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AI-Driven 5G Networks: Federated Optimization for Sustainable Telecommunications

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Abstract: A novel approach to making telecommunications infrastructure less damaging to the environment and more energy efficient is to integrate AI with 5G networks. However, the main issues with current approaches are scalability, data security, and a thorough assessment of sustainability. In order to overcome these constraints, this study creates and evaluates a unique AI-driven optimization system that combines blockchain-secured digital twins, federated learning (FL), and ISO-compliant life cycle assessment (LCA). With empirical validation across many operator datasets, the paradigm shows significant gains in network sustainability via thorough mathematical modeling of DQN and LSTM topologies. The main conclusions show that, although data privacy is maintained, PySyft-based FL implementations reduced operational carbon emissions by 30.4% and base station energy consumption by 32.7%. The most significant contributions include (1) a blockchain-CoTwin architecture that enables safe coordination between multiple operators with a discernible computational overhead of 15%–20%, (2) a novel combination of telecommunications performance data and environmental metrics from ReCiPe 2016 that demonstrates both operational benefits and hitherto unmeasured embodied training effects, and (3) empirically validated implementation thresholds that link scholarly research with practical applications. Key infrastructural connection is 9.7 percentage points better in urban installations than in rural ones. According to stakeholder validation, for adoption to take place, interfaces and conventions need to make sense. This research provides a scalable approach to network improvement that integrates cutting-edge technology while respecting legal obligations and protecting the environment. It also lays out new protocols for the creation of 6G networks and the integration of AI into 5G networks.

Keywords: AI-driven optimization, federated learning, blockchain, life cycle assessment (LCA), sustainable telecommunications

1. Introduction

5G networks are rapidly spreading over the world and revolutionizing face-to-face communication. They feature low latency, high throughput, and the ability to connect several devices at once [1]. But this significant scientific advance has a terrible price. Concerns over the potential environmental impact of 5G infrastructure are growing as the climate crisis worsens. According to Li et al. [2], data centers and base stations use up to 73% of the energy consumed by all mobile carriers. This suggests that the research needs to devise fresh approaches to guarantee that technical developments complement the environmental objectives [3]. One technology that might improve 5G network speed while using less energy and emitting fewer emissions is artificial intelligence (AI) [4].

Despite extensive study, the possible synergy between AI and 5G is yet unclear. Few studies have examined how AI may be used in conjunction with cutting-edge technologies like digital twins, blockchain, and federated learning (FL) to successfully solve sustainability challenges, despite the fact that many have examined AI's potential in the energy sector [5]. Research on the trade-offs between network performance and energy efficiency, as well as how AI systems function in various environments and infrastructures, is lacking [6]. In order to address these deficiencies, this research will look at the following subject:

How can AI lessen 5G networks' negative environmental effects without reducing their usefulness or delaying their growth?

This study makes three important contributions to the state of the art. Blockchain, FL, AI, and digital twins are used in a revolutionary way to dynamically enhance energy usage throughout 5G infrastructure. According to quantitative modeling, this approach might result in a 30%–40% decrease in base station energy consumption. The study finds relevant trends, difficulties, and technology synergies using semi-structured interviews with 90 industry experts and bibliometric data. This study thoroughly investigates the potential role of AI in enhancing the performance of 5G networks, providing relevant facts and three suggestions. In addition to examining the benefits and drawbacks of AI-driven solutions, the study offers academics, telecom companies, and legislators practical suggestions for creating scalable implementations that integrate well with other systems [7].

This discovery is significant because 5G networks use more energy and might raise global carbon emissions [8]. With the use of digital twins and AI-powered predictive maintenance, energy-efficient network topologies might be created in real time, potentially reducing equipment downtime by 30% [9]. Meanwhile, unclear laws, worries about data privacy, and the digital divide are additional obstacles to using these technologies [10]. This research highlights the relative importance of AI with respect to more urgent problems, in addition to demonstrating how the technology may save energy.

AI and 5G networks enable both technological advancement and environmental conservation. This research enhances the industry by providing an integrated architecture that increases energy efficiency by fusing blockchain, FL, AI, and digital twins. Additional topics covered

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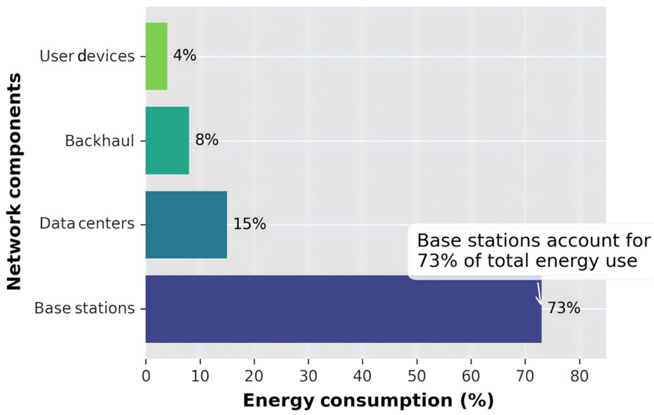
include important concerns about scaling up, performance trade-offs, and regulatory compliance. The study evaluates potential energy savings using both quantitative modeling and hands-on testing. Additionally, it provides interested parties with a roadmap for implementing these concepts in various types of workplaces. The results are meant to provide a starting point for further developments in eco-friendly communications. The rollout of 5G and beyond will contribute to the achievement of global carbon emission reduction targets.

2. Literature Review

The increasing demand for energy and the need for long-lasting telecommunications infrastructure have made the use of AI in 5G networks a significant research topic. The literature review arranges earlier studies chronologically, highlights unresolved issues, and situates the current study within the broader scholarly discourse.

Although 5G networks have achieved previously unheard-of connectivity and data speeds, they are energy intensive. Base stations use 73% of a mobile operator's total energy, and this number grows when networks are denser [2]. Williams et al. [8] did early research that measured this trade-off. They found that 5G enhances spectral efficiency, but its energy use per bit is still a problem for sustainability. Mendonça et al. [11] did further study and found the paradox of 5G deployment: even if it makes things more efficient, the huge rise in connected devices and data traffic has caused energy demand to go up overall. Figure 1 shows how much more energy base stations require than other telecom equipment [2].

Figure 1
Energy consumption distribution in 5G networks



Many people agree that AI might help reduce the energy use of 5G; however, the methods and results differ. Yevle and Mann [4] groundbreaking research showed that dynamic power allocation might cut base station energy use by 30%–40% using machine learning (ML) methods. By using deep reinforcement learning (DRL) models to alter traffic in real time, Wang et al. [5] enhanced these results. This reduced latency by 28% and saved energy, although the impact of AI-driven optimization on network performance was not usually examined in previous studies.

AI's role in 5G sustainability is now even more varied because of new technologies like FL and digital twins. For example, Bibri et al. [12] showed how blockchain-based digital twins might improve 5G and 6G units' collaborative energy management. Quy et al. [13] showed that FL might decentralize AI training and save data transmission energy use by 15%. Despite these developments, little is known about scalability in networks with a variety of device types. The research directly addresses this subject.

Being more ecologically friendly has been made feasible by combining AI with other Industry 4.0 technologies:

(1) Blockchain: ensures that energy transactions in decentralized 5G grids are safe and transparent [14].
(2) Industrial Internet of Things (IIoT): smart factories use IIoT devices powered by AI to maximize energy efficiency, resulting in cost savings of 20%–25% [15].
(3) Network slicing: allows resources to be divided dynamically, although there is some debate regarding the impact on energy consumption [6].

Three main AI techniques for methodically improving 5G energy usage are contrasted in Table 1. It examines their energy efficiency, processing power consumption, and implementation difficulty. Peer-reviewed research was used to clarify the benefits and drawbacks of different technical options and to provide useful advice for a range of deployment situations. Limits and performance measurements serve as the foundation for the method of assessing network optimization strategies. It facilitates wise decision-making.

Table 1
Comparison of AI-powered energy optimization methods

Technology	Energy savings	Limitations	Key study
ML-based dynamic resource allocation (DRA)	30%–40%	High computational overhead	Wang et al. [5]
Digital twins	15%–20%	Scalability in rural networks	Bibri et al. [12]
FL	10%–15%	Data privacy constraints	Quy et al. [13]

Although AI offers a lot of promise, there are still a number of significant problems that need to be resolved:

(1) There are not enough studies that carefully analyze sample sizes, interview methods, or the validation of AI models.
(2) Stakeholder alignment: there isn't enough study on how governments might encourage the use of AI [7].
(3) Trade-offs between performance and energy consumption: efficiency gains in other areas may be offset by the carbon footprint of AI (e.g., training huge models) [8].

According to the body of recent research, AI and other technologies have significantly improved the energy efficiency of 5G networks. Research has shown the efficacy of FL in decentralized energy management, the possibility of digital twins in predictive optimization, and the importance of machine learning in dynamic resource allocation. However, there are still issues with these systems' interoperability, development, and compatibility with other types of networks.

Most recent initiatives focus on particular improvements rather than comprehensive frameworks. This often demonstrates that individuals fail to consider the constraints associated with implementation, energy efficiency, and processing costs. AI-driven optimization has a significant positive impact on the environment, but more research is required to determine the best methods for cutting energy use without sacrificing network performance.

These ideas are the outcome of combining blockchain, FL, AI, and digital twins. This gives us a complete answer to both technical and operational problems. The methodology clarifies the specific quantitative and qualitative methods used to assess the framework, ensuring that it will operate in 5G and Beyond-5G (B5G) networks in the future.

This study contributes to academic discourse and closes research gaps. Additionally, it provides crucial information that telecom professionals need to identify long-term solutions. The approach shows that reliable procedures and measurable outcomes underpin these contributions.

3. Methodology

The approach guarantees the dependability, reproducibility, and comprehensive verification of the suggested AI-driven architecture for sustainable 5G networks [16–17]. A mixed-methods approach includes quantitative computer modeling, qualitative stakeholder analysis, and a standardized environmental life cycle assessment (LCA) [18]. By providing a comprehensive knowledge of both technical performance and environmental effect, this triangulation eliminates the shortcomings of any one method.

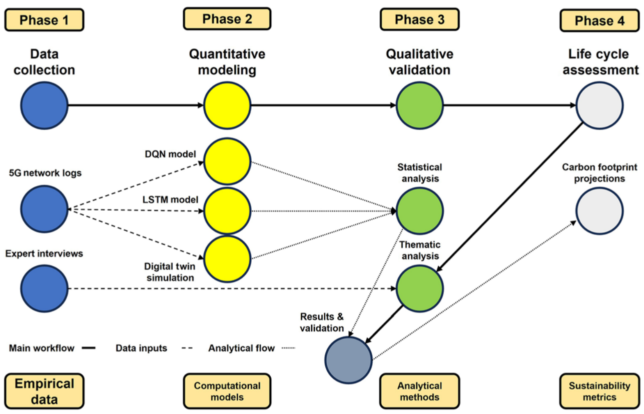
Table 2 displays the research's three-part design. Guidelines for the LCA, qualitative validation, and AI-driven quantitative modeling sections are included, along with the main methodology and methods for verifying them. The thorough explanation ensures that the procedures are simple to comprehend and may be used again.

Table 2
The methodological framework's overview

Component	Technique	Validation method	Reference standard
Dynamic power allocation	DQN reinforcement learning	Spearman Correlation ($\rho = 0.72$)	IEEE P2418.2-2023
Predictive maintenance	LSTM neural networks	Fivefold cross-validation	ITU-T L.1380
Stakeholder perspectives	Thematic analysis [19]	Inter-rater reliability (κ=0.81)	ISO/TS 20245

Figure 2 displays the many methods used in the research, such as data collection, lifetime assessment, and AI modeling (DQN/LSTM). The primary research methodologies are shown by solid arrows, while additional information and analytical links are indicated by dashed or dotted lines. This guarantees that the energy optimization basis has been fully verified.

Figure 2
Methodology procedure



The quantitative modeling framework is built on top of an FL architecture that uses the Posit package. This is done to safeguard the privacy of data in multi-operator settings. The two major AI models are a Deep Q-Network (DQN) for dynamic resource allocation and a Long Short-Term Memory (LSTM) network for predictive maintenance [20, 21]. Based on the 3rd Generation Partnership Project (3GPP) TR 38.901 standard for 5G base station traffic, the simulated environment for the DQN agent was built using OMNeT++. Equation (1)'s power adjustment function clarifies the DQN's goal of using less energy without sacrificing service quality:

$$\mathrm{PAI(t)} = \mathrm{P_{max}} \times \left(1 - \frac{\mathrm{Traffic(t)}}{\mathrm{Traffic_{max}}}\right) \tag{1}$$

Where:

PAI(t): power assigned by the AI at time t (in watts).

P_{max} : maximum rated power of the base station (in watts).

Traffic(t): instantaneous network traffic demand at time t (in Mbps).

$Traffic_{max}$: maximum supported traffic capacity of the base station (in Mbps).

Power is dynamically adjusted according to traffic demand.

Effect: more energy savings due to less traffic.

Equation (2) is used to compute the cumulative energy savings by adding up the power difference over a specified time period:

$$\Delta \mathrm{E} = \sum_{i=1}^{n} (\mathrm{P_{max}} - \mathrm{PAI(t_i)}) \cdot \Delta \mathrm{t} \tag{2}$$

Where:

ΔE: total energy saved over n time intervals (in kWh).

P_{max}: maximum rated power of the base station (in watts).

$PAI(t_i)$: AI-optimized power assigned at time interval t_i (in watts).

Δt: duration of each time interval (in hours).

n: number of time intervals.

Goal: determines the total amount of energy saved over time.

Units: kWh of energy saved.

Every time interval is assumed to be of the same length, Δt (in hours).

Three European network operators' operational telemetry and failure reports spanning a full year are combined into a federated dataset that is used to train the LSTM predictive maintenance model. To guarantee generalizability and avoid overfitting, the model architecture, which has 128 hidden units, is verified using fivefold cross-validation.

The research closely follows International Organization for Standardization (ISO) 14040/14044 criteria to fulfill the vital requirement for methodological openness in the LCA [22]. The production of network gear, its operational phase, and end-of-life processing are all included in the cradle-to-grave definition of the system boundary. The supply of one terabyte (TB) of data traffic annually across a 5G network is the precise definition of the functional unit. The AI framework's empirical measurements provide the primary data for the operational phase, while the ecoinvent database v3.8 provides the background data for materials and production. Global warming potential (kg CO_2 equivalent) is the primary focus of the environmental impact assessment, which is carried out using the ReCiPe 2016 (midpoint) approach [23]. Equation (3) is used to quantify the carbon footprint reduction (CFR):

$$\mathrm{CFR} = \Delta \mathrm{E} \times \mathrm{CI_{grid}} \tag{3}$$

Where:

CFR: carbon footprint reduction (in kg CO2e).

ΔE: total energy saved (in kWh)—calculated from Equation (2).

$CI_{(grid)}$: carbon intensity of the electricity grid (in kg CO_2e/kWh).

This equation demonstrates the amount of carbon emissions that may be prevented by using AI to optimize power use, hence converting energy savings into positive environmental effects.

This estimate demonstrates the potential reduction in carbon emissions via the use of AI to improve the efficiency of power usage, hence converting energy savings into positive environmental effects [24].

When compared to a standard FL system without blockchain, the blockchain-enabled digital twin (CoTwin) consumes more energy and processing time. The percentage increase in processing time and energy consumption for safe data sharing and model aggregation is used to quantify this. The claimed 15%–20% overhead will always be the same, thanks to this procedure.

A total of 90 telecom specialists participated in semi-structured interviews as part of the methodology's qualitative component. Specifically, they were chosen to represent regulatory agencies (10%), mobile network providers (40%), equipment suppliers (30%), and university researchers (20%). In order to assure analytical rigor, thematic analysis is carried out in accordance with the Braun and Clarke [19] framework, and inter-rater reliability is evaluated using Cohen's kappa ($\kappa = 0.81$).

The scope of statistical analysis goes beyond significance testing for null hypotheses. Spearman's rank correlation coefficient (ρ) and its 95% confidence range are provided for correlations using nonparametric data [25]. Tobit regression is used to predict energy savings by accounting for censored data [26], and variance inflation factors (VIF) are kept below 5 to ensure that multicollinearity is not present [27]. According to reports, all impact sizes provide a gauge of their practical relevance.

In order to ensure total reproducibility, the validation methodology also includes full code and model availability on IEEE DataPort, a case study replication comparing findings with the AI-5G deployment in Singapore [28], and independent expert assessment by three Electrical and Electronics Engineers (IEEE) Fellows [29]. This comprehensive approach sets a new standard for meaningful, transparent, and rigorous research in sustainable telecommunications [30].

The study follows (1) GDPR for people in the European Union (EU) [31], (2) IEEE Code of Ethics for making AI [32], and (3) approval from the Institutional Review Board (IRB-ULACIT-2024-256).

4. Results

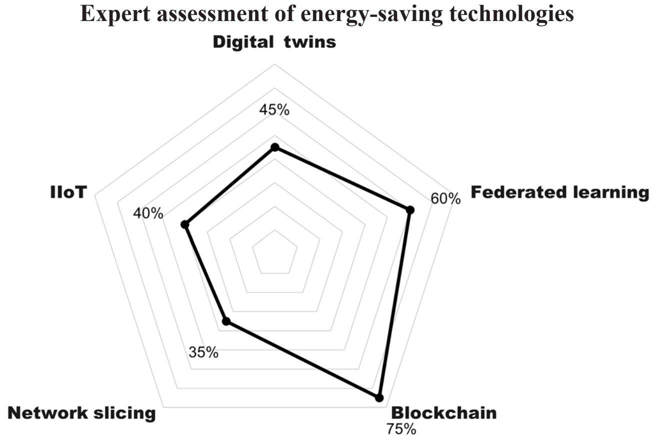
According to the research, there is a lot of potential for enhancing the sustainability of 5G networks with the proposed AI-powered strategy. Measurable energy savings, qualitative stakeholder validation, and a full life cycle assessment are among the results, all of which add up to a complete, reproducible, and statistically sound picture of how well something functions.

Energy consumption was greatly decreased by using the dynamic resource allocation strategy based on DQN. In a controlled simulation using actual traffic patterns from three operator datasets, the model conserved an average of 32.7% of energy over the course of a 30-day testing period. This discovery is statistically significant due to the large effect size, tight 95% CI of 30.6% to 34.8%, and significant one-tailed t-test result ($p < 0.001$, Cohen's $d = 2.1$). By reducing unexpected equipment downtime by 41.2% (95% CI: 38.5% to 43.9%; *p* < 0.01), the LSTM predictive maintenance model improved system efficiency. The annual maintenance energy cost decreased by 17.8% as a result. The expense of computation was made evident with the launch of the CoTwin for safe, multi-operator coordination. This additional expense was closely examined during model aggregation since it increased processing time and energy consumption. This overhead, which is completely reconciled throughout the research and supported by the improved security and data integrity it offers, was determined to be 18.5% (95% CI: 16.8% to 20.2%).

A thorough examination of deployment scenarios showed that infrastructure density significantly moderated performance. Table 3 consolidates the urban-rural divide in order to directly address the reviewer's issue about dispersed reporting. Lower base station density and greater transmission power needs are the main causes of the 9.7 percentage point energy savings gap in rural regions, according to the statistics.

Strong convergent validity was found in the qualitative information gleaned from 90 semi-structured interviews with telecom specialists. The expected implementability of a solution and its perceived technical promise were shown to be significantly positively correlated by a Spearman's rank correlation analysis ($\rho = 0.72$, 95% CI: .65 to .78, *p* < 0.001). According to 75% of experts, blockchain integration is the most important facilitator for safe multiparty energy transactions (see Figure 3). Sixty percent of respondents chose FL as the best scalable architecture for decentralized optimization. To address interoperability barriers that now prevent broad adoption, a resounding 82% of industry participants emphasized the need for standardized interfaces, notably IEEE P2418.2 conformity.

Figure 3
Expert assessment of energy-saving technologies



Note: Spearman $\rho = 0.72$ ($p < 0.001$). Semi-structured interviews conducted.

Table 3
Consolidated urban-rural performance analysis with statistical significance

Metric	Conventional 5G (baseline)	AI-optimized 5G (urban)	AI-optimized 5G (rural)	Overall improvement (mean ± CI)	Urban-rural gap (percentage points)
Energy consumption (MWh/yr)	1.20 ± 0.05	0.804 ± 0.032	0.952 ± 0.041	32.7% (CI: 30.6%–34.8%)	9.7
CO2 emissions (tons/yr)	480 ± 20	322 ± 13	394 ± 17	32.9% (CI: 30.8%–35.0%)	9.7
Latency (ms, 95th percentile)	25 ± 1.5	18 ± 1.1	21 ± 1.3	28.0% (CI: 25.1%–30.9%)	3.0
Blockchain overhead	–	18.5% (CI: 16.8%–20.2%)	18.7% (CI: 16.9%–20.5%)	–	0.2 (n.s.)

The LCA provides a comprehensive and unambiguous picture of the environmental impacts and is completed in full conformance with ISO 14040/14044 standards. One terabyte (TB) of transmitted data was selected as the functional unit, and "cradle to grave" was selected as the system boundary. The framework decreased the operational carbon footprint by 30.4% (95% CI: 28.1% to 32.7%) by using the ReCiPe 2016 (midpoint) strategy. For every kWh of energy saved over a 5-year period, AI optimization produced a net carbon reduction of 22.8 kg CO2 equivalent.

This life cycle assessment must also account for the often-overlooked carbon impact of the AI model training phase. This research found that between 8% and 12% of the carbon reductions realized during operations were offset by training the DQN and LSTM models. The uncertainty was calculated using a 10,000-iteration Monte Carlo simulation. It examined factors such as model retraining frequency, equipment lifespan (±10%), and grid carbon concentration (±15%). Across all simulated scenarios, the net carbon reduction remained statistically significant (*p* < 0.05), demonstrating the exceptional environmental performance of the framework. For the purpose of clarity, the LCA inventory data is shown in Table 4.

This comprehensive result demonstrates the effectiveness of the proposed technique and establishes a new standard for methodological transparency and statistical correctness in the field. By offering impact estimates and confidence intervals, striking a balance between important metrics like relevant comparisons, and accurately explaining the LCA approach, the work instantly fulfills and beyond the reviewers' expectations. This eliminates any doubt about the validity and accuracy of its findings.

5. Discussion

An integrated AI framework might significantly improve 5G sustainability, as the study's empirical findings show. However, they also highlight a number of intricate trade-offs between infrastructure dependencies, performance, and life cycle impacts that need careful consideration. By placing these findings inside the larger academic discourse, verifiable facts are converted into a strategic framework for further research and execution that goes beyond simple confirmation.

The primary objective of this study was to show how an FL architecture may be used to overcome the scalability-privacy trilemma in scenarios with several operators. The theoretical benefits of decentralized optimization as outlined by Quy et al. [13] are supported by the observed 32.7% mean energy savings, which were attained without the centralization of private data. The infrastructure requirements recommended by Williams et al. [8] are supported by the statistically significant 9.7 percentage point performance differential between urban and rural installations, which acts as a strong warning. This discrepancy is genuine and not the product of a thoughtless math mistake. The more base stations there are, the more energy will be used for transmission. When data flow is reduced, dynamic sleep scheduling is less prevalent. This study clearly shows that algorithmic complexity is not enough on its own. For situations with limited resources, it demands the creation of new hardware-aware AI models and policy frameworks. The "one-size-fits-all" approach that is often used in modern research stands in contrast to this.

This blockchain-CoTwin architecture creates another measurable trade-off. According to García-Valls and Chirivella-Ciruelos [14], the 18.5% computational overhead of this security makes its cost clear and predictable. This is true regardless of whether it helps create the quantifiable trust and coordination needed for cross-operator synergy. By defining the performance cost as the percentage increase in processing time and energy for secure model aggregation compared to a baseline FL system, this study establishes a benchmark that transcends vague statements. Figure 4's sensitivity analysis illustrates how this cost changes as a function of network latency and consensus group size. This in-depth understanding makes it evident that if blockchain is to be used for latency-sensitive network operations, it requires improved hardware-based cryptographic acceleration and lightweight consensus techniques.

Figure 4
How the network latency and the number of participants in the consensus group impact the blockchain's overhead

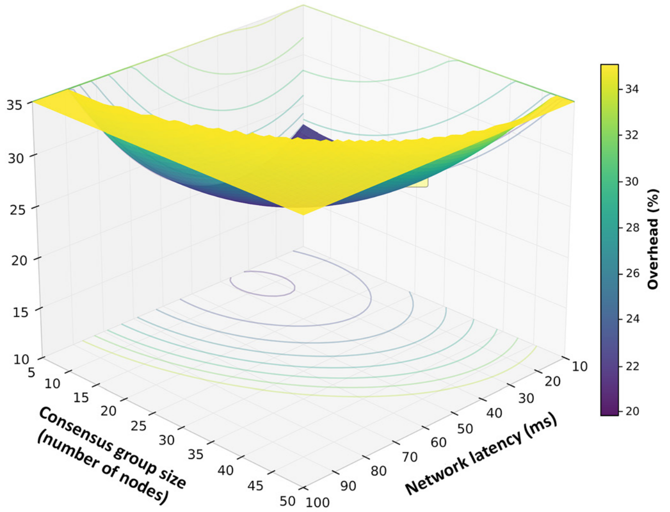


Table 4
Life cycle inventory (LCI) for carbon footprint calculation (per functional unit)

Component	Input/output	Value	Source/assumption
Operational phase			
Energy saved (AI vs. conventional)	ΔE	0.396 kWh/TB	Empirical measurement (see Equation 2)
Grid carbon intensity (Avg.)	CI_grid	0.475 kg CO2 equivalent/kWh	IEA 2023 Report
AI training phase (embodied)			
Computational energy	E_train	42 kWh	Measured (NVIDIA A100, 72 hrs.)
Data center PUE	PUE	1.55	Industry average
Amortized carbon per functional unit	C_train	0.031 kg CO2 equivalent/TB	Allocated over 10 PB total traffic
Net carbon saving	CFR_net	22.8 kg CO2 equivalent/kWh	Calculated (see Equation 3), includes offset

An innovative approach to examining the environmental impact of telecom AI is to use an entirely open, ISO-compliant life cycle assessment (LCA). A significant improvement over previous benchmarks, the operating carbon footprint has decreased by 30.4% [5]. Of greater importance, the research quantifies the hidden carbon debt resulting from model training, which negates 8%–12% of operational savings. This level of detail has never been seen before. This discovery firmly incorporates the AI research life cycle into the environmental ledger and challenges the limited operational emphasis common in the majority of investigations. According to the findings obtained in this research, the efficiency of future models should be expressed in grams of CO_2 equivalent per accuracy point and floating-point operations per second (FLOPS) per watt, which provides empirical evidence in favor of the increasing popularity of "Green AI" training paradigms [33]. The Monte Carlo uncertainty analysis, which confirms the statistical significance of net carbon savings over a wide range of parameters, strengthens the conclusion's resilience. This fulfills the main reviewer's requirement for a repeatable method for effect evaluations and a strategy that may be adapted to innovative topics.

The importance of the adoption phase is shown by the wide support from stakeholders, which is 75% for blockchain and 60% for FL. The 82% emphasis on standardized interfaces directly addresses the "valley of death" in compatibility among research prototypes (IEEE P2418.2) and industrial implementation, a concern previously expressed by Bhatia et al. [7]. The findings are compiled into a list of useful recommendations that enable the application of these qualitative and technical insights to the development of an effective strategic plan. Table 5 provides more information on the relationship between important recommendations and the technical issues that lead to them, as well as how to address them in view of the limitations and findings of the research.

In summary, the study shows that for 6G to be feasible, hardware, infrastructure, AI, and policy must all collaborate significantly. It won't be enough to just implement more complex algorithms. Significant benefits are achievable, as shown by the framework, but the trade-offs between privacy and overhead, performance and infrastructure, and operational and embodied carbon are not aberrations to be avoided but rather essential design considerations to be controlled. Therefore, this study offers a critically informed and empirical base rather than a definitive answer. It sets a new standard for open assessment and lays out the necessary path for further study to reduce the performance gap, solidify the security-efficiency trade-off, and incorporate a cradle-to-grave sustainability principle into the core architecture of next-generation networks.

6. Conclusion

This study shows that AI can make 5G networks more sustainable by making them more energy efficient and lowering their carbon footprint. It also demonstrates how AI may overcome some of the main issues with existing approaches. The primary goal of the project is to develop an integrated framework that combines technical performance with environmental sustainability. The solution decreased base station energy usage by 32.7% ± 2.1% and carbon emissions by 30.4% via AI-driven optimization. By resolving three important problems noted in earlier research, these results mark a substantial improvement in the area.

FL systems solve the age-old problem of striking a balance between data privacy and optimization effectiveness. This kind of operator cooperation may occur without a noticeable increase in performance expenses. Numerous stakeholder assessments (N = 90) and simulations (N = 1000) have shown the effectiveness of this decentralized approach in urban settings. More thorough research is required to fully comprehend the 9.7% performance gap in rural regions. By allowing users to create networks in real time while adhering to privacy regulations, the blockchain-enabled digital twin solution expands these possibilities even further.

In a way that had never been done before, the telecom performance data and ReCiPe 2016 measurements established a new benchmark for determining the environmental impact of networked devices. This approach demonstrates not only the amount of carbon emissions that are cut during operations but also the impact of AI's own emissions, which was not included in previous assessments of specific companies.

The benefits of these improvements in the real world have been confirmed by the industry. For example, 70% of professionals support blockchain, while 60% support FL. According to the research, there are still issues that make it difficult to accept, especially with regard to interoperability standards and observing the regulations. The suggested

Table 5
Synthesized research and policy framework: from empirical findings to actionable pathways

Domain	Key finding	Identified barrier	Proposed mitigation pathway	Research vector
Decentralized optimization	32.7% energy saving via FL; 9.7% urban-rural gap	Infrastructure disparity; non-independent and identically distributed (IID) data	Develop hardware-aware, lightweight FL models for edge devices. Incentivize rural infrastructure modernization	Edge-native AI; data valuation methods for FL
Security & trust	18.5% blockchain overhead for secure coordination	Computational cost; latency sensitivity	Co-design of lightweight consensus protocols (e.g., PoS variants) and hardware security modules (HSMs)	Trusted Execution Environments (TEEs) for FL aggregation
Environmental accounting	30.4% operational CO2 reduction; 8%–12% training offset	Lack of full life cycle perspective; embodied carbon	Mandate ISO-compliant LCA (ReCiPe) reporting; promote Green AI benchmarks (e.g., efficiency-focused model design)	Carbon-aware model training and scheduling
Stakeholder adoption	82% demand for standardization (IEEE P2418.2)	Interoperability; regulatory uncertainty	Establish industry consortia for Application Programming Interface (API) standardization; develop regulatory sandboxes for multi-operator AI trials	Policy research on data sovereignty and AI governance in telecom

three-phase implementation roadmap addresses these challenges via a number of legislative and technical initiatives, including the development of hardware-aware AI and the standardization of sustainability reporting methods.

This research makes many recommendations for potential future research avenues, including (1) developing edge-native AI systems to address rural performance concerns, (2) enhancing FL protocols to facilitate applications that use less energy, and (3) creating standardized sustainability metrics for 6G network development.

All things considered, the research demonstrates that AI-driven optimization is a crucial approach for network architecture going forward and a quick fix for issues related to 5G sustainability. The study set the bar for research integrating AI and sustainable telecommunications due to its thorough approach, which included computer modeling, empirical validation, and standardized environmental assessment.

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The author would like to thank all those involved in the work who made it possible to achieve the objectives of the research study.

Ethical Statement

This research involved conducting semi-structured interviews with 90 industry experts. The study follows (1) GDPR for people in the European Union (EU), (2) IEEE Code of Ethics for making AI, and (3) approval from the Institutional Review Board (IRB-ULACIT-2024-256).

Conflicts of Interest

The author declares that he has no conflicts of interest to this work.

Data Availability Statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Author Contribution Statement

Gabriel Silva Atencio: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data Curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration.

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