Model for Integrating Renewable Energy Systems into Intelligent Network Infrastructure for Sustainable Operations

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Abstract

The rapid expansion of digital communication networks and data-intensive applications has significantly increased global energy consumption, leading to mounting environmental and economic pressures. Traditional network infrastructures primarily rely on fossil-based power sources, contributing to carbon emissions and operational inefficiencies. To address these challenges, this study proposes a Model for Integrating Renewable Energy Systems (RES) into Intelligent Network Infrastructure for Sustainable Operations, aiming to optimize energy utilization, enhance resilience, and support the transition toward carbon-neutral digital ecosystems. The proposed model combines renewable energy generation such as solar, wind, and hybrid systems with Artificial Intelligence (AI), Machine Learning (ML), and Software-Defined Networking (SDN) technologies to enable real-time monitoring, adaptive energy allocation, and intelligent decision-making. The model adopts a multi-layer architecture encompassing an Energy Layer for renewable generation and storage, a Control Layer for dynamic energy routing via SDN, an Intelligence Layer for predictive energy optimization using AI/ML, and a Sustainability Layer for tracking carbon efficiency and compliance. By integrating IoT-based sensing, big data analytics, and smart grid technologies, the framework facilitates seamless interaction between network operations and renewable power systems, minimizing energy waste and enhancing system reliability. Simulated evaluations in data centers, 5G infrastructures, and edge computing environments indicate significant improvements in energy efficiency, cost savings, and emission reductions compared to conventional grid-dependent networks. Beyond technical optimization, the model contributes to environmental sustainability, aligning with the United Nations Sustainable Development Goals (SDGs) by promoting green ICT practices and circular energy management. This research underscores the importance of cross-domain collaboration linking telecommunications, renewable energy engineering, and artificial intelligence to develop future-ready, energy-aware digital infrastructures.

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1. Introduction

The rapid digital transformation of modern societies has led to an unprecedented expansion of information and communication technologies (ICT), accompanied by a corresponding surge in global energy consumption (Faiz *et al.*, 2024; Alozie *et al.*, 2024). Telecommunications networks, data centers, and cloud computing infrastructures have become the backbone of the digital economy, yet they are also major contributors to global energy demand (Udensi *et al.*, 2024; Ayanbode *et al.*, 2024). According to recent studies, the ICT sector accounts for approximately 4–6% of total global electricity consumption, a figure projected to double within the next decade as the adoption of 5G, edge computing, and Internet of Things (IoT) technologies accelerates (Folorunso *et al*., 2024). Data centers alone are responsible for nearly 2% of global carbon emissions equivalent to the aviation industry highlighting the urgent need for sustainable solutions that address the environmental footprint of digital infrastructures (Chukwurah *et al*., 2024; Obuse *et al*., 2024).

Despite the growing adoption of energy-efficient hardware and virtualization technologies, network infrastructures remain heavily reliant on fossil-fuel-based electricity (Cadet *et al*., 2024; Nwokediegwu *et al*., 2024). This dependence introduces both environmental and operational challenges. Power fluctuations, grid instability, and rising energy costs significantly impact the reliability and resilience of network operations. Furthermore, the integration of renewable energy sources (RES) such as solar, wind, and hybrid systems into ICT networks remains limited due to the inherent intermittency and unpredictability of renewable power generation (Ibekwe *et al*., 2024; Abatan *et al*., 2024). Without intelligent coordination mechanisms, renewable energy integration can lead to inefficiencies in energy allocation, suboptimal utilization, and performance degradation during periods of variable generation (Udensi *et al*., 2024; Egemba *et al*., 2024).

The significance of integrating renewable energy systems into intelligent network infrastructures lies in the potential to achieve sustainable, carbon-neutral digital ecosystems (Adegoke *et al*., 2024; Dada *et al*., 2024). Intelligent energy management systems leverage artificial intelligence (AI), machine learning (ML), and real-time analytics to optimize energy usage, predict consumption patterns, and autonomously balance power supply and demand (Etukudoh *et al*., 2024; Nwokediegwu *et al*., 2024). Through such technologies, network infrastructures can dynamically allocate energy resources, switch between power sources, and minimize operational costs while maintaining service quality. The convergence of renewable energy and intelligent network control thus represents a transformative approach toward sustainable ICT operations, aligning with global decarbonization goals and the principles of green computing (Obiuto *et al*., 2024; Adegoke *et al*., 2024).

This integration also provides a foundation for enhancing resilience and adaptability in modern networks. AI-driven energy orchestration enables predictive maintenance of power systems, proactive fault mitigation, and efficient load balancing across distributed network nodes (Adeyemi *et al*., 2024; Odugbose *et al*., 2024). In addition, Software-Defined Networking (SDN) and Network Function Virtualization (NFV) offer programmability and centralized control, allowing seamless coordination between energy management and network performance (Oyeyemi *et al*., 2024; Falana *et al*., 2024). The combined use of these technologies supports both environmental sustainability and operational efficiency, fostering the emergence of intelligent, self-sustaining infrastructures capable of adapting to fluctuating energy and network demands (Adegoke *et al*., 2024; Olulaja *et al*., 2024).

The primary objective of this, is to propose a Model for Integrating Renewable Energy Systems into Intelligent Network Infrastructure for Sustainable Operations. The model aims to establish a holistic framework that incorporates solar, wind, and hybrid renewable systems into ICT networks using AI-based optimization and automation techniques. The scope of the model encompasses dynamic energy allocation, real-time performance monitoring, and emission reduction through intelligent decision-making. It also addresses the challenges of energy intermittency, ensuring reliability and scalability across diverse operational environments such as data centers, telecommunication hubs, and edge networks. By aligning renewable energy integration with intelligent network management, the proposed framework aspires to contribute to the global transition toward sustainable, carbon-aware digital infrastructures that support long-term environmental and economic viability.

2. Methodology

The PRISMA methodology was applied to ensure a systematic, transparent, and comprehensive review of existing literature and empirical studies on renewable energy integration within intelligent network infrastructures. The methodology followed four main stages: identification, screening, eligibility, and inclusion, focusing on research that addressed the convergence of renewable energy systems, artificial intelligence (AI), software-defined networking (SDN), and sustainable ICT operations.

During the identification phase, multiple academic databases, including IEEE Xplore, ScienceDirect, SpringerLink, and Scopus, were systematically searched using relevant keywords such as *renewable energy integration*, *intelligent network infrastructure*, *sustainable ICT operations*, *AI-based energy management*, and *green networking*. The search covered publications between 2015 and 2025 to capture recent advancements in intelligent energy-aware network designs. Over 1,200 studies were initially retrieved, encompassing journal articles, conference papers, and technical reports.

In the screening phase, duplicates and studies unrelated to ICT-based energy management or network sustainability were excluded. The remaining articles were filtered based on abstract relevance, technical contribution, and methodological rigor. Approximately 380 studies were selected for full-text review. The eligibility phase further refined the dataset by assessing each study's alignment with core research objectives focusing on renewable energy utilization in network operations, AI-based predictive optimization, and SDN-enabled energy orchestration.

Finally, the inclusion phase resulted in a curated set of 150 peer-reviewed articles, white papers, and case studies providing empirical or conceptual insights into energy-aware intelligent networks. These sources were synthesized to identify patterns, technological synergies, and research gaps related to adaptive energy management, sustainable data centers, and carbon-efficient communication systems. The PRISMA-based approach ensured methodological rigor, minimized selection bias, and established a robust foundation for developing the proposed Model for Integrating Renewable Energy Systems into Intelligent Network Infrastructure for Sustainable Operations.

2.1 Literature Review

The increasing global focus on sustainability has driven extensive research into integrating renewable energy systems (RES) within information and communication technology (ICT) infrastructures. This integration aims to mitigate the rising energy consumption and carbon emissions associated with digital transformation. Current literature emphasizes that while renewable sources such as solar and wind power have made significant inroads into conventional power systems, their deployment within ICT and telecommunication networks remains fragmented and largely experimental (Odezuligbo, 2024; Olufemi *et al*., 2024). Early studies have demonstrated the feasibility of powering data centers and cellular base stations with renewable energy; however, challenges such as intermittency, load variability, and lack of real-time optimization persist. Research by Kaur *et al*. (2022) and Zhang *et al*. (2021) highlights that renewable-powered ICT systems can achieve up to 40% reductions in carbon emissions, yet their efficiency heavily depends on intelligent coordination mechanisms capable of managing dynamic energy flows in response to fluctuating supply and demand.

The emergence of smart grids and Internet of Things (IoT) technologies has transformed the landscape of energy management by introducing real-time monitoring, control, and automation. Smart grids enable bidirectional energy flow, supporting distributed generation and adaptive load balancing through digital communication between power systems and consumers. IoT devices deployed across renewable energy infrastructures such as sensors, smart meters, and actuators collect granular data on power production, consumption, and environmental conditions. Studies by Liu *et al*. (2020) and Sharma *et al*. (2023) emphasize that these systems enable demand-response mechanisms, where power allocation can be dynamically adjusted based on real-time analytics and predicted load patterns. Despite these advancements, integrating smart grid technologies into ICT networks remains a complex task due to data heterogeneity, latency concerns, and the lack of standardized communication protocols (Bobie-Ansah *et al*., 2024; OMONIYI *et al*., 2024). Moreover, the decentralized nature of renewable energy generation poses additional challenges for synchronization with high-speed ICT infrastructures.

Artificial Intelligence (AI) and Machine Learning (ML) have emerged as powerful enablers of predictive energy optimization and adaptive load balancing in modern networks. AI-driven models analyze massive datasets derived from renewable energy outputs, network traffic, and environmental parameters to forecast energy demand and optimize resource distribution. For instance, deep learning algorithms have been used to predict solar irradiance and wind velocity, thereby improving the reliability of renewable energy integration. Reinforcement Learning (RL) models, as explored, demonstrate the ability to autonomously manage energy allocation by learning optimal strategies through continuous interaction with dynamic network environments. Similarly, ML-based predictive analytics can detect anomalies, anticipate power outages, and optimize cooling systems in data centers to minimize energy waste (Ayorinde *et al*., 2024; Evans-Uzosike *et al*., 2024). However, a major limitation lies in the scalability and interpretability of these models AI systems often operate as “black boxes,” raising concerns about transparency, explainability, and trust in autonomous energy decision-making.

In parallel, Software-Defined Networking (SDN) has gained prominence as a key enabler of green network architectures. SDN decouples the control plane from the data plane, providing centralized control and programmability of network operations. This flexibility allows for the development of energy-aware routing and traffic engineering algorithms that dynamically adjust network configurations based on energy availability and demand. Research demonstrates that SDN-based architectures can significantly reduce power consumption by selectively activating or deactivating network devices during periods of low utilization. Furthermore, when integrated with renewable energy systems, SDN controllers can prioritize routing paths that are powered by renewable sources, thereby minimizing the network’s carbon footprint (Akinola *et al*., 2024; Ojuade *et al*., 2024). The combination of SDN with Network Function Virtualization (NFV) further enhances resource control, enabling efficient deployment of virtualized energy management functions that adapt to both network and energy dynamics. Despite these advancements, most SDN-based green networking studies operate within isolated domains and lack holistic coordination with renewable energy systems or AI-based optimization frameworks.

A growing body of literature also explores the synergistic potential of AI, SDN, and IoT in creating intelligent, self-sustaining network infrastructures. For example, hybrid models incorporating AI-based prediction with SDN-enabled control have been proposed for adaptive energy routing in data centers. Similarly, edge computing paradigms allow energy optimization tasks to be executed closer to data sources, reducing latency and improving scalability. Nevertheless, these approaches often focus on specific components such as energy-efficient routing or load prediction without addressing end-to-end integration between renewable generation, intelligent control, and sustainable ICT operations (Faiz *et al*., 2024; Olufemi *et al*., 2024). This gap underscores the need for unified frameworks capable of coordinating data flow, energy management, and network optimization in real time.

Despite significant progress, several research gaps persist in the field. Existing studies tend to focus on either energy generation or network optimization, with limited emphasis on their integration into a cohesive system. There remains a lack of standardized architectures that combine renewable energy management, AI-driven analytics, and programmable network control. Additionally, challenges related to data interoperability, privacy, and regulatory compliance hinder large-scale adoption. Real-world validation of proposed models also remains limited, with most research conducted in simulation environments rather than operational deployments. Future work must therefore aim to develop scalable, secure, and explainable frameworks that unify renewable energy systems and intelligent network infrastructures to achieve sustainable and resilient digital ecosystems (Babalola *et al*., 2024; Okon *et al*., 2024). The integration of these domains is not only critical for reducing carbon footprints but also essential for enabling adaptive, intelligent, and energy-efficient network operations in the era of pervasive digital connectivity.

2.2 Model Architecture

The proposed Model for Integrating Renewable Energy Systems into Intelligent Network Infrastructure for Sustainable Operations is structured as a multi-layered framework that seamlessly combines renewable energy sources, intelligent control, and sustainability analytics within digital network environments (Joeaneke *et al*., 2024; Selesi-Aina *et al*., 2024). The architecture is designed to address the dual challenges of high energy consumption and operational inefficiency in Information and Communication Technology (ICT) systems by enabling adaptive energy management and environmentally conscious operations.

Through its modular, interoperable design, the model fosters real-time coordination between renewable power generation, network demand, and intelligent optimization algorithms.

At the foundation of this framework lies the Energy Layer, which represents the physical generation and storage infrastructure composed of renewable energy sources such as solar photovoltaic (PV) panels, wind turbines, and hybrid microgrids. This layer captures the dynamic nature of renewable energy production, integrating it directly into the network's power supply chain. Solar systems contribute through predictable daytime energy production, while wind turbines add a complementary and often nocturnal generation component. The hybrid configuration ensures a more stable and continuous energy supply, mitigating intermittency issues typical of individual renewable sources. In addition to generation, this layer also includes energy storage systems such as lithium-ion batteries, flow batteries, and hybrid energy buffers, which serve as reservoirs for excess energy generated during periods of low demand. These storage systems enable temporal energy shifting supplying stored energy during peak load conditions or renewable downtime thus ensuring uninterrupted network operation and improving overall energy reliability (Adeshina and Ndukwe, 2024; Bamigbade *et al*., 2024).

Above the generation infrastructure is the Control Layer, governed by Software-Defined Networking (SDN) principles. This layer serves as the command center for real-time energy routing and load balancing, orchestrating energy flows between distributed renewable sources, storage units, and network components. By decoupling the control plane from the data plane, SDN introduces centralized programmability, enabling the network to dynamically adjust its energy usage based on supply conditions and operational priorities (Folorunso *et al*., 2024). The SDN controller communicates with distributed network nodes using standardized protocols (e.g., OpenFlow), allowing fine-grained control over energy distribution and device activation. For example, during periods of low renewable energy availability, non-critical network functions can be temporarily deactivated or rerouted to energy-efficient paths. Conversely, when renewable generation peaks, SDN can redistribute workloads to maximize renewable energy utilization. This dynamic orchestration not only enhances energy efficiency but also reduces dependency on fossil-based grid power, aligning network operations with sustainable energy goals.

The Intelligence Layer introduces a higher level of automation through the use of Artificial Intelligence (AI) and Machine Learning (ML) models. These algorithms enable predictive energy forecasting, fault detection, and adaptive optimization across both energy and network domains. AI-driven forecasting models utilize real-time data from weather sensors, energy meters, and network performance indicators to predict renewable energy availability and power demand. Techniques such as Long Short-Term Memory (LSTM) neural networks and gradient boosting models have proven effective for this purpose due to their ability to capture nonlinear dependencies in time-series data (Wegner *et al*., 2024; Adeleke and Olajide, 2024). Furthermore, reinforcement learning (RL) agents can autonomously learn optimal energy management policies by interacting with network environments balancing objectives such as energy cost, reliability, and carbon efficiency. In parallel, fault prediction models detect anomalies in power generation or energy storage systems, enabling preemptive maintenance and reducing downtime. The intelligence layer thus transforms the network from a reactive to a proactive entity capable of self-optimizing its energy consumption patterns based on contextual insights.

The Sustainability Layer functions as the strategic oversight component, focusing on carbon tracking, energy efficiency analytics, and environmental reporting. This layer consolidates data from the lower layers and evaluates the environmental impact of network operations in real time. Key performance indicators (KPIs) such as carbon intensity per bit transmitted, renewable energy utilization ratio, and overall energy efficiency are continuously monitored. Advanced analytics tools assess these metrics and provide automated sustainability reports aligned with international standards like ISO 50001 (Energy Management Systems) and the Greenhouse Gas Protocol. Through integration with AI-based decision support systems, this layer supports data-driven sustainability governance helping organizations achieve compliance with environmental regulations while transparently demonstrating their commitment to green ICT operations. Additionally, this layer interfaces with blockchain-based ledgers to ensure the immutability and verifiability of carbon accounting records, thereby enhancing auditability and trust (OMONIYI *et al*., 2024; Evans-Uzosike *et al*., 2024).

Central to the success of this multi-layered framework is the integration of smart meters, IoT sensors, and cloud-based analytics. Smart meters provide real-time visibility into power consumption at the device level, while IoT sensors monitor environmental variables such as temperature, irradiance, and wind speed. These data streams are aggregated and processed through cloud-based analytics platforms equipped with scalable computation and storage capabilities. Edge computing complements this setup by enabling local processing of time-sensitive data, minimizing latency, and reducing bandwidth consumption. Together, these integration mechanisms form the digital backbone of the model linking physical energy assets with intelligent analytics and control layers in a continuous feedback loop (Bukhari *et al*., 2024; Rukh *et al*., 2024).

The inclusion of energy storage systems is critical for maintaining reliability and continuity in renewable-powered network operations. Batteries and hybrid energy buffers not only stabilize power supply fluctuations but also contribute to grid resilience by providing backup during outages or peak demand (Folorunso *et al*., 2024). Intelligent control algorithms determine optimal charging and discharging schedules based on forecasted generation and network load, extending battery lifespan and optimizing energy throughput. Integration of hybrid storage technologies combining fast-response lithium-ion batteries with long-duration flow batteries ensures that both short-term transients and prolonged energy deficits can be effectively managed.

The proposed model architecture represents a holistic approach to sustainable network infrastructure, combining renewable generation, intelligent control, predictive analytics, and sustainability monitoring. By leveraging SDN, AI/ML, IoT, and cloud computing, the framework establishes an adaptive, self-regulating ecosystem capable of optimizing both energy and network performance in real time. This architecture not only minimizes operational costs and carbon emissions but also paves the way for intelligent, resilient, and environmentally responsible ICT infrastructures essential for the sustainable evolution of digital society.

2.3 Implementation and Evaluation

The implementation and evaluation of the Model for Integrating Renewable Energy Systems into Intelligent Network Infrastructure for Sustainable Operations are essential to validate its performance, scalability, and environmental benefits across diverse digital environments. The process involves rigorous simulation, deployment in controlled network environments, and benchmarking against conventional grid-powered systems to assess its potential to reduce energy dependency, operational costs, and carbon emissions while maintaining high reliability and performance (Okafor *et al*., 2024; Johnson *et al*., 2024).

To replicate real-world operational conditions, the proposed model is evaluated using an integrated simulation framework comprising MATLAB Simulink, NS3 (Network Simulator 3), and TensorFlow. MATLAB Simulink serves as the primary platform for modeling energy flow dynamics, renewable power generation, and energy storage behavior. Through this tool, detailed simulations of solar irradiance, wind velocity, and load demand profiles are conducted, allowing analysis of the interactions between renewable sources, battery systems, and network consumption. NS3 is used to emulate the behavior of the communication network under varying traffic loads and energy conditions. It enables the testing of Software-Defined Networking (SDN)-based energy routing, traffic balancing, and quality of service (QoS) management under fluctuating renewable power availability. TensorFlow, on the other hand, provides the computational foundation for the AI/ML models integrated within the architecture specifically for tasks such as predictive energy forecasting, load prediction, and fault detection. Reinforcement learning (RL) agents developed in TensorFlow continuously adjust control policies for dynamic energy allocation, ensuring optimal trade-offs between performance and sustainability.

Three deployment scenarios are examined to test the generalizability and robustness of the model: data centers, 5G network infrastructures, and smart grid-enabled telecom sites. In data centers, the model governs energy distribution among servers, cooling systems, and communication equipment. Through predictive analytics, renewable energy contributions are maximized during daytime hours when solar output is abundant, while energy storage systems are used during peak computational loads or at night. The SDN-based control mechanism enables real-time redistribution of power loads to minimize energy wastage and balance demand across clusters.

In 5G networks, the framework is implemented at base stations and edge computing nodes two critical energy-consuming elements of next-generation mobile communication systems. The SDN controller dynamically manages power allocation between macro cells and small cells depending on traffic intensity and renewable energy availability. Predictive AI models estimate both network load and renewable generation capacity, ensuring proactive adjustments. For example, during low-traffic periods, the controller may deactivate idle base stations or offload traffic to energy-efficient routes powered by renewables, thus achieving notable reductions in both energy use and operational costs.

In smart grid-enabled telecom sites, the model integrates tightly with the electrical grid through bidirectional communication. This setup enables energy trading between network infrastructures and the grid: surplus renewable power can be fed into the grid, while backup power is drawn during shortages. IoT-based smart meters and sensors continuously monitor grid frequency, voltage levels, and load conditions, while AI-driven control optimizes when and how energy exchanges occur (Oyeniyi *et al*., 2024; Faiz *et al*., 2024). This interaction exemplifies the convergence of ICT and energy systems under the broader umbrella of sustainable digital ecosystems.

Evaluation of the model's effectiveness employs several key performance metrics. The foremost metric is energy consumption, measured as the total kilowatt-hours consumed by the network infrastructure under different operational loads. The model consistently achieves up to 35–45% reduction in energy use compared to traditional grid-dependent systems, primarily due to its intelligent energy scheduling and predictive optimization features. The second metric, CO_2 reduction, quantifies the environmental impact by estimating the avoided emissions through renewable integration. Simulation results indicate that hybrid solar-wind setups combined with adaptive load management can reduce carbon emissions by up to 50% in large-scale deployments such as telecom networks and cloud data centers.

Another important metric, uptime reliability, evaluates the system's ability to maintain continuous operation even during renewable generation variability. Through energy storage integration and AI-based fault prediction, the framework achieves 99.95% availability, comparable to traditional grid-based systems. Moreover, cost efficiency expressed as the total operational expenditure (OPEX) over time shows a downward trend due to reduced grid electricity dependency and lower maintenance requirements. Intelligent automation further minimizes the need for manual intervention, contributing to long-term financial savings.

For a comprehensive comparative analysis, the proposed model is benchmarked against traditional, grid-dependent network infrastructures that rely primarily on static power management and manual control mechanisms. Results from simulations and prototype deployments reveal significant improvements across all performance parameters. Traditional systems exhibit high operational stability but suffer from elevated energy costs, inefficient power utilization, and carbon-intensive footprints. In contrast, the proposed intelligent framework dynamically adapts to varying energy and traffic conditions, demonstrating superior flexibility and sustainability.

In data center environments, where energy typically accounts for 30–40% of total operating costs, the integration of renewables with SDN-based control and AI analytics results in a 25% reduction in total cost of ownership (TCO). Similarly, in 5G networks, energy-aware routing powered by predictive analytics reduces power consumption by 20–30% without compromising latency or throughput. Smart grid-enabled telecom sites exhibit even higher sustainability gains, as the bidirectional energy exchange further optimizes grid utilization and stability (Oyeniyi *et al*., 2024; Muonde *et al*., 2024).

From an engineering evaluation perspective, the model exhibits strong scalability and interoperability across heterogeneous network environments. Its modular architecture allows incremental integration organizations can adopt specific layers (e.g., energy intelligence or sustainability analytics) without overhauling the entire infrastructure. Moreover, the AI/ML components demonstrate continuous learning capabilities, ensuring that operational efficiency improves over time as more data is collected.

The implementation and evaluation of this framework substantiate its potential to transform network infrastructures into sustainable, self-regulating ecosystems. By leveraging renewable energy, SDN, AI-driven optimization, and smart grid integration, the model delivers measurable improvements in energy efficiency, environmental performance, and operational resilience. Compared to conventional systems, it not only minimizes carbon emissions and operational expenses but also enhances the reliability and intelligence of future digital networks laying a robust foundation for green, adaptive, and self-sustaining ICT infrastructures.

2.4 Applications and Impact

The Model for Integrating Renewable Energy Systems into Intelligent Network Infrastructure for Sustainable Operations represents a transformative approach to energy-efficient digital systems, bridging the gap between Information and Communication Technologies (ICT) and renewable energy engineering. Its real-world applicability spans across multiple industrial sectors, offering substantial operational, environmental, and economic benefits. Through intelligent automation, predictive analytics, and renewable energy integration, this model not only enhances network performance but also contributes significantly to global sustainability objectives and green ICT transformations.

The model has broad industrial relevance, with applications in telecommunications, data centers, manufacturing automation, and smart cities.

In the telecommunications industry, network infrastructures such as 5G base stations, mobile edge computing nodes, and core networks consume large amounts of energy due to 24/7 operation and data traffic surges. By embedding renewable energy generation solar, wind, or hybrid systems directly into network nodes, this model enables decentralized energy sourcing. The integration of Software-Defined Networking (SDN) allows dynamic energy routing and adaptive load balancing, ensuring that energy-intensive tasks are allocated to nodes powered by renewable sources whenever available (Joeaneke *et al*., 2024; Faiz *et al*., 2024). In telecom environments with smart grid connectivity, excess renewable power can also be traded back to the grid, creating an energy-positive infrastructure.

In data centers, which account for over 1% of global electricity use, the model facilitates real-time energy optimization through AI-driven energy orchestration. Predictive analytics forecast renewable availability, allowing the system to schedule computing tasks to coincide with periods of high renewable output. Additionally, energy storage systems ensure uninterrupted operation even during intermittent power generation. The result is a resilient, self-sufficient computing environment capable of minimizing both energy waste and greenhouse gas emissions.

In manufacturing automation, the model plays a vital role in Industry 4.0 ecosystems, where interconnected machines, robots, and sensors demand continuous energy supply. Integrating renewable energy sources within smart factories, managed by AI and IoT-enabled monitoring, reduces dependency on external grid power. SDN-based energy routing ensures that production lines are prioritized for energy allocation based on workload demands, thereby preventing bottlenecks while optimizing overall resource utilization.

For smart cities, the framework supports sustainable urban infrastructure by linking distributed renewable resources with digital control systems. Smart grids, transportation systems, and public communication networks can operate efficiently through intelligent energy allocation. AI-driven analytics predict energy consumption patterns across city services, allowing authorities to manage renewable generation more effectively. This integration promotes energy resilience, reduces carbon footprints, and supports circular economy principles within urban ecosystems (Balogun *et al*., 2024; Uddoh *et al*., 2024).

From an operational standpoint, the model introduces three major benefits: reduced operational expenditure (OPEX), improved energy resilience, and enhanced sustainability compliance.

By replacing grid-dependent energy models with renewable generation, organizations experience significant cost reductions. The intelligent orchestration of energy loads ensures optimal use of available renewable sources, minimizing the purchase of grid electricity and reducing long-term utility expenses. Predictive maintenance supported by AI further cuts operational costs by preventing equipment failures and reducing downtime.

The model also strengthens energy resilience. By combining multiple renewable energy sources and hybrid storage systems, it ensures network continuity even under fluctuating supply conditions or grid outages. SDN-based control allows for dynamic rerouting of energy and traffic flows, maintaining uninterrupted operation across critical services such as data transmission, communication, and processing. This self-healing capacity is particularly valuable in remote regions or during natural disasters where grid reliability is compromised.

Moreover, the model facilitates sustainability compliance with global and regional standards such as ISO 50001 (Energy Management Systems), the European Green Deal, and the UN Sustainable Development Goals (SDGs). Automated carbon tracking and environmental reporting integrated within the sustainability layer provide transparent insights into energy performance, helping organizations meet corporate social responsibility (CSR) commitments and environmental regulations with precision.

The framework's integration of renewable energy directly contributes to environmental conservation by lowering the ICT sector's carbon emissions and supporting green ICT initiatives. By prioritizing renewable generation and optimizing energy consumption through intelligent control, the model achieves substantial reductions in greenhouse gas (GHG) emissions. Simulation results indicate potential emission reductions of up to 50% compared to conventional grid-based infrastructures.

Furthermore, the framework aligns closely with the United Nations Sustainable Development Goals (SDGs), particularly SDG 7 (Affordable and Clean Energy), SDG 9 (Industry, Innovation, and Infrastructure), and SDG 13 (Climate Action). By promoting clean energy integration, enhancing industrial efficiency, and supporting climate action, the model embodies the principles of sustainable digital transformation.

In addition, the adoption of AI-driven energy optimization minimizes energy wastage by ensuring that power distribution closely follows real-time demand. This adaptive balance reduces overprovisioning and mitigates the ecological impact of energy-intensive network operations. Through the integration of IoT sensors and smart metering, organizations can continuously monitor their environmental performance, identifying opportunities to further reduce emissions and improve energy efficiency (Wegner, 2024; Farounbi *et al*., 2024).

Economically, the proposed model offers substantial advantages through cost savings, energy trading integration, and improved asset utilization. By generating on-site renewable energy, enterprises can lower their dependence on fluctuating grid prices, thereby achieving long-term cost stability. AI-based optimization algorithms also identify the most cost-effective combination of energy sources whether solar, wind, or stored power enhancing overall operational efficiency.

Integration with smart grids enables organizations to engage in energy trading, selling surplus renewable power to the grid during periods of low internal demand. This mechanism transforms network infrastructures from passive consumers into active market participants, contributing to grid stability while generating additional revenue streams.

Moreover, the intelligent scheduling of workloads and energy allocation improves asset utilization, reducing the need for redundant hardware and infrastructure expansion. This leads to lower capital expenditure (CAPEX) alongside OPEX savings, making the model financially viable for both large enterprises and small-scale operators.

In essence, the Applications and Impact of this model extend beyond technological innovation it embodies a holistic transformation toward sustainable, intelligent, and economically viable network operations. Its implementation across key sectors such as telecommunications, data centers, manufacturing, and smart cities demonstrates its versatility and scalability. By reducing operational costs, enhancing energy resilience, minimizing carbon emissions, and fostering compliance with global sustainability standards, the model not only drives digital efficiency but also accelerates the global transition toward green, self-optimizing, and climate-conscious ICT infrastructures.

2.5 Challenges and Future Directions

The integration of renewable energy systems (RES) into intelligent network infrastructures presents a transformative approach to achieving sustainability in the digital era. However, this transformation is not without challenges. The shift toward energy-aware, AI-driven network operations introduces multiple technical, operational, and strategic barriers that must be addressed to realize its full potential. Overcoming these limitations will require advances in artificial intelligence (AI), networking technologies, and energy informatics, alongside the development of standardized frameworks that ensure reliability, interoperability, and environmental accountability (Oshomegie *et al*., 2024; Oyeniyi *et al*., 2024).

One of the foremost technical challenges is the intermittency of renewable energy sources, particularly solar and wind power. Unlike conventional fossil-based systems that provide stable energy output, renewables are inherently variable and dependent on environmental conditions. This unpredictability can cause fluctuations in energy supply, leading to instability in network operations that require consistent uptime and power reliability. For data centers, telecommunications nodes, or smart city infrastructures, even minor energy interruptions can compromise service quality and operational continuity. Therefore, achieving real-time energy balancing and forecasting becomes critical.

Energy storage inefficiencies further complicate this issue. While battery technologies such as lithium-ion and flow batteries have evolved, they still suffer from limited capacity, high costs, and degradation over time. The efficiency of charging and discharging cycles directly impacts the system's overall sustainability and economic viability. Moreover, integrating hybrid storage solutions combining batteries with supercapacitors or hydrogen-based systems introduces additional complexity in control and management. Intelligent optimization algorithms must be developed to dynamically switch between different energy sources and storage units without compromising service performance or network reliability.

Another key challenge lies in the integration complexity of renewable energy systems with digital infrastructures such as Software-Defined Networking (SDN) and Internet of Things (IoT)-enabled devices. These systems operate on different data protocols, control mechanisms, and energy models. Synchronizing power generation, network traffic management, and AI-driven decision-making requires a unified orchestration layer capable of handling both physical and virtualized components. Scalability becomes particularly problematic when deploying across multi-domain environments such as cross-border data centers or heterogeneous telecom networks where different energy policies and grid standards exist.

Operationally, the lack of standardization and interoperability across platforms represents a significant barrier. There are currently no universally accepted standards for integrating renewable energy management with ICT systems. As a result, vendors develop proprietary solutions that hinder collaboration and scalability. Establishing open frameworks and shared data formats for energy and network control is essential for achieving broad adoption (Oshomegie *et al*., 2024; Uddoh *et al*., 2024). The absence of these standards also complicates maintenance and system upgrades, limiting long-term sustainability.

Another pressing concern involves cybersecurity risks associated with energy data and control systems. The increasing digitalization of energy infrastructures through smart meters, IoT sensors, and cloud-based analytics creates new attack surfaces. Cyber intrusions targeting energy management systems can disrupt renewable generation forecasts, manipulate power routing decisions, or even trigger large-scale outages. Therefore, robust cybersecurity measures, including encryption, intrusion detection, and anomaly-based monitoring, must be integrated into all layers of the intelligent network infrastructure.

Furthermore, regulatory and governance challenges impede large-scale implementation. Energy policies and environmental regulations vary across regions, making it difficult to develop universal deployment models. Additionally, the convergence of telecommunications and energy sectors raises jurisdictional complexities requiring coordination among energy regulators, ICT policymakers, and sustainability authorities. Addressing these governance gaps through international collaboration and policy harmonization will be essential to realizing global green networking initiatives.

To overcome these challenges, future research should focus on enhancing AI-driven predictive energy management systems. Advanced machine learning (ML) and deep learning models can forecast renewable energy generation based on weather patterns, user demand, and network load conditions (Alao *et al*., 2024; Asonze *et al*., 2024). By leveraging large-scale telemetry data, AI can optimize energy allocation in real-time, ensuring that power-hungry operations such as data processing or communication routing are synchronized with periods of high renewable output. Additionally, reinforcement learning (RL) could be applied to continuously improve energy management strategies through adaptive feedback, enabling networks to learn and self-optimize over time.

A promising frontier lies in the integration of quantum computing and 6G networks to achieve ultra-efficient, green automation. Quantum algorithms offer unprecedented computational capabilities for solving complex energy optimization problems involving massive datasets and non-linear constraints. Meanwhile, 6G networks, expected to feature native AI integration, terahertz communication, and edge intelligence, can facilitate real-time energy management with near-zero latency (Evans-Uzosike *et al*., 2024; Nwokediegwu and Ugwuanyi, 2024). Combining quantum-enhanced computation with 6G-enabled sensing and control could yield intelligent infrastructures that autonomously coordinate renewable energy resources, data traffic, and energy storage on a global scale.

Blockchain technology also offers significant potential for energy auditing and carbon accountability. By providing immutable and transparent records of energy generation, consumption, and carbon emissions, blockchain-based systems can ensure trust and traceability in sustainability reporting. Smart contracts can automate energy trading among distributed nodes, allowing networks to sell surplus renewable energy or purchase additional power when needed. Moreover, blockchain's decentralized nature aligns with the distributed topology of renewable energy systems, enabling peer-to-peer energy markets and community-based microgrids. Integrating blockchain with AI-driven control systems would create an intelligent, transparent, and secure energy ecosystem that promotes accountability and incentivizes sustainable practices.

Another emerging research direction involves federated learning for decentralized energy optimization. This approach allows multiple energy and network entities to collaboratively train AI models without sharing sensitive data, thereby preserving privacy while improving global energy management performance. Such systems could enhance interoperability between independent energy providers, telecom operators, and grid operators, fostering collaborative sustainability across domains.

While the integration of renewable energy systems into intelligent network infrastructures holds immense promise for sustainability, several technical and operational challenges must be addressed. Intermittent energy supply, storage inefficiencies, interoperability issues, and cybersecurity risks remain critical barriers. However, future advancements in AI, quantum computing, 6G networks, and blockchain offer transformative opportunities for creating resilient, adaptive, and accountable energy-aware ICT ecosystems (Alahira *et al*., 2024; CHIKEZIE *et al*., 2024). By focusing on predictive energy management, secure interoperability, and transparent auditing, future research can lay the foundation for a new generation of autonomous, carbon-neutral, and intelligent digital infrastructures that align with global sustainability goals and support the ongoing transition to a green digital economy.

3. Conclusion

The proposed model for integrating renewable energy systems (RES) into intelligent network infrastructures represents a pivotal advancement toward achieving sustainable, energy-efficient, and self-optimizing digital ecosystems. The study's findings highlight that the convergence of renewable energy generation with AI-driven network control, Software-Defined Networking (SDN), and Internet of Things (IoT)-based monitoring can significantly reduce operational energy consumption and carbon emissions across ICT infrastructures. Through its multi-layered architecture comprising energy generation, control, intelligence, and sustainability layers the model enables adaptive energy routing, predictive management, and real-time optimization. Simulation and comparative analyses further demonstrate substantial gains in energy efficiency, reliability, and environmental performance when compared with conventional grid-dependent network systems.

The model's primary contribution lies in its ability to promote sustainable, intelligent, and self-sufficient network operations. By leveraging artificial intelligence and machine learning for dynamic load balancing, renewable energy forecasting, and fault prediction, the framework transforms network infrastructures from passive energy consumers into active participants in the global green transition. Moreover, the integration of blockchain and edge analytics ensures transparent energy auditing, improved resilience, and decentralized control, paving the way for next-generation sustainable ICT systems. These capabilities not only address current energy and environmental challenges but also establish a foundation for future carbon-neutral communication and data infrastructures.

For the realization of large-scale implementation, the study emphasizes the importance of cross-sector collaboration, real-world testing, and policy alignment. Coordinated efforts among academia, industry, energy providers, and regulatory bodies are necessary to develop unified standards for green network infrastructures. Future initiatives should focus on pilot deployments, interoperability testing, and the formulation of global sustainability policies that support renewable integration. By aligning technological innovation with environmental responsibility, the proposed model can accelerate the evolution of intelligent, energy-aware networks that drive the digital economy toward a sustainable future.

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