Station, Low-Carbon Operation, Energy Consumption Optimization, Renewable Energy Integration, Intelligent Management and Control

1. Introduction

The energy consumption of 5G macro base stations differs markedly between high load and low load periods. The power consumption of a single site is approximately 3.5-4.5 kW, which is three to four times that of a 4G base station. The radio frequency unit typically accounts for 65%-75% of the total power consumption, the baseband unit for approximately 10%-15%, and auxiliary equipment for approximately 15%-25%. In addition, during nighttime or in low population density areas, the traffic load of a base station may be only 5%-15% of its peak value, whereas the power consumption of the AAU and BBU may still reach 40%-60% of the peak level. This indicates that existing base stations have limited capability to adjust power consumption under low load conditions [1].

Accordingly, prior studies on hardware optimization focus on high-efficiency power amplifiers, advanced cooling, and heterogeneous computing. Software energy saving includes symbol and channel shutdown, deep sleep, and AI-based predictive scheduling. Energy substitution covers photovoltaics, energy storage, and virtual power plants, while intelligent management emphasizes hierarchical coordination, digital twins, and federated learning [2-4]. However, most studies concentrate on single approaches, lacking coordination and research on retrofitting, interoperability, and balancing energy efficiency with service quality. Based on these considerations, this paper analyzes energy consumption composition and dynamic characteristics, and reviews and compares four technical approaches: hardware energy saving, software-based consumption reduction, energy substitution, and intelligent management and control. It further discusses the collaborative optimization mechanisms of multiple strategies and their applicability and performance tradeoffs in different deployment scenarios, providing a reference for optimizing the low-carbon operation of 5G base stations.

2. Energy consumption analysis and low-carbon demand identification for 5G base stations

2.1. Power consumption composition and equipment differences

The energy consumption of a 5G macro base station mainly consists of the BBU, AAU, and auxiliary equipment, whose power characteristics differ significantly, as shown in Table 1. From the overall architecture, the AAU is the dominant energy consuming unit and therefore the primary target for energy saving optimization. The BBU has relatively low and stable power consumption, and its efficiency can be improved through computing resource optimization. Auxiliary equipment is highly affected by environmental conditions and offers significant optimization potential in specific scenarios [5]. Therefore, base station energy saving should focus on AAU equipment while jointly optimizing the BBU and auxiliary systems to achieve hierarchical energy efficiency improvement [6].

Table 1. Power consumption composition and optimization directions of major 5G base station equipment

Equipment type	Power consumption characteristics	Power consumption share/typical value	Main power consumption sources	Main optimization directions
Baseband unit (BBU)	Stable power consumption	150-250 W	Protocol processing, baseband computing, core-network interaction	ASIC/FPGA acceleration, heterogeneous computing, dynamic power management
Active antenna unit (AAU)	Dominant energy consuming unit	800-1500 W per unit; approximately 2400-4500 W for three units; approximately 65%-75% share	Power amplifier (50%-60%), intermediate frequency processing (15%-20%), radio frequency circuits	High efficiency power amplifiers, dynamic power control, channel/symbol shutdown

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Table 1. (continued)

Auxiliary equipment	Environment-sensitive	Approximately 15%-25% share	Air conditioning, power conversion, battery temperature control	High-efficiency cooling, free-cooling utilization, energy-storage system optimization

2.2. Load characteristics and baseline power consumption

Base-station traffic load exhibits a pronounced temporal tidal effect. For example, in urban residential areas, resource utilization may reach 70%-85% during evening peak hours, whereas it may decrease to 5%-10% in the early morning. Despite large traffic fluctuations, conventional base stations still have high baseline power: the AAU constantly transmits signals, the power amplifier stays at high load, and the BBU keeps the full stack and core connection [1]. In an idle state, AAU power consumption can still reach 60%-70% of the peak value, the BBU accounts for approximately 10%-15%, and the overall baseline power consumption accounts for 40%-60% of the peak value, resulting in substantial static energy consumption. From a spatial perspective, base-station loads differ significantly across regions. Commercial districts and industrial parks are generally under medium-to-high load during the daytime (approximately 50%-80%) and decrease to 10%-15% or below at night. Campus scenarios exhibit periodic fluctuations with semesters and daily schedules, and the overall load during non-teaching periods is typically below 10%. Consequently, a large number of base stations remain in light-load or idle states for long periods outside peak hours; in edge areas and low-population-density regions, the proportion of light-load base stations may even exceed 50% [7].

2.3. Energy-consumption model and low-carbon strategies

In 5G base station research, energy consumption models are used to characterize power consumption composition and the impacts of different operation strategies on energy consumption. The total power consumption of a base station can be expressed as:

$$P_{total}=P_{base}+\sum_{i=1}^{N}\left(P_{AAU,i}^{static}+\eta_i \bullet P_{AAU,i}^{dynamic}\bullet\rho_i\right)+P_{BBU}+P_{cool} \tag{1}$$

where P_{base} is the common baseline power consumption, including cabinet fans and power modules; N is the number of AAU modules; P_{AAU}^{static} corresponds to static power consumption, such as reference signals and control channels; $P_{AAU}^{dynamic}$ denotes traffic-related dynamic power consumption; η_i is the power-amplifier efficiency, typically 40%-55%; and ρ_i is the traffic load ratio. Meanwhile, cooling power consumption P_{cool} can be approximately expressed as $\alpha\bullet(P_{AAU}+P_{BBU})$, where α is the coefficient related to the energy-efficiency ratio of the air-conditioning system (0.2-0.4).

Meanwhile, base-station operation generates carbon emissions, including indirect emissions from purchased electricity and direct emissions from diesel backup power. The total emissions can be expressed as:

$$C=\sum_t\left(E_{grid,t}\bullet EF_{grid}+E_{diesel,t}\bullet EF_{diesel}\right) \tag{2}$$

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where EF_{grid} is the average carbon-emission factor of the power grid (currently around 0.581 kg CO_2/kWh in China), and EF_{diesel} is the diesel emission factor (approximately 2.63 kg CO_2/L) [8]. When renewable energy sources such as photovoltaics and wind power are introduced, the overall carbon-emission intensity can be reduced by substituting grid electricity. Based on this model, four technical paths including hardware energy saving, software-enabled consumption reduction, energy substitution, and intelligent management and control can be analyzed in terms of their synergistic effects and impacts on energy consumption and carbon emissions.

3. Key technologies and optimization strategies for low-carbon base-station operation

3.1. Power hardware and thermal optimization

In 5G base stations, low-power operation mainly relies on the coordinated improvement of AAU power-amplifier efficiency and thermal-system optimization. The former determines the energy-efficiency level on the radio-frequency side, while the latter directly affects the stable operating range of high-power devices. First, AAU power-amplifier efficiency is a key factor affecting the energy consumption of the whole system. Conventional LDMOS power amplifiers have low efficiency in the power back-off region, which corresponds to the dominant operating state in actual services and causes the system to operate inefficiently for long periods. The adoption of GaN devices with Doherty architecture extends the high-efficiency operating range and improves energy efficiency at back-off power. Under medium-load conditions, the power consumption of a single AAU power amplifier can be significantly reduced [6]. In addition, thermal management issues caused by high power density indirectly affect system energy efficiency. The performance and applicable scenarios of different cooling methods are compared in Table 2.

Table 2. Comparison of major cooling methods for 5G base stations

Cooling method	Heat-flux-density capability	Main characteristics	Applicable scenarios
Air cooling	≤50 W/cm^2	Simple structure and low cost, but strongly affected by ambient temperature	Low power base stations
Liquid cooling	100-200 W/cm^2	High heat exchange efficiency; reduces equipment temperature and improves stability	Mainstream upgrade solution for current macro base stations
Phase change cooling	≥200 W/cm^2	Uses latent heat absorption and offers strong cooling capability, but has high cost and complexity	Ultra high density/millimeter wave scenarios

From the perspective of thermal strategies, liquid cooling has become the mainstream solution for macro base stations, whereas phase change cooling is suitable for ultra high density and millimeter wave scenarios. Due to cost and engineering complexity, phase change cooling is still at the pilot stage [9, 10]. On the baseband side, power consumption can be reduced via heterogeneous computing and architectural decentralization: control and high-real-time tasks are handled by ASIC/FPGA devices, while low-real-time tasks run on CPUs. Combined with dynamic voltage and frequency scaling (DVFS), CPU power under light loads can be reduced by over 50% [5].

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3.2. Software-based energy saving and intelligent scheduling

Base-station power regulation depends on the coordinated operation of multilayer software strategies under different load conditions, so as to achieve dynamic energy saving across time, space, and load dimensions. At the symbol level, symbol shutdown turns off the power-amplifier supply during idle OFDM symbols. For voice or low-rate data services, the proportion of idle symbols can reach 30%-50%, reducing AAU power consumption by 10%-15%. Micro-sleep technology further places radio-frequency circuits into a low-power state during consecutive idle symbols and relies on fast physical-layer wake-up to save energy without affecting transmission.

At the antenna and channel level, massive MIMO base stations can dynamically adjust active channels according to real-time traffic load, such as from 64T64R to 16T16R or 8T16R. And channel shutdown reduces radio-frequency power consumption and computational overheads including digital predistortion and beamforming. Field results indicate that reducing 64T to 8T decreases AAU power consumption by about 35% with minimal coverage loss [7]. Under lower load, deep-sleep strategies can further shut down non-essential radio-frequency channels and part of the baseband units, retaining only low-power modules for basic signaling and controlling wake-up latency within 200-500 ms using traffic prediction. Meanwhile, multi-carrier base stations can shut down partial carriers and migrate users to achieve a dynamic balance between capacity and energy consumption.

On this basis, energy-saving mechanisms can be optimized across multiple dimensions. Symbol shutdown and channel shutdown operate in the time and spatial domains with cumulative gains under low load, while deep sleep and carrier shutdown target extreme low-load conditions and reduce base station power consumption to 15%–20% of peak. Meanwhile, AI scheduling serves as an upper-layer controller, coordinating activation and switching of strategies based on historical PRB utilization, RRC connections, and traffic data using a Markov decision process. Deep sleep requires long dwell time to reduce wake-up overhead, whereas symbol shutdown needs millisecond-level response, and their combination may lead to state oscillation; channel shutdown and carrier shutdown may also reduce spatial multiplexing and system capacity. Edge AI scheduling introduces 1%-2% additional computing and signaling overhead, which can be reduced to within 0.5% through lightweight models and optimized decision intervals [11]. Under the coordination of these mechanisms, the system achieves up to 67% energy savings during low-load periods in the early morning, with an average daily saving of about 34%; downlink rate degradation is kept within 5%, and no significant change in call-drop rate is observed [7]. Therefore, hierarchical software strategies can effectively reduce base-station energy consumption while maintaining communication quality.

3.3. Coordination of renewable energy and energy storage

Low-carbon 5G base station operation combines hardware and software optimization with distributed renewable energy and energy storage, thereby enabling coordination with the power grid [12]. In this context, base-station load is shiftable and reducible, allowing response to price signals or dispatch instructions, while maintaining communication quality.

In terms of distributed energy supply, photovoltaic generation is the main form of renewable energy applicable to base-station scenarios. The rooftop or tower area of a macro base station can typically accommodate 30-50 m2 of photovoltaic modules, corresponding to an installed capacity of approximately 5-8 kWp. Under Class-II solar-radiation conditions, annual electricity generation can reach 6000-9000 kWh, covering 20%-40% of the daytime electricity consumption of a base station

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[2]. The matching degree between photovoltaic output and base-station load varies by region. Office areas have relatively high daytime loads, with a self-consumption rate close to 100%, whereas residential areas have lower daytime loads, with a self-consumption rate of approximately 60%-70%; surplus electricity can be fed back to the grid to improve overall energy-utilization efficiency.

On this basis, energy-storage systems enhance power-supply stability through peak shaving, valley filling, and fluctuation smoothing. For example, a single base station equipped with a 30 kWh lithium iron phosphate energy-storage system can generate an annual benefit of approximately 9000 yuan through one charge-discharge cycle per day, while also increasing the photovoltaic self-consumption rate [13]. Furthermore, energy storage from multiple base stations can be aggregated to form a virtual power plant (VPP), which provides peak shaving, frequency regulation, and reserve services through centralized dispatch. In this mode, the aggregated storage capacity of one hundred base stations can reach the megawatt scale, the response time can be controlled at the second level, and revenue can be allocated according to actual response performance [14]. Thus, base-station energy storage not only supports its own low-carbon operation, but can also serve as a flexibility resource for the power system, enabling bidirectional coordination between communication and electricity networks.

4. Intelligent management and low-carbon collaborative optimization of base stations

4.1. Hierarchical collaboration and regional control

For network-level energy optimization, multilayer control is needed. Thus, a three-tier management architecture comprising the central cloud, edge nodes, and base stations is proposed. This architecture enables both global strategy planning and rapid response to local conditions, supporting fine-grained energy-saving scheduling and load balancing. The central cloud aggregates historical data from base stations across the network, which is used to train global traffic prediction models and energy saving policy metamodels, and periodically distributes them to edge nodes. In addition, the central cloud obtains electricity market information, including price signals and carbon allowances, to guide network level optimization. Edge nodes are deployed at the municipal or regional level and manage hundreds of base stations. They are responsible for regional collaborative optimization, such as balancing neighboring cell loads, preventing local overload caused by the deep sleep of a specific base station, and adapting models delivered by the central cloud to local data distributions. At the base station, lightweight agents monitor load, energy use, and temperature in real time, executing millisecond-level energy-saving actions. Even when an edge node is offline, the base station agent can still operate independently, ensuring the continuous effectiveness of low-carbon strategies [3].

4.2. Digital twin and carbon visualization

Energy-efficient operation of 5G base stations has attracted increasing attention due to their high energy consumption [15]. To enable fine-grained low-carbon management, a digital twin model can be built for a single site or a cluster of similar base stations. The model includes the physical layer (thermal and power systems), the service layer (traffic and load distribution), and the control layer (energy-saving strategy responses). By assimilating multi-source real-time data, the twin remains synchronized with the physical system, enabling pre-evaluation of strategies and assessment of their impacts on energy use, QoS, and device temperatures, thereby minimizing online trial-and-error

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risks [4]. Updates typically occur at minute-level intervals, with synchronization error maintained within 3% under stable conditions. At the operation and maintenance level, the digital twin supports root-cause analysis of base station energy-efficiency anomalies. By comparing historical and real-time states, it identifies whether anomalies are caused by hardware degradation, parameter drift, or environmental changes, improving diagnostic efficiency. In parallel, a real-time carbon-emission metering model can be constructed using smart meter data and a dynamic carbon factor database for time-of-use accounting. Thus, carbon flow diagrams map energy flows and emissions, identifying high-carbon periods and high-energy-consuming equipment. On this basis, green electricity procurement and dispatch can be optimized according to the spatiotemporal distribution of carbon emissions and load characteristics. For example, renewable energy utilization can be raised during high carbon-factor periods, or load strategies can be modified to reduce overall carbon intensity, forming a closed loop for operational low-carbon optimization.

4.3. Federated learning and cross-domain collaboration

In large scale multi-operator deployments, data silos and privacy constraints hinder the optimization of global energy saving strategies. Federated learning addresses this issue by keeping data local and moving models, enabling cross-domain knowledge fusion while preserving privacy. In this process, each participant trains a digital twin model locally and then uploads encrypted parameters to the central server for aggregation, generating a global model that is subsequently distributed for local fine-tuning to handle extreme load and few-sample scenarios. This improves the reliability of energy saving strategies and guides the execution of symbol shutdown, channel shutdown, deep sleep, and AI scheduling [3]. In addition, cross-domain aggregation can identify common anomalies, such as deep sleep wake-up failures caused by rain or snow, and optimize pre-wake-up strategies to reduce the network level call drop rate. Simulation results show that cross-domain federated strategies achieve an additional 4%-7% energy saving compared with independent models, while limiting communication overhead to under 15%. This extends hierarchical collaboration from single domain optimization to cross-domain cooperation, transforms digital twins from local simulation to cross-domain symbiosis, and enables quantifiable low-carbon operation of large scale base stations [3].

5. Conclusion

This paper addresses the low-carbon operation of 5G base stations and proposes a systematic optimization framework integrating hardware, software, energy, and intelligent management and control. Its energy saving potential is analyzed from theoretical perspectives and existing studies. The analysis indicates that the energy consumption of 5G base stations has significant tidal characteristics, and ineffective energy consumption accounts for approximately 40%-60%, providing a spatial and temporal basis for collaborative optimization by multilayer strategies. On this basis, software-enabled energy saving strategies can achieve an energy consumption reduction of approximately 20%-35%, and AI-based predictive scheduling can further improve system operational efficiency. On the energy side, coordination of photovoltaics and energy storage reduces reliance on grid electricity and cuts system carbon emissions by 15%-40%. Furthermore, intelligent management based on layered architecture, digital twins, and carbon accounting allows ongoing optimization and real-time control of operational states. Overall, the above strategies can achieve approximately 30%-45% energy savings in typical macro base station scenarios. However, the proposed methods are mainly validated for typical macro base stations, and their applicability to millimeter wave systems, ultra dense networking, and indoor distributed systems requires further investigation. In addition, the carbon emission assessment is mainly based on the average grid carbon emission factor and has not fully considered regional differences in green electricity structures or fluctuations in electricity market prices. Future research may integrate multi-agent reinforcement learning with Pareto optimization to balance energy saving and service quality and to optimize fast wake-up mechanisms for services like URLLC. In addition, deeper coordination between base stations and power systems, including virtual power plants and demand response, can be investigated.

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