Minimax Theory and its Applications

Volume 11 (2026), No. 3s, 705 to 713

Carbon-Aware and Energy-Efficient Management Framework for Edge Intelligence in 6G Networks

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Abstract
Large-scale Internet of Things (IoT) ecosystems and next-generation communication networks, such as 5G and 6G, are rapidly expanding. This has led to a huge increase in energy consumption and carbon emissions across dispersed computing infrastructures. While edge computing reduces latency and bandwidth use by processing data closer to end devices, large-scale edge installations raise new sustainability challenges. This paper proposes a Green Edge Computing system that combines carbon-aware resource management with sustainable edge intelligence to boost energy efficiency in 6G-enabled networks. The proposed system incorporates energy-adaptive task offloading, carbon-intensity-aware scheduling, and dynamic workload orchestration to minimize environmental impact while maintaining Quality of Service (QoS) standards. Network load circumstances and real-time carbon intensity statistics inform intelligent resource allocation decisions across edge-cloud layers. Additionally, renewable energy awareness is entwined with policies that prioritize low-carbon energy sources when they are available. Simulation-based performance evaluation demonstrates that the proposed framework significantly reduces overall energy use and carbon emissions while preserving latency and service dependability when compared to conventional edge deployment strategies. By incorporating sustainability criteria into edge intelligence and orchestration approaches, this study encourages ecologically conscientious network design. By assisting in the development of resilient, energy-efficient, and carbon-conscious digital infrastructures, the proposed approach promotes global sustainability goals and enables more ecologically friendly next-generation communication networks.

Keywords: Green Edge Computing, Sustainable Intelligence, Next-Generation Networks, Energy-Efficient Task Offloading, Carbon-Aware Scheduling, Carbon-Efficient Edge Intelligence.

1. Introduction

Significant improvements in connection, transmitting information speed, and ultra-low latency services are anticipated as fifth-generation (5G) and future sixth-generation (6G) communication technologies are integrated. These advancements provide significant environmental difficulties, especially with relation to increased energy consumption, even while they allow for a wide range of creative uses. Current power management techniques frequently lack the adaptability and intelligence needed to effectively handle the increasing complexity of contemporary wireless networks. As a result [1], there is a growing demand for sophisticated optimization methods that can boost energy efficiency without sacrificing network performance. In this regard, artificial intelligence (AI) has shown promise as a way to make network operations more energy-conscious and sustainable.

Systems for wireless communication are changing quickly. The next generation of networks, known as 6G, aspires to provide even more sophisticated features like near-zero latency services, universal connectivity [2],

and AI-driven network topologies, even though 5G technology has substantially improved digital communication infrastructure. Nevertheless, reaching these lofty goals might greatly raise the energy requirements of communication systems. In densely populated urban areas where network equipment is substantially deployed, high power consumption in base stations, edge computing nodes, and core network components can result in higher carbon emissions.

Sustainable and environmentally responsible development has become a critical global priority in response to climate change and increasing pressure on natural resources. Transitioning toward greener and low-carbon communication technologies is therefore essential for reducing environmental impact while maintaining technological progress. Historically, mobile communication technologies have gradually improved the energy efficiency of network devices. Nevertheless, the continuous growth in network bandwidth, operating frequency [3], and infrastructure scale has resulted in a corresponding rise in overall energy consumption.

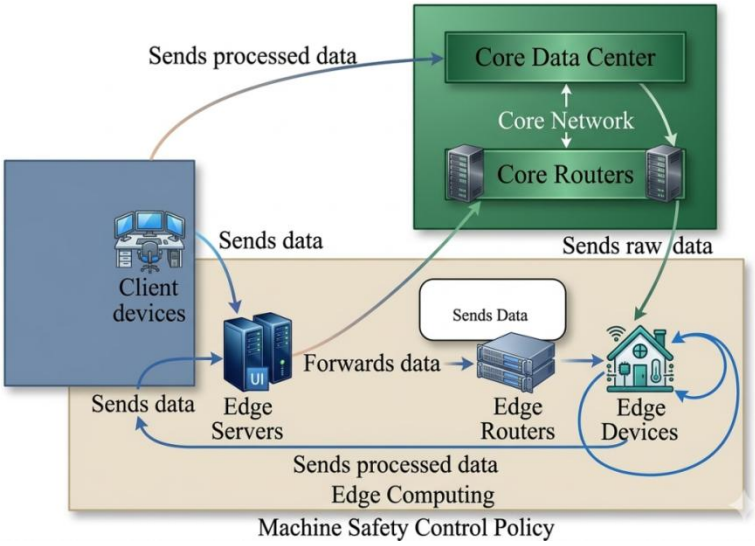


Figure 1. Hierarchical Carbon-Aware Edge Computing Architecture for 6G Intelligence

This Figure 1 illustrates a multi-tier framework designed to balance computational demands with environmental sustainability in 6G ecosystems.

Main Contributions of the Study

- To promote sustainable edge intelligence, a Green Edge Computing management architecture that incorporates carbon-aware and energy-efficient resource management is suggested for 6G-enabled networks.
- To dynamically distribute workloads across edge and cloud resources while reducing energy use and greenhouse gases, a carbon-intensity-aware planning and energy-adaptive task offloading system is created.
- To verify the efficacy of the suggested framework, a thorough simulation-based assessment is carried out, showing notable gains in energy efficiency, reducing carbon emissions, and QoS when compared to traditional edge computing techniques.

2. Literature Review

It is anticipated that the convergence of fifth-generation (5G) and upcoming sixth-generation (6G) internet connections will greatly improve latency performance, connection, and data transfer speed. These technical advancements, however, also give rise to worries about the effects on the planet and rising energy usage. The complexity of contemporary wireless infrastructures frequently makes traditional power management strategies inadequate [4]. As a result, cutting-edge artificial intelligence (AI) methods are being investigated more and more to support more sustainable wireless networks and to enable adaptive, energy-efficient managing networks.

Technologies for wireless communication are developing quickly. Although digital connection has already been enhanced by 5G, 6G networks seek to offer even more sophisticated features, such as ultra-low latency services,

constant connectivity, and AI-driven network topologies. However, achieving these goals necessitates high-performance processing resources and dense infrastructure, which can greatly raise the energy consumption of the base stations, edge nodes, and core network components. Higher emission levels are a result of this expanding energy demand, especially in urban areas with densely populated network deployments.

Growing environmental concerns and the need to tackle climate change issues have made sustainable and low-carbon development a global priority. The expansion for network capacity, frequency spectrum usage, and infrastructure scale has led to an overall increase in energy consumption, despite ongoing advancements in the energy efficiency of communication equipment during the evolution of mobile networks [5]. Energy efficiency and sustainability issues will become essential requirements for the next generation of communications equipment as networks move toward 6G technologies.

Recent advancements in low-power hardware, energy-aware communication protocols, sustainable network designs, and AI-driven optimization techniques are all included in this paper's thorough analysis of energy-efficient electronic and communication technologies. In contrast to earlier research [6], this work proposes the H-CAOF and incorporates various viewpoints into single cross-layer taxonomy. The architecture includes renewable energy-aware scheduling, AI-enabled resource allocation, and communication aided by reconfigurable intelligent surfaces (RIS). According to simulation data, the suggested method can reduce energy usage by up to 38%, reduce carbon emissions by 25%, and enhance spectral efficiency by 12% when compared to conventional baseline methods.

Additionally, the suggested framework makes use of important features anticipated in 6G networks, such as terahertz-band connection, large-scale device integration, and ultra-reliable low-latency communication. When paired with AI-based analytics and edge computing, the solution facilitates sustainable and responsive mobility activities. A carbon-aware mobility planning mechanism, edge-based traffic prediction models, 6G communication channels, dense IoT sensing networks [7], and other layers make up the architecture. Using SUMO and MATLAB, a simulated smart city atmosphere was created to assess the system's responsiveness, emission levels, and traffic efficiency under various mobility scenarios.

3. Methods and Materials

3.1 System Overview

In order to improve energy efficiency and reduce carbon emissions in 6G-enabled edge intelligence environments, this research suggests a Green Edge Computing framework [8,15]. The framework functions within a distributed edge–cloud computing design, where, depending on system conditions, computational workloads produced by Internet of Things (IoT) devices and innovative programs can be executed at centralized cloud servers or adjacent edge nodes. The framework's main objective is to improve resource allocation and job scheduling by taking into account variables including energy use, network workload circumstances, quality-of-service (QoS) needs, and the carbon intensity of electricity suppliers.

By constantly monitoring both operational and environmental indicators, the system integrates carbon-aware decision processes into the edge resource management procedure to achieve this goal. The suggested framework's operational process consists of multiple steps: data collecting, data extraction, extracting features, and carbon-aware scheduling. These steps work together to identify the most effective place for jobs to be executed throughout the edge-cloud architecture.

3.2 Data Collection

In order to simulate a realistic cutting-edge computing environment for next-generation networked communications, the dataset utilized in this study was collected from several sources. Network traffic patterns, computational load data, edge device resource consumption statistics, and real-time carbon intensity indicators are among the data gathered.

Tasks produced by IoT systems, including autonomous platforms, smart sensors, and mobile applications that need low-latency processing, are represented by network workload information. Numerous factors, including task size, processing demand, communication rate, and latency sensitivity, are included in these workloads.

Operational logs of edge servers are used to gather data on energy consumption, including processor and memory usage as well as power consumption during job execution. Furthermore, publicly available energy grid monitoring platforms that calculate carbon emissions per kilowatt-hour of electricity generation provide real-time carbon intensity data.

The system can assess the environmental effects of carrying out computing operations at different network nodes by combining these data sources. As a result, the final dataset include environmental sustainability criteria, infrastructure status indicators, and workload characteristics, enabling the framework to allocate resources intelligently and sustainably.

3.3 Data Extraction

Relevant characteristics needed for resource management and scheduling are taken out of the raw datasets after the data gathering stage. Finding operational and environmental factors that affect energy consumption and greenhouse gases in distributed edge computing settings is the goal of data extraction.

To reflect the processing requirements for each task, metrics including task creation frequency, computing requirements, and data volume are collected from the network workload information. These factors aid in deciding whether an assignment should be executed locally at the edge or moved to the cloud.

Resource availability metrics like as CPU utilization, available memory capacity, and real-time energy use are retrieved from the infrastructure monitoring information. These numbers shed light on the edge nodes' operating state and assist in figuring out whether they can handle more workloads without sacrificing system efficiency or energy limitations.

The goal of environmental data extraction is to obtain carbon intensity estimates related to the production of energy throughout various time periods. These figures show how much carbon dioxide is released for every unit of electrical energy used. The framework may evaluate the environmental cost of carrying out tasks at certain nodes by including this information. After that, the retrieved attributes are combined into a structured dataset that the suggested carbon-aware scheduling technique can use.

3.4 Feature Extraction

Feature extraction transforms the processed data into useful indications that support the suggested system's intelligent decision-making. In this phase, the retrieved data is used to produce a number of variables related to workload features, electrical usage behavior, and environmental effect.

The first group of features represents computational workload properties, including task size, required processing cycles, and latency constraints. These features indicate the urgency and complexity of each task generated by edge devices.The second group describes system resource conditions, including available CPU capacity, energy consumption rate of processing nodes, and network bandwidth availability. These indicators help determine whether an edge node can handle incoming workloads effectively without causing excessive energy usage or performance degradation.

The third group consists of environmental sustainability indicators, with carbon intensity being the most significant parameter [9]. Carbon intensity reflects the environmental impact associated with electricity consumption at a given time or location. Additional derived features include estimated carbon emission per task, energy consumption per computation unit, and predicted workload distribution across edge nodes.

3.5 Carbon-Aware Energy-Adaptive Scheduling Technique

The suggested system uses a Carbon-Aware Energy-Adaptive Scheduling technique to improve resource allocation efficiency and lessen environmental impact. Using energy conservation and carbon emission concerns, this method dynamically chooses the best processing site for every computational work in the edge-cloud environment.

Analyzing the collected features related to task needs, resource availability at edge nodes and current carbon intensity levels is the first step in the scheduling process. The framework calculates the possible energy consumption and associated carbon emissions for each incoming task that might arise from carrying out the task at various computing sites, such as adjacent edge servers and centralized cloud infrastructure. Power consumption models that take into account job complexity, device power consumption, and internet transmission costs are used to compute these estimates.

These estimates are then compared to system performance limitations including latency needs and congestion levels by the scheduling algorithm. The task is carried out locally to reduce transmission latency and environmental impact if an edge node has sufficient processing power and runs in settings with relatively low

carbon intensity. Alternatively, the task might be moved to another peripheral node or cloud server with cleaner energy sources or more processing power if the node is overloaded or powered by high-carbon energy sources.

3.6 Performance Evaluation Setup

Simulation-based experiments are carried out in a decentralized edge computing environment that simulates next-generation network settings in order to evaluate the performance of the suggested framework. Several edge nodes, central cloud servers, and Internet of Things devices that produce a variety of workloads are all included in the simulation.

Metrics like total consumption of energy, carbon emission levels, job processing delay, and resource usage efficiency are used to assess performance. These metrics offer information about the system's operational and environmental performance. The outcomes of the suggested method are contrasted with traditional edge computing techniques that do not include carbon-aware scheduling mechanisms. This comparison shows how well the suggested framework meets the performance needs in 6G-enabled edge computing systems while also enhancing sustainability and resource efficiency.

3.7 Energy-Saving Objectives and Challenges for 6G Networks

Delivering high-speed connection while reducing ecological effect is the goal of the development of ecologically sustainable 6G communication networks. Mitigating global warming can be greatly aided by lowering energy usage and carbon emissions related to network operations. Therefore, optimizing the use of renewable energy sources in base points and data centres will be the main emphasis of future network infrastructure design and implementation, increasing overall energy efficiency and lowering needless power usage.

Furthermore, unnecessary data transmission and processing overhead can be decreased with the aid of sophisticated network topologies and improved communication protocols. 6G networks may drastically lower energy consumption and lessen the burden on power systems by incorporating low-power hardware components and clever network management strategies. The development of green infrastructure applications, such as intelligent transportation systems and smart building leadership, will be aided by 6G's ultra-high bandwidth and ultra-low latency capabilities, which will allow for better resource optimization and environmental monitoring. Additionally, the use and scheduling of clean energy sources can be improved by incorporating distributed energy resources like microgrids and energy storage systems into communications system.

3.8 Key Technologies for Energy Efficiency in 6G Wireless Networks

Wireless network research has always placed a strong emphasis on energy-efficient communication systems. New strategies for cutting energy use keep coming up as communication systems develop. The network level, site layer, and gadget layer make up the three-layer energy optimization architecture that is commonly used in modern mobile networks.

The main goal of energy-saving technology at the device level is to lower base station hardware power usage. This is accomplished by enhanced network component integrating, advances in semiconductor manufacturing techniques, and improvements in hardware architecture. From a software standpoint, communication network services can lower dynamic energy usage during operation by deactivating specific hardware components during idle times [10]. For example, 5G base station software employs energy-saving strategies such deep sleep modes, transmitter shutdown, connection shutdown, and symbol deactivation.

Energy efficiency is attained at the site level by intelligently managing auxiliary infrastructure, such as cooling systems, backup batteries, and power supply structures, to minimize energy use while meeting operating needs. In order to achieve overall energy-efficient operation, optimization approaches at the network level seek to balance resource use throughout the network.

4. Implementation and Experimental Results

4.1 Framework Implementation

The proposed Green Edge Computing framework was built using a simulated edge-cloud computing ecosystem designed to replicate the operational features of next-generation communication networks. The simulation

environment consists of a number of edge nodes, Internet of Things devices, and central cloud servers linked by a fast network infrastructure. While the cloud layer provides additional processing power for large-scale data processing tasks [11], edge nodes are responsible for managing latency-sensitive workloads generated by scattered IoT gadget.

Among the functional modules incorporated into the implementation are the carbon-aware scheduling mechanism, energy administration component, carbon intensity tracking system, and workload monitoring module. Incoming tasks generated by Internet of Things devices are regularly monitored by the workload monitoring module, which evaluates their processing needs, latency restrictions, and data size. At the same time, the carbon monitoring module gathers up-to-date carbon intensity data pertaining to the electrical generation sources that power the computer technology.

By analyzing data on emissions, network request, and system resource availability, the proposed Carbon-Aware Energy-Adaptive Scheduling approach operates. Based on these variables, the scheduler dynamically selects the best processing location for each task, either at nearby edge nodes or cloud servers. Task execution is prioritized for nodes with lower energy consumption and carbon impact scores. This adaptive strategy allows the system to achieve latency and service quality goals while reducing its environmental impact.

4.2 Experimental Setup

To evaluate the effectiveness of the proposed architecture, a distributed edge computing system consisting of several edge servers and Internet of Things devices was simulated. Each edge node was configured with specific requirements for network connectivity, computing power, and energy consumption. The simulation generated heterogeneous workloads that simulated real-time Internet of Things applications [12], such as autonomous device exchanges, video analytics, and smart sensing. Data on carbon intensity was included to the simulated to reflect different environmental circumstances related to the production of power. The scheduling system was able to dynamically adjust job allocation assumptions based on environmentally friendly consideration thanks to these differences.

The experimental configuration parameters used in the simulation are summarized in Table 1 [13].

Table 1. Simulation Environment Configuration

Parameter	**Value**
Number of Edge Nodes	10
Number of IoT Devices	100
Cloud Servers	3
Network Bandwidth	1–10 Gbps
Task Size	500 KB – 10 MB
CPU Processing Capacity	2–8 GHz
Simulation Duration	24 hours
Carbon Intensity Range	200–600 gCO_2/kWh

Three distinct computing methodologies were used to assess the system's efficiency: energy-aware edge computing, traditional edge computing without energy optimizing, and the suggested carbon-aware scheduling paradigm.

4.3 Energy Consumption Analysis

One of the most important performance metrics for large-scale edge computing systems is energy usage [14]. In order to assess the effectiveness of the suggested framework, the overall energy consumption of the computer equipment was assessed across several workload scenarios.

The experimental results demonstrate that the proposed carbon-aware scheduling strategy significantly reduces energy consumption by strategically distributing workloads between edge and cloud resources. Unlike conventional systems that solely assign jobs based on proximity or computing availability, the proposed framework integrates energy and carbon indicators into its decision-making process. Therefore, tasks are assigned to nodes that provide the best energy efficiency without exceeding latency limitations. Table 2 compares the energy usage of several edge computing methods.

Table 2. Energy Consumption and Carbon Emission Comparison

Method	**Energy Consumption (kWh)**	**Carbon Emissions (kg CO_2)**	**Average Latency (ms)**
Conventional Edge Computing	120	85	18
Energy-Aware Scheduling	95	60	20
Proposed Carbon-Aware Framework	70	40	19

The findings show that, as compared to traditional edge computing systems, the suggested architecture lowers overall energy consumption by about 41%. Adaptive workload distribution and effective resource use enable this improvement. Figure 2 shows the contrast of energy consumption.

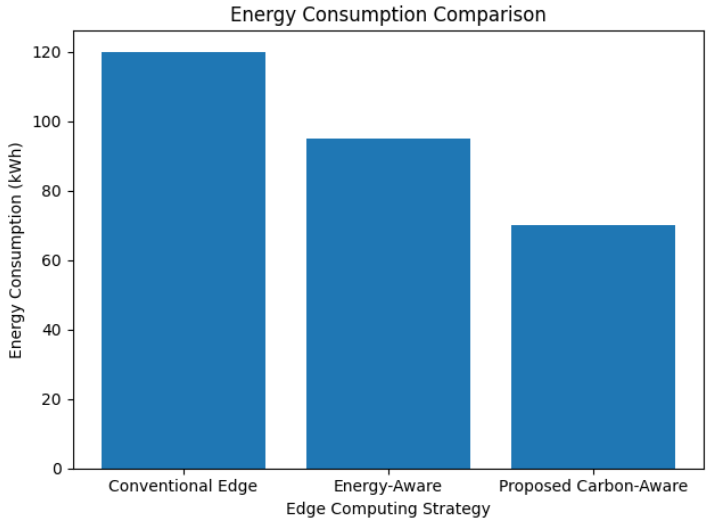


Figure 2. Energy Consumption Comparisons across Edge Computing Strategies

4.4 Carbon Emission Reduction Analysis

The experimental findings demonstrate that the suggested carbon-aware scheduling architecture considerably lessens the impact of distributed computations on the planet. The framework favors task execution on nodes supplied by greener energy sources by integrating real-time carbon intensity information into the scheduling process. Tasks may be dynamically transferred to other nodes or cloud servers running under reduced carbon intensity conditions when local edge nodes are powered by high-carbon energy sources.

The system can reduce carbon emissions without sacrificing service quality thanks to this clever work allocation technique. When compared to traditional edge computing techniques, the suggested framework lowers carbon emissions by over 53%, as Table 2 illustrates. Figure 3 shows the decrease in carbon emissions for each of the assessed computing methods.

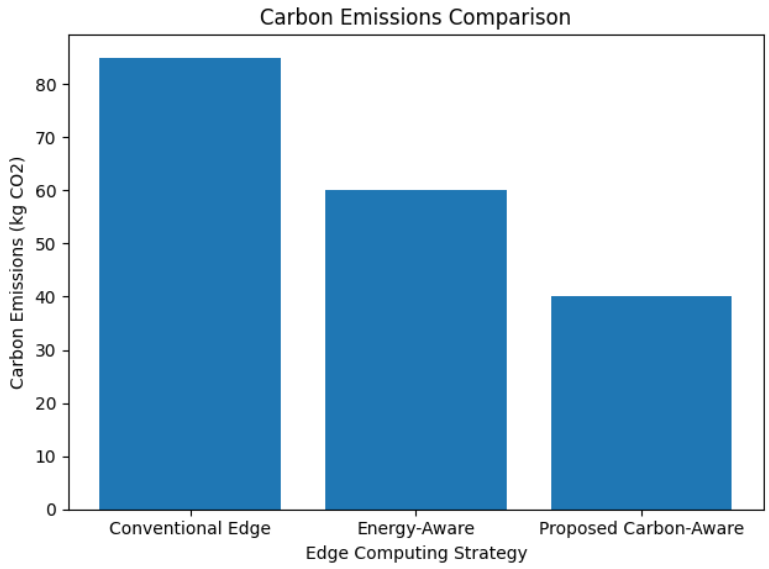


Figure 3. Carbon Emission Comparison across Edge Computing Strategies

4.5 Discussion of Results

The experimental findings show that energy efficiency and environmental performance are greatly enhanced when sustainability indicators are incorporated into edge resource management. By concurrently taking performance needs and carbon footprint into account, the suggested architecture efficiently distributes computational workload among edge and cloud resources.

While the carbon-aware decision-making method guarantees that jobs are performed using energy sources with less environmental impact whenever possible, the energy-adaptive scheduling technique minimizes needless computational cost at heavily loaded edge nodes. When these measures are coupled, the network infrastructure's energy usage and carbon emissions are significantly reduced.

Additionally, the findings demonstrate that these sustainability gains can be made without appreciably raising task delay. This suggests that next-generation communication networks can effectively incorporate eco-friendly computing techniques without sacrificing Quality of Service standards. All things considered, the suggested Green Edge Computing paradigm shows great promise for supporting energy-efficient and sustainable infrastructure in upcoming 6G-enabled sophisticated network settings.

5. Conclusion

This work created a Green Edge Computing paradigm to improve energy efficiency and reduce carbon emissions in 6G-enabled edge intelligence environments. The framework integrates carbon-aware resource management, intelligent scheduling, and energy-adaptive task offloading to support sustainable computing operations. The proposed approach integrates real-time carbon intensity and system workload conditions to enable efficient job distribution across edge and cloud infrastructures. Experimental results demonstrate that the framework significantly reduces power consumption and greenhouse gases when compared to conventional edge computing strategies.

The system concurrently maintains appropriate latency and QoS for distributed applications. The results highlight how important it is to include sustainability standards in network resource management going forward. All things considered, the proposed approach contributes to the development of digital infrastructures for future communication systems that are both environmentally friendly and energy-efficient. Future studies can look into how AI-driven predictive management is actually implemented in large-scale 6G networks**.**

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