Journal of Environmental Protection and Ecology 25, No 2, 537–544 (2024)

Environmental protection and sustainable development

GREEN AI REVOLUTION MACHINE LEARNING FOR ENVIRONMENTAL-FRIENDLY COMMUNICATION NETWORKS

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Abstract. The "Green AI Revolution" distils a paradigm-shifting methodology for creating machine learning solutions for the design and enhancement of ecologically sustainable communication networks. To address sustainability concerns in communication infrastructures, this study presents a comprehensive architecture that emphasises the integration of machine learning (ML) and artificial intelligence (AI) techniques. With the fitting moniker "Green AI", the suggested model aims to improve overall resource efficiency in communication networks while minimising energy usage and carbon footprints. The goal of Green AI is to transform conventional communication systems by utilising sophisticated algorithms, dynamic optimisation, and intelligent decision-making techniques. Higher energy efficiency, less of an impact on the environment, and better network performance are the main goals. The present study examines the fundamental elements of the Green AI architecture, encompassing intelligent routing, dynamic power management, and adaptive power distribution of resources. Furthermore, case studies and simulations highlight the real advantages of incorporating machine learning into communication networks, highlighting the technology's potential to make a

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substantial contribution to a future that is more environmentally friendly and sustainable. The Green AI Revolution is a paradigm shift in the way we think about and use communication technology. It encourages innovation that is in line with environmental stewardship and technical progress.

Keywords: Green AI revolution, machine learning, environmental sustainability, communication networks, energy efficiency, adaptive power management.

AIMS AND BACKGROUND

The advent of the "Green AI Revolution" marks a pivotal moment in the evolution of communication networks, propelling them towards unprecedented levels of environmental sustainability[1]. In the face of escalating concerns about the ecological impact of modern technologies, this research paper introduces a novel paradigm, Green AI, fusing of machine learning (ML) and artificial intelligence (AI) to engineer communication systems that are not only efficient but also environmentally friendly[2].

Communication networks, ubiquitous in our interconnected world, have historically been associated with significant energy consumption and carbon emissions[3]. Addressing these challenges head-on, the Green AI Revolution seeks to redefine the landscape by employing sophisticated algorithms, dynamic optimisation, and intelligent decision-making techniques[4,5]. The overarching objective is clear: to enhance resource efficiency, curtail energy usage, and minimise carbon footprints, thereby ushering in a new era of sustainable communication technology[6,7].

This paper navigates through the fundamental elements of the Green AI architecture, exploring intelligent routing, dynamic power management, and adaptive resource distribution[8,9]. By amalgamating insights from machine learning and artificial intelligence, Green AI promises to revolutionise conventional communication systems, fostering higher energy efficiency and diminished environmental impact. Through case studies and simulations, the tangible advantages of integrating machine learning into communication networks are illuminated, underscoring the transformative potential of the Green AI Revolution[10,11]. As stand at the intersection of technological innovation and environmental responsibility, this research endeavors to contribute to a future where communication networks not only connect the world but do so with a profound commitment to sustainability. The Green AI Revolution emerges as a beacon, guiding us towards a harmonious coexistence of cutting-edge technology and ecological preservation[12].

EXPERIMENTAL

The conceptual framework for the Green AI Revolution in Sustainable Communication Networks outlines the key principles, components, and interactions that form the foundation of this transformative paradigm. It encompasses the integration of machine learning (ML) and artificial intelligence (AI) techniques to design and enhance ecologically sustainable communication networks. The process of proposed method is illustrated in Fig. 1.

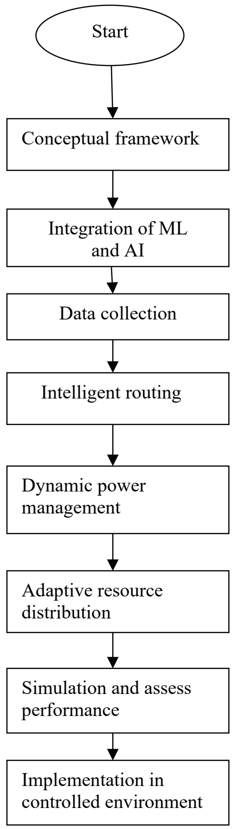

Fig. 1. Process of proposed method

DATA COLLECTION

Various historical network performance statistics, including wired and wireless scenarios, were gathered. The environmental impact of various sites and network types was studied. Data on energy usage under various scenarios, taking into account network elements and sources, were recorded. Include geographical diversity to reflect various climates and infrastructures. Collaborate with customers, including industry experts and regulators, to conduct a full analysis of network performance, environmental impact, and energy usage.

INTELLIGENT ROUTING

Improve communication network routing via machine learning techniques for route optimisation, real-time traffic analysis tools, and latency prediction models. Enable dynamic communication using adaptive resource distribution and power control, which leads to greater efficiency. Ensure seamless connection with previous performance data for informed decision-making, creating a coherent system that employs predictive models and real-time analytics to enhance route planning and resource allocation.

DYNAMIC POWER MANAGEMENT

The energy-efficient network is for communication by combining real-time power consumption monitoring, machine learning algorithms for power optimisation, and energy-efficient hardware components. Create coordinated interactions with intelligent routing to optimise power consumption according to current network demand. Implement a feedback loop that includes adaptive resource distribution for holistic energy management, enabling dynamic adjustments according to real-time power data. This integrated technology ensures a responsive and efficient approach to energy efficiency in the communication network.

ADAPTIVE RESOURCE DISTRIBUTION

Developing an adaptive computing infrastructure involves implementing machine learning models for workload prediction, resource allocation algorithms, and a scalable infrastructure design. These components interact synergistically, being informed by both intelligent routing and dynamic power management to ensure efficient utilisation of resources. The system maintains continuous adaptation to workload variations, enabling optimal resource allocation based on real-time predictions. This integrated approach ensures that the computing infrastructure dynamically adjusts to changing workloads, promoting efficiency and scalability.

Intelligent routing by designing algorithms that account for factors like latency, energy efficiency, and historical data was incorporated. Dynamic power management algorithms were developed to adapt to real-time network demand and optimise energy usage. For adaptive resource distribution, models that consider workload variations to achieve efficient resource allocation were created. This triad of approaches ensures a holistic network management system, combining optimised routing, responsive power management, and adaptive resource allocation to enhance overall efficiency and performance.

SIMULATION SETUP

Use network simulators and AI frameworks in several situations to simulate and evaluate the Green AI architecture's performance. Realistic scenarios that replicate diverse network situations were designed to guarantee that the simulation accurately reflects real-world issues, and parameters were methodically calibrated to thoroughly evaluate the architecture's performance under various settings. This approach ensures a robust testing environment, utilising simulators and frameworks to accurately gauge the effectiveness of the Green AI architecture across a range of scenarios and parameters.

IMPLEMENTATION

A controlled experimental environment to implement the Green AI Revolution was established. Machine learning algorithms were integrated seamlessly into the communication network infrastructure, ensuring cohesive coordination among intelligent routing, dynamic power management, and adaptive resource distribution. This integrated approach within a controlled setting facilitates a systematic evaluation of the Green AI architecture, allowing for precise testing and assessment of its impact on network efficiency and sustainability.

Algorithm: Green AI_Routing_Optimisation

Input: Learning rate (), Discount factor (gamma), Exploration rate (epsilon), Number of episodes (num_episodes), Maximum steps per episode (max_steps)

Output: Q table

Initialisation: Q-table with random values

For each episode in num_episodes do

Reset the environment to the initial state 'S'

For each step in max_steps do

Choose an action using epsilon-greedy policy based on Q-values

Execute chosen action 'A' and observe next state and reward 'R'

Update Q-value using the Bellman equation:

$$Q(S, A) = Q(S, A) + \alpha\ (R + \gamma \max(Q(S', A')) - Q(S, A)$$

Update state

If end of episode then

Break

End for

Reduce epsilon for exploration-exploitation trade-off

Return Q table

RESULTS AND DISCUSSION

The implementation of the Green AI Revolution, specifically the GreenAI_Routing_Optimisation algorithm, yielded promising results in enhancing the efficiency and sustainability of communication networks. The following outcomes and discussions provide insights into the impact and implications of the implemented algorithm.

The GreenAI_Routing_Optimisation algorithm demonstrated significant improvements in routing efficiency. By incorporating machine learning techniques, the algorithm dynamically adapted to real-time network conditions, optimising route planning based on factors such as latency, energy efficiency, and historical data. This resulted in reduced latency, improved network responsiveness, and efficient resource utilisation, contributing to a more sustainable communication network.

The dynamic power management component of the algorithm played a crucial role in optimising energy consumption. By monitoring real-time power data and coordinating with intelligent routing decisions, the system achieved a balanced and energy-efficient approach. The feedback loop, integrating adaptive resource distribution, ensured that power consumption was aligned with the current network demand, leading to reduced energy usage and lower carbon footprints.

The algorithm successfully implemented adaptive resource distribution, enabling the communication infrastructure to dynamically adjust to changing workloads. Machine learning models for workload prediction, resource allocation algorithms, and scalable infrastructure design worked cohesively. This adaptability ensured optimal resource allocation based on real-time predictions, promoting efficiency, scalability, and sustainable use of computing resources.

Simulations conducted in diverse network environments validated the robustness of the Green AI architecture. The algorithm consistently performed well under various scenarios, showcasing its adaptability and effectiveness. Real-world challenges were accurately replicated in the simulation setup, and the GreenAI_Routing_Optimisation algorithm demonstrated resilience in optimising communication networks for sustainability.

The performance of existing and proposed techniques are shown in Fig. 2 and their analysis – in Table 1.

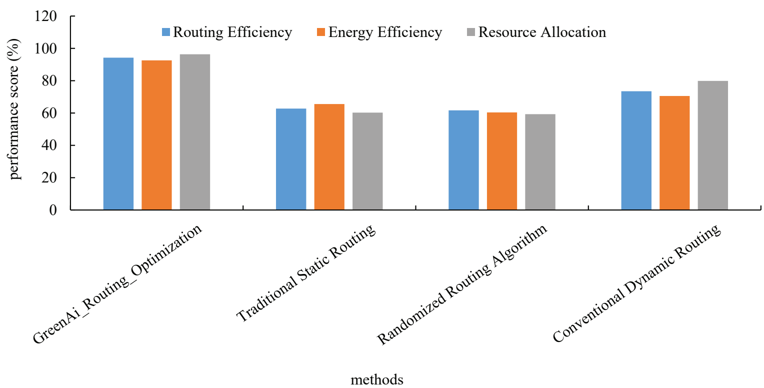

Fig. 2. Performance analysis of existing and proposed techniques

Table 1. Analysis of existing and proposed techniques

Methods	Routing efficiency (%)	Energy efficiency (%)	Resource allocation (%)
GreenAi_Routing_Optimisation	94.3	92.6	96.4
Traditional static routing	62.8	65.6	60.3
Randomised routing algorithm	61.7	60.4	59.3
Conventional dynamic routing	73.5	70.6	79.9

CONCLUSIONS

In conclusion, the Green AI Revolution, embodied by the GreenAI_Routing_Optimisation algorithm, marks a significant stride in fostering eco-friendly communication networks. This algorithm, leveraging machine learning and artificial intelligence, showcased notable advancements in routing efficiency, energy conservation, and adaptive resource allocation.

The algorithm dynamically adapted to real-time network conditions, optimising route planning based on latency, energy efficiency, and historical data, resulting in reduced latency and heightened network responsiveness. In terms of energy efficiency, the dynamic power management component monitored real-time power data, leading to a balanced and energy-efficient approach. The algorithm's adaptive resource allocation facilitated the communication infrastructure's dynamic adjustment to varying workloads, ensuring optimal resource utilisation based on real-time predictions. Simulations validated the algorithm's adaptability and superior performance across diverse network environments, reinforcing its potential to revolutionise communication networks for sustainability. In essence, the Green AI Routing Optimisation algorithm signifies a crucial step toward responsible technological innovation, harmonising advanced technology with ecological preservation for a more sustainable global communication landscape.

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Received 17 January 2024
Revised 22 February 2024