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Hybrid artificial intelligence-driven eco-energy management for carbon-neutral 6G wireless networks

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Abstract

The transition toward carbon-neutral sixth-generation (6G) wireless networks requires a fundamental shift in how communication infrastructures manage energy consumption, computational resources, and environmental impact. This narrative review presents a comprehensive and interdisciplinary synthesis of hybrid artificial intelligence (AI)-driven eco-energy management strategies, green radio-frequency (RF) technologies, sustainability evaluation metrics, and lifecycle-oriented environmental modeling for next-generation wireless systems. Unlike existing surveys that primarily focus on communication efficiency, AI optimization, or green networking independently, this work integrates three interconnected domains: AI-driven resource optimization, carbon-aware network management, and lifecycle sustainability assessment (LCA) within a unified analytical framework. The review first examines the sustainability challenges associated with emerging 6G technologies, including the increasing energy demands of terahertz (THz) communication, ultra-massive multiple-input multiple-output (MIMO) systems, AI-native network architectures, and dense edge-cloud infrastructures. It then analyzes multidimensional sustainability indicators, including energy efficiency, energy-per-bit, carbon footprint, embodied energy, carbon-per-connection, green throughput, and AI computational energy overhead, while highlighting current limitations in benchmarking methodologies and standardized sustainability evaluation frameworks. Furthermore, the review critically investigates green RF technologies, including reconfigurable intelligent surfaces (RIS), simultaneous wireless information and power transfer (SWIPT)-enabled systems, low-power THz hardware, ultra-massive MIMO, and energy-efficient beamforming architectures, emphasizing the trade-offs between operational energy savings and lifecycle environmental impact. In addition, emerging hybrid AI approaches combining deep reinforcement learning (DRL), evolutionary optimization, federated learning (FL), graph neural networks (GNNs), and Green AI methodologies are examined for sustainability-aware resource allocation and carbon-conscious network orchestration. To support integrated sustainability analysis, this review introduces literature-derived conceptual frameworks, including the Green RF Technology Evaluation Matrix (GRTEM), Hybrid AI for Sustainable Power

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Allocation (HYASPA), and Eco-Digital Twin Architecture (Eco-DTA), which provide structured perspectives for evaluating RF sustainability, AI-driven optimization, and lifecycle environmental impact. These frameworks are presented as analytical synthesis models rather than validated deployment architectures, highlighting future validation requirements through simulations, benchmark datasets, and real-world 6G test environments. Finally, the review identifies key research challenges and future directions, including carbon-aware AI optimization, lifecycle-aware RF design, sustainable digital twins, Green federated learning, recyclable communication hardware, and standardized carbon-aware key performance indicators (KPIs). Overall, this work provides a unified eco-energy management roadmap for developing intelligent, adaptive, and environmentally sustainable 6G wireless networks.

Keywords Carbon-Neutral 6G Networks, Green RF Technologies, Hybrid AI for Eco-Energy Management, AI-Driven Resource Optimization, Lifecycle Assessment (LCA), Eco-Digital Twin Architecture, Carbon-Aware Network Optimization

1 Introduction

The evolution toward sixth-generation (6G) wireless networks is expected to transform digital connectivity through ultra-high data rates, pervasive intelligence, massive machine-type communication (mMTC), integrated sensing and communication (ISAC), and ultra-reliable low-latency communication (URLLC) capabilities [1]. These advancements are anticipated to support emerging applications such as immersive extended reality, autonomous transportation, industrial automation, digital twins, and large-scale Internet of Things (IoT) ecosystems [2, 3]. However, the rapid expansion of 6G capabilities is accompanied by increasing computational complexity, infrastructure densification, and hardware requirements, resulting in significant challenges related to energy consumption, carbon emissions, and long-term environmental sustainability.

Emerging 6G architectures rely heavily on energy-intensive technologies, including terahertz (THz) communication, ultra-massive multiple-input multiple-output (UM-MIMO) systems, AI-native network orchestration, edge-cloud intelligence, and reconfigurable intelligent surfaces (RIS) [4, 5]. While these technologies provide significant improvements in spectral efficiency, connectivity, intelligence, and network adaptability, they also introduce new sustainability challenges associated with operational power consumption, computational overhead, embodied carbon emissions, semiconductor manufacturing impacts, and electronic waste generation [6]. Consequently, sustainability has become a fundamental design objective for future wireless systems, requiring a transition from conventional performance-oriented optimization toward carbon-aware and lifecycle-conscious network management.

Recent studies have investigated several approaches for improving the sustainability of future wireless networks, including AI-driven resource allocation, energy-efficient RF architectures, renewable-energy-assisted communication infrastructures, and lifecycle assessment (LCA)-based environmental modeling [7–10]. In parallel, Green AI methodologies, including model compression, energy-aware learning, federated optimization, lightweight inference, and computationally efficient neural architectures, have emerged as promising approaches for reducing the environmental cost of intelligent network operation [11, 12]. Despite these advances, existing research remains fragmented, with many studies focusing independently on communication efficiency, AI-based

optimization, green RF technologies, or environmental assessment rather than addressing their interdependence within a unified sustainability framework [13–18].

This fragmentation represents a critical research challenge because achieving carbon-neutral 6G operation requires coordinated optimization across communication, computation, hardware, and environmental dimensions. For instance, AI-driven power allocation and resource management strategies may reduce transmission energy consumption while simultaneously increasing energy demand due to intensive model training, inference, and distributed computation [19, 20]. Similarly, RIS-assisted communication can reduce operational transmission power but may introduce additional lifecycle impacts associated with material production, manufacturing processes, deployment, maintenance, and disposal. These complex trade-offs demonstrate the need for integrated frameworks capable of jointly evaluating energy efficiency, carbon impact, computational sustainability, and lifecycle environmental performance [21–26].

Although several review studies have examined green 6G communication, AI-enabled wireless networks, or energy-efficient resource management, most existing surveys primarily focus on individual technological domains. For example, AI-oriented surveys mainly emphasize optimization performance, while green communication reviews often focus on energy efficiency and RF technologies without deeply considering AI computational overhead or lifecycle environmental impacts. Therefore, a comprehensive review that simultaneously integrates AI-driven optimization, sustainable RF technologies, and lifecycle-aware environmental assessment remains insufficiently explored.

Motivated by this research gap, this narrative review investigates the following research question:

How can AI-driven optimization, green RF technologies, and lifecycle sustainability assessment be systematically integrated to support environmentally sustainable and carbon-aware 6G networks?

To address this question, this review develops a cross-domain synthesis of recent advances in hybrid AI-enabled eco-energy management, sustainability evaluation metrics, green RF architectures, and AI-assisted environmental modeling. Unlike existing reviews that mainly summarize technological developments, this work provides a critical analysis of sustainability benefits, limitations, implementation challenges, performance evaluation approaches, and unresolved research gaps. In particular, the review examines how emerging technologies influence both operational energy efficiency and broader environmental sustainability considerations.

A key contribution of this work is the introduction and analysis of three literature-derived conceptual frameworks: the Green RF Technology Evaluation Matrix (GRTEM), the Hybrid AI for Sustainable Power Allocation (HYASPA) framework, and the Eco-Digital Twin Architecture (Eco-DTA). Unlike conventional technology-focused classifications, these frameworks provide an integrated perspective for evaluating green RF technologies, optimizing AI-driven energy management decisions, and enabling lifecycle-aware sustainability assessment in future 6G networks. GRTEM organizes green RF technologies according to energy efficiency, lifecycle impact, deployment complexity, and sustainability challenges. HYASPA highlights the integration of hybrid AI techniques, adaptive power management, and carbon-aware optimization. Eco-DTA extends digital twin concepts by incorporating AI-driven environmental prediction and lifecycle sustainability modeling.

Furthermore, this review emphasizes quantitative sustainability evaluation by discussing key performance indicators, including energy efficiency, energy-per-bit, carbon footprint, carbon-per-connection, green throughput, embodied energy, and AI computational overhead. It also highlights current challenges related to benchmarking datasets, standardized sustainability metrics, and the absence of unified evaluation methodologies for comparing AI-driven eco-energy management approaches.

Overall, this review contributes a unified roadmap for carbon-neutral 6G development by connecting AI optimization, green RF technologies, and lifecycle sustainability assessment. The manuscript provides both a synthesis of current research progress and a critical discussion of future challenges required to achieve environmentally responsible, intelligent, and energy-efficient wireless ecosystems.

The remainder of this paper is organized as follows. Section 2 presents the review methodology and literature selection strategy. Section 3 discusses the carbon-neutral 6G vision and sustainability objectives. Section 4 reviews sustainability metrics and environmental impact models. Section 5 examines green RF technologies for sustainable 6G systems. Section 6 analyzes hybrid AI approaches for eco-energy management. Section 7 discusses AI-integrated environmental impact modeling and eco-digital twin concepts. Section 8 presents cross-layer eco-energy management strategies, while Sect. 9 highlights open research challenges and future directions. Finally, Sect. 10 concludes the paper.

2 Review methodology

This study adopts a structured narrative review methodology to systematically synthesize recent advances in AI-driven eco-energy management, green RF technologies, and lifecycle-oriented sustainability assessment in carbon-aware 6G wireless networks. Unlike conventional review studies that often treat communication engineering, artificial intelligence, and environmental sustainability as separate research domains, this review integrates these interdisciplinary perspectives to critically examine how future 6G systems can simultaneously achieve high communication performance, energy efficiency, and long-term ecological sustainability.

The review methodology was designed to provide a transparent and analytical synthesis of current research by identifying major technological developments, evaluating reported sustainability outcomes, assessing methodological limitations, and highlighting unresolved research challenges. The selected literature was analyzed from both technological and sustainability perspectives, with particular emphasis on energy consumption, carbon emissions, lifecycle environmental impact, AI computational overhead, and practical deployment feasibility.

2.1 Literature search strategy

A comprehensive literature search was conducted across major scientific databases, including IEEE Xplore, Scopus, ScienceDirect, SpringerLink, ACM Digital Library, and Wiley Online Library. The review considered peer-reviewed journal articles, conference papers, and high-quality review studies published between 2019 and 2026 to capture recent developments in sustainable 6G communication systems.

The search strategy employed a combination of keywords related to green communications, artificial intelligence, sustainability, and future wireless technologies. Key search

terms included *green 6G networks*, *carbon-neutral wireless communication*, *AI-driven energy optimization*, *green AI in wireless systems*, *reconfigurable intelligent surfaces sustainability*, *terahertz energy efficiency*, *lifecycle assessment in telecommunications*, *carbon-aware resource allocation*, *federated learning for sustainable networks*, and *eco-energy management in 6G*.

To improve coverage and minimize the likelihood of omitting relevant studies, additional publications were identified through backward and forward citation tracking of highly cited articles. The initial search results were screened based on title relevance, abstract content, and full-text evaluation. Studies were further assessed according to their contributions to sustainable wireless communication, AI-enabled optimization, green RF technologies, or environmental impact assessment. This screening process ensured that only studies directly relevant to carbon-aware and energy-efficient future wireless networks were included in the review.

2.2 Inclusion and exclusion criteria

Studies were included in the review if they satisfied one or more of the following criteria: they addressed sustainability challenges in 5G-Advanced, beyond-5G, or 6G networks; proposed or evaluated AI-based optimization techniques for communication, computation, or energy management; investigated green RF technologies such as RIS, THz communication, energy-efficient MIMO architectures, or energy harvesting systems; examined environmental sustainability indicators including lifecycle assessment, carbon reduction, or energy-aware network management; reported performance evaluation through simulations, analytical modeling, experiments, or case studies; were published in peer-reviewed journals, conference proceedings, or recognized technical sources; and were available in English.

Studies were excluded if they focused solely on conventional communication performance without sustainability considerations, lacked sufficient technical or methodological detail, presented duplicate findings, addressed environmental issues unrelated to wireless communication systems, or did not contribute to the understanding of AI-driven or energy-aware sustainable networking.

2.3 Literature classification and analytical synthesis

Following the screening process, the selected studies were categorized into four major thematic areas.

The first category, Sustainability Metrics and Environmental Impact Assessment, includes studies focused on energy efficiency, carbon footprint estimation, lifecycle assessment, embodied energy, carbon-aware networking, and sustainability benchmarking methodologies.

The second category, Green RF and Communication Hardware Technologies, covers energy-efficient RF architectures, RIS, THz communication, ultra-massive MIMO, hybrid beamforming, and energy harvesting technologies, with emphasis on both operational efficiency and lifecycle sustainability.

The third category, Hybrid AI-Driven Eco-Energy Optimization, examines AI-based approaches such as DRL, FL, evolutionary optimization, GNNs, and Green AI methods for sustainable resource management.

The fourth category, Cross-Layer Sustainability Orchestration, focuses on integrated approaches that jointly optimize communication, computation, infrastructure, and environmental management across multiple network layers.

A thematic synthesis approach was subsequently applied to identify common research trends, reported performance improvements, sustainability trade-offs, methodological limitations, and existing research gaps across the selected studies. Based on this synthesis, three literature-derived conceptual frameworks were developed: the GRTEM, HYASPA, and Eco-DTA.

These frameworks are not presented as experimentally validated deployment architectures; rather, they represent analytical synthesis models derived from recurring concepts, design patterns, and research challenges identified across existing literature. Their primary purpose is to provide structured perspectives for integrating energy efficiency, AI-driven optimization, and lifecycle sustainability assessment in future carbon-neutral 6G networks.

2.4 Review quality assessment and analytical considerations

To improve analytical rigor, the reviewed studies were evaluated using several key dimensions, including energy efficiency improvement, carbon reduction potential, AI computational complexity and associated overhead, hardware sustainability considerations, lifecycle environmental impact, benchmarking methodology, and practical deployment feasibility.

This multidimensional evaluation framework enabled comparative assessment beyond conventional communication performance metrics and provided a broader understanding of the trade-offs between sustainability objectives and system performance in emerging 6G technologies.

2.5 Scope and limitations of the review

Although this review provides an interdisciplinary synthesis of AI-driven sustainable 6G research, several limitations should be acknowledged. First, the narrative review methodology introduces challenges in directly comparing quantitative findings because existing studies often employ different datasets, simulation environments, evaluation metrics, and sustainability assumptions.

Second, many sustainable 6G technologies including AI-native architectures, THz communication, RIS-enabled networks, and eco-digital twins, remain at varying stages of development. As a result, large-scale experimental validation and real-world deployment evidence remain limited.

Third, the absence of universally accepted sustainability benchmarks, standardized carbon accounting methods, and unified evaluation frameworks makes direct comparison of energy and environmental performance across studies particularly challenging.

Despite these limitations, this review provides a structured and analytical synthesis of current research progress, sustainability trade-offs, evaluation challenges, and future research opportunities for developing environmentally sustainable and carbon-aware 6G wireless systems.

Although several review studies have investigated green communication, AI-enabled wireless optimization, and sustainable 6G development, most existing surveys focus on individual aspects such as energy efficiency, AI-based networking, or specific enabling

technologies. This review differs by integrating AI optimization, green RF technologies, lifecycle sustainability assessment, and carbon-aware network orchestration within a unified eco-energy management perspective. Table 1 summarizes the differences between this review and representative existing surveys.

3 Overview of carbon-neutral 6G vision

The transition toward 6G wireless systems represents a major shift from conventional communication networks toward intelligent, autonomous, and highly interconnected ecosystems. Future 6G networks are expected to support ultra-high data rates, pervasive AI, massive mMTC, ISAC, digital twins, and URLLC capabilities [1, 2]. These advancements will enable emerging applications such as immersive extended reality, autonomous transportation, industrial automation, smart cities, and large-scale IoT ecosystems. However, the rapid expansion of these capabilities introduces significant sustainability challenges associated with increasing energy demand, computational complexity, carbon emissions, and environmental impact.

Unlike previous generations of wireless networks where performance metrics such as throughput, latency, and spectral efficiency dominated system optimization, carbon-neutral 6G requires a broader sustainability perspective. Future network design must simultaneously consider operational energy consumption, embodied carbon emissions, AI computational cost, hardware lifecycle impact, and environmental resource utilization [3, 4]. Therefore, achieving sustainable 6G operation requires a transition from isolated energy-efficiency optimization toward integrated eco-energy management approaches that combine communication, computation, infrastructure, and environmental considerations.

This section discusses the sustainability objectives of future 6G systems, examines how emerging architectural technologies influence energy and environmental performance, and introduces a multi-dimensional eco-energy taxonomy derived from recurring sustainability themes identified in the reviewed literature [5]. The taxonomy provides a conceptual foundation for understanding sustainability challenges across RF, computational, deployment, and lifecycle dimensions.

3.1 Key sustainability targets in 6G

Sustainability has become a fundamental design objective in beyond-5G and 6G research due to the increasing environmental footprint of large-scale digital infrastructures [8]. A primary sustainability target is the reduction of both operational and embodied carbon emissions associated with communication networks [13]. Operational emissions mainly result from electricity consumption during wireless transmission, computation, cooling, and data processing activities, whereas embodied emissions originate from semiconductor manufacturing, hardware production, infrastructure deployment, transportation, maintenance, and equipment replacement cycles [14].

Although improving operational energy efficiency remains important, recent research highlights that reducing transmission power alone may not guarantee overall environmental sustainability. For example, a highly energy-efficient communication system may still have significant environmental impact if the manufacturing process of its hardware components involves high embodied energy or carbon-intensive materials. Therefore,

Table 1 Comparison of this review with existing surveys, highlighting its integrated perspective on AI-driven optimization, green RF technologies, lifecycle sustainability assessment, and carbon-aware 6G network management

Review Study	Main Focus	AI Optimization Coverage	Green RF Technologies Coverage	Lifecycle Assessment (LCA)	Carbon/Sustainability Metrics	Quantitative Evaluation	Proposed Frameworks	References
Green 6G architecture and sustainability surveys	Green 6G vision, architecture, and energy-efficient communication technologies	Limited discussion of AI-based optimization	Covers energy-efficient communication architectures and enabling technologies	Limited lifecycle consideration	Mainly focuses on energy efficiency and power consumption	Mostly conceptual and technology-oriented analysis	No integrated sustainability framework	[1, 7]
AI-enabled 6G network surveys	Artificial intelligence applications in future wireless networks	Extensive coverage of AI, ML, DRL, and intelligent resource management	Limited focus on RF lifecycle sustainability	Limited environmental impact assessment	Mainly communication performance and optimization metrics	AI performance-focused evaluation	AI-enabled network architectures	[8, 10, 12]
AI-driven green communication reviews	AI models for sustainable communication systems	Strong focus on AI-based optimization, learning, and resource allocation	Partial discussion of energy-efficient communication technologies	Limited lifecycle analysis	Energy efficiency and computational sustainability indicators	AI optimization performance analysis	AI-based green communication approaches	[4, 26]
Green RF and intelligent surface surveys	Sustainable RF technologies, RIS, MIMO, and energy-efficient hardware	Limited AI integration	Strong coverage of RIS, intelligent surfaces, and RF optimization	Partial lifecycle consideration	Hardware energy efficiency and communication performance metrics	Technology-specific evaluation	RF technology-oriented frameworks	[15, 22]
Lifecycle sustainability and carbon-neutral 6G reviews	Environmental impact, carbon reduction, and sustainable infrastructure	Limited AI-driven optimization discussion	Includes communication infrastructure sustainability	Strong lifecycle and environmental assessment focus	Carbon footprint, embodied energy, and sustainability indicators	Environmental assessment approaches	Lifecycle sustainability models	[2, 17, 19]
Energy-aware 6G IoT and network optimization surveys	Energy-efficient IoT communication and resource management	Moderate AI optimization coverage	Includes energy-aware networking and emerging communication technologies	Limited lifecycle perspective	Energy consumption and efficiency metrics	Network performance evaluation	Energy management strategies	[3, 13]
This Review: Hybrid AI-Driven Eco-Energy Management for Carbon-Neutral 6G Wireless Networks	Integrated AI, green RF, carbon-aware optimization, and lifecycle sustainability framework	DRL, federated learning, GNN, evolutionary optimization, and Green AI methodologies	RIS, THz communication, UM-MIMO, SWIPT, RF-chain optimization, and sustainable hardware considerations	Integrated lifecycle-aware environmental assessment	Energy efficiency, energy-per-bit, carbon footprint, carbon-per-connection, AI computational overhead, lifecycle impact	Includes quantitative comparison, sustainability metrics, benchmarking challenges, and deployment considerations	GRTEM, HYASPA, Eco-DTA conceptual sustainability frameworks	This review

future 6G sustainability evaluation requires lifecycle-oriented assessment approaches that consider both operational and embodied environmental costs.

Another important sustainability objective is the reduction of energy-per-bit (EPB), which represents the energy required to generate, process, transmit, and store a unit of information. Minimizing EPB is particularly challenging in 6G environments characterized by THz communication, ultra-massive MIMO, dense edge computing, and AI-driven network intelligence [14, 15]. Current approaches, including adaptive beamforming, dynamic sleep-mode control, intelligent resource allocation, and energy-aware scheduling, aim to reduce unnecessary energy consumption while maintaining communication quality [12].

In addition, carbon-aware resource management (CARM) has emerged as an important sustainability paradigm where communication and computation decisions are influenced by environmental indicators such as real-time grid carbon intensity, renewable-energy availability, and carbon budgets [6, 16, 17]. Applications of CARM include carbon-aware computation offloading, energy-adaptive scheduling, renewable-aware traffic management, and sustainability-driven network orchestration [18].

Despite these advances, several sustainability trade-offs remain unresolved. AI-driven optimization can improve energy efficiency and resource utilization but may introduce additional environmental costs due to model training, inference, and distributed computation. Similarly, advanced RF technologies can improve spectral efficiency but may increase manufacturing complexity, material consumption, and lifecycle emissions. These challenges demonstrate the need for integrated sustainability frameworks capable of jointly evaluating communication performance, computational overhead, and environmental impact.

3.2 6G architectural features impacting energy and sustainability

Several emerging 6G technologies provide significant performance improvements while introducing new sustainability challenges.

a. THz Communication and Ultra-Massive MIMO

THz communication and ultra-massive MIMO (UM-MIMO) architectures are expected to enable extremely high data rates and improved spatial multiplexing capabilities [8, 12]. However, these technologies require dense antenna arrays, advanced beamforming algorithms, high-frequency RF components, and sophisticated signal processing mechanisms. Consequently, they may significantly increase power consumption, cooling requirements, hardware complexity, and manufacturing-related environmental impact.

The sustainability challenge is therefore not only improving THz communication efficiency but also designing low-power RF front-ends, energy-efficient signal processing techniques, and lifecycle-aware hardware architectures.

b. Integrated Sensing and Communication (ISAC)

ISAC enables communication and sensing functions to share infrastructure, potentially reducing hardware duplication and improving spectrum utilization [15–17]. This integration provides sustainability benefits through improved resource utilization and reduced infrastructure requirements.

However, joint sensing and communication operations introduce additional computational workloads, signal processing complexity, and AI-driven analytics requirements.

Therefore, the sustainability impact of ISAC depends on balancing infrastructure savings against increased processing energy consumption.

c. AI-Native Network Architectures

AI-native 6G systems rely on deep learning, reinforcement learning, distributed optimization, and autonomous network control to improve adaptability and efficiency [7, 11, 18]. AI-based orchestration can support intelligent power management, traffic prediction, resource allocation, and network automation.

Nevertheless, AI introduces its own sustainability challenges. Large-scale model training, continuous inference, data exchange, and distributed learning can contribute significantly to computational carbon emissions. Therefore, future sustainable AI-native networks require Green AI approaches, including lightweight models, efficient learning strategies, and energy-aware AI optimization.

d. Reconfigurable Intelligent Surfaces (RIS)

RIS-assisted communication has attracted significant attention as a low-power technology capable of improving propagation conditions and reducing transmission power requirements [14, 17]. RIS can enhance energy efficiency by minimizing reliance on active RF components.

However, existing sustainability evaluations of RIS often focus primarily on operational energy savings while overlooking embodied carbon, manufacturing processes, electronic control circuitry, material selection, and end-of-life disposal [19]. Therefore, sustainable RIS deployment requires lifecycle-aware evaluation rather than relying only on communication performance indicators.

e. Edge-Cloud Continuum (ECC)

The edge-cloud continuum improves computational flexibility by distributing workloads across edge devices, fog nodes, and centralized cloud platforms [16, 17, 19]. This architecture supports low-latency AI services and efficient workload management.

However, sustainability challenges arise from cooling requirements, workload migration overhead, heterogeneous energy availability, and increased computational demand. Effective eco-energy management therefore requires coordination between communication networks, computing resources, and environmental conditions.

Collectively, these technologies demonstrate that carbon-neutral 6G cannot be achieved through isolated improvements in individual components. Instead, sustainability requires cross-layer coordination between RF systems, AI computation, network operation, and lifecycle environmental management.

3.3 Multi-dimensional eco-energy taxonomy for 6G

To provide a holistic understanding of sustainability challenges in future wireless networks, this review develops a multi-dimensional eco-energy taxonomy based on recurring sustainability themes identified across the reviewed literature. Unlike conventional energy-efficiency models that focus mainly on operational power consumption, this taxonomy considers sustainability across four interconnected dimensions:

a. RF Sustainability

RF sustainability focuses on reducing energy consumption associated with wireless transmission hardware and communication techniques. Key areas include low-power transceivers, adaptive beamforming, RIS-assisted communication, energy-efficient MIMO architectures, and low-power THz front-end designs [19, 20].

The main challenge is balancing communication performance improvements with hardware complexity, manufacturing impact, and lifecycle sustainability.

b. Computational Sustainability

Computational sustainability addresses the environmental impact of AI training, inference, distributed learning, and edge-cloud processing [21]. Important approaches include model compression, pruning, quantization, low-complexity learning, energy-aware neural architectures, and Green AI methodologies.

This dimension recognizes that intelligent networking must not only optimize communication energy but also minimize the computational carbon footprint of AI systems.

c. Deployment Sustainability

Deployment sustainability considers infrastructure planning, network topology optimization, hardware density, renewable-energy integration, and operational scalability [15, 18].

Future sustainable deployments require adaptive infrastructure management that considers energy availability, traffic demand, cooling requirements, and environmental constraints.

d. Lifecycle Sustainability

Lifecycle sustainability evaluates environmental impact across manufacturing, transportation, deployment, maintenance, recycling, and end-of-life disposal stages [20, 22].

This dimension emphasizes embodied energy, e-waste reduction, circular economy principles, recyclable materials, and environmentally responsible hardware design.

Rather than representing a validated predictive model, this taxonomy serves as a literature-derived analytical framework for organizing sustainability challenges across multiple layers of future 6G systems. It provides the conceptual basis for subsequent discussions on GRTEM, HYASPA, and Eco-DTA by linking RF efficiency, AI optimization, and lifecycle environmental assessment into a unified sustainability perspective. Figure 1 presents the relationship between these interconnected sustainability dimensions and their contribution toward carbon-neutral 6G network development.

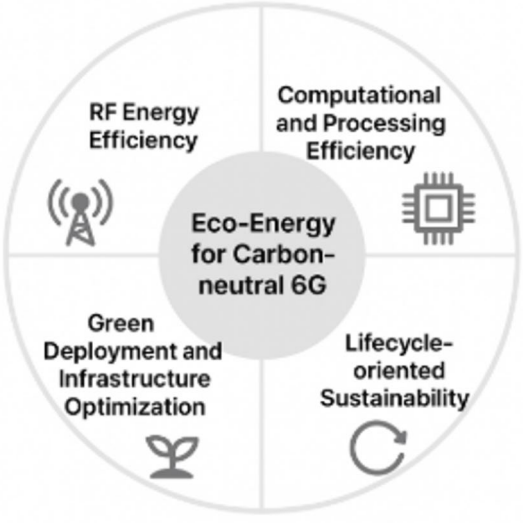


Fig. 1 Multi-Dimensional Eco-Energy Taxonomy for 6G. Multi-dimensional eco-energy taxonomy for carbon-neutral 6G networks, highlighting RF, computational, deployment, and lifecycle sustainability dimensions

4 Sustainability metrics and environmental impact models

Evaluating the environmental sustainability of 6G wireless systems requires comprehensive quantitative assessment frameworks that capture operational energy consumption, carbon emissions, computational overhead, hardware lifecycle impacts, and broader ecological consequences across the entire communication ecosystem [1, 3]. As future networks evolve toward AI-native, ultra-dense, and highly intelligent architectures, conventional communication metrics such as throughput, latency, and spectral efficiency are no longer sufficient to comprehensively evaluate sustainability performance [16, 17].

Unlike traditional network optimization approaches that primarily focus on reducing transmission power or improving energy efficiency, carbon-neutral 6G systems require multidimensional sustainability evaluation frameworks that jointly consider communication performance, computational cost, infrastructure impact, and lifecycle environmental effects [4, 14, 23]. This need is further emphasized by emerging technologies such as THz communication, ultra-massive MIMO, RIS, edge-cloud computing, and AI-driven orchestration, which may simultaneously enhance operational efficiency while increasing hardware complexity, manufacturing emissions, and computational energy demand.

This section reviews key sustainability indicators in green wireless communication research, including energy-centric metrics, environmental impact indicators, and network-level sustainability measures. It also discusses benchmarking challenges, evaluation methodologies, and the need for integrated sustainability frameworks that link AI optimization decisions to measurable environmental outcomes. A summary of representative sustainability metrics for carbon-aware 6G systems is presented in Table 2.

4.1 Energy-centric metrics

Energy-centric metrics form the foundation for evaluating wireless system efficiency by quantifying how effectively network resources are converted into communication performance [24]. Among these, energy efficiency (EE), typically expressed in bits-per-Joule, is one of the most widely used indicators in sustainable wireless communication research.

Energy efficiency captures the relationship between achievable throughput and total energy consumption, making it particularly relevant for energy-intensive 6G technologies such as THz communication, ultra-massive MIMO, AI-assisted signal processing, and dense edge-computing infrastructures [25]. Although improvements in EE indicate better utilization of power resources, this metric alone does not account for lifecycle emissions or the environmental costs of hardware production.

Power efficiency, which measures the ratio of useful output power to total consumed power at the hardware level, is also an important indicator. It is especially relevant for RF front-end components, power amplifiers, beamforming units, and THz transceiver architectures, where energy losses significantly affect overall network sustainability [14, 23].

Joule-per-bit provides a more fine-grained measure by estimating the energy required to process or transmit a single information bit, enabling comparisons across heterogeneous network components such as communication modules, computing platforms, and storage systems [22].

Table 2 Key Sustainability Metrics in Carbon-Aware 6G Systems Representative energy-centric, environmental, network-level, and AI sustainability metrics for evaluating carbon-aware and environmentally sustainable 6G wireless systems

Metric Category	Metric	Definition / Measurement	Relevance to 6G Sustainability Evaluation	References
Energy-Centric	Energy Efficiency (EE)	Bits/Joule	Measures communication performance achieved per unit energy; widely adopted for evaluating THz communication, ultra-massive MIMO, and AI-assisted wireless systems	[24, 25]
Energy-Centric	Power Efficiency	Useful Output Power / Total Power	Evaluates RF front-end efficiency, power amplifier performance, beamforming units, and transceiver energy utilization	[14, 23]
Energy-Centric	Joule-per-Bit	Energy consumed per transmitted or processed bit	Provides subsystem-level comparison of energy consumption across communication, computation, and storage components	[22]
Environmental	Carbon Footprint	$kgCO_2$-eq per device, network, or lifecycle stage	Quantifies greenhouse gas emissions associated with network operation, manufacturing, deployment, and disposal	[25, 26]
Environmental	Embodied Energy	Manufacturing-related energy consumption per component/system	Captures hidden environmental costs associated with semiconductor fabrication, hardware production, and infrastructure deployment	[19, 22]
Environmental	Lifecycle Assessment (LCA)	Environmental impact across raw materials, manufacturing, operation, recycling, and disposal stages	Enables holistic sustainability evaluation beyond operational energy consumption	[20, 22]
Environmental	E-Waste Indicators	Recyclability, disposal impact, and hardware replacement burden	Evaluates environmental impact caused by rapid hardware evolution and electronic waste generation	[22]
Network-Level	Carbon-per-Connection	$kgCO_2$ per user/device connection	Supports user-centric sustainability evaluation in ultra-dense 6G networks with massive connectivity	[1–3]
Network-Level	Green Throughput	Bits/s per $kgCO_2$	Relates communication performance to environmental impact by balancing throughput and carbon emissions	[4]
Network-Level	Carbon Budget Model	Maximum allowable network emissions	Supports carbon-aware optimization, traffic management, computation offloading, and network orchestration	[18, 19, 27]
AI Sustainability	Energy-per-Inference	Energy consumed for one AI decision or prediction process	Evaluates computational sustainability of AI-native 6G networks and intelligent orchestration systems	[21, 28]

Table 2 (continued)

Metric Category	Metric	Definition / Measurement	Relevance to 6G Sustainability Evaluation	References
AI Sustainability	Training Energy Intensity	Energy required for AI model training and optimization	Measures environmental cost associated with large-scale AI learning and distributed training processes	[11, 26]
AI Sustainability	AI Lifecycle Carbon Impact	Total environmental impact of AI models, computing hardware, and deployment processes	Supports sustainable AI evaluation considering model development, operation, and hardware lifecycle effects	[21, 28]

Recent studies have also explored adaptive energy-management strategies, including dynamic base-station sleep modes, traffic-aware cell activation, AI-assisted power scaling, and intelligent resource allocation [13, 14]. These approaches demonstrate potential energy savings by reducing unnecessary operational power consumption while still maintaining quality-of-service requirements.

However, energy-centric metrics alone are insufficient for a complete sustainability assessment because they do not capture embodied carbon, manufacturing impacts, material usage, or end-of-life environmental effects. Therefore, they must be integrated with lifecycle and carbon-based indicators for holistic evaluation.

4.2 4.2 Environmental Sustainability Metrics

Beyond operational energy use, sustainable 6G development requires environmental metrics that capture the full lifecycle ecological impact of communication systems [24].

Carbon footprint analysis is a key indicator used to estimate greenhouse gas emissions associated with communication infrastructures. These emissions arise from electricity consumption during operation, semiconductor fabrication, hardware transportation, cooling systems, maintenance activities, and equipment disposal processes [25, 26].

Carbon accounting is increasingly critical in 6G networks because technologies such as RIS panels, THz chipsets, AI accelerators, and ultra-dense edge-computing platforms often involve energy-intensive manufacturing and specialized materials [15, 19]. As a result, reductions in operational energy consumption do not necessarily translate into lower overall environmental impact.

Lifecycle assessment provides a broader framework by evaluating environmental impacts across multiple stages, including raw material extraction, component manufacturing, infrastructure deployment, operational usage, maintenance, recycling, and end-of-life disposal. LCA is particularly important for RIS hardware, massive MIMO systems, THz transceivers, and edge-computing devices due to their significant material and infrastructure requirements.

Embodied energy is another important metric, representing the energy consumed prior to system operation and highlighting hidden environmental costs associated with manufacturing and deployment [19].

Additionally, electronic waste (e-waste) indicators are becoming increasingly important due to rapid hardware replacement cycles driven by AI-enabled networks and high-frequency communication technologies. Consequently, sustainable hardware design,

modular architectures, recyclable materials, and circular economy strategies are essential for future carbon-neutral 6G systems [22].

4.3 Network-level sustainability metrics

While hardware- and environmental-level metrics provide important insights, future 6G systems also require network-level indicators that evaluate sustainability at operational scale.

Carbon-per-connection is an emerging metric that estimates the carbon emissions associated with serving individual users or devices [1–3]. This is particularly relevant in ultra-dense networks where large numbers of connected devices collectively contribute to environmental impact.

Green throughput extends conventional throughput by incorporating environmental costs, relating communication performance to energy consumption or carbon emissions. This enables a more balanced evaluation of efficiency and sustainability [4].

Sustainability-aware reliability metrics are also emerging, where energy constraints and carbon-aware scheduling influence reliability performance. For instance, in power-domain NOMA systems, reduced transmission power and adaptive resource allocation may affect interference management and decoding performance [8, 10].

Carbon budget models provide a system-level framework by defining allowable emission limits and embedding sustainability constraints into network optimization. These models support carbon-aware traffic routing, base-station activation, computation offloading, and AI workload management [18, 19, 27].

4.4 Benchmark datasets and simulation platforms for sustainable 6G evaluation

Reliable evaluation of sustainable 6G wireless networks requires standardized datasets, simulation platforms, and benchmarking methodologies capable of jointly assessing communication performance, energy consumption, computational overhead, and environmental impact. However, existing sustainability-focused studies frequently rely on heterogeneous simulation assumptions, network configurations, and evaluation criteria, making direct comparison of reported results challenging.

Current research on AI-driven eco-energy management in sustainable 6G networks commonly employs a combination of wireless communication simulators, AI learning environments, hardware measurements, and environmental datasets. Widely adopted simulation platforms include MATLAB for controlled evaluation of energy-efficient power allocation, beamforming, RIS optimization, and AI-based resource management under diverse channel conditions; ns-3 for large-scale network-level analysis of communication protocols, traffic control, energy-aware networking, and sustainability optimization; AI-driven reinforcement learning environments for adaptive resource allocation, energy management, and carbon-aware decision-making; and digital twin simulation platforms for predictive sustainability assessment, enabling virtual evaluation of energy consumption, carbon emissions, and lifecycle impacts prior to physical deployment [20, 27].

Representative benchmark datasets and evaluation inputs used in sustainable 6G studies can be categorized into four major groups. Wireless channel and network datasets provide information on channel characteristics, user distributions, mobility patterns, traffic demand, and interference conditions required for evaluating adaptive

communication strategies. Energy consumption datasets capture operational power usage of base stations, edge servers, RF components, and communication infrastructures, supporting energy efficiency analysis. Carbon intensity and renewable-energy datasets provide electricity grid carbon intensity, renewable energy availability, and energy source variability, thereby enabling carbon-aware optimization. Hardware lifecycle datasets, typically derived from lifecycle assessment databases, support estimation of embodied carbon, manufacturing emissions, material usage, and end-of-life environmental impacts associated with communication infrastructure.

To ensure consistent and meaningful evaluation, future sustainable 6G research should adopt standardized sustainability metrics that extend beyond traditional communication performance indicators. Important evaluation metrics include energy efficiency (bits/Joule), energy-per-bit (J/bit), carbon emissions per transmitted bit, carbon-per-connection, AI training and inference energy consumption, lifecycle carbon footprint, renewable-energy utilization ratio, and sustainability-aware Quality-of-Service (QoS) indicators [21].

Despite recent progress, a major research gap remains the lack of unified benchmark datasets that jointly capture communication performance, AI computational overhead, hardware lifecycle impact, and environmental sustainability indicators. The development of open and standardized sustainability benchmarks for 6G networks will be essential for enabling fair comparison of AI-driven eco-energy management strategies, improving reproducibility, and accelerating the practical deployment of environmentally sustainable wireless communication systems [22].

4.5 Toward AI-integrated sustainability assessment

A key limitation in current research is the fragmented evaluation of energy efficiency, environmental impact, and AI-driven optimization. Many studies assess energy consumption or carbon footprint independently, without fully capturing how AI-based decisions influence sustainability across multiple system layers [21, 28].

For example, AI-driven beamforming, adaptive resource allocation, computation offloading, and federated learning can reduce operational energy consumption while simultaneously increasing computational overhead due to training, inference, synchronization, and data processing requirements [22].

Therefore, future sustainability frameworks must incorporate AI-specific indicators such as energy consumption per inference, training energy intensity, carbon footprint of AI models, communication overhead in distributed learning, and lifecycle impact of AI-enabled hardware.

In this context, AI-integrated sustainability assessment is viewed as a multidimensional framework that links AI optimization objectives with measurable environmental indicators, including energy consumption, carbon intensity, embodied emissions, and lifecycle impact. Rather than serving as a fully validated methodology, this framework provides an analytical foundation for understanding sustainability trade-offs and guiding future benchmarking approaches for carbon-neutral 6G.

5 Green RF technologies for carbon-neutral 6G

The RF front-end and communication hardware infrastructure of future 6G networks are expected to account for a substantial share of total energy consumption, embodied carbon emissions, and overall environmental impact [2, 4]. As communication systems transition toward higher frequencies, massive connectivity, and AI-enabled network intelligence, improving RF energy efficiency alone is no longer sufficient. Sustainable RF design must therefore incorporate hardware lifecycle impacts, manufacturing emissions, deployment complexity, material usage, and long-term environmental sustainability considerations.

Accordingly, green RF technologies have emerged as key enablers for carbon-neutral 6G networks. Current research emphasizes energy-efficient transmission architectures, low-power RF hardware, adaptive beamforming, intelligent reflecting surfaces, energy harvesting communication, and sustainable hardware design strategies. However, even technologies classified as "green" may still introduce environmental burdens due to embodied energy, semiconductor fabrication processes, hardware complexity, and end-of-life disposal challenges [29].

This section reviews major green RF technologies relevant to carbon-aware 6G systems, including RIS, THz/mmWave communication hardware, ultra-massive MIMO (UM-MIMO), hybrid beamforming, and wireless energy harvesting technologies. Beyond improvements in communication performance, the discussion highlights sustainability trade-offs, lifecycle environmental impacts, deployment challenges, and the need for multidimensional evaluation frameworks.

5.1 Reconfigurable Intelligent Surfaces (RIS)

RIS-assisted communication has attracted significant attention as an energy-efficient approach for enhancing wireless propagation, extending coverage, managing interference, and improving spectral efficiency [29]. By enabling passive or semi-passive beam steering, RIS reduces reliance on energy-intensive active RF chains and can significantly lower transmission power requirements in dense network environments [24, 25].

From a sustainability perspective, RIS offers important operational energy savings because passive reflecting elements consume far less power than conventional active relay-based architectures. However, evaluating RIS sustainability solely based on operational energy reduction is insufficient.

A major limitation in existing RIS research is the limited consideration of lifecycle environmental impacts. The fabrication of metasurfaces, semiconductor control circuits, electronic components, and supporting infrastructure may result in substantial embodied carbon emissions. In addition, large-scale RIS deployment introduces further sustainability challenges related to material selection, maintenance requirements, hardware replacement cycles, and end-of-life disposal [30].

Emerging UAV-assisted RIS systems further underscore the need for sustainability-aware design. While aerial RIS platforms enhance coverage flexibility and dynamic network optimization, their energy consumption, mobility management overhead, and hardware lifecycle impacts require deeper investigation.

Therefore, sustainable RIS evaluation must adopt a lifecycle-oriented perspective that jointly considers operational efficiency, manufacturing impact, deployment costs, and overall environmental sustainability.

Recent UAV-assisted RIS architectures introduce additional opportunities for sustainable 6G deployment by enabling adaptive aerial communication, flexible coverage extension, and energy-aware network orchestration. However, UAV-RIS systems introduce new sustainability considerations related to flight energy consumption, trajectory optimization, hardware lifecycle impact, and intelligent resource management. Integrating UAV-RIS optimization with AI-driven eco-energy frameworks represents an important direction for future green 6G research [31].

5.2 THz and mmWave hardware technologies

THz and mmWave communication technologies are expected to play a central role in enabling ultra-high-capacity 6G networks through extremely wide bandwidth availability and efficient high-frequency spectrum utilization [30]. Advances in low-power THz transceivers, graphene-based antennas, plasmonic devices, and energy-efficient RF front-end architectures have demonstrated potential for improving communication performance while reducing operational energy consumption [27].

Despite these advantages, THz hardware introduces significant sustainability challenges. High-frequency systems typically require advanced semiconductor fabrication processes, specialized materials, complex integrated circuits, and sophisticated thermal management solutions. These factors substantially increase manufacturing energy demand and embodied environmental impact.

Furthermore, many existing studies focus primarily on communication performance metrics such as data rate and spectral efficiency, with limited consideration of lifecycle sustainability. Key issues including rare-material dependency, hardware recyclability, fabrication emissions, and long-term infrastructure sustainability remain insufficiently addressed [28, 29].

Future sustainable THz communication systems therefore require joint optimization of communication efficiency, hardware design, manufacturing processes, and lifecycle environmental impact.

5.3 Ultra-massive MIMO and hybrid beamforming

Ultra-massive MIMO systems enhance spectral efficiency, coverage, and reliability through extremely large antenna arrays and advanced spatial processing techniques [31–33]. Hybrid beamforming further improves energy efficiency by reducing the number of active RF chains through a combination of analog and digital beamforming strategies [30].

However, the sustainability implications of UM-MIMO involve important trade-offs. While large antenna arrays can reduce retransmissions and improve transmission efficiency, they also increase hardware complexity, material consumption, manufacturing requirements, and cooling demands [34].

In large-scale 6G deployments, the embodied carbon associated with manufacturing extensive antenna systems may partially offset operational energy savings. Consequently, sustainability-aware UM-MIMO design must extend beyond conventional performance metrics such as throughput and spectral efficiency.

Future research should incorporate joint optimization of antenna density, RF-chain activation, energy consumption, lifecycle emissions, hardware reliability, and deployment scalability to achieve balanced sustainability outcomes [35].

5.4 SWIPT and energy-harvesting communication

Simultaneous wireless information and power transfer, RF energy harvesting, ambient backscatter communication, and hybrid RF–solar harvesting systems represent promising approaches for enabling low-power and partially self-sustaining communication infrastructures [34–36].

These technologies are particularly relevant for large-scale IoT networks, sensor deployments, and edge devices where frequent battery replacement and maintenance introduce significant economic and environmental burdens [32]. Energy harvesting can reduce reliance on conventional grid power and potentially lower operational carbon emissions.

However, sustainability benefits are constrained by practical limitations, including unstable harvested energy availability, limited conversion efficiency, environmental dependency, storage requirements, hardware durability constraints, and deployment challenges [33, 34].

Moreover, many studies emphasize harvesting efficiency without sufficiently accounting for lifecycle impacts associated with energy harvesting devices, storage systems, and manufacturing processes. As a result, more comprehensive sustainability evaluation frameworks are required.

5.5 Comparative sustainability assessment of green RF technologies

A key limitation in current green RF research is the absence of standardized evaluation frameworks that jointly assess operational energy efficiency, lifecycle environmental impact, deployment complexity, and sustainability trade-offs across RF technologies [34, 35], which motivates the introduction of the GRTEM as a structured comparative framework that evaluates RF systems across these four dimensions using a normalized Low-Medium-High scale [36, 37].

GRTEM operates by characterizing RF technologies, mapping them to sustainability dimensions, and synthesizing comparative trade-offs, revealing that high operational efficiency does not necessarily correspond to low lifecycle impact due to manufacturing, cooling, and material-related emissions [37, 38].

Accordingly, GRTEM serves as a literature-derived synthesis tool rather than a predictive model and highlights key sustainability gaps while motivating unified RF benchmarking frameworks integrating communication performance with lifecycle assessment, as summarized in Table 3.

6 Hybrid AI techniques for eco-energy management

Artificial intelligence has become a fundamental enabling technology in 6G wireless networks due to its ability to support adaptive resource allocation, intelligent beamforming, traffic prediction, autonomous network orchestration, and real-time decision-making [32, 39]. Conventional AI approaches, including supervised deep learning, DRL, and FL, have demonstrated significant potential for improving communication efficiency and network adaptability under dynamic operating conditions [40].

However, most existing AI-driven wireless communication studies focus primarily on optimizing communication-centric objectives such as throughput maximization, latency reduction, and spectral efficiency improvement, while giving limited attention to the environmental cost of AI deployment. Large-scale AI models introduce additional

Table 3 Green RF Technology Evaluation Matrix (GRTEM). Comparative sustainability-oriented assessment of representative green RF technologies for carbon-aware 6G systems based on operational energy efficiency, lifecycle environmental impact, deployment complexity, and unresolved sustainability challenges

Technology	Energy Efficiency	Lifecycle Emissions	Deployment Complexity	Sustainability Challenges	References
Reconfigurable Intelligent Surfaces (RIS)	High	Medium	Moderate	Limited lifecycle assessment; embodied carbon of metasurface fabrication, control electronics, and disposal requires further investigation	[29, 37]
THz Front-End / THz Hardware	Medium	High	High	High semiconductor fabrication energy demand, specialized materials, cooling requirements, and limited recyclability analysis	[27, 28, 30]
Ultra-Massive MIMO (UM-MIMO)	Medium	Medium	High	Trade-off between spectral efficiency gains and embodied carbon from antenna density, hardware complexity, and cooling requirements	[31–33]
Hybrid Beamforming Architectures	Medium-High	Medium	Moderate	Need for optimized RF-chain reduction while maintaining performance and minimizing hardware impact	[30, 32]
SWIPT / Energy-Harvesting Nodes	Medium	Low-Medium	Low-Moderate	Harvested energy variability, conversion efficiency limitations, storage impact, and lifecycle sustainability modeling challenges	[34–36]
UAV-Assisted RIS Systems	Medium	Medium-High	High	Energy cost of aerial deployment, mobility management, hardware lifecycle, and adaptive optimization challenges	[38]

energy consumption through data acquisition, model training, parameter exchange, inference operations, and hardware acceleration requirements. Consequently, future AI-native 6G networks require sustainability-aware AI strategies that jointly optimize communication performance, computational efficiency, and environmental impact [41, 42].

This section reviews emerging hybrid AI paradigms for eco-energy management and examines how Green AI principles can support carbon-aware wireless communication. Particular emphasis is placed on AI sustainability trade-offs, energy-aware optimization, RF-chain efficiency enhancement, and the role of hybrid intelligence frameworks such as HYASPA in sustainable 6G network management.

6.1 Hybrid AI approaches for sustainable network optimization

Hybrid AI approaches integrate multiple learning and optimization techniques to improve adaptability, robustness, and scalability in complex communication environments. Recent research has explored combinations such as DRL integrated with evolutionary algorithms, federated learning enhanced through transfer learning, and graph neural network (GNN)-assisted reinforcement learning frameworks [41–44].

These approaches are particularly relevant for sustainable 6G systems because they enable multi-objective optimization involving energy consumption reduction,

carbon-aware resource allocation, communication reliability, spectrum efficiency, and computational sustainability.

For instance, DRL-based methods can dynamically optimize power allocation, spectrum utilization, user association, and traffic management in response to changing network conditions. Evolutionary optimization techniques enhance global search capability in complex sustainability problems involving conflicting objectives such as maximizing throughput while minimizing energy consumption and carbon emissions [45].

Similarly, federated learning reduces the need for centralized data transmission by enabling distributed model training across edge devices, potentially lowering communication energy consumption while improving data privacy [38, 39]. However, FL introduces additional sustainability challenges, including frequent model synchronization, communication overhead, client heterogeneity, and increased computational load at edge nodes.

Therefore, hybrid AI-based sustainability optimization requires a careful balance between intelligent decision-making benefits and the energy and carbon costs of AI execution itself.

6.2 Green AI and computational sustainability

Green AI has emerged as a key research direction focused on reducing the environmental impact of artificial intelligence systems [45, 46]. Unlike conventional AI approaches that prioritize accuracy and computational performance, Green AI explicitly considers energy efficiency, resource utilization, and carbon footprint across the AI lifecycle.

Key Green AI techniques include model pruning, quantization, knowledge distillation, sparse learning, lightweight neural architectures, adaptive inference mechanisms, and energy-aware training strategies.

In wireless communication systems, these techniques can reduce the computational burden of AI-enabled network management and improve scalability in resource-constrained edge environments [41, 42]. However, significant sustainability trade-offs remain. For example, aggressive model compression may reduce energy consumption while degrading prediction accuracy, robustness, or adaptability. Similarly, federated learning can reduce centralized communication overhead but may increase aggregate energy consumption across distributed devices.

An emerging aspect of Green AI in 6G systems is RF-chain optimization using intelligent algorithms to control power amplifier operation, RF-chain activation, beamforming configurations, and nonlinear compensation processes. While these techniques can reduce hardware energy waste, their computational overhead must also be considered in sustainability evaluations [47].

These challenges highlight the need for integrated sustainability assessment frameworks that jointly evaluate AI efficiency, communication performance, and environmental impact.

6.3 Emerging sustainability-oriented hybrid AI paradigms

Recent research increasingly explores AI-driven approaches that directly incorporate environmental objectives into communication system optimization, moving beyond traditional performance-centric design.

Representative approaches include carbon-aware DRL, where carbon intensity, energy availability, or environmental constraints are incorporated into reward functions; energy-adaptive federated learning, where training schedules adapt to device energy status and network conditions; multi-objective evolutionary AI optimization, where throughput, energy efficiency, reliability, and carbon emissions are jointly optimized; and GNN-based sustainability prediction models that estimate environmental impact based on network topology and operational states [48, 49].

Although many of these approaches remain in early research stages, they reflect a clear transition toward environmentally aware AI orchestration in future wireless systems.

A key unresolved challenge is the lack of standardized sustainability benchmarks for evaluating AI-based optimization approaches. Future frameworks should extend beyond communication metrics to include AI training energy, inference energy, carbon intensity, hardware utilization, lifecycle environmental impact, and deployment scalability as shown in Table 4.

6.4 HYASPA framework for sustainable power allocation

The Hybrid AI for Sustainable Power Allocation (HYASPA) framework is a conceptual architecture derived from literature [49–51] that extends conventional AI-based power allocation by jointly optimizing communication performance, carbon intensity, AI computational overhead, energy availability, and lifecycle sustainability costs in future 6G networks [52].

HYASPA operates through an iterative workflow in which network state information and environmental indicators are processed by an AI-driven optimization module that computes power allocation decisions, evaluates communication–carbon trade-offs, and

Table 4 Hybrid AI Approaches for Eco-Energy Management. Representative hybrid AI paradigms for sustainability-aware and carbon-conscious optimization in future 6G communication systems, highlighting their benefits, challenges, and evaluation considerations

Hybrid AI Paradigm	Description	Sustainability Benefit	Research Challenges	References
Carbon-Aware DRL	DRL incorporating sustainability indicators such as energy cost, carbon intensity, or emission constraints into optimization objectives	Enables carbon-conscious power allocation, scheduling, and adaptive network control	Limited standardization of carbon-aware reward functions and sustainability benchmarks	[32, 42, 47]
Energy-Adaptive Federated Learning	Federated learning with adaptive training scheduling based on device energy availability and network conditions	Reduces centralized data transfer and supports distributed sustainable AI learning	Communication overhead, synchronization energy, and edge-device computation cost	[35, 43, 48]
GA-DRL Multi-Objective Optimization	Evolutionary algorithms combined with DRL for balancing multiple objectives including throughput, energy efficiency, and emissions	Supports joint optimization of communication performance and environmental objectives	High computational complexity and limited real-world validation	[35, 43, 47, 49]
GNN-Based Sustainability Prediction	Graph neural networks used for topology-aware prediction of energy consumption and environmental impact	Enables intelligent sustainability-aware network planning and optimization	Limited integration with lifecycle assessment models and real-world datasets	[47, 48, 50-52]
AI-Driven RF Chain Optimization	AI-based optimization of power amplifiers, RF-chain activation, beamforming, and hardware configuration	Reduces RF energy waste and improves hardware-level energy efficiency	AI computational overhead and hardware implementation complexity	[51–53]

updates policies through feedback learning to adapt to dynamic network conditions, as illustrated in Fig. 2.

Although HYASPA is not a fully implemented system, it provides a structured representation of sustainability-aware decision-making, with future work requiring validation through simulation platforms and standardized benchmarks.

6.4.1 Mathematical formulation of HYASPA sustainability optimization

The HYASPA framework can be formulated as a multi-objective optimization problem that jointly optimizes communication performance, energy efficiency, computational overhead, and carbon impact. Unlike conventional power allocation schemes, which primarily focus on throughput maximization or spectral efficiency, HYASPA integrates sustainability-aware objectives into the resource allocation process to achieve environmentally responsible wireless network optimization.

The optimization objective is expressed as [49–51]:

$$_{P,\,A}{}^{max}U = \alpha\,\mathrm{R}\,(\mathrm{P},\mathrm{A}) + \beta\,\mathrm{EE}\,(\mathrm{P},\mathrm{A}) - \gamma\,\mathrm{C}_{\mathrm{AI}}\,(\mathrm{P},\mathrm{A}) - \delta\,\mathrm{C}_{\mathrm{carbon}}\,(\mathrm{P},\mathrm{A}) \tag{1}$$

where:

P denotes the transmission power allocation variables,

A denotes adaptive resource allocation decisions,

$\mathrm{R}\,(\mathrm{P},\mathrm{A})$ represents the achievable communication rate,

$\mathrm{EE}\,(\mathrm{P},\mathrm{A})$ represents energy efficiency,

$\mathrm{C}_{\mathrm{AI}}\,(\mathrm{P},\mathrm{A})$ represents the computational energy cost associated with AI processing,

$\mathrm{C}_{\mathrm{carbon}}\,(\mathrm{P},\mathrm{A})$ represents the carbon emission impact, and.

α, β, γ, and δ are weighting coefficients that regulate the relative importance of communication performance, energy efficiency, computational cost, and carbon sustainability objectives.

The optimization is subject to practical communication constraints. The total allocated transmission power must satisfy:

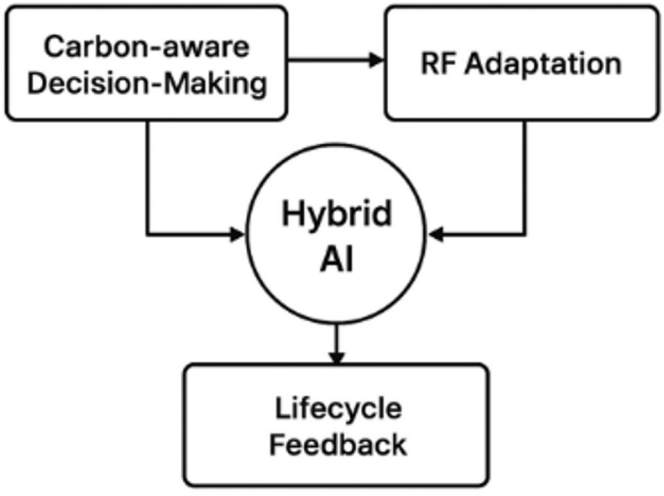


Fig. 2 Hybrid AI Framework for Eco-Energy Management (HYASPA). Conceptual illustration of the HYASPA framework integrating carbon-aware AI optimization, RF adaptation, and lifecycle-oriented sustainability feedback mechanisms

$$\sum_{i=1}^{N} P_i \leq \mathrm{p}_{\max} \tag{2}$$

where P_i represents the transmission power allocated to user i, and P_{max} denotes the maximum available transmission power.

Additional constraints may include: Quality-of-Service (QoS) requirements, latency limitations, reliability constraints, hardware energy capacity limitations, and carbon budget restrictions [53, 54].

This mathematical formulation highlights the capability of HYASPA to effectively balance conventional communication objectives with environmental sustainability requirements. Future work will focus on validating the proposed framework using simulation platforms such as MATLAB, ns-3, and AI-driven wireless network simulation environments under diverse channel conditions, user distributions, and energy constraints to comprehensively assess system performance, robustness, and sustainability benefits.

To provide a quantitative perspective on the reported performance of AI-driven eco-energy management approaches, Table 5 summarizes representative studies from the reviewed literature based on optimization technique, evaluation scenario, reported energy efficiency improvements, carbon reduction potential, major advantages, and existing limitations. Unlike conventional classification tables that categorize AI approaches based on methodology, this comparison highlights reported sustainability outcomes and practical implementation considerations. The analysis reveals that although AI-based optimization techniques demonstrate significant potential for reducing energy consumption and improving sustainability, challenges remain regarding standardized evaluation methods, AI computational overhead, lifecycle assessment, and real-world deployment validation [55–68].

7 AI-integrated environmental impact modeling

AI-assisted environmental impact modeling is emerging as a key enabler of sustainability-oriented 6G network management, as future wireless infrastructures will require intelligent mechanisms capable of monitoring, predicting, and optimizing energy–carbon dynamics in real time [3, 6]. Unlike conventional sustainability assessment approaches that evaluate energy consumption or carbon emissions only after network deployment, AI-integrated environmental modeling enables proactive decision-making by predicting the environmental consequences of communication and computing activities in advance.

As AI-native 6G systems become increasingly complex, incorporating dense edge-cloud infrastructures, intelligent RF management, digital twins, and autonomous network orchestration-traditional static sustainability assessment methods are becoming insufficient. These approaches often fail to capture dynamic interactions among traffic demand, computational workload variations, renewable energy availability, hardware utilization, and lifecycle environmental impacts [68, 69]. Consequently, future sustainable 6G networks require adaptive environmental modeling frameworks capable of continuously learning and updating sustainability predictions.

Recent advances in machine learning and deep learning demonstrate strong potential for AI-based environmental modeling by uncovering complex relationships between network operation and environmental performance. AI models can learn mappings

Table 5 Quantitative Performance Comparison of AI-Driven Eco-Energy Management Studies in Sustainable 6G Networks. Quantitative comparison of representative AI-driven eco-energy management approaches in sustainable 6G wireless networks, summarizing reported energy-efficiency improvements, carbon-aware benefits, advantages, and implementation challenges

Approach	Quantitative Performance	Sustainability Impact	Main Advantage	Main Limitation	References
AI-based dynamic resource allocation	DRL-based frameworks commonly report 15–30% energy-efficiency improvement or comparable reductions in energy use in dynamic 5G/6G settings	Lower transmission and processing energy tends to reduce operational emissions	Adapts power, scheduling, and beamforming in real time under changing traffic and channel conditions	Training complexity, policy lag, and AI energy overhead remain recurring concerns	[55, 56]
Carbon-aware DRL optimization	Direct carbon-aware reward formulations are less mature, but carbon-optimized network AI frameworks report large emissions reductions, including up to 74.9% carbon reduction in a federated edge intelligence prototype	Explicitly optimizes operation against carbon intensity, energy trading, or renewable availability rather than energy alone	Integrates environmental objectives into control policies instead of treating carbon as a byproduct	Needs accurate carbon accounting, lifecycle modeling, and standardized metrics	[6, 57, 58]
Energy-adaptive federated learning	FL often reduces communication overhead and can improve system energy efficiency; one zero-touch slicing framework reported more than 10× energy-efficiency gain and 11× lower monitoring overhead after convergence	Local training can reduce centralized data transfer and associated communication energy	Preserves privacy while enabling distributed optimization across slices, devices, or operators	Edge-side computation and synchronization energy can offset some gains	[47, 59, 60]
GA-DRL or multi-objective optimization	Multi-objective AI frameworks consistently improve energy use while retaining QoS; recent joint optimization for IoT reported up to 34% lower energy consumption than baselines	Better balances energy, latency, throughput, and reliability than single-objective schemes	Useful where sustainability must be traded against service constraints	Computational complexity grows quickly in large-scale heterogeneous networks	[61, 62]
GNN-based sustainability prediction	GNNs are mainly used for better forecasting and topology-aware control rather than direct headline energy percentages	Supports proactive planning by predicting energy consumption and resource usage across nodes	Captures spatial and temporal dependencies that simpler predictors miss	Integration with lifecycle carbon assessment and deployment standards remains limited	[63, 64]
AI-driven RF-chain optimization	AI/ML-driven RF frontend optimization is supported, but papers in this corpus rarely give a single common percentage benchmark	Hardware-level control can reduce RF waste and power losses before higher-layer optimization	Extends sustainability gains into the physical layer, including beamforming and RF adaptation	Hardware validation and deployment overhead are still underexplored	[65, 66]
Eco-digital twin sustainability optimization	Digital-twin frameworks consistently report improved planning and lower energy use, though many results remain preliminary or scenario-specific	Best-supported approach for lifecycle-aware and pre-deployment sustainability analysis	Enables predictive optimization and testing before physical deployment	Requires accurate models, synchronization, and real-world validation	[67, 68]

between traffic demand, energy consumption, carbon intensity, infrastructure utilization, and hardware behavior to enable predictive sustainability analysis [18, 51, 52].

Representative applications include carbon emission forecasting, energy demand prediction, neural eco-simulation, sustainability-aware network optimization, and AI-assisted lifecycle impact estimation. These approaches can support intelligent decision-making for beamforming optimization, power allocation, computation offloading, traffic management, and infrastructure planning by jointly considering environmental objectives and conventional communication performance metrics [39, 49, 53].

However, a key limitation of existing research is the focus on operational energy reduction without sufficiently accounting for AI-related computational overhead, embodied carbon emissions, and full lifecycle environmental impact. In many cases, AI models improve network energy efficiency while simultaneously introducing additional energy consumption during training, inference, data exchange, and hardware acceleration. Therefore, comprehensive sustainability evaluation must consider the complete environmental footprint of AI-enabled network management systems.

In parallel, LCA methodologies are increasingly being integrated with AI-based analytics to enable predictive environmental evaluation of communication infrastructures. AI-enhanced LCA approaches can estimate embodied carbon emissions, operational energy requirements, maintenance-related environmental costs, and end-of-life impacts associated with network components such as base stations, RIS panels, THz transceivers, edge-computing servers, and cloud data-center infrastructures [70].

Integrating AI with LCA enables sustainability considerations to be incorporated earlier into network planning, hardware selection, and infrastructure design, rather than being treated as post-deployment evaluation metrics [68–70].

7.1 AI-based carbon-aware network optimization

AI-assisted carbon-aware optimization is an emerging research direction aimed at balancing communication performance, energy efficiency, and environmental sustainability in real time. Unlike conventional optimization methods that focus primarily on throughput, latency, or spectral efficiency, carbon-aware approaches incorporate environmental factors such as carbon intensity, renewable energy availability, energy pricing, traffic demand, and computational workload conditions into decision-making processes [71, 72].

Recent studies have explored multi-objective optimization strategies, including DRL-based energy–carbon optimization, evolutionary sustainability-aware resource allocation, AI-assisted eco-routing, carbon-aware computation offloading, and renewable-energy-adaptive scheduling. These approaches enable dynamic adaptation of transmission power, workload distribution, beamforming configurations, RF-chain activation, and edge–cloud resource allocation while jointly considering communication objectives and environmental constraints [46, 52].

Despite their promise, current AI-based carbon-aware optimization techniques face several limitations. First, evaluation methodologies remain inconsistent, as studies often use different datasets, simulation platforms, sustainability indicators, and optimization assumptions, making direct comparison of reported results difficult [73, 74–78].

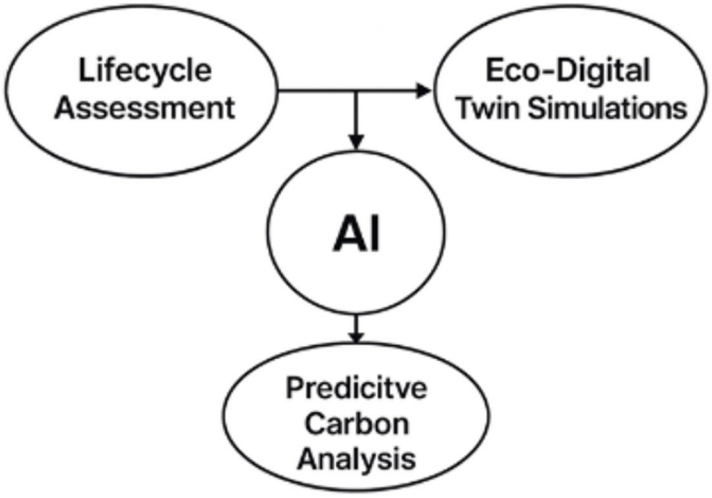


Fig. 3 AI-Integrated Environmental Impact Modeling. Conceptual framework for AI-integrated environmental impact modeling in sustainable 6G systems, illustrating predictive carbon analysis, lifecycle-oriented assessment, and eco-digital twin simulation processes

Second, many approaches focus only on operational energy reduction and neglect embodied carbon from hardware, lifecycle environmental impacts, AI model energy consumption, and computational overhead.

Third, real-world deployment remains challenging due to limited availability of carbon-aware datasets, incomplete environmental monitoring infrastructures, and uncertainty in renewable energy supply dynamics.

These challenges highlight the need for integrated sustainability modeling frameworks that jointly evaluate communication efficiency, AI computational sustainability, and lifecycle environmental impact.

7.2 Eco-digital twin architecture for sustainability assessment (Eco-DTA)

The Eco-Digital Twin Architecture (Eco-DTA) is a conceptual framework for integrating AI-based environmental prediction, digital twin modeling, and lifecycle sustainability assessment in 6G networks [52, 53, 69–74], extending traditional digital twins by incorporating environmental intelligence for carbon- and energy-aware decision-making.

Eco-DTA consists of AI-based environmental prediction, lifecycle assessment, carbon-aware optimization, and sustainability feedback modules that collectively simulate network behavior across multiple deployment scenarios to estimate energy consumption, carbon emissions, and infrastructure lifecycle impacts [75, 76].

Through a structured workflow involving data acquisition, digital twin simulation, environmental impact estimation, optimization, and decision output, Eco-DTA enables pre-deployment evaluation of sustainable network configurations, as conceptually represented in Fig. 3. However, Eco-DTA remains a literature-derived conceptual model requiring future development of standardized datasets and scalable simulation platforms for practical validation.

7.2.1 Eco-DTA sustainability modeling workflow

The Eco-DTA framework operates through a continuous sustainability feedback loop consisting of four major stages:

a. **Data Acquisition Layer**: Collects network operational data, including traffic demand, energy consumption, hardware utilization, renewable-energy availability, and carbon intensity.
b. **AI Prediction Layer**: Applies machine-learning models to estimate future energy demand, carbon emissions, and sustainability performance under different network conditions.
c. **Lifecycle Assessment Layer**: Evaluates embodied energy, hardware environmental impact, maintenance cost, and end-of-life sustainability factors.
d. **Optimization and Decision Layer**: Provides sustainability-aware recommendations for resource allocation, infrastructure planning, and network configuration.

This workflow enables Eco-DTA to evaluate environmental consequences before real-world deployment, supporting proactive sustainability optimization in future 6G networks.

8 Cross-layer eco-energy management strategies

Cross-layer eco-energy management has emerged as a critical requirement for achieving environmentally sustainable and carbon-aware 6G operation, as sustainability objectives cannot be effectively realized through isolated optimization of individual network layers. Future 6G systems will consist of tightly interconnected layers spanning RF communication, AI-driven computation, edge-cloud infrastructures, hardware platforms, and environmental monitoring systems [4, 7] [77].

Although layer-specific optimization techniques can improve local performance and efficiency, they do not necessarily minimize overall system-level environmental impact. For example, reducing transmission power at the physical layer may increase computational burden at higher layers due to more complex optimization requirements, while AI-based resource management may reduce communication energy consumption but introduce additional computational carbon emissions. Consequently, sustainable 6G networks require coordinated cross-layer optimization strategies that jointly consider communication efficiency, computational sustainability, lifecycle impact, and carbon-aware decision-making [69, 74].

This section discusses emerging cross-layer eco-energy management strategies across the physical layer, MAC/network layer, and edge–cloud computing layer, highlighting their sustainability benefits, limitations, and future research needs [78].

8.1 Physical-layer eco-energy optimization

At the physical layer, energy-efficient communication techniques provide important opportunities to reduce operational power consumption while maintaining communication quality. Existing approaches include low-power modulation schemes, adaptive beamforming, energy-efficient hybrid beamforming, RIS-assisted propagation optimization, carbon-aware transmission control, and dynamic RF-chain activation.

These techniques enable optimization of transmission parameters such as power levels, antenna activation, and beamforming configurations based on both communication requirements and sustainability indicators, including energy-per-bit, carbon-per-transmission, power efficiency, and lifecycle energy impact [3, 47].

However, physical-layer sustainability optimization involves significant trade-offs. For instance, increasing antenna density or incorporating more advanced signal processing

can improve spectral efficiency but may also increase hardware complexity, cooling requirements, and embodied carbon emissions. Therefore, future physical-layer optimization must extend beyond operational energy reduction to include lifecycle environmental impacts.

Sustainability-aware RF optimization should also incorporate hardware-level factors such as power amplifier efficiency, RF-chain utilization, semiconductor energy cost, hardware aging, and replacement cycles.

8.2 MAC and network-level eco-energy management

At the MAC and network layers, sustainable 6G operation depends on intelligent management of network resources, traffic demand, and infrastructure utilization. Existing approaches include adaptive base-station sleeping, energy-aware load balancing, traffic-aware scheduling, intelligent user association, and renewable-energy-aware resource allocation [6, 9, 75].

These mechanisms can significantly reduce unnecessary operational energy consumption, particularly in ultra-dense networks where continuously active infrastructure leads to substantial energy waste.

When integrated with AI-based prediction models, network-level optimization can dynamically adapt system behavior based on traffic fluctuations, user mobility patterns, renewable energy availability, carbon intensity, and service requirements [76]. For example, AI-enabled network controllers can activate or deactivate infrastructure components based on predicted demand while minimizing both energy consumption and service degradation.

However, current network-level sustainability approaches remain limited in scope, as many studies focus primarily on operational energy efficiency without considering embodied carbon emissions, hardware lifecycle impacts, AI computational costs, or long-term environmental constraints. Future network orchestration frameworks must therefore evolve from energy-aware optimization toward comprehensive carbon-aware management strategies.

8.3 Edge-cloud continuum and computational eco-energy management

The edge-cloud continuum plays a central role in sustainable 6G systems because AI-native applications require significant distributed computational resources across devices, edge nodes, and centralized cloud infrastructures [77, 78].

Applications such as digital twins, immersive extended reality (XR), autonomous systems, industrial IoT, and intelligent transportation systems require continuous data processing, prediction, and decision-making, which can substantially increase computational energy demand.

To address these challenges, emerging eco-energy management approaches include carbon-aware computation offloading, adaptive AI model placement, distributed inference optimization, energy-aware edge computing, and workload migration based on renewable energy availability [77]. These strategies aim to reduce computational carbon emissions by dynamically allocating workloads according to energy availability, latency requirements, and environmental conditions.

However, computational sustainability introduces new trade-offs. For instance, offloading workloads from cloud to edge nodes may reduce communication latency but

increase energy consumption at distributed edge devices. Similarly, frequent AI model updates can improve system intelligence but increase synchronization overhead and energy usage.

Therefore, sustainable edge–cloud management requires joint optimization of communication, computation, and environmental objectives across the entire continuum.

8.4 Integrated cross-layer sustainability optimization

A major limitation in existing research is the fragmented treatment of RF optimization, AI-driven management, and environmental assessment. Many studies optimize communication performance, computational efficiency, or carbon reduction independently, which limits the development of fully integrated eco-energy management frameworks [73].

Future sustainable 6G systems require cross-layer optimization frameworks capable of jointly considering RF transmission efficiency, AI computational overhead, renewable energy dynamics, embodied carbon emissions, lifecycle sustainability, reliability constraints, and quality-of-service requirements [79].

Hybrid AI techniques offer a promising solution because they can simultaneously optimize multiple conflicting objectives. For example, AI-driven cross-layer optimization can balance throughput performance against energy consumption and carbon emissions by embedding sustainability indicators directly into optimization objectives.

However, practical deployment faces several key challenges:

a. Lack of standardized sustainability benchmarks: Inconsistent datasets, metrics, and assumptions across studies hinder fair comparison of results.
b. Limited real-world validation: Many proposed eco-energy frameworks remain simulation-based with limited experimental or field deployment evidence.
c. AI energy overhead: The energy cost of training, inference, and maintaining AI models must be explicitly included in sustainability evaluations.
d. Lifecycle accounting limitations: Most existing approaches focus on operational energy while neglecting full lifecycle environmental impacts.

Addressing these challenges requires integrated sustainability-aware architectures capable of coordinating communication, computation, and environmental management across the entire 6G ecosystem.

In summary, cross-layer eco-energy management represents a paradigm shift from conventional energy-efficient networking toward holistic carbon-aware network intelligence. By integrating AI optimization, green RF technologies, lifecycle assessment, and environmental feedback mechanisms, future 6G systems can achieve a more balanced trade-off between high-performance connectivity and long-term ecological sustainability [78–80].

9 Challenges, open issues, and future research directions

Although significant progress has been made in sustainable wireless communication research, the transition toward carbon-aware and environmentally sustainable 6G networks remains constrained by a range of technical, operational, methodological, and standardization challenges [6, 61]. Future 6G sustainability cannot be achieved through isolated improvements in energy efficiency alone; instead, it requires integrated

optimization across AI systems, RF technologies, computing infrastructures, and lifecycle environmental management.

This section discusses key unresolved challenges and outlines future research directions necessary for enabling practical deployment of sustainable 6G networks.

9.1 AI computational sustainability and green AI challenges

One of the major challenges in AI-native 6G architectures is the environmental cost associated with large-scale AI training, inference, and distributed optimization processes [69–73]. Future networks are expected to rely heavily on DRL, FL, GNNs, generative AI models, and autonomous orchestration frameworks, all of which introduce substantial computational energy consumption during both development and operational phases [7, 72].

Although AI techniques can improve network energy efficiency through intelligent resource allocation, adaptive power control, and predictive optimization, the energy consumed by AI itself may partially offset these gains. Complex models often require significant computational resources, specialized hardware accelerators, and frequent retraining or updates, thereby increasing operational carbon emissions [77, 78].

Future research should therefore prioritize lightweight AI architectures, energy-efficient model training, adaptive inference strategies, Green AI benchmarking frameworks, and carbon-aware model selection mechanisms.

Sustainable AI evaluation should incorporate metrics such as energy-per-inference, training energy intensity, AI lifecycle carbon footprint, and computational energy efficiency.

9.2 Dynamic carbon awareness and renewable-energy integration

A major challenge in sustainable 6G networks is the dynamic and geographically variable nature of electricity-grid carbon intensity. Reducing power consumption does not necessarily lead to reduced carbon emissions because environmental impact depends on the carbon intensity of the energy source [1, 2, 17].

For example, operating network infrastructure at low power during periods of carbon-intensive electricity generation may still result in high emissions. Therefore, future 6G systems must integrate renewable energy availability and carbon intensity into real-time optimization decisions.

Key research directions include carbon-aware traffic scheduling, renewable-energy-aware computation offloading, adaptive network operation based on grid conditions, and carbon-budget-constrained resource allocation. These approaches can enhance frameworks such as HYASPA by enabling real-time environmental feedback integration into network control.

9.3 Hardware-level sustainability and lifecycle optimization

A significant research gap lies in linking AI-driven optimization with hardware-level sustainability constraints. Many existing approaches focus on software-level performance while neglecting hardware-related environmental factors such as RF component efficiency, antenna activation strategies, semiconductor manufacturing impact, cooling requirements, hardware replacement cycles, and electronic waste generation [79].

For instance, RIS, THz transceivers, and ultra-massive MIMO systems may reduce operational energy consumption but simultaneously increase embodied carbon due to complex manufacturing processes and material usage.

Future research should integrate LCA into hardware design and network planning through sustainable RF component design, recyclable materials, low-carbon semiconductor fabrication, and lifecycle-aware infrastructure deployment strategies. This direction directly aligns with the objectives of the GRTEM by extending evaluation beyond operational efficiency to full lifecycle environmental impact.

9.4 Lack of standardized sustainability benchmarks

A critical limitation in current sustainable 6G research is the absence of universally accepted benchmarking methodologies. Existing studies often rely on heterogeneous datasets, simulation environments, sustainability metrics, optimization objectives, and hardware assumptions, making direct comparison of reported results difficult [80].

Future research should establish standardized sustainability benchmarks that jointly evaluate energy consumption, carbon emissions, communication performance, AI computational cost, lifecycle impact, and reliability. Such benchmarks would enable fair comparison between competing approaches and accelerate the development of practical carbon-aware 6G systems.

9.5 Sustainability-aware RIS and emerging RF architectures

Although RIS has demonstrated strong potential for improving communication efficiency, future research must extend its evaluation beyond transmission energy reduction. Key challenges include optimal RIS placement, deployment density, hardware durability, manufacturing emissions, and lifecycle management [76, 81].

Future RIS research should explicitly incorporate environmental objectives into optimization frameworks by balancing communication gains with lifecycle environmental impact.

Similarly, THz and mmWave systems require further investigation into low-carbon semiconductor technologies, energy-efficient RF chains, sustainable cooling mechanisms, and recyclable hardware materials to ensure long-term environmental viability [82].

9.6 Sustainable digital twins and Eco-DTA validation

Eco-digital twin technologies provide promising opportunities for evaluating sustainability trade-offs prior to physical deployment. However, current Eco-DTA concepts remain largely theoretical and require validation through large-scale simulations, real-world network measurements, standardized sustainability datasets, and digital twin test platforms [83–85].

Future Eco-DTA research should focus on developing accurate environmental models capable of predicting energy consumption, carbon emissions, hardware lifecycle impacts, and sustainability outcomes under diverse deployment scenarios. This capability would enable proactive, sustainability-aware network planning and optimization.

9.7 Future research directions

Based on the identified challenges, several key research directions are recommended:

a. **Carbon-Aware Hybrid AI Optimization**: Future AI systems should incorporate environmental indicators directly into optimization objectives and reward functions. Carbon-aware DRL and hybrid AI models can jointly optimize communication performance, energy consumption, and carbon emissions [77, 78].
b. **Lifecycle-Aware RF Design**: Future RF architectures should integrate lifecycle assessment at the design stage to reduce embodied energy, material waste, and environmental impact associated with RIS, THz systems, and antenna infrastructures [79, 80].
c. **Green AI Methodologies**: Energy-efficient learning strategies, including lightweight models, compressed learning, sparse inference, and low-overhead federated learning, should be developed to reduce the computational carbon footprint of AI-native wireless systems [80].
d. **Sustainability-Aware RIS Deployment**: RIS optimization should incorporate environmental constraints alongside communication objectives, considering placement, density, durability, lifecycle emissions, and material sustainability [78, 79].
e. **Sustainable Digital Twin Systems**: Eco-digital twin platforms should be developed as comprehensive sustainability evaluation environments capable of simulating energy, carbon, and lifecycle impacts prior to infrastructure deployment [81].
f. **Environmentally Sustainable Materials**: Research into recyclable, biodegradable, and low-impact semiconductor and RF materials is required to reduce electronic waste and support circular economy principles in future communication infrastructures.
g. **Green Federated Learning**: Future federated learning systems should minimize communication overhead, synchronization energy, and computational burden while maintaining privacy and learning performance in large-scale distributed environments [48, 52, 82].

9.8 Toward self-sustaining 6G networks

Building on these research directions, this review proposes the concept of Self-Sustaining 6G Networks as a long-term sustainability vision in which communication infrastructures integrate renewable energy harvesting, environmentally aware AI orchestration, lifecycle-conscious resource management, and adaptive carbon-aware control mechanisms.

Rather than representing a finalized deployment architecture, this concept outlines a future direction in which 6G networks evolve toward autonomous, environmentally adaptive, and sustainability-oriented operation [43, 46, 83–88].

Achieving this vision will require coordinated advances in AI, RF engineering, digital twin technologies, sustainability assessment methodologies, and green infrastructure design.

10 Conclusion

This narrative review has examined emerging strategies for achieving environmentally sustainable and carbon-aware 6G wireless networks through the integration of AI-driven optimization, green RF technologies, sustainability evaluation metrics, and lifecycle-oriented environmental assessment approaches, and it synthesizes research across communication engineering, artificial intelligence, energy-efficient networking, and environmental sustainability to provide a comprehensive understanding of the

challenges, trade-offs, and opportunities associated with future carbon-neutral wireless infrastructures. The review demonstrates that sustainable 6G operation requires a fundamental shift from conventional communication optimization approaches focused mainly on throughput, latency, and spectral efficiency toward integrated eco-energy management strategies that jointly consider operational energy consumption, AI computational overhead, embodied carbon emissions, hardware lifecycle impacts, and environmental resource constraints. It further highlights that emerging 6G technologies such as THz communication, ultra-massive MIMO, RIS, AI-native architectures, and edge–cloud computing offer substantial performance and efficiency gains while simultaneously introducing new sustainability challenges, where AI-based optimization can reduce transmission energy consumption but increase computational energy demand, and green RF technologies can improve operational efficiency while introducing embodied carbon and lifecycle impacts, thereby necessitating multidimensional sustainability evaluation rather than isolated energy-efficiency metrics. A key finding of this review is that existing research remains fragmented across AI optimization, green communication technologies, and environmental assessment, with most studies evaluating communication performance, energy efficiency, or carbon emissions independently without adequately capturing their interactions within unified sustainability frameworks, which underscores the need for integrated approaches that jointly optimize communication performance, computational sustainability, and environmental impact. To structure these research directions, the review introduced literature-derived conceptual frameworks including the GRTEM for RF sustainability assessment, the HYASPA framework for integrating AI-driven optimization with carbon-aware resource allocation, and the Eco-DTA for AI-assisted environmental prediction and lifecycle-aware network simulation, all of which are presented as analytical synthesis models rather than experimentally validated architectures. The review also identifies critical research gaps such as the lack of standardized sustainability benchmarks, limited datasets for carbon-aware optimization, insufficient integration of lifecycle assessment in RF design, AI computational energy overhead and Green AI challenges, limited real-world validation, and the absence of unified carbon accounting frameworks. It therefore recommends future research directions focused on standardized sustainability evaluation methods, energy-efficient AI architectures, lifecycle-aware RF technologies, renewable-energy-integrated communication systems, and experimentally validated eco-digital twin platforms, alongside stronger interdisciplinary collaboration among communication, AI, hardware, and environmental researchers. In summary, the study concludes that sustainable 6G networks require a transition from isolated energy-saving techniques to holistic eco-energy management frameworks that integrate communication efficiency, computational sustainability, lifecycle environmental assessment, and carbon-aware orchestration to enable intelligent, adaptive, and environmentally responsible wireless systems for future digital ecosystems.

Author contributions

Writing - Original Draft Preparation OFC, OMB, UJN, UOPC, AKI, and UCN. Conceptualization OFC, AKI, OMB, UCN, UOPC and UJN. Writing-Review & Editing OFC, OMB, UJN, AKI and UCN. SupervisionUOPC, OMB, UCN, OFC and AKI.

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Data availability

No datasets were generated or analysed during the current study.

Declarations

Ethics approval and consent to participate
Ethical approval was not required for this study because it does not involve human participants, animal experiments, clinical trials, or the collection of personal data. The study is based entirely on the analysis and synthesis of previously published literature.

Consent for Publication
Not applicable. This manuscript does not contain individual participant data, identifiable information, or personal images requiring consent for publication.

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