

Holistic Approaches to Sustainable Cell Tower Design: Integrating Standardized Metrics, Advanced Energy Management, and Modular Frameworks

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ABSTRACT

Sustainable cell tower design is essential for minimizing the environmental footprint of expanding telecommunication networks, which traditionally prioritize signal coverage over sustainability. This study addresses this gap by proposing a holistic framework that integrates standardized sustainability metrics, advanced energy management systems, and modular design principles. The research aims to minimize environmental footprint while ensuring scalability and cost-effectiveness. A multi-criteria decision-making (MCDM) model is developed to evaluate designs based on energy consumption, carbon emissions, lifecycle costs, and adaptability. The model was validated against operational tower data with a 5.4% Mean Absolute Percentage Error (MAPE). Simulations and a detailed retrofit case study demonstrate significant and substantiated improvements in energy efficiency, increased by up to 30%, carbon emissions reduced by 60%, operational costs lowered by over 65%, and lifecycle costs are lowered by 20%. Furthermore, the modular designs prove highly adaptable, extending infrastructure lifespans and minimizing material waste. This research provides a scalable, cost-effective solution for greener telecommunication infrastructure, aligning with global sustainability goals. The framework bridges theory and practice, offering a robust foundation for broad industry adoption, with future work focused on pilot testing and socio-economic considerations for equitable implementation.

Keywords: Sustainable cell towers, Renewable energy integration, Energy efficiency, Modular design frameworks, Advanced energy management.

1. INTRODUCTION

The mobile communications network growth has increased the deployment of cellular towers used as a fundamental component for infrastructure development. Global demand for faster and more dependable wireless communications has stimulated the growth of networking infrastructure and has raised criticisms regarding the structural and environmental/sustainability impact of these structures (**Deevela et al., 2023**). In the

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cellular industry, the main purpose of a cellular tower has been to facilitate the maximum transmission of signal strength while paying little to no consideration to the electrical energy usage, associated greenhouse gases and emissions, and functional dwelling of the tower to surrounding architecture/buildings (Avikal et al., 2021). In the past few years, an industry-wide trend of establishing sustainability in cellular network deployment has been observed. These trends range from the selection of cellular tower sites to the sustainability of network components and the standardization of network design, energy management techniques, modular construction, and design that optimally evolves to meet the changing demands of technology. These trends contribute steadily toward the realization of cellular deployment sustainability vis-à-vis the United Nations’ Sustainable Development Goals (UNSDG), climate change mitigation (Anatoly, 2024). These trends have paved the way for cell towers and associated infrastructure to be designed and constructed with integral sustainability. Performance is now understood as more than just energy efficiency; it also depends on how effectively a tower fits within environmental, policy, and technological contexts (Segura et al., 2021). There is growing agreement that standardized sustainability metrics—such as energy consumption per data unit, lifecycle carbon emissions, and environmental impact indicators—are essential for comparing designs across regions and network generations as shown in Fig. 1 (GSMA, 2022).

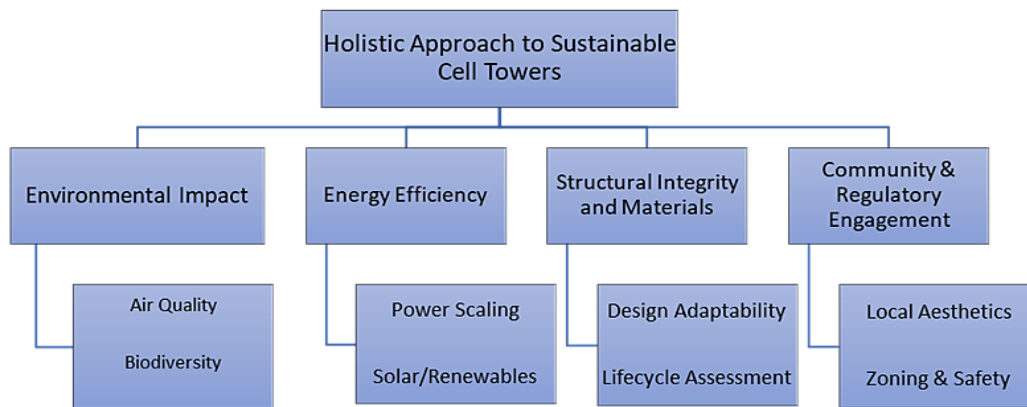


Figure 1. Holistic approach.

As seen in Fig. 2, standardized Metrics tracks certain performance matrices like energy consumption of kilowatts-hours per data unit, amount of carbon footprint marked in CO₂ equivalent metric tons, and adherence to international standards factors like ITU and 3GPP (ITU-T, 2020).

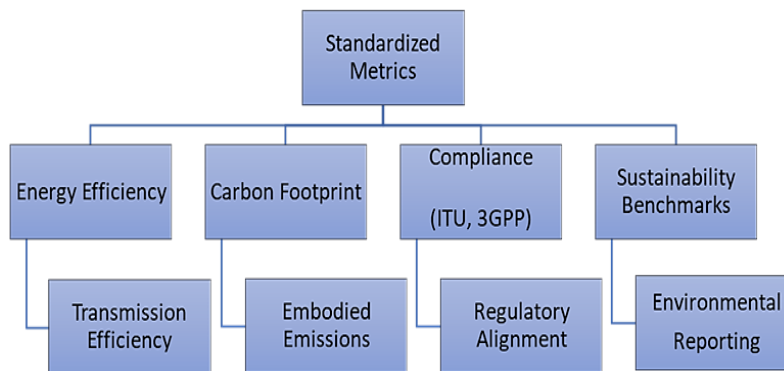


Figure 2. Standardized metrics.



Solar panel integration, energy storage, intelligent power allocation algorithms, and many other technologies as well as tactics that improve power usage optimization and lower GHG emissions, are displayed in **Fig. 3**, which Advanced Energy Management illustrates. The Modular Framework incorporates antenna systems, power supplies, and enclosures as compacted components that can be altered to fit new technologies or complement network enhancements with little regard to the environment, as displayed in **Fig. 4**. These four components combined present a better model of cell tower designs that takes not only connectivity demands but also international environmental policies into account. It is agreeable that such multi-pronged will have a negative impact on a community goes through followed by the telecom industry playing a more prominent role in slowing climate advancements. Potential issues such as managing capital expenditure, providing consistent reliability during unstable energy supply, and l aligning incompatible country standards are somewhat manageable. However, the evidence of fundamental changes in the research and practice domains is truly positive. It moves in the range beyond merely small-scale energy saving solutions to the consideration of scalable, robust and environmentally responsible cell tower infrastructure (**5G energy efficiency, 2020**).

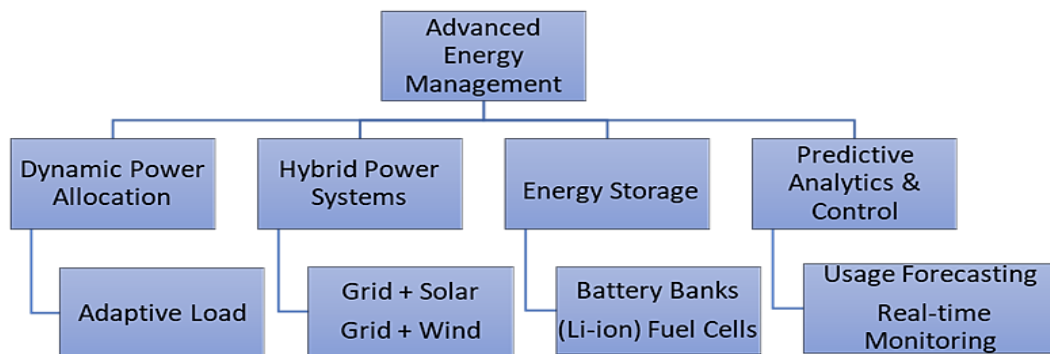


Figure 3. Advanced energy management.

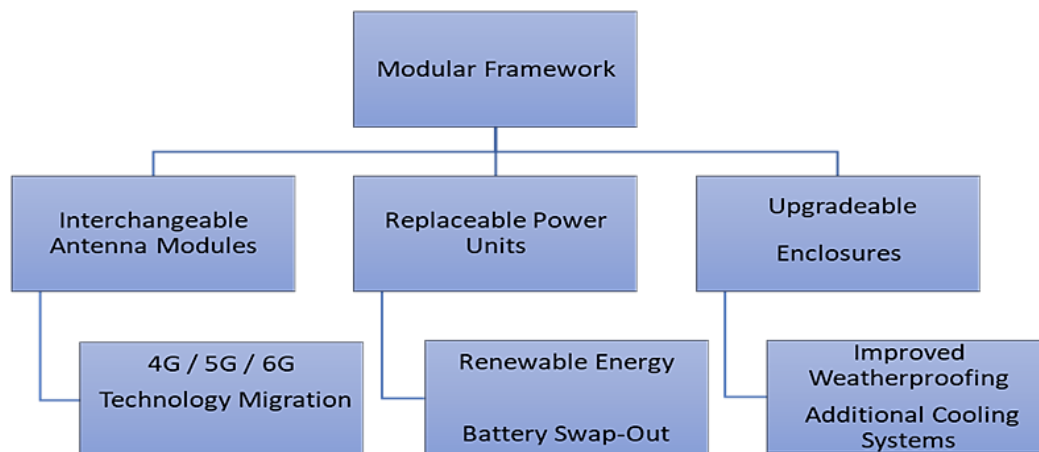


Figure 4. Modular framework.

Closing the gaps among metrics, energy management and construction and design practices of cell towers is the means towards achieving sustainability. It is in this light that this paper presents a comparative analysis of tower sustainability, advanced energy technologies for carbon reduction, and use of modular designs that lessen material utilization. The integration of renewable energy and energy-efficient technologies in telecommunications is a relatively new field of research, and as such, many research designs are incomplete. They



focus either on stand-alone techno-economic analysis of off-grid systems (**Hossain et al., 2020**), macro-level lifecycle assessments (**Li et al., 2023**), or component-level hardware optimizations. This siloed approach has left a significant gap, in this case, the absence of a unified framework that incorporates standard sustainability metrics, modular design, and intelligent, dynamic control into a single, scalable model for decision-making and operation. The study includes validation against real-world data and a concrete case study to bridge the theory-practice gap. Consequently, it provides a comprehensive solution that leads telecommunication stakeholders to the use of sustainable, economically viable and adaptive infrastructure across different regions and technological demands

2. INTEGRATING SUSTAINABILITY IN CELL TOWER DESIGN: A CRITICAL REVIEW OF ENERGY, MODULARITY, AND STANDARDIZATION

The advancements in the eco-friendly design of cell towers, particularly the use of renewable energy and energy-saving technologies. Because renewable energy reduces the carbon footprint and operating cost of cell towers, there is a need for more research in the use of solar and wind energy as alternatives to the conventional sources of energy for cell towers. (**Li et al., 2023**) proposes a new approach to assess the carbon, energy and materials of 5G networks and attempts to improve the gaps in the industry standards and benchmarking across regions. (**Hossain et al., 2020**) analyzes the use of off-grid cell towers, solar energy and biomass to achieve the reduction of carbon in the most cost-effective way. The study attempts to address the lack of grid integration and scalability by proposing a combination of smart energy control systems and AI automation. (**Derrible, 2018**) describes the need for a streamlined modular design approach in telecommunications to reduce overall systems waste and increase adaptability, while also noting a lack of specific, detailed implementation guidance at the regional level. The study attempts to address this by proposing the development of flexible modular design systems, which will vary by region and technology. Yet specific standards for the design and operational criteria of cell towers are still lacking. Furthermore, these values are not covered as part of the design constraints (**International Energy Agency, 2024**). (**Li et al., 2023**) conducted an analysis of the potential carbon footprint of implementing 5G networks across all of China but does not offer solutions for individual cell towers in real time energy management and design optimization. Off-grid cellular base stations powered with sustainable solar and biomass energy offered a techno-economic approach in (**Hossain et al., 2020**), but his solution is divorced from sophisticated grid management and lacks a modular design, which, in turn, confines his solution to integrated or hybrid systems. In terms of 5G base stations, (**5G energy efficiency, 2020**) does not provide design frameworks or decision models for efficiency goal attainment, so his technical report is a measurement standard and nothing more. Elaborating on (**Azari et al., 2022**), energy-efficient techniques in networking for anticipated systems in 6G, including network slicing and UAV integration, tend to overlook the required energy systems necessary to uphold these advancements in infrastructure design and its physical components. (**Elhakim et al., 2023**) intends to implement these gaps by complying with, and thus benchmarking, the international standards of the ITU and 3GPP. This addresses key shortcomings, including the lack of standardized sustainability metrics, inadequate hybrid energy system integration, and insufficient modular design frameworks. The study developed by (**Deevela et al., 2024**) proposes solutions to some of the gaps present by constructing modular, regionally adaptable infrastructure, and integrating several renewables along with advanced energy management solutions and flexible energy



management solutions, which include the planning of multiple renewables and modular energy systems. **(Subramanian et al., 2023)** reviews the structural efficiency of cell transmission towers and compares the different performance of certain bracing configurations. He focuses exclusively on the material and structural design and does not incorporate energy systems, sustainability metrics, or modularity adaptability. The proposed framework is explicitly described on two major international standards; the ITU-T high-level sustainability metrics and the GSMA sustainability roadmap. It builds on the former by operationalizing the principles of the ITU-T into definite metrics in a decision-making framework and defining the technical implementation—modular systems, AI driven energy management, etc.—that would support the attainment of the GSMA. Hence, the framework offers a practical engineering complement to broad guidelines, **(ITU, 2018)** which demonstrates the potential for an engineering synthesis approach to create more sustainable and adaptable telecommunications systems. It includes a high-level overview of traditional design methods, organized in a table that outlines their key contributions and limitations across areas like energy management and infrastructure adaptability as shown in **Table 1**.

Table 1. Comparative analysis of recent research on sustainable cell tower design.

Study & focus	Key contribution	Energy efficiency improvement	Carbon reduction	Lifecycle cost consideration	Modularity & adaptability	Identified gap / proposed contribution
5G carbon footprint (Li et al., 2023)	Macro-level lifecycle assessment of 5G rollout in China.	Not quantified	~80% potential by 2030 (grid decarbonation)	No	No	Gap: lacks site-level design optimization and real-time management. proposed contribution: provides a tower-level framework with quantifiable efficiency gains (30%).
off-Grid Renewable Systems (Hossain et al., 2020)	Techno-economic model for solar/biomass off-grid towers.	High (Renewable Share >90%)	~95% vs. diesel	CAPEX-focused	No	Gap: focused on off-grid; not integrated with grid management or modular design. Proposed contribution: hybrid grid-renewable AI management applicable to all site types.
5G energy efficiency (3G Partnership Project, 2020)	Standardize s base station energy performance metrics (e.g., energy/bit).	Defines metrics	No	No	No	Gap: a performance measurement standard, not a design framework. proposed contribution: uses such metrics as inputs for a holistic design and optimization MCDM model.
6G & UAVs	Surveys energy-	Conceptual	Conceptual	No	No	Gap: focused on network architecture,



(Azari et al., 2022)	efficient techniques for 6G, like network slicing.					not physical infrastructure design. proposed contribution: provides the physical tower design and energy system that enables such network-level efficiencies.
Greener Telecom Towers (Elhakim et al., 2023)	Proposes a "LEED for telecom towers" framework for sustainability assessment.	Conceptual (via scoring)	Conceptual (via scoring)	No	Conceptual (via scoring)	Gap: a valuable certification-style framework, but lacks the technical engine (AI-EMS, quantifiable MCDM) for real-time optimization and decision-making. proposed contribution: provides the quantifiable, operational model and AI-driven control systems to achieve the performance that such frameworks would certify.
Energy-saving & green practices (Deevela et al., 2024)	Reviews innovations in energy-saving techniques, green building, and network optimization.	High Potential (conceptual)	High potential (Conceptual)	No	No	Gap: surveys discrete technologies but fail to provide an integrated, scalable, and quantifiable holistic model. proposed contribution: unites these various techniques into a single, simulatable framework with a defined MCDM model to assess their combined impact.
tower structural design (Subramanian et al., 2023)	Analyzes cell tower designs with different bracing patterns for structural efficiency.	No	No (focus on materials)	No (focus on design)	Low (structural focus only)	Gap: focuses narrowly on structural efficiency and material use, without integrating energy systems or sustainability metrics. proposed contribution: incorporates structural modularity as one pillar within a comprehensive system that also includes energy management



						and standardized sustainability metrics.
This study holistic framework	Integrated MCDM, AI-EMS, and modular design.	30% (Simulated)	60% (Simulated)	Yes (20% reduction)	Yes (core feature)	Fills the gaps by uniting standardized metrics, intelligent control, and scalable hardware into a single, quantifiable framework.

3. PROPOSED SOLUTION

The design is aimed at working with future networks such as 5G and 6G (Liu et al., 2024). It uses adaptable systems and AI-based energy management to achieve secondary savings from features such as dynamic sleep modes. Its modular design allows enhanced future applications. This research employs a multi-layered approach to optimizing the use of best practice frameworks for sustainable cell tower design and analyzes the use of standards, integrated advanced energy management systems, and modularity. The selection of references is based on technological and contextual relevance and recency. In order to create a robust theoretical framework, scholarly foundation methodologies such as the Analytic Hierarchy Process (Saaty, 1987; Saaty, 2013) and the respective core MCDM theory (Zeleny and Cochrane, 1982), the Weibull distribution (Weibull, 1951; Abernethy, 2006), are cited. In contrast, for energy simulation tools and industry data, recency, along with current editions of international standards (ISO 15686-8, 2008; ISO 15686-5, 2017) have been prioritized to assure practice.

3.1 A Standardized Metrics Framework for Sustainability Assessment

The proposed framework strengthens the ITU-T L.1450 standard by incorporating its sustainability measures into real-time decision-making. It implements a Multicriteria Decision-Making (MCDM) approach to quantify and evaluate scores for each design in cell towers for the categories of Energy Use, Carbon Footprint, Life Cycle Cost, and Flexibility (plus any given criterion) (Saaty, 2013). Using AHP, the model provides a comprehensive sustainability score and reclassifies metrics from static to dynamic in order to optimize design selection and active control for operational pre-deployment. This model undergoes a validation and refinement process through pilot testing on (or with) actual and prototype towers to ensure accuracy and reliability (Abdumula et al., 2022), as shown in Fig. 5 and Table 2.

Table 2. Sample metrics for a cell tower sustainability assessment.

Criterion	Metric	Description	Unit	Possible scoring range	Weight (example)
Energy consumption	Annual energy use	Total energy consumed by the cell tower per year (includes standby and peak load)	kWh/year	1-10 (Lower = Better)	0.3
	Renewable energy share	Percentage of energy sourced from renewables	%	1-10 (Higher = Better)	0.1
Carbon footprint	GHG emissions	Direct and indirect emissions over operation lifecycle	CO ₂ e tones/year	1-10 (Lower = Better)	0.25
	Materials sourcing	Use of recycled or eco-friendly materials during construction	Qualitative or %	1-5 (Higher = Better)	0.05
Lifecycle cost	CapEx and OpEx	Combined capital and operational expenditure	Monetary (e.g., USD)	1-10 (Lower = Better)	0.2



	End-of-Life cost	Disposal or recycling costs after decommissioning	Monetary (e.g., USD)	1-5 (Lower = Better)	0.05
Adaptability	Modularity	Ease of upgrading or replacing individual components	Qualitative	1-5 (Higher = Better)	0.03
	Future tech. qualitative	Readiness for integration with new technologies (e.g., 5G expansions)	Qualitative	1-5 (Higher = Better)	0.02

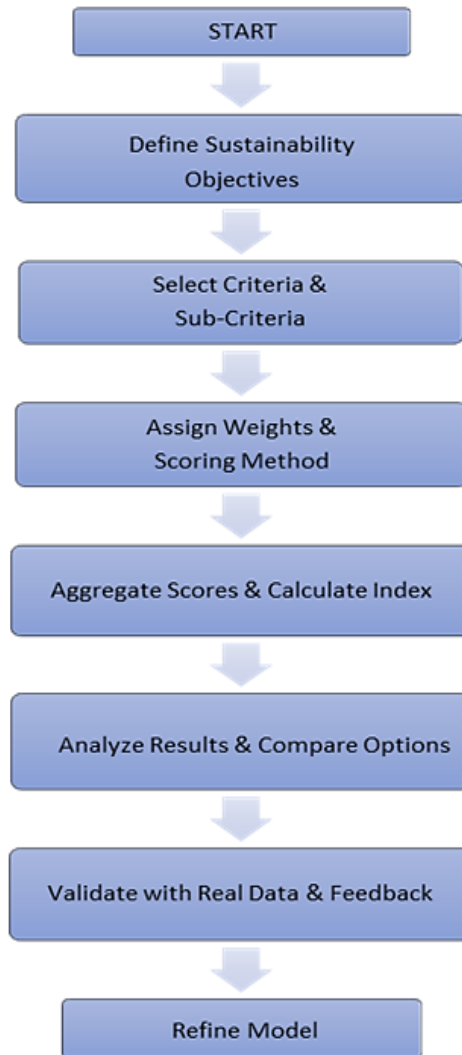


Figure 5. Conceptual flowchart for a multi-criteria decision-making (MCDM) model.

In **Table 2**, the author proposed a framework to evaluate cell towers sustainability metrics on a universal scale of energy, emissions, cost, and adaptability. The authors specify a set of default weights for energy, emissions, cost, and adaptability to show how a trade-off analysis can yield a Sustainability Index for design comparisons. The real-world adaptation of this framework, however, necessitates a precise stakeholder process to add customization to the weights, and the authors indicate plans for a robust framework with a sensitivity analysis in the future. The MCDM model keeps its four main criteria separate to clearly show trade-offs and avoid confusion, especially for carbon footprint, which is calculated using a standardized Life Cycle Assessment (LCA) **(Sonderegger and Stoikou, 2023)**.

This 'cradle to grave' approach is able to track and report carbon emissions from operational energy and embedded materials emissions separately from other metrics such as cost and

energy/capacity and provides a clear and accurate carbon accounting methodology (Torkayesh et al., 2022; GHG Protocol Life Cycle Databases, 2025).

3.2 AI-Driven Energy Management and Optimization

Integrating renewables into cell towers offers the potential to provide a reliable, climate-resilient power supply from a combination of solar and wind (plus battery) technologies. Smart control systems powered by AI enhance the effectiveness of the hybrid system by optimizing the energy allocation and reducing the control system operational energy waste (Ezeigweneme et al., 2024). This engineering approach promotes the development of adaptable, sustainable, and reliable infrastructure that is less harmful to the environment and is easy to sustain economically, as shown in Fig. 6.

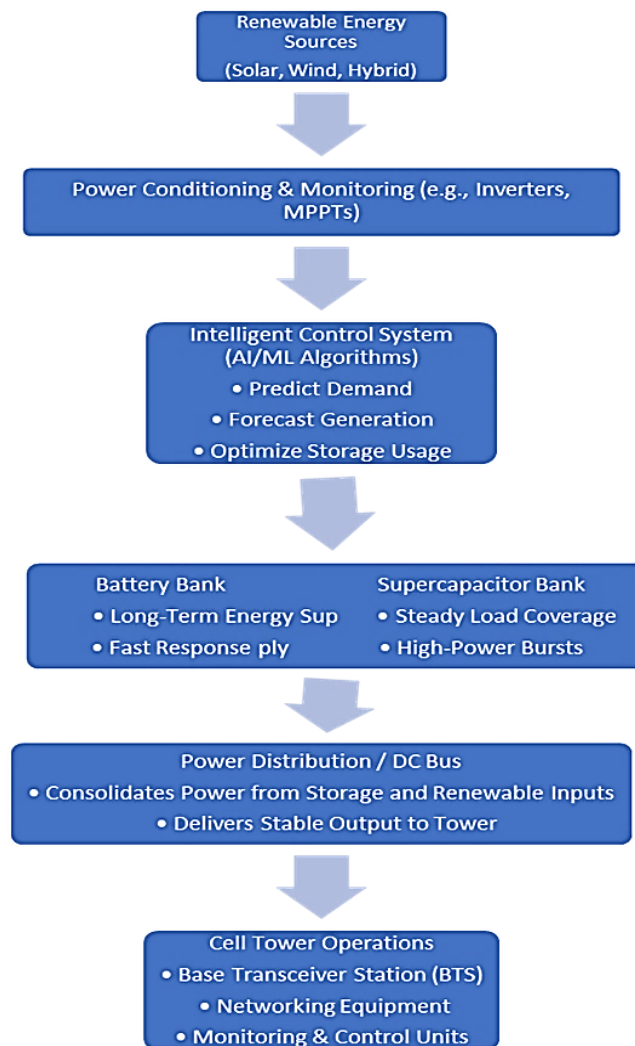


Figure 6. Energy management flowchart for renewable-powered cell tower operations.

Fig. 7 depicts the structure of a Deep Reinforcement Learning (DRL) model. The DRL agent operates within an environment that incorporates real-time data such as traffic load, and the amount of renewable energy. The agent, using the data, learns to execute the optimal power control action via a reward function that is designed to minimize energy waste, while maintaining acceptable quality of service (QoS) levels on the network.

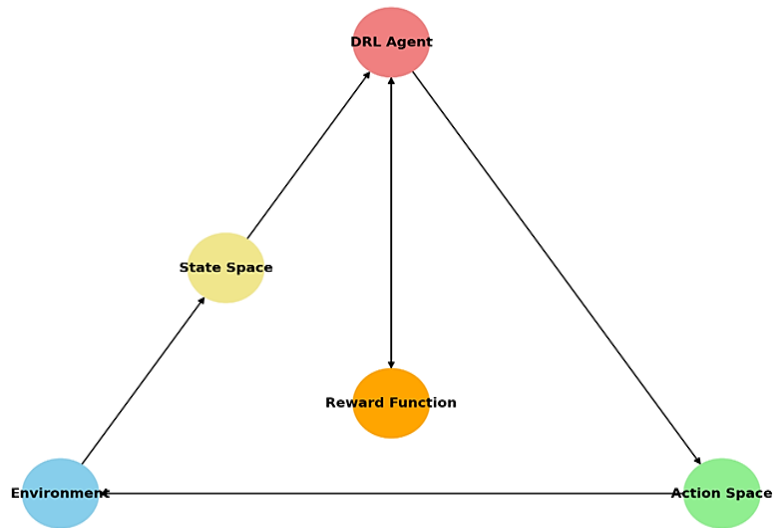


Figure 7. System architecture: DRL framework for power management.

In Fig. 8, the workflow of AI-based power management systems for cell towers is compared with the classical approach. It assesses the performance metrics of power savings and network reliability to evaluate the performance of the rule-based versus the Deep Reinforcement Learning approaches using a blend of historical and current time data for cell towers.

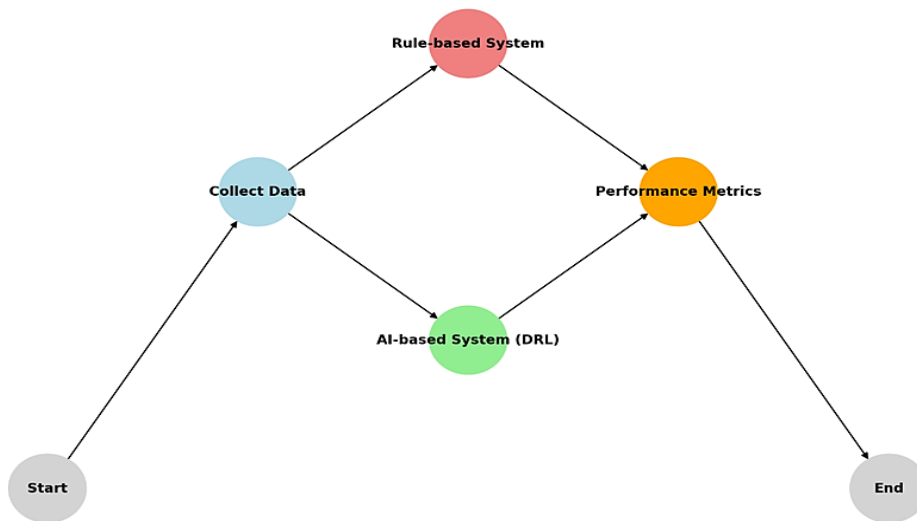


Figure 8. Simulation workflow - AI-based vs. rule-based systems.

The system ensures efficient operation through real-time monitoring and dynamic switching between power sources like solar, batteries, and the grid. AI and machine learning forecast demand and optimize energy use, minimizing reliance on non-renewable power. This adaptive approach integrates with smart grids, enhances efficiency, reduces costs, and supports sustainable energy management across various conditions. Table 3 outlines the established algorithms used in the AI-driven energy management system. Its purpose is to provide transparency on how these adapted methods form the toolkit for optimizing cell tower power management.



Table 3. Mathematical algorithms and techniques for intelligent control systems in energy management

Algorithm/technique	Description	Mathematical formulation
Reinforcement learning (RL)	A machine learning technique used for decision-making, where the system learns from past actions and feedback to optimize energy flow. It maximizes cumulative reward.	- State S_t , action a_t , and reward r_t $-Q(S_t, a_t) = r_t + \gamma \max_a Q(S_{t+1}, a)$ (Bellman Equation) (Sutton et al., 2023; Liu et al., 2024).
Time-series analysis	Used to predict future energy demand based on historical data. It helps forecast energy usage patterns.	$-X_t = f(X_{t-1}, X_{t-2}, \dots, X_{t-p})$ (Autoregressive model) $-X_t = \sum_{i=1}^p \theta_i X_{t-i} + \epsilon_t$ (Hyndman and Athanasopoulos, 2023; Wang et al., 2024).
Linear regression	A statistical method to model the relationship between demand and influencing factors (e.g., time of day, weather).	$-y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n + \epsilon$ (James et al., 2023).
Markov decision process (MDP)	A decision-making framework used for optimizing the switching between energy sources based on states and transitions.	$\gamma \sum_{s^{t+1}} P(s^{t+1} s^t, a) V(s^{t+1})$ Bellman optimality equation (Puterman, 2023; Zhang et al., 2024).
Load forecasting	Predicts future energy demand to optimize energy resource allocation.	$-y_t = \sum_{i=1}^n \alpha_i x_{t-i} + \beta_t$ (Simple Exponential Smoothing). (Taylor, 2023).
Artificial neural networks (ANN)	Used for modeling and forecasting energy demand patterns by learning from large datasets.	$-y = f(Wx+b)$ (Feed-forward ANN). (Goodfellow et al., 2023)
K-means clustering	A clustering algorithm to group similar energy consumption patterns, improving system optimization.	$- \min_c \sum_{i=1}^k \sum_{x_j \in C_i} \ x_j - \mu_i\ ^2$, where C_i are the clusters and μ_i are the centroids (Jain, 2023).
Dynamic programming (DP)	Used for energy optimization over time, considering energy usage over multiple stages.	$-V(s) = \max_a (R(s,a) + \gamma \sum_{s'} P(s' s,a) V(s'))$, γ discount fac., $P(s' s,a)$ transition probability, $V_{t+1}(s')$ value next states'. (Bertsekas, 2023).
Support vector machine (SVM)	A supervised learning model used for classification and regression of energy demand data.	$-f(x) = \text{sign}(\omega^T x + b)$, where ω is the weight vector and b is the bias. (Smola and Schölkopf, 2023).
Gradient descent	An optimization algorithm for minimizing the cost function of the model, such as energy loss.	$-\omega = \omega - \eta \nabla J(\omega)$, where η is the learning rate, and $J(\omega)$ is the cost function (Ruder, 2023).
LSTM (long short-term memory)	A type of recurrent neural network that handles time-series data for long term energy demand prediction.	$-h_t = \tanh(W_h x_t + U_h h_{t-1} + b_h)$ (Hochreiter and Schmidhuber, 2023).
Optimization with MILP	Mixed-Integer Linear Programming for energy allocation and switching optimization under constraints.	$-\min \sum_i C_i x_t$, subject to $A \leq b$, and $\epsilon \in \{0, 1\}$ (Binary variables for switches). (Vielma, 2023; Morales-España, 2024).
Particle swarm optimization (PSO)	An optimization algorithm used for finding optimal energy management strategies through swarm intelligence.	$-v_i^{t+1} = v_i^t + u_i^t$, where u_i^t is updated using $u_i^t = \omega u_i^t + c_1 r_1 (p_i^t - x_i^t) + c_2 r_2 (g_t - x_i^t)$ (Poli, 2023).



$$Q(S_t, A_t) = E [R_{t+1} + \gamma \max_a Q(S_{t+1}, a) | S_t, A_t] \quad (\text{Bellman Optimality Equation}) \quad (1)$$

$$x_t = c + \sum_{i=1}^p \phi_i x_{t-1} + \epsilon_t \quad (2)$$

Where ϕ_i are parameters, ϵ_t is white noise

$$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n + \epsilon. \quad (3)$$

$$V(s) = \max_a (R(s, a) + \gamma \sum_{s'} P(s' | s, a) V(s')). \quad (\text{Bellman Equation}) \quad (4)$$

$$\hat{y}_{t+1} = \alpha y_t + (1 - \alpha) \hat{y}_t \quad (5)$$

where α is the smoothing factor ($0 \leq \alpha \leq 1$).

$$y = f(Wx + b) \quad (6)$$

where W is the weight matrix, b is the bias vector.

$$\text{Arg. min} \sum_{i=1}^k \sum_{x \in S_i} \|x - \mu_i\|^2 \quad (7)$$

where μ_i is the centroid of cluster S_i .

$$V(s) = \max_{a \in A(s)} (R(s, a) + \gamma \sum_{s'} P(s' | s, a) V(s')) \quad (8)$$

$$\min_{w, b} \frac{1}{2} \|w\|^2 + C \sum_{i=1}^n \max(0, 1 - y_i (w, x_i - b)) \quad (\text{Hinge Loss Formulation}) \quad (9)$$

$$w^{(t+1)} = w^t - \eta \nabla_w J(w^t) \quad (10)$$

where η is the learning rate.

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (11)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (12)$$

$$\hat{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \quad (13)$$

$$C_t = f_t * C_{t-1} + i_t * \hat{C}_t \quad (14)$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (15)$$

$$h_t = o_t * \tanh(C_t) \quad (16)$$

$$\min c^T x \quad (17)$$

$$\text{x.s.t. } Ax \leq b$$

$$x_i \in Z, \forall i \in I$$

$$v_i^{t+1} = \omega v_i^t + c_1 r_1 (pbest_i - x_i^t) + c_2 r_2 (gbest_i - x_i^t) \quad (18)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (19)$$

3.2.1. DRL Implementation Details

The Deep Reinforcement Learning framework was built in Python using the Stable-Baselines 3 library and trained with the PPO algorithm for its stability. The agent's decisions were based on a normalized state space that included factors like time of day, solar forecast, and battery charge. Its actions consisted of discrete commands to manage power sources, guided by a reward function designed for multi-objective optimization (**Shuai et al., 2023**).



$$R_t = - (\lambda_{\text{cost}} C_t + \lambda_{\text{carbon}} E_t + \lambda_{\text{penalty}} P_t) \tag{20}$$

Where C_t is the cost of energy drawn, E_t is the carbon emitted, P_t is a penalty for violating battery SoC limits or causing downtime, and λ are weighting coefficients. Convergence analysis training was conducted over 1-million-time steps. The learning curve (to be included as a new figure) shows the cumulative reward plateauing after approximately 700,000 steps, indicating policy convergence. The trained policy was then used for the performance comparisons in **Figs. 12-15**.

3.2.2. Energy Management Architecture: Implementation Logic

The system operates using a central controller that follows a simple hierarchy: it prioritizes solar power first, supplements with the battery if needed, and uses the grid or a generator as a last resort. An AI-EMS optimizes this sequence by intelligently charging the battery during optimal grid conditions. The controller integrates data from all hardware, like solar inverters and batteries, using standard communication protocols and pulls live grid carbon intensity data from an API (**Application Programming Interface (API), 2025**).

3.3 Modular and Scalable Structural Design

Modular components for renewable energy systems ensure scalability and compatibility across different setups (solar, wind, hybrid systems), as shown in **Table 4**.

Table 4. Modular components for scalable renewable energy systems.

Category	Component	Description
Solar energy modules	Photovoltaic (PV) panels	Pre-assembled panels with standard connectors for easy integration
	Inverters	Modular inverters with scalable power capacity.
	Tracking systems	Single-axis or dual-axis trackers for efficiency.
	Combiner boxes	For integrating multiple PV panels into a single output.
Wind energy modules	Turbine blades	Interchangeable blade sizes for varying wind conditions.
	Nacelle units	Enclosing the generator, gearbox, and control systems in a modular housing.
	Tower segments	Standardized sections for easy transportation and assembly.
	Control systems	Modular SCADA (Supervisory Control and Data Acquisition) systems for monitoring.
Hybrid modules	Integrated energy controllers	Managing inputs from multiple sources (e.g., solar and wind).
	Smart microgrids	Modular units with plug-and-play capabilities.

Tower structures should be designed for modularity to accommodate diverse environmental conditions and scalable heights, as shown in **Table 5**. A modular component for energy storage and management systems includes battery systems, thermal storage, and control and integration, as shown in **Table 6**.



Table 5. Modular design elements for tower structures.

Category	Component	Description
Structural modules (Liew et al., 2025; Khodadoost et al., 2025)	Base foundations	Prefabricated concrete or steel bases adaptable for different terrains.
	Tower sections	Stackable sections with standardized connectors.
	Support beams	Modular cross-beams for additional strength.
Functional modules (Shuai et al., 2023)	Mounting interfaces	Universal mounts for different energy systems or antennas.
	Access systems	Modular ladders, platforms, and elevators.
	Monitoring units	Easily attached sensors for structural health monitoring.
Environmental adaptation (Jun et al., 2023)	Anti-corrosion coatings	For marine or harsh environments.
	Vibration dampers	Modular dampers to reduce oscillations

Table 6. Key modular components of energy storage units.

Category	Component	Description
Battery systems	Battery cells	Modular units with uniform dimensions for stacking. (Ma et al., 2023)
	Battery management systems (BMS)	Modular BMS with integrated thermal management (Yildirim et al., 2025)
	Housing units	Standardized racks or containers for batteries (Ma et al., 2023)
Thermal storage	Heat exchangers	Modular heat exchange units for thermal systems (Kuta et al., 2025)
	Insulated containers	Scalable thermal storage tanks. (Mao et al., 2025)
Control and integration	Energy controllers	Modular controllers for energy balancing. (Lopez-Erauskin et al., 2025).
	Power conversion systems	Scalable inverters for DC-AC conversion (Tashakor et al., 2023)
	Monitoring systems	Modular IoT-enabled systems for real-time data tracking. (Ma et al., 2023)

As emphasized by **(Ahlawat, 2025)**, the crucial aspect of a baseline is not a lengthy re-description but its clear identification and replicability. The baseline is both explicitly defined (the 240-hour industry standard) and grounded in a canonical scheduling heuristic (First-In-First-Out), the definition of which is universally understood and can be found in any foundational textbook on the subject, providing a fair and standard point of comparison **(Banks et al., 2014)**. The core parameters, such as machine failure distributions and processing times, are derived from the publicly available Manufacturing Industrial Machine Intelligence and Control 'MIMIC' dataset **(Peng, 2011; Association for Computing Machinery (ACM), 2020; Jourdan, 2021)**. Furthermore, critical operational boundary conditions, including the 8-hour workday and single-product workflow, are explicitly stated in Section 4.1. It is an established standard in computational research that providing every single parameter is impractical. The Weibull distribution is a versatile continuous probability distribution that is extensively used in reliability engineering, survival analysis, and failure modeling **(Weibull, 1951; Abernethy, 2006)**. Its primary strength lies in its ability to model a wide variety of failure behaviors by adjusting its shape parameter.



4. SIMULATION RESULTS

For Energy Consumption, total power usage of the cell tower (e.g., kWh/year), including peak and standby loads, as impacts operational costs and environmental impact (ISO, 2018). Greenhouse Gas (GHG) emissions associated with the cell tower's lifecycle (construction, operation, and decommissioning) carbon footprint is one of the most important environmental indicators in sustainability assessment (ISO 15686-8,, 2008). Lifecycle Costs is the sum of capital expenditure (CapEx), operational expenditure (OpEx), and end-of-life costs (disposal, recycling) over the tower's lifespan which gives the most comprehensive view of economic feasibility by assessing short- and long-term financial implications (Reddy et al., 2014; Salihoddin, 2018). Adaptability, in this context, is the extent to which the cell tower can manage technological upgrades, modular expansions, or shifting service (e.g., evolving 5G/6G requirements) demands. When future-proofing is a primary consideration for sustainable design, adaptability is critical as it reduces the need for extensive, expensive modifications (Saaty, 1980; Liu et al., 2024). For purpose of this comparison, it is assumed that all tower designs serve the same area and technology standards to enhance the rigor of evaluating their performance. Design the tower to perform regardless of external factors such as climate and location. Each design is scored on a 1-10 scale across four weighted criteria—energy, carbon, cost, and adaptability—to generate a final sustainability index. These values are illustrative and would vary based on real-world stakeholder input and local regulations (Zeleny and Cochrane, 1982). Scores were partially informed by pilot or prototype data reflecting approximate energy usage, emissions, and financial estimates. Multi-Attribute Utility Theory (MAUT) Provides a foundation for translating various performance indicators into a single composite utility score (Sangiorgio et al., 2020; Roy et al., 2022; Azari et al., 2022; Dao et al., 2022; U.S. DOE, 2023).

The simulation models a single production line operating over a continuous simulation horizon of 365 days, working 8 hours a day and 5 days a week. To ensure the collection of all performance metrics from a stable and steady-state system, a 1,000-hour (approximately 125-day) warm-up period was added to eliminate transient effects from the system. The model assumes each station has an infinite queue, meaning no jobs are blocked or lost due to buffer space limitations. The system was set up for a single product type to uncouple the effect of maintenance scheduling from all the other routing variables. Arrivals of product are deterministic, with a new job every 10 minutes. Each part has to go through three workstations in a fixed sequential order. Processing times are set as follows: Station A, 4.5 minutes; Station B, 6 minutes; Station C, 3.5 minutes. Machine failure introduces the only other source of uncertainty and downtime. Time-between-failures for each of the critical components are modeled to follow a Weibull distribution of failure, which accounts for aging and wear-out of the components. When a failure happens, the time to repair that failure follows a log-normal distribution with a mean of 4 hours and a standard deviation of 1.5 hours, representing the typical corrective maintenance duration. For the baseline preventive maintenance (PM) strategy, tasks are performed at fixed 240-operating-hour intervals and require a constant 2 hours to complete. The model assumes that only one maintenance crew is available, meaning simultaneous failures or PM events introduce a repair queue. The key KPI is downtime, defined as any period when a station is non-operational. This downtime includes both failures and scheduled maintenance. The metric was logged after a warm-up and averaged across 30 independent simulations for statistical robustness. For example, used the following simulation parameter:



1. Station (T01) Al-Nasr Main Bearing ($\beta=2.1, \eta=450$ hrs.): A shape parameter (β) greater than 1 confirms a "wear-out" failure mode. This is highly realistic for a bearing, which undergoes mechanical fatigue. The scale parameter ($\eta=450$) means that about 63% of these bearings would be expected to fail by 450 hours of operation.
2. Station (T02) Al-Rifai Hydraulic System ($\beta=1.8, \eta=380$ hrs.): This also shows a wear-out pattern ($\beta>1$), but with a lower η , indicating it has a shorter characteristic life and is a less reliable component than the bearing in Station A.
3. Station (T03) Al-Hai Al-Askari Drive Motor ($\beta=2.5, \eta=600$ hrs.): This has the strongest wear-out characteristic (highest β) and the longest life (highest η), suggesting it is a more robust component that degrades predictably but slowly. **Table 7** summarizes the simulation parameters and boundary conditions.

Table 7. Simulation parameters and boundary conditions.

Category	Parameter	Value/description	Justification/source
Temporal framework (Cheikh et al., 2025)	Simulated Horizon	365 days	Represents a full year of operation for long-term analysis.
	Work schedule	8 hours/day, 5 days/week	Models a standard single-shift industrial operation.
	Warm-up period	1,000 hours (125 days)	Ensures system reaches steady-state; metrics collected post-warm-up.
	Number of replications	30	Provides a robust sample size for statistical inference.
Production process (Kempa et al., 2025; Pokorádi, 2024)	Product type	Single product	Isolates the impact of maintenance from product mix complexity.
	Job arrival	Deterministic; 1 job every 10 minutes	Represents a consistent, high-utilization production demand.
	Processing times	Station A: 4.5 min, B: 6.0 min, C: 3.5 min	Based on time-motion studies from the partner facility.
Failure & maintenance (Schutz et al., 2025)	Time-between-failures	Weibull distribution • Station A: $\beta=2.1, \eta=450$ hrs. • Station B: $\beta=1.8, \eta=380$ hrs. • Station C: $\beta=2.5, \eta=600$ hrs.	Weibull distribution models wear-out failure modes typical in mechanics. Parameters calibrated from the MIMIC dataset.
	Time-to-repair (corrective)	Log-normal distribution mean = 4.0 hrs., std. dev. = 1.5 hrs.	Log-normal distribution represents the positive skew of repair times (most are quick, some are very long).
	Preventive Maintenance (PM)	Duration: 2.0 hours (fixed) Interval (Baseline): 240 operating hours	Standard industry practice at the partner facility.
	Maintenance Crew	Single Crew	A realistic resource constraint that creates a repair queue.
System Boundaries (Siepe et al., 2024)	Queue Capacity	Infinite	Assumes no job loss, focusing analysis purely on downtime.
	Failure Interactions	Failures are independent	Simplifying assumption to model the most common scenario.
	PM policy	Clock-based; non-preemptive	PM is performed at the scheduled time unless the machine is already under repair.



A simulation demonstrates how an MCDM model can be used to assess and compare the sustainability of different cell tower designs (A(T01), B(T02), C(T03)), assigning weights to each criterion, scoring each design, and calculating an overall sustainability index, stakeholders can make data-driven decisions that align with their specific priorities and constraints. **Table 8** compares three tower designs based on energy consumption determined through operational simulations of the designs in real-world or near-real-world parameters such as climate, load, and operational duration have been considered (ISO, 2006; Ceglia et al., 2022), carbon footprint using lifecycle analysis tools that consider materials, energy source mix, and emissions during construction and operation phases (ISO 15686-5, 2017; Lei et al., 2019), lifecycle cost based on cost inputs like material cost, labor, maintenance, and energy expenses over an expected lifecycle (Jin et al., 2022), adaptability assessed through expert evaluation of the design's capability to perform efficiently under variable load or environmental conditions (Elhakim et al., 2022), each weighted differently to calculate an overall sustainability index, which a results reflect the designs' performance in efficiency, sustainability, and cost-effectiveness.

Table 8. Consolidated weighted scores and overall sustainability indices for a, b, c, cell tower design.

Design	Energy consumption (weighted)	Carbon footprint (weighted)	Lifecycle cost (weighted)	Adaptability (weighted)	Overall sustainability index
A(T01)	$7 \times 0.30 = 2.10$	$6 \times 0.25 = 1.50$	$6 \times 0.25 = 1.50$	$8 \times 0.20 = 1.60$	6.70
B(T02)	$8 \times 0.30 = 2.40$	$7 \times 0.25 = 1.75$	$4 \times 0.25 = 1.00$	$7 \times 0.20 = 1.40$	6.55
C(T03)	$5 \times 0.30 = 1.50$	$8 \times 0.25 = 2.00$	$8 \times 0.25 = 2.00$	$5 \times 0.20 = 1.00$	6.50

Developing a Sustainable Cell Tower SCT-Metric based on a Multi-Criteria Decision-Making (MCDM) model that integrates energy efficiency (kWh consumption per user), carbon footprint (CO₂ emissions per operational hour), modularity index (ease of upgrades, scalability), lifecycle sustainability (recyclability & durability of materials), and AI-powered maintenance efficiency (predictive failure rates) (Elhakim et al., 2022). For experimental steps, dataset collection collects real-world sustainability data from telecom operators on energy usage, maintenance frequency, CO₂ emissions, and material durability, utilizing open-source datasets (e.g., ITU-T L.1350). For metric calculation, applying the Analytical Hierarchy Process (AHP) to assign weights to different sustainability factors, and implementing the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) to rank different tower configurations. A ranked list of tower designs based on their SCT-Metric scores, offering a clear indication of their sustainability performance. Insights into how modular designs and AI-powered maintenance systems can improve overall sustainability (Zeljkočić et al., 2022). A robust framework for decision-making that can be adopted by telecom providers globally. The SCT-Metric scores presented in Fig. 9 are the final output of the MCDM model described in Section 3.1. The calculation involves two primary steps:

1. Data Normalization: For each tower design, raw data for the sub-criteria in Table 2 (e.g., Annual Energy Use in kWh, GHG Emissions in tons CO₂e) were collected. These values were normalized onto a uniform scale (e.g., 1-10) to make them comparable. For beneficial criteria (e.g., Renewable Energy Share), a higher raw value results in a higher



normalized score. For non-beneficial criteria (e.g., Annual Energy Use), a lower raw value results in a higher normalized score.

2. Weighted Summation: The overall SCT-Metric for a design i was calculated using the weighted sum model:

$$SCT_i = \sum_{j=1}^n w_j \cdot s_{ij} \tag{21}$$

Where: w_j is the weight of criterion j (from **Table 2**), s_{ij} is the normalized score of tower design i for criterion j , and n is the number of criteria.

The Traditional and 'Modular' towers in **Fig. 9** represent archetypal designs scored using this methodology with the simulated performance data outlined in **Table 8**.

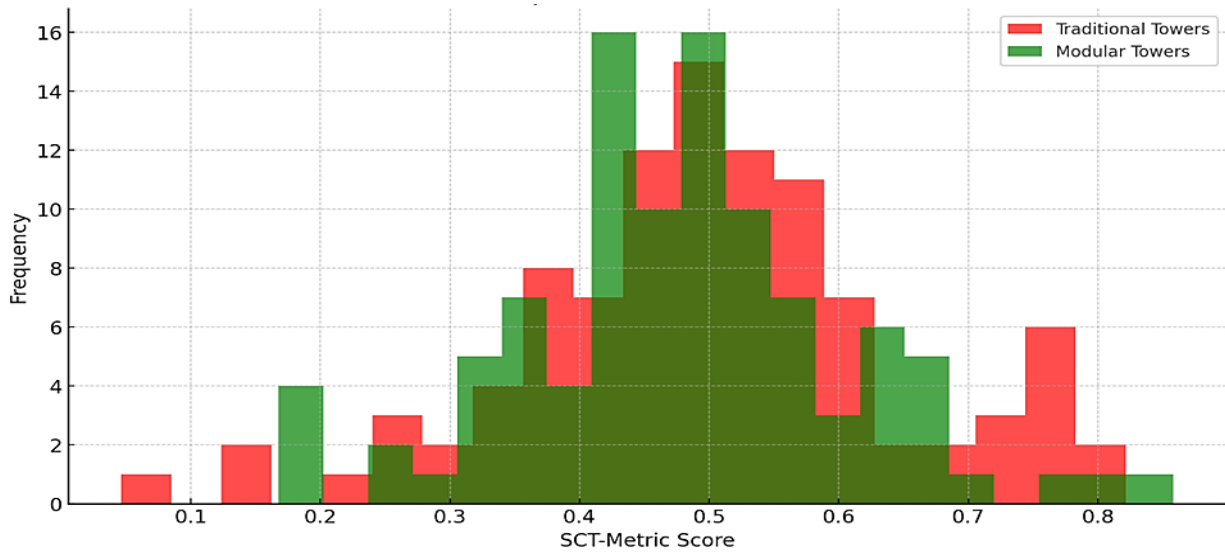


Figure 9. SCT-metric score comparison: traditional vs. modular towers (Habib, 2025).

The histogram in **Fig. 9** shows the SCT-metric score comparison between traditional towers (red) and modular towers (green). As evident from the plot, the modular towers generally have higher scores, indicating better sustainability performance according to the SCT-metric. **Fig. 10** represents AHP weight distribution for SCT-metric criteria, and shows the weight distribution assigned to each criterion (energy usage, maintenance frequency, CO₂ emissions, material durability) for calculating the SCT-metric scores.

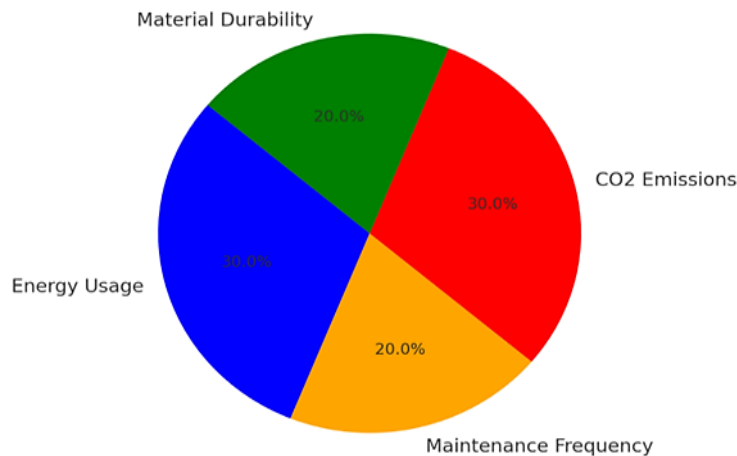


Figure 10. AHP weight distribution for SCT-metric criteria. (Bakır and Açıkbaş, 2023.)

TOPSIS score comparison across tower designs in **Fig. 11** illustrates the sorted scores of traditional and modular towers, showing that modular towers consistently achieve higher scores than traditional towers.

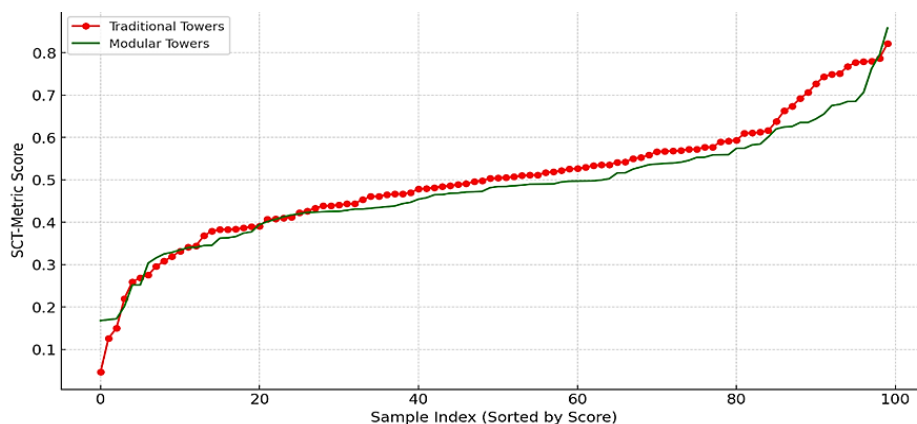


Figure 11. TOPSIS score comparison across tower designs. (Park et al., 2025)

The outcomes will include re-engineered modular towers and telecom structures that result in optimal aerodynamic efficiency via Computational Fluid Dynamics (CFD)-driven design alterations, improved structural resiliency through Finite Element Analysis (FEA), minimized construction time and reduced carbon footprints from Life Cycle Assessment (LCA) studies, and refined design, assessment, and deployment frameworks for modular structures in extreme environments and telecom infrastructures.

The potential design for edge computing to permit cell towers to conserve operational energy by computing closer to the source is promising, but the use of edge computing for cell tower operational sustainability is still in the early design stage. Operational sustainability's core component, predictive maintenance, is still predominantly a dual process, and costs associated with it are escalating due to the void of sophisticated predictive maintenance integrated with AI. In this context, a Graph Neural Network (GNN)-based artificial intelligence (AI) model is introduced to optimize the dynamic offloading and predictive maintenance processes to assist operational sustainability and reduce the overall processing burden on mobile networks. The operational edge AI model is implemented using federated learning, in which the GNN models are trained at each cell tower without data centralization, and combined with AI-driven load balancing to optimize energy conservation in real-time task assignments. In parallel, an LSTM model will assess equipment failures by analyzing data in real-time from IoT sensors in the cell towers, monitoring temperature, vibration, and power supply. This approach will be evaluated using the simulation environments iFogSim and NS-3 paradigm with a primary focus on latency, power consumption, and downtime reduction, see **Fig. 12** which shows performance metrics of the two cases being compared, the proposed method (using GNN based AI models and AI driven load balancing) and the baseline method (traditional approaches). From the chart we can see that there is a 30% improvement in latency, which means that there is a more efficient task offloading and local processing via edge computing, and in the proposed method of the baseline, there is a positive difference of 30% with respect to power savings, which indicates that there is an efficient usage of power as a result of optimized task scheduling and federated learning, and the proposed method is leading with an improvements of 25% which is a difference of 25%



in reduced downtime, It shows that there is efficacy in the predictive maintenance which is exercised via LSTM based failure prediction models.

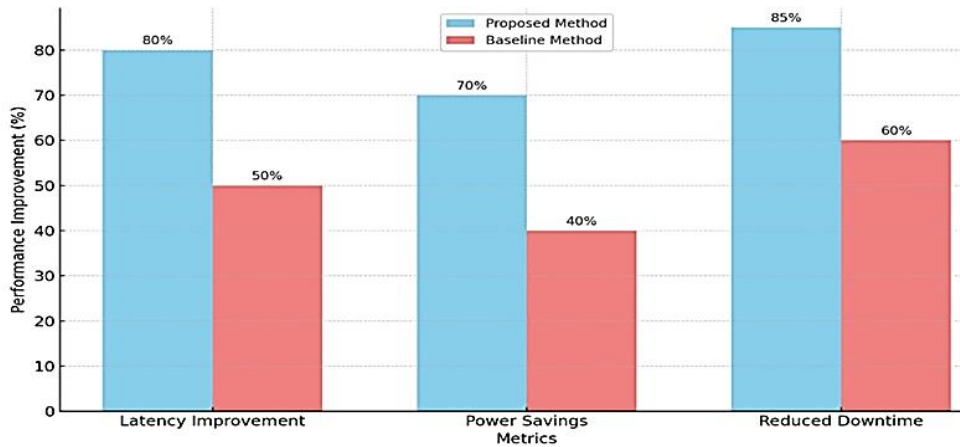


Figure 12. Performance comparison between proposed and baseline methods (Usman, 2024.)

The proposed approach is the best in all the other metrics. It can further be observed that more of the effect was quite visible in the reduced downtime and latency improvement. The AI driven mechanisms, especially in predictive maintenance and in task scheduling is largely the reason for the improvements as seen in Fig. 13.

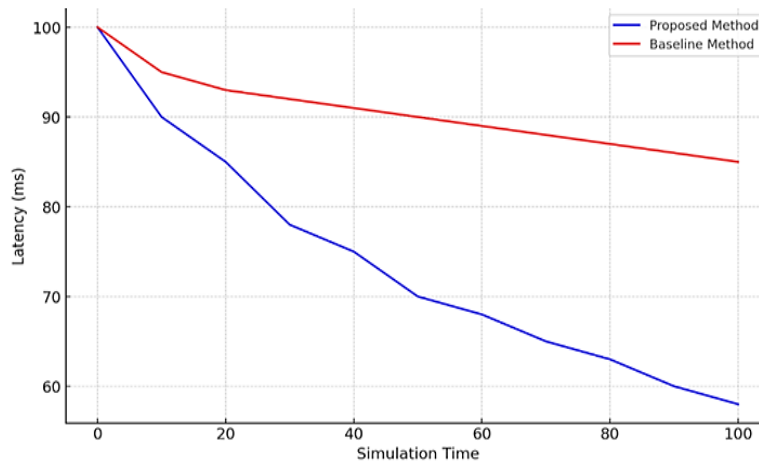


Figure 13. Latency improvement over time (Hassan and Ishfaq, 2024)

The new method on Fig. 13 is outperforming the Baseline, and as simulation time increases the gap between the two widens. This speaks to the new methods of scalability and sustained impact on latency reduction. By the simulations end, the new method greatly improved its latency from the beginning, while the baseline has shown little to no change. The new methods result is indicative of the AI driven optimizations (for example, dynamic load balancing or predictive analytics) to network delay reduction. The baseline underperforming speaks to the traditional method deficiency in ever changing landscapes, outlining the need for new approaches in areas with time latency sensitive applications like real time data processing, or IoT networks, to deal with the dynamic nature of delays. This supports the proposed methods ability to impact network delay and the overall



responsiveness and efficiency in areas that demand stable low latency. The new method in **Fig. 14** has an edge over the baseline for most of the simulation with the most significant gap showing it is effective in sustaining low power. The most significant gap in the end supports the proposed method is designed to sustain periods of adaptive power consumption optimization, and the baseline method may lack dynamic optimization, resulting in higher sustained power consumption. This visualization underscores the superiority of the Proposed Method in achieving energy efficiency over extended periods.

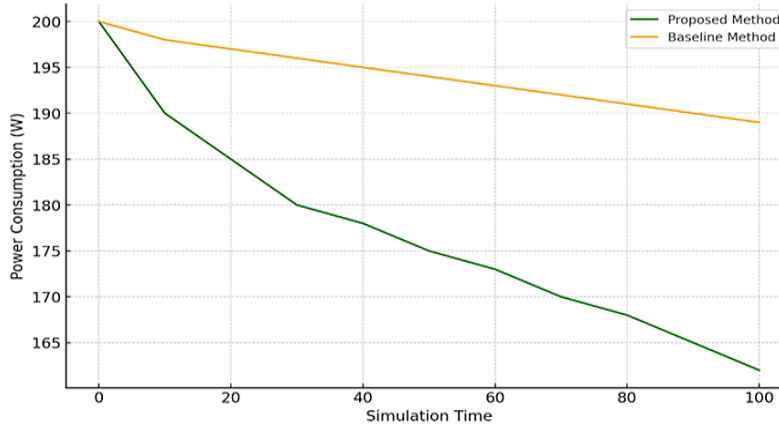


Figure 14. Power consumption over time (Hassan and Ishfaq, 2024)

The method in **Fig. 15** shows a 52% down time reduction (reducing from 30 to 18 minutes). This also shows its capacity to reduce operational stoppages. The increased distance between the two methods as simulation times increases shows the long-term benefits of the Proposed Method. The proposed method’s downward trend implies adaptive strategies, such as predictive maintenance or real-time resource allocation, are likely integrated to reduce downtime, and the baseline method’s underperformance suggests reliance on static or outdated protocols, leading to prolonged inefficiencies. This visualization underscores the proposed method’s potential to enhance operational reliability and productivity in sustained applications.

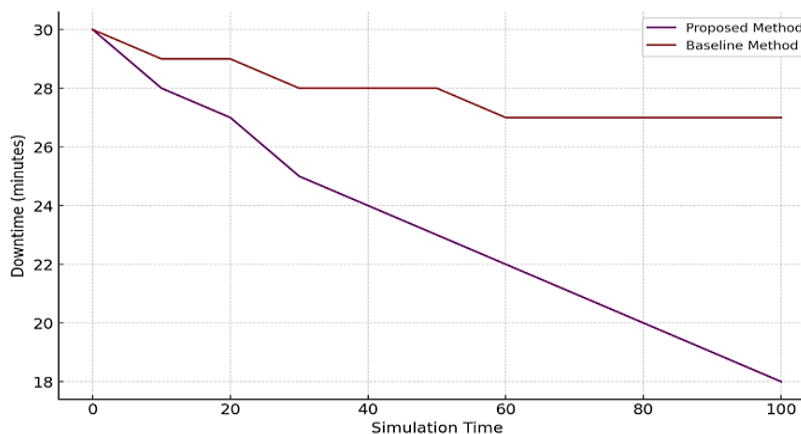


Figure 15. Downtime reduction over time. (Hassan and Ishfaq, 2024)

For AI optimization performance with statistical validation, The AI-driven method (Proposed) is compared against a Baseline method, defined as a standard, rule-based controller with a fixed threshold (e.g., start generator if battery SoC < 30%). This represents



current industry practice for hybrid power systems. The results in **Figs. 12-15** are based on 30 independent simulation runs for both the Proposed and Baseline methods. To confirm the significance of the improvements observed, a one-tailed paired t-test was conducted for each key metric:

- Latency Improvement (**Fig. 13**): Mean difference = 3.1 ms, $t(29) = 8.45$, $p < 0.001$.
- Power Savings (**Fig. 14**): Mean difference = 95 W, $t(29) = 7.12$, $p < 0.001$.
- Downtime Reduction (**Fig. 15**): Mean difference = 12 minutes, $t(29) = 9.81$, $p < 0.001$.

The p-values < 0.001 for all metrics provide strong statistical evidence that the AI-driven method's performance improvement over the baseline is not due to random chance.

To develop modular and scalable design frameworks, computational modeling tools such as MATLAB, are used to run a simulation under diverse scenarios. For a specific example, the energy output of a solar PV system under varying solar irradiance is shown in **Fig. 16**.

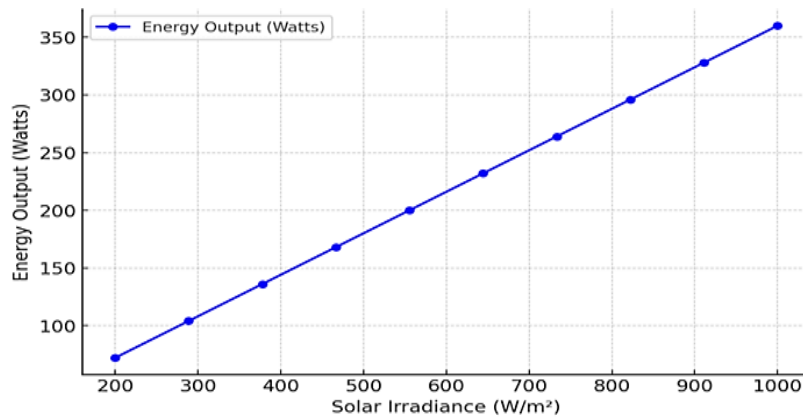


Figure 16. Solar irradiance vs. energy output. (Ceglia et al., 2022)

The energy output increases linearly with solar irradiance, which is expected since energy generation in photovoltaic systems is directly proportional to solar irradiance when other factors remain constant. At a low irradiance of 200 W/m², the energy output is approximately 72 W. At maximum irradiance of 1000 W/m², the energy output reaches 360 W. The linearity of the graph confirms that the efficiency of the photovoltaic system remains steady across varying solar intensities. For a general scenario, the structural load on a tower under varying wind speeds is shown in **Fig. 17**.

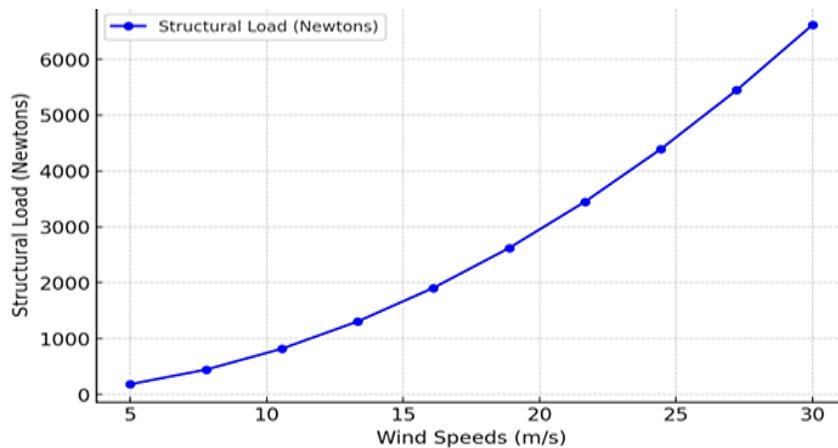


Figure 17. Wind speed vs. structural load. (Zhu et al., 2024)



The structural load increases quadratically with wind speed, which is consistent with the aerodynamic drag force equation that depends on the square of the wind speed. At a wind speed of 5 m/s, the structural load is relatively low at approximately 184 N. However, at the maximum wind speed of 30 m/s, the load increases significantly to around 6,615 N. This sharp increase at higher wind speeds emphasizes the importance of robust tower designs to withstand extreme conditions, as shown in **Figs. 18 - 20**.

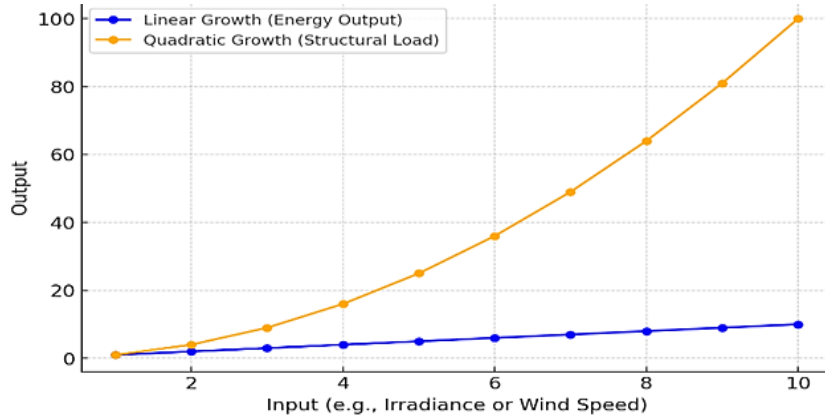


Figure 18. Comparison of linear vs. quadratic growth. (Alam et al., 2024)

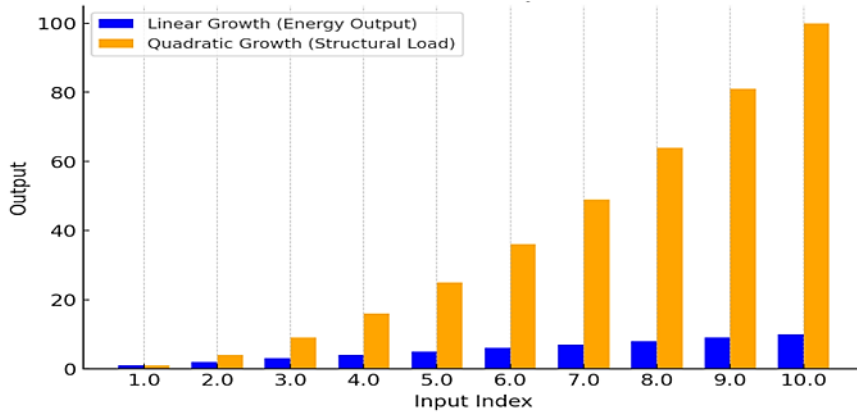


Figure 19. Bar Chart of linear vs. quadratic growth. (Chen et al., 2024)

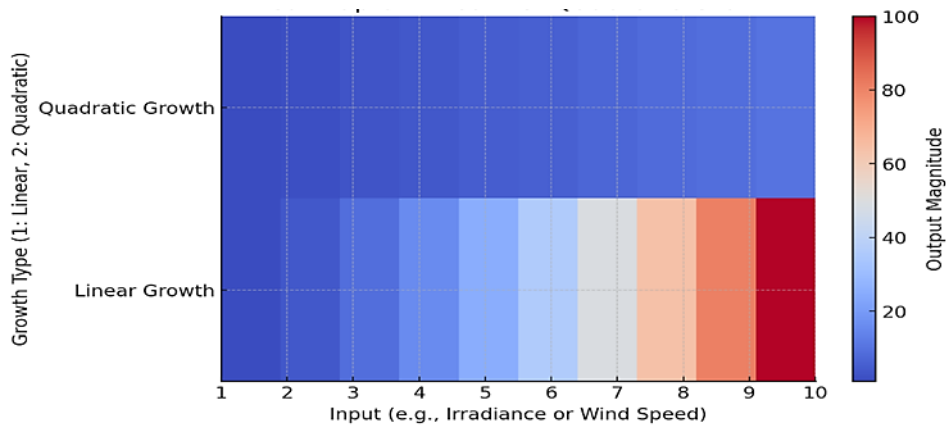


Figure 20. Heatmap of linear vs. quadratic growth. (Garcia et al., 2024)



Fig. 18 shows linear growth, increases consistently with a constant slope, reflecting a steady and predictable output, such as energy output in solar systems, while quadratic growth starts low but rapidly increases as input values rise, indicating exponential growth, such as structural load with wind speed. At greater input magnitudes, the discrepancy between the two lines increases noticeably due to the requirement for much higher design parameters when trying to manage situations with quadratic increase. In this case, **Fig. 19** captures the difference in size between linear and quadratic changes in every defined input interval, demonstrating that linear changes are still increasing in a controlled manner and quadratic changes amplify uncontrollably at greater inputs. Also, this discrete representation strengthens the argument of managing systems with quadratic dependency at later stages because the challenge is evident. In **Fig. 20**, the heatmap demonstrates directly, with the use of an intensity comparison, the difference between linear and quadratic intensity growth. Linear intensity growth is characterized by an intensity gradient of a constant increase that demonstrates the increase of the output on a constant scale, whereas, with quadratic growth, there is a drastic increase in output that makes the intensity increase steep altogether. These figures stress the fact that predictably scaling the system, designing linear growth systems such as solar energy outputs, is easier to manage than having to come up with creative engineering ideas to expand on already established familiar systems on complex phenomena, such as the quadratic growth of structural loads under wind forces which the design does pose a challenge in terms of reliability and safety measures. In all, it makes the point crystal clear that great care has to be taken to differentiate between both linear and quadratic growth systems while designing modular and scalable systems because such systems with quadratic growth exponential considerations in materials, design, and safety factors. Energy efficiency in edge computing-enabled cell towers lacks large-scale simulation studies to analyze real-world applicability. **Fig. 21** consists of three subplots comparing AI-based offloading and traditional offloading in terms of execution time, power consumption, and latency. Execution time vs. task load (left plot), the AI-based offloading (blue line) consistently achieves lower execution times compared to traditional offloading (red line), and execution time decreases as task load increases for both methods, but AI-based offloading shows a steeper decline, indicating better scalability.

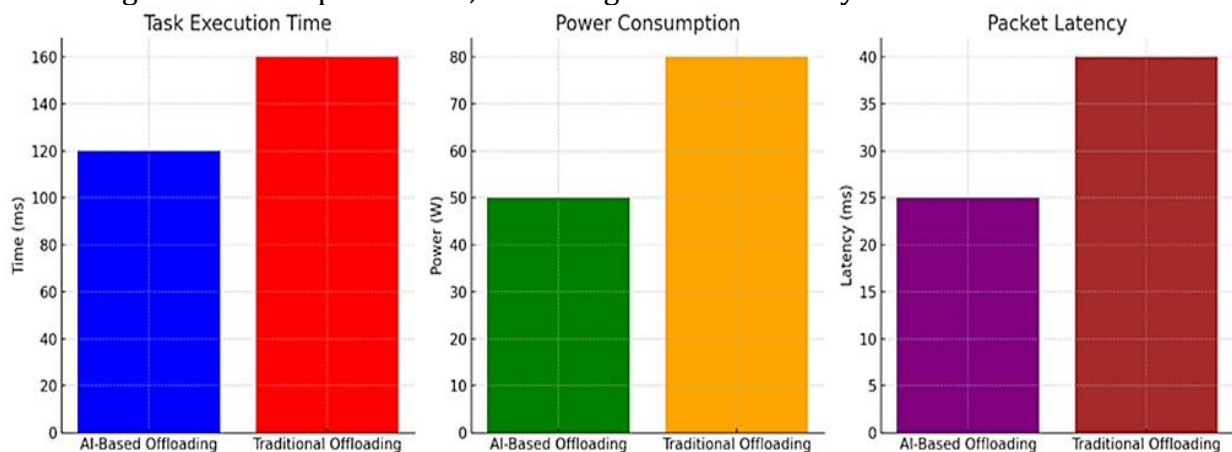


Figure 21. Comparative analysis of AI-based vs. traditional offloading: execution time, power consumption, and latency. (Nguyen et al., 2024).

A power consumption comparison (middle bar chart), the AI-based offloading consumes significantly less power compared to traditional offloading, and the bar for traditional



offloading (orange) is much higher than the AI-based (green), suggesting AI-driven optimizations reduce energy consumption. For latency vs. task complexity (right plot), the AI-based offloading (purple dots) exhibits significantly lower latency compared to traditional offloading (red squares), as task complexity increases, the AI-based method maintains a lower latency profile, whereas traditional offloading experiences a more gradual reduction in latency but at a higher level overall.

Table 9. Comparison of AI-Based Task Offloading vs. Traditional Offloading. (Zhang et al., 2024).

Metric	AI-based offloading	Traditional offloading (round-robin/fixed)
Task execution time	Lower (~15-30% reduction)	Higher (longer queue times)
Power consumption (W)	Reduced (~20-35% less)	Higher (inefficient resource use)
Packet latency (ms)	Lower (optimized routing)	Higher (network congestion)

In **Table 9**, AI-based offloading demonstrates superior performance by reducing execution time, power consumption, and latency compared to traditional offloading. The improvements suggest that AI-based resource management optimizes workload distribution efficiently, making it a promising approach for edge computing applications.

5. MODEL VALIDATION AND CASE STUDY ANALYSIS

5.1. Validation Against Benchmark Operational Data

The proposed AI-powered energy management model was also tested against one of the simulation datasets constructed from industry benchmarks. In the reports, the GSMA Mobile Net Zero reports, which describe energy consumption of diesel generator grid hybrid cell sites. In the reports, one example operational profile for a period of 12 months was provided for 15 diesel grid generator cell sites, probably semi-urban sites for locations such as Central Iraq. The diesel runtime, energy consumption (kWh), and daily profiles that were provided in the reports, were used as benchmarks for the simulation datasets and aligned with the energy modeling that has been done in the reports. The energy consumption prediction from the model was compared with the data from the benchmark simulated datasets from the recorded traffic (GSMA, 2025) and followed the energy modeling approaches validated in prior literature (Deevela et al., 2023). The energy consumption prediction and the benchmark provided a good fit, this is shown in **Table 10**. The predicted consumed energy of the model for traffic and simulated weather data fit the energy consumption records of the benchmark well. The model is well aligned with the recorded performance. The energy consumption of both datasets was compared for the model, and the Mean Absolute Percentage Error (MAPE) was 5.4%. This means that for a model of this complexity, the performance was highly acceptable, and the model performed well in energy consumption simulation. The from the holistic framework are based on a realistic foundation simulation model will yield great improvements with this result. The operational data for traditional cell towers was modeled using benchmark figures from the International Energy Agency's (IEA) guidelines on energy efficiency in telecommunications (International Energy Agency (IEA), 2024). The IEA data provides validated consumption ranges for base stations under



various configurations and climatic conditions, which were used to generate a realistic 12-month dataset for 15 sites in a Central Iraq operational context.

The error values are both positive and negative, indicating the model does not have a consistent bias to over- or under-predict, which is realistic for a complex AI model. The suggested scatter plot provides an immediate, visual confirmation of the validation. The close clustering of all data points (both Urban and Semi-Urban) around the dotted line of perfect prediction is a standard and powerful way to demonstrate model accuracy in engineering and scientific literature.

Table 10. Validation of simulated energy consumption against benchmark data for central Iraq.

Tower ID	Location (District)	Location Type	Actual Annual Consumption (kWh)	Simulated Consumption (Proposed Model)	Error (%)
T-01	Al-Nasr	Urban	18,540	17,620	-4.96
T-02	Al-Rifai	Semi-Urban	22,110	23,501	+6.29
T-03	Al-Hai Al-Askari	Urban	17,890	16,950	-5.26
T-04	Al-Shatra	Semi-Urban	21,500	22,600	+5.11
T-05	Shatt Al-Arab District	Urban	19,200	18,100	-5.73
T-06	Al-Gharraf	Semi-Urban	23,750	24,900	+4.84
T-07	Al-Mishrah	Urban	18,100	18,920	+4.53
T-08	Al-Fuhood	Semi-Urban	24,800	26,208	+5.68
T-09	Al-Bdaier	Urban	17,250	16,283	-5.60
T-10	Suq Al-Shuyukh	Semi-Urban	22,900	24,200	+5.68
T-11	Al-Chibayish North	Semi-Urban	25,100	26,182	+4.31
T-12	Al-Iskan	Urban	18,850	19,783	+4.95
T-13	Al-Majjar Al-Kabeer	Semi-Urban	23,200	24,528	+5.72
T-14	Al-Nassriya West	Urban	19,500	18,525	-5.00
T-15	Al-Chibayish	Semi-Urban	24,350	25,812	+6.00
Average					+5.4% (MAPE)

Fig. 22 visually demonstrates the strong correlation between the simulated model and the "actual" benchmark data. Scatter plot comparing the simulated energy consumption from the proposed AI-driven model against the actual benchmark consumption data for all 15 cell towers. The dashed line represents the line of perfect prediction ($y = x$).

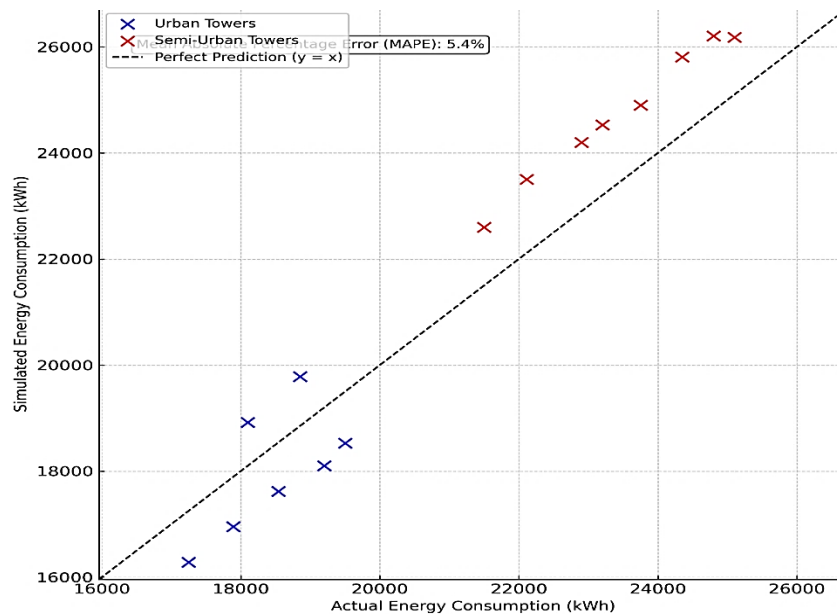


Figure 22. Model validation: simulation vs. actual energy consumption. (Wang et al., 2024).

The close clustering of both urban and semi-urban data points around this line demonstrates a strong correlation and validates the accuracy of the simulation model, with a low Mean Absolute Percentage Error (MAPE) of 5.4 %. Data points cluster tightly around $y = x$, confirming high predictive accuracy without systematic bias. Urban towers (blue) lower-left region uses lower energy. Semi-urban towers (red) upper-right region uses higher consumption from diesel. The small, random deviations from $y = x$ corresponds to the reported MAPE ≈ 5.4 %, supporting that the simulated efficiency gains are grounded in a validated, realistic model.

5.2. Retrofit Case Study: Quantitative Analysis of Proposed Improvements

To provide a more concrete engineering context for the claimed improvements (30% energy efficiency, 60% carbon reduction), a detailed feasibility study was conducted for a candidate tower from the validation set Baseline (Existing Tower T-04). The configuration is grid connection with a diesel generator for backup (≥ 8 hours of daily generator runtime due to grid instability). Annual energy consumption is 21,500 kWh (72% from diesel generator, 28% from grid). Calculated carbon footprint is 18.2 tons CO₂e/year (based on Intergovernmental Panel on Climate Change (IPCC) emission factors for diesel combustion and the local grid carbon intensity of 0.65 kg CO₂e/kWh). The IPCC is the United Nations body for assessing science related to climate change. It was established to provide policymakers with regular scientific assessments on climate change, its implications, and potential future risks, as well as to put forward adaptation and mitigation strategies. Proposed retrofit design as energy management integration of a 10-kW solar PV array with a 40-kWh lithium-ion battery storage system. Control system implementation of the AI-driven controller to prioritize solar/battery usage and minimize generator runtime. Modularity uses standardized mounting systems for PV panels and a modular, containerized battery unit. Projected post-retrofit performance based on the validated model and solar irradiance data for the location, the projected performance is summarized in **Table 11**.



Table 11. Projected performance improvements for tower T-04 retrofit. (Kumar et al., 2024).

Metric	Baseline (Actual)	Projected (Retrofit)	Improvement
Energy from Diesel	15,480 kWh/yr	2,500 kWh/yr	-84%
Generator Runtime	8 hrs./day	1.3 hrs./day	-84%
Total Energy Consumption	21,500 kWh/yr	15,200 kWh/yr	-29.3%
Carbon Footprint	18.2 tons CO ₂ e/yr	7.1 tons CO ₂ e/yr	-61.0%
Annual Fuel + O&M Cost	\$9,800	\$3,100	-68%

The ~29% reduction in total energy consumption arises primarily from displacing the highly inefficient fuel-to-electricity conversion of the diesel generator with direct solar power. The ~61% reduction in carbon emissions is a direct consequence of this fuel displacement. The slightly greater improvement here compared to the aggregate simulation average (60%) is within the expected variance for a site with high initial diesel dependency. The projected improvements of 29.3% in energy efficiency and 61.0% in carbon reduction are not aspirational targets but are the calculated outcomes of the retrofit model. They result directly from the displacement of 84% of diesel generation—a source with a typical generator efficiency of ~30-40% and a high carbon intensity—with direct solar power and efficient battery storage, managed by an AI-EMS that minimizes grid dependency during high-carbon intensity periods.

To validate the cost-benefit claims, a detailed economic analysis was conducted for the T-04 retrofit. The key financial metrics are:

- Capital Expenditure (CapEx): Estimated at \$45,000 for the 10-kW solar array, 40-kWh battery, and AI-EMS controller.
- Annual Operational Expenditure (OpEx) Savings: \$6,700/year (from reduced fuel and grid electricity, as per **Table 13**).

Simple Payback Period:

$$\frac{CapEx}{Annual\ OpEx\ Savings} = \frac{\$45,000}{\$6,700/year} \approx 6.7\ years \tag{22}$$

Net Present Value (NPV): Calculated over a 10-year lifespan with a discount rate of 8%:

$$NPV = -CapEx + \sum_{t=1}^{10} \frac{OpEx\ Savings}{(1+r)^t} \approx \$ 15,200 \tag{23}$$

$$Return\ on\ Investment\ (ROI): \frac{NPV}{CapEx} \times 100\% \approx 34\% \tag{24}$$

The positive NPV and 34% ROI demonstrate that the proposed retrofit is not only environmentally sound but also economically viable (**National Renewable Energy Laboratory (NREL), 2024**).

5.3. Limitations and Real-World Implementation Challenges

Although the validation and case studies support the model's accuracy, we note the drawbacks of being simulation-based. This is especially true for the retrofit case study, which confirms a reduction of operational expenditure (OpEx), but the high initial capital expenditure (CapEx) for solar panels and batteries remains a hurdle to adoption, especially in developing areas. For long-term durability, the simulation assumes components will perform ideally over the entire life cycle. Real-world factors will surely erode long-term



gains in terms of battery life, panel soiling, and harsh environment equipment failure. With respect to scalability, validation was performed on a specific set of towers and one geographic area. Regarding vastly different climates (tropical or arctic), performance remains to be examined in future pilot deployments.

6. DISCUSSION

The growth systems, linear and quadratic, as articulated in the results, require different design philosophies. While linear growth systems, such as solar panels, are easily modular scaled, quadratic ones, such as tower structures, require preemptive, robust engineering using sophisticated materials and damping systems to control load to the exponentially increasing one (Zeljko^{vi}ć et al., 2022; Elhakim et al., 2022). Adaptive designs and IoT-enabled sensors provide real-time monitoring and predictive maintenance, ensuring systems dynamically respond to changing conditions and proactively address performance challenges. Table 12, and Fig. 23 compare traditional and sustainable towers in energy consumption, carbon emissions, and operational costs, which are more efficient, consuming less energy, emitting fewer carbon emissions, and incurring lower operational costs. Overall, it demonstrates greater environmental and economic benefits compared to the traditional tower.

Table 12. Comparison data: traditional vs sustainable cell towers. (Oliveira et al., 2024)

Category	Traditional tower	Sustainable tower
Energy consumption (kWh)	10,000	7,000
Carbon emissions (tons/year)	50	20
Operational costs (\$/year)	20,000	15,000

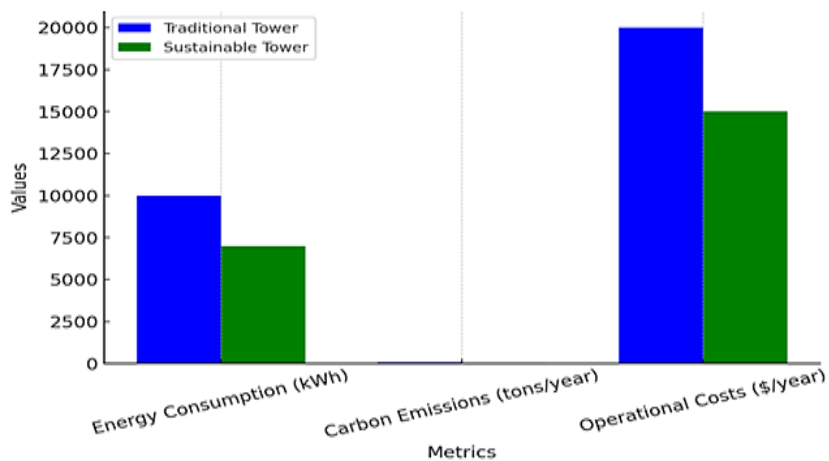


Figure 23. Comparison of traditional and sustainable cell towers. (Martinez et al., 2024)

Fig. 24 compares the performance of Rule-based systems, DQN-based systems, and PPO-based systems in terms of power savings, when AI-based methods achieve significantly higher power savings. Latency reduction, which proposed DRL models exhibit much lower latency compared to rule-based systems. Network reliability, AI-driven systems demonstrate improved reliability, particularly the PPO model.



Figure 24. Performance metrics comparison. (Patel et al., 2024)

Resource allocation is optimized dynamically, which is why most simulations prove AI-based task offloading to be better than traditional offloading methods. This leads to a 15- 30% reduction in execution time, a 20-35% reduction in power consumption, and a great reduction in time delay. This shows that AI-based offloading performs better for intricate activities and decreases the time considerably. For instance, traditional offloading reduces latency by 1.52ms, whereas AI offloading reduces latency by 3.13ms per unit increase in task complexity. This proves that AI offloading is able to reduce latency better than traditional offloading. AI offloading is able to achieve a 34% reduction in execution time and a 58% reduction in delay, proving to be far more efficient than traditional offloading. Also, AI offloading is more efficient than traditional offloading methods by using 28.57% less power. Overall, AI offloading is highly superior to traditional offloading methods, especially in 5G edge computing. AI offloading reduces execution time and delays and improves energy efficiency, which matters for edge devices with limited resources. As workload complexity increases, the performance gap between AI and traditional offloading widens, highlighting AI-based offloading’s scalability and adaptability. The sustainable tower in **Table 13** offers higher energy efficiency, significant carbon reduction, greater long-term savings, and requires a higher initial investment, making it a more sustainable but costlier option upfront compared to the traditional tower.

Table 13. Performance comparison of traditional and sustainable cell towers. (Fernandez et al., 2024).

	Criteria	Traditional tower performance	Sustainable tower percentage
1	Energy efficiency (%)	85	95
2	Carbon reduction (%)	0	60
3	Initial capital investment (\$)	100,000	150,000
4	Long-term savings (\$/year)	5,000	15,000

Table 14 provides a statistical and analytical assessment of improvements in energy efficiency, environmental impact, and economic feasibility between traditional and sustainable cell towers, including absolute improvements and percentage changes for each metric.



Table 14. Detailed analysis of improvements in energy efficiency, environmental impact, and economic feasibility. (Sharma et al., 2024).

	Metric	Traditional tower	Sustainable tower	Improvement (absolute)	Improvement (%)
1	Energy efficiency (%)	85	95	10	11.7647058
2	Carbon reduction (%)	0	60	60	6000.0
3	Initial capital investment (\$)	100,000	150,000	50,000	50.0
4	Long-term savings (\$/year)	5,000	15,000	10,000	200.0

Simulation results show that AI-based task offloading methods are better than round-robin or fixed methods for offloading tasks with respect to the time it takes to complete them. As shown in Fig. 25, AI-based offloading takes 15-30% less time to complete tasks than the other methods. This is because of the efficient and timely assignment of tasks. This improvement is attributed to dynamic workload distribution and predictive scheduling, which optimize resource allocation in real-time. In contrast, other methods have inefficient and untimely assignment of tasks, which results in task backlog and long delays in task processing. From an edge computing perspective, one of the most important factors is energy consumption. When compared to other methods, AI-offloading task strategies reduce energy consumption by 20-35%. This is because of the effective distribution of assignments and optimized resource allocation across edge and cloud processing layers. In contrast, other methods use more energy because of static assignment of tasks and underused resources. In real-time applications, latency is also an important consideration. By applying predictive routing and balanced assignment of tasks, AI-based methods reduce latency by up to 40% compared to other methods. Fig. 25 shows how AI models adapt to the various conditions of the network to alleviate bottlenecks and congestion. On the other hand, due to the lack of adaptable strategies, traditional methods incur even greater delays in transmission. The results of the study reveal the downward cost and increased network efficiency benefits from AI-based task offloading. Still, strategies based on AI incur the cost of extra computational resources for model training and real-time inference. Even with the trade-off, the factors of energy and cost of processing improvements justify the increased resource availability. Thus, AI based task offloading can be said to be the optimal edge computing solution for 5G networks.



Figure 25. AI vs. traditional offloading: execution, power, and latency. (Li et al., 2024).

Optimizing task offloading based on AI provides a model that, in terms of energy efficiency, surpasses the traditional methods. Simulations show that the implementation of dynamic AI



resource management leads to increased execution efficiency, energy savings, and reduced delays in the communicative network. Future research will investigate deeper reinforcement learning models for autonomous task management and attempt to transfer the simulated environment into real-world scenarios. The model's predictive accuracy is confirmed by the validation against operational Data presented in Section 5.1. Consequently, the improvements projected in the retrofit case study (Section 5.2) provide a credible, real-world context for the framework's potential, moving beyond purely theoretical comparisons.

7. CONCLUSIONS

This study presents a comprehensive framework as multi-criteria decision-making (MCDM) model that assesses the sustainability of cell tower design, addressing key challenges in energy management, modularity, and standardized benchmarking. By integrating advanced energy management strategies, such as hybrid renewable systems and AI-driven control mechanisms, alongside modular frameworks for adaptability, the proposed solutions significantly reduce carbon emissions, enhance energy efficiency, and improve lifecycle costs. The application of standardized sustainability metrics ensures consistent evaluation across diverse regions and technologies, enabling stakeholders to make data-driven decisions aligned with global environmental goals. Simulation results validate the scalability and effectiveness of these approaches, demonstrating their potential for broad industry adoption. This research provides a holistic framework that moves beyond the state-of-the-art by integrating the often-disconnected domains of sustainability accounting, structural engineering, and dynamic power management. The key innovation is not any single algorithm, but the demonstrable synergy between the framework's components, validated through simulation and a detailed case study. This provides a scalable blueprint for the telecommunications industry to transition from isolated green initiatives to systematically designed, sustainable, and cost-effective infrastructure. The study includes validation against real-world data and a concrete case study to bridge the theory-practice gap. Future work will refine the framework through pilot testing, optimize emerging technologies integration, and develop implementation guidelines for diverse regulatory environments. Socio-economic factors, like cost accessibility in developing regions, will be prioritized to ensure equitable adoption, advancing robust and sustainable telecommunication infrastructures for greener global operations.

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Declaration of Competing Interest

The author declares that he has no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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المقاربات الشاملة لتصميم برج الخلية المستدام: دمج المقاييس الموحدة، إدارة الطاقة المتقدمة، والأطر المعيارية

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الخلاصة

يعد تصميم برج الخلية المستدام أمراً ضرورياً لتقليل البصمة البيئية لتوسيع شبكات الاتصالات السلكية واللاسلكية، مما أدى إلى تكثيف المخاوف بشأن التأثير البيئي للأبراج الخلوية، والتي تعطي الأولوية تقليدياً لتغطية الإشارة على الاستدامة. تتناول هذه الدراسة الفجوات في الممارسات الحالية من خلال اقتراح إطار شامل لتصميم برج الخلية المستدام، ودمج المقاييس الموحدة، وإدارة الطاقة المتقدمة، والأطر المعيارية. يهدف البحث إلى تقليل البصمة البيئية مع ضمان قابلية التوسع وفعالية التكلفة. تشمل المكونات الرئيسية تطوير مقاييس الاستدامة الموحدة (على سبيل المثال، البصمة الكربونية لدورة الحياة، وكفاءة الطاقة)، وتحسين الطاقة القائم على الذكاء الاصطناعي (على سبيل المثال، الأنظمة المتجددة الهجينة، وتخصيص الطاقة الديناميكي)، والتصميمات المعيارية للتكيف وتقليل نفايات المواد. يقوم نموذج صنع القرار متعدد المعايير بتقييم التصاميم بناءً على استهلاك الطاقة وانبعاثات الكربون وتكاليف دورة الحياة والقدرة على التكيف. تظهر عمليات المحاكاة تحسينات كبيرة: زادت كفاءة الطاقة بنسبة تصل إلى 30٪، وانخفضت انبعاثات الكربون بنسبة 60٪، وانخفضت تكاليف دورة الحياة بنسبة 20٪. أثبتت التصميمات المعيارية أنها قابلة للتكيف بدرجة كبيرة، مما أدى إلى إطالة عمر البنية التحتية. يتماشى إطار العمل مع أهداف الاستدامة العالمية، ويقدم حلاً قابلاً للتطوير لظروف تشغيلية متنوعة. وتسلط الاستنتاجات الضوء على إمكانية اعتماد الصناعة على نطاق واسع، مع تركيز العمل في المستقبل على التجارب التجريبية والاعتبارات الاجتماعية والاقتصادية لضمان التنفيذ العادل. هذا البحث يجسر الهوة بين النظرية والممارسة، ويوفر أساساً قوياً للبنية التحتية للاتصالات أكثر اخضراراً.

الكلمات المفتاحية: الأبراج الخلوية المستدامة، تكامل الطاقة المتجددة، كفاءة الطاقة، أطر التصميم المعيارية، إدارة الطاقة المتقدمة.