An Optimized and Energy-Efficient Approach for Smart Information Retrieval in Sustainable Next-Generation Green Networks

Program PPMI STEI 2026 Riset Kelompok Keahlian

Rila Mandala[1], Cutifa Safitri[2], Judhi Santoso[1], Dody Dharma[1], Afwarman[1], and Dicky Prima Satya[1]

1 School of Electrical Engineering and Informatics (STEI), Institut Teknologi Bandung, Bandung, 40132, Indonesia
2 School of Computer Science, Bina Nusantara University, Bandung, 40181, Indonesia

Abstract

This research critically evaluates techniques for sustainable networking in green computing, focusing on measuring and optimizing packet success rates while reducing power consumption. We conducted comprehensive study of the impact of hybridizing Reinforcement Learning with smart prefix-based mapping through information retrieval in content forwarding to optimize both network performance and energy consumption. Based on that, we build an architecture that incorporates energy considerations into the network protocol, which we call the Energy-Aware Next Generation Green Network (called EANGGN) architecture.

This architecture integrates Reinforcement Learning (RL) agent with Information-Centric Networking (ICN) forwarding and energy management modules. Results indicate that EANGGN performs up to a 55.73% reduction in energy consumption in the mobility scenario compared to traditional forwarding approaches. Additionally, the network performance analysis demonstrates promising outcomes, with an Interest Satisfaction Ratio (ISR) of 87.76% and a Packet Delivery Ratio (PDR) of 82.85%.

Keyword: Information Retrieval, ICN, NDN, RL, ISR, PDR.

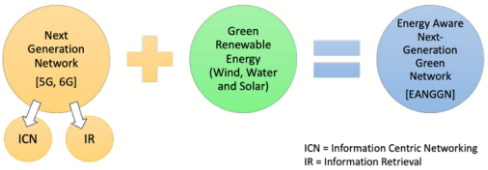
Introduction

In this research, we build Energy-Aware Next Generation Green Network (EANGGN) architecture, an ICN forwarding design that combines prefix-face Q-learning, energy-source preferences, and charge-aware eligibility. The main advantages of this architecture are as follows:

1. Energy-aware forwarding design: EANGGN incorporates energy-source category preferences into prefix–face selection scores and outcome rewards. Solar, wind, and water share a common renewable-source penalty, while fuel and battery categories receive their specified penalties. This formulation combines explicit source preferences with learned forwarding outcomes.
2. Delivery feedback and charge-aware operation: EANGGN updates the selected prefix–face entry using attributable Data, negative acknowledgment (NACK), and timeout outcomes. Charge feasibility and the declared fallback rules are checked to determine forwarding eligibility. Category costs are used in selection and reward mechanisms.
3. Evaluation: We evaluates EANGGN using architectural energy scenarios and forwarding comparisons with traditional NDN strategies, adaptive learning-based baselines, and renewable-aware greedy selection. Controlled learning variants examine selected design components, and repeated-run summaries characterize variation in energy consumption, delivery, delay, and forwarding overhead.

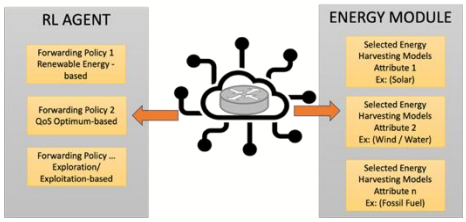
Research Method

The EANGGN architecture works on the existing ICN/NDN Content Store (CS), Pending Interest Table (PIT), and Forwarding Information Base retrieval framework. It selects outgoing faces using tabular Q-learning, source-category preferences, and charge-aware eligibility criteria. Eligibility is reset on each new trial so that the action set can adapt to changes in reachability. Controlled-change experiments evaluate affected requests, visitation, Q-values, and recovery within the given observation window. EANGGN obtains values for discrete prefix-face pairs.



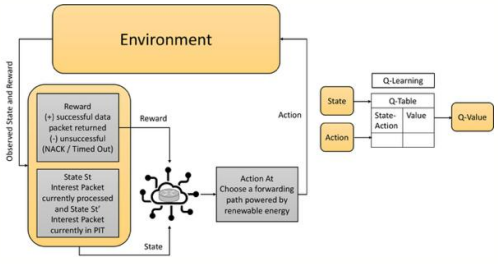
Picture 1. Reinforcement learning (RL) agent framework in energy-aware forwarding

A decision epoch occurs when a CS miss and PIT processing require a new outgoing attempt. The state is a prefix obtained through one consistently configured mapping, and the action is one currently eligible face.



Picture 2. ICN Node with RL Agent and Energy Module

After observations are refreshed and the declared physical fallback is enforced, the eligible action set is recalculated, excluding ingress and faces disallowed by NDN Forwarding Daemon (NFD) rules. Selection is ε-greedy over eligible faces: exploration samples uniformly; exploitation maximizes. The strategy balances the preference for faces of lower category cost with learned delivery outcomes. EANGGN incorporates source preference into delivery-based learning. A low-category cost can benefit a face initially, but later outcomes change its stored Q-value.

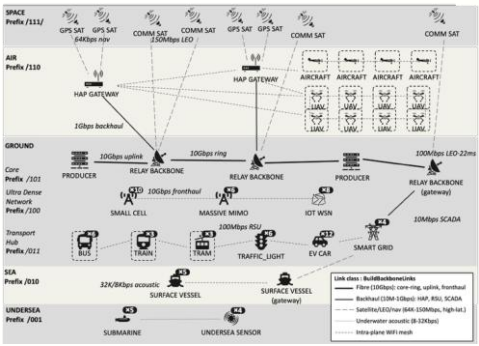


Picture 3. RL Agent Framework in the Energy-Aware Forwarding

Discussion & Result

The evaluation includes reliability and delivery, traffic and throughput, application delay and request results, and retransmission and routing efficiency. The energy dimension is provided by ledger records of energy consumption, storage, and supply. Together, these measures characterize the forwarding performance and its energy implications. The topology in Picture 4 describes node identifiers, groups, roles, prefixes, CS/FIB configuration, mobility, and source/reservoir mappings.

The improvement remarks can be summarized: EANGGN achieves a higher Interest Satisfaction Ratio (87.76% compared to 85.85% for Best-Route, 85.37% Multicast, 83.48% SDN-Qache, 76.43% Cache-MAB), a higher Packet Delivery Ratio (82.85% compared to 80.13%, 79.38%, 77.29%, 67.59%), a lower NACK rate (14.31% compared to 17.01%, 17.90%, 22.65%, 26.45%), and a lower timeout rate (12.24% compared to 14.15%, 14.63%, 16.52%, 23.57%) than Best-Route, Multicast, SDN-Qache, and Cache-MAB, respectively.



Picture 4. Heterogeneous ISAGUN simulation topology with domain-labeled node groups

Conclusion and Future Work

The proposed EANGGN architecture integrating the ICN, reinforcement learning, and renewable energy sources has the potential to enhance energy efficiency and sustainability in future next-generation network environments. Simulation results demonstrate that the proposed EANGGN, can achieve high performance in reducing energy consumption, which lays the foundation for greener future networks.

In this research, we assume that the energy source, the cost, and the State-of-Charge of each face are accurately communicated through the neighboring nodes. Future work may include cross-validation of a node's suggested State-of-Charge path with its recorded forwarding/energy-consumption history (anomaly detection), or adding a small trust/reputation element to the reward function, so that a node's history of NACKs/timeouts partially reduces unreliable neighbors' impact.