RAA-DRL: Renewable-Aware AI-Driven Resource Allocation for Green Communications and Energy-Efficient Wireless Networks

K. Ramash Kumar[1], S. Padma[2]
[1]Department of Electrical and Electronics Engineering, Dr.N.G.P.Institute of Technology Coimbatore, Tamilnadu, India
[2]Professor, EEE, Sona College of Technology, Salem-5

Article Info

Article History:
Received Jul 13, 2025
Revised Aug 10, 2025
Accepted Sep 03, 2025

Keywords:
Renewable-aware communications
Deep reinforcement learning
AI-driven resource allocation
Energy-efficient wireless networks
Green communications

ABSTRACT

The continual rise in the demand for greater capacity from such systems has evoked concern regarding energy consumption and ultimately, an environmental impact. Traditional resource allocation methods generally prioritize performance and overlook the unpredictability of renewable energy; therefore, such methods could lead to waste and the use of non-renewable resources. To help tackle these aspects, this paper offers RAA-DRL (Renewable-Aware AI-Driven Resource Allocation), an innovative framework for optimizing network performance while incorporating green energy. RAA-DRL utilizes deep reinforcement learning (DRL) to allocate resources in real-time, based on the current traffic and available level of renewable energy. Unlike static methods, the DRL-based system will learn dynamically from historical traffic and renewable generation data regarding long-term energy efficiency, throughput and spectral efficiency. The simulation results show that RAA-DRL can deliver significant improvements in energy efficiency and QoS compared to conventional schemes. It can reduce the reliance on the grid and continue to support high network performance, serving as an example of what AI technology can offer for sustainable communications. This research contributes to the establishment of green communication technologies through a scalable, adaptive, and renewable-aware approach to future wireless networks. Ultimately, RAA-DRL enables viable, sustainable, performance oriented networks for the future 6G and IoT systems.

Corresponding Author:

K. Ramash Kumar,
Department of Electrical and Electronics Engineering, Dr.N.G.P.Institute of Technology Coimbatore, Tamilnadu, India.

1. INTRODUCTION

In the past ten years, wireless communication technologies have grown rapidly. Wireless networks can no longer keep up with the rapid uptake of mobile devices, cloud services and Internet of Things (IoT) applications. These technologies demand higher data rates, lower latencies, and seamless connectivity [1]. These demands will only accelerate with the introduction of 6G networks, which will provide the backbone for future smart cities, autonomous systems, and immersive applications (e.g., augmented and virtual reality). As rapid advancements are expected to provide tremendous benefits both socially and economically, the demand for energy in wireless infrastructures is also expected to increase significantly [2].

The Information and Communication Technology (ICT) industry is already regarded as one of the fastest-growing utilizers of global energy and one of the fastest-growing contributors to greenhouse gas emissions. Base stations, core networks, and data centers use enormous amounts of electricity, much of which is still derived from fossil fuels [3]. If left unaddressed, rising energy consumption could greatly impede global sustainability goals and necessitates green communication to be included in next-generation wireless systems to prioritize energy efficiency as well as performance [4].

Resource allocation in wireless networks has traditionally utilized resource allocation techniques like spectrum scheduling, power control, and load balancing with a performance-centered view. The primary purpose has been geared toward maximizing throughput, providing fairness among users, or minimizing latency. While these methods can satisfy user requests temporarily, they overlook the fluctuating availability of renewable energy, thus misusing sustainable resources and relying too much on the grid power source [5]. This can subsequently increase operational costs for network operators and does not support the goal of establishing an environmentally-friendly communication system [6].

To address this issue, there is a rising interest in combining renewable energy sources such as wind or solar, into wireless networks. However, renewable energy is by its nature variable and stochastic, and hence challenging to depend on for static allocation methodologies. A solution will need to adapt to both the variability of renewable energy generation, as well as the variability of users' traffic demands [7]. Figure 1 shows an overview of AI for green wireless networks.

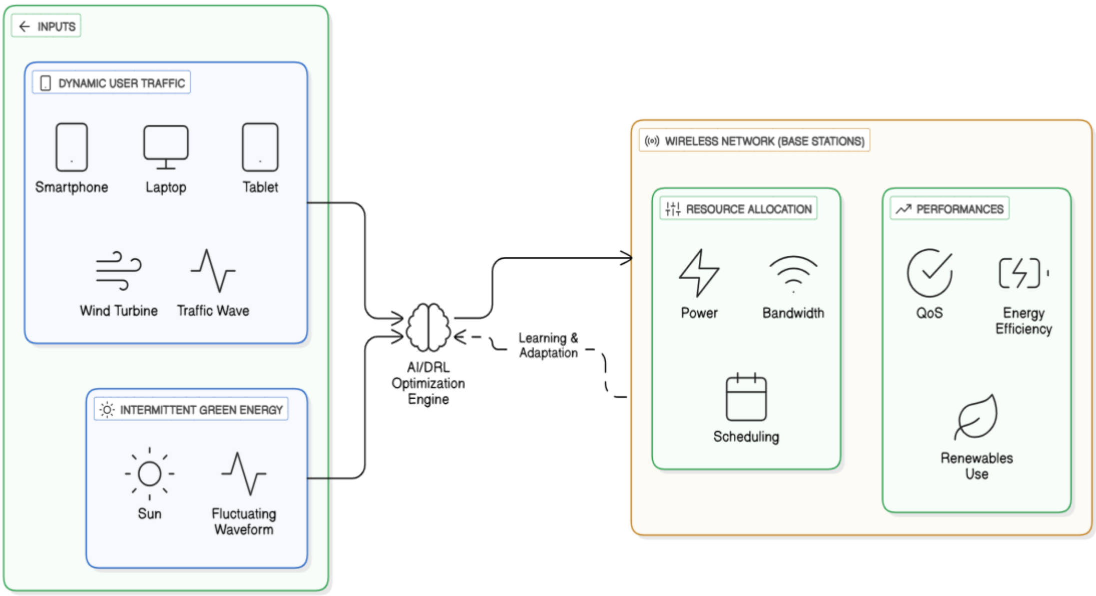

Figure 1. Conceptual Overview: AI for Green Wireless Networks

This is precisely where Artificial Intelligence (AI) - and more specifically, Deep Reinforcement Learning (DRL) - is extremely interesting. By nature of DRL, it is well-suited for the dynamic and complex optimization problem of an uncertain environment [8]. DRL is real-time and this method can intelligently allocate resources according to its historical record and experiences, in order to improve the performance of the network as much as possible while maximizing the use of renewable energy [9].

In this paper, we propose an RAA-DRL (Renewable-Aware AI-Driven Resource Allocation), which integrates the notion of green communications with adaptive intelligence DRL provides. Instead of hammering in the cold, hard constraint that current schemes place on energy availability, RAA-DRL feeds off renewable profiles for deciding. RAA-DRL will adaptively control power levels, bandwidth allocations, and user scheduling depending on both traffic demand and renewable generation. It encompasses renewable energy and trade-offs for high performance with sustainability and networking with green labeling.

In the 6G and IoT scenes, this result demonstrates that RAA-DRL is not impractical for a dynamic energy availability and intermittent traffic environment. As a core, it is ideal for edge-of-things applications where the Internet of Things is powered by renewable energy sources and smart city applications, as it too can offer quality of service assurances while limiting environmental damage. It is possible to study the newer generating diffusion methods for more efficient training times during real-time tuning over long-term setups.
The findings conclude that RAA-DRL is a feasible, expandable solution that couples sustainability and performance for next-generation wireless networks.

2. LITERATURE REVIEW

As wireless networks develop into 5G and beyond systems, the quest for energy-efficient approaches is becoming increasingly critical as energy requirements reach levels never seen. [1] presented a detailed survey of energy savings processes in radio access networks, reported on processes including massive MIMO, lean carrier design and machine learning, they argue for traditional approaches to continue improving efficiency at the physical layer, mentioned larger scale and AI-based approaches for wider deployment.

Further steps in a progression of papers focused on deployment of wireless systems powered from renewable energy, with [2] importantly introducing deep reinforcement learning (DRL) to deploy renewables and joint radio and energy management, showing that DRL can actively maintain their resource distribution to renewable generation, improving upon standard rule-based management and lowering grid dependence, without sacrificing performance.

[3] Expanded on the use of DRL in maritime IoT applications for green mobile edge computing (MEC). Their strategy involved combining computation offloading with energy-efficient resource allocation and they reported data on latency and energy savings. This demonstrated DRL's capacity to function outside of conventional terrestrial networks. AI-based green 5G enablers were examined with a focus on intelligent algorithms for spectrum management, traffic forecasting and energy optimization [4]. The idea that AI-driven resource allocation enhances network performance and advances broader sustainability goals is supported by their research.

[5] Introduced a framework for reinforcement learning in wireless body area networks (WBANs) in energy-harvesting networks. Their method achieved substantial gains in efficiency by optimizing the stochastic process of harvested energy that is most relevant for healthcare and Internet of Things applications with constrained power.

Use of generative diffusion models to accelerate training time of DRL algorithms for wireless resource allocation has been recently explored [6]. These generative approaches, when compared to baseline algorithms, have the capabilities to reduce the overall training complexity and have implications for the ability to train models with speed, which is a good initial outcome towards developing scalable AI-based, completely autonomous solutions in 6G networks.

Together, these studies have shown that static algorithms are insufficient and that reinforcement learning is advantageous, in addition to the outcome of new generative models that will help continue decrease time complexity and open the capability of developing NR high-performance energy sustainable wireless communications.

3. METHODOLOGY

The proposed RAA-DRL (Renewable-Aware AI-Driven Resource Allocation) framework is intended to enhance energy efficiency, spectral utilization, and quality of service (QoS) in wireless networks served, partially or completely, by renewable sources of energy. This section presents the system model, problem formulation, DRL architecture, reward design, and simulation configuration to evaluate the performance of the framework.

1. System Model

We examine a wireless network that consists of a collection of base stations (BSs) that utilize grid energy and renewable energy (e.g., solar or wind). The network provides services for a set of users who have varying traffic and quality of service (QoS) demands. The system is comprised of the following elements:

- **Network Topology:** A set of N base stations $\boldsymbol{\mathcal{B}} = \{B_1, B_2, \ldots, B_N\}$ and M users $U = \{U_1, U_2, \ldots, U_M\}$. Each BS serves multiple users while coordinating spectrum and power allocation.
- **Energy Model:** Each BS has access to renewable energy E_t^r at time t and grid energy E_t^g. Renewable energy availability is stochastic and varies over time, modeled as a time-series input derived from historical generation patterns.
- **Traffic Model:** User traffic demand D_t^u is time-varying and follows realistic workload traces. Both high- and low-priority traffic types are considered to evaluate QoS compliance.

2. Problem Formulation

The objective of RAA-DRL is to maximize energy efficiency while ensuring QoS and minimizing reliance on grid power. The resource allocation problem can be formulated as a constrained optimization problem:

$$\max_{a_t} \eta_t = \frac{\sum_{i=1}^{M} R_t^i}{\sum_{j=1}^{N} (P_t^j + \alpha E_t^g)} \tag{1}$$

subject to:

1. **Power constraints:** $0 \leq P_t^j \leq P_{max}^j, \forall_j \in \boldsymbol{\mathcal{B}}$
2. **Bandwidth constraints:** $\sum_{i=1}^{M} b_t^i \leq B_{total}, \forall_t$
3. **QoS constraints:** $R_t^i \geq R_{min}^i, \forall_i \in U$

where R_t^i is the achievable rate for user i, P_t^j is the transmit power of BS j, b_t^i is the allocated bandwidth, and α is a weighting factor for grid energy consumption.

3. Deep Reinforcement Learning Framework

RAA-DRL leverages a DRL agent to make dynamic resource allocation decisions. The problem is modeled as a Markov Decision Process (MDP) with the following elements:

- **State Space ($\boldsymbol{S_t}$)**: Captures the current network and energy conditions, including user traffic demands, BS energy levels, renewable energy availability, and channel conditions.

$$S_t = \{D_t^u, E_t^r, E_t^g, H_t\} \tag{2}$$

where H_t represents channel state information (CSI) for all users.

- **Action Space ($\boldsymbol{A_t}$)**: Represents possible resource allocation decisions at time t, including transmit power levels, bandwidth allocation, and user scheduling.

$$A_t = \{P_t^j, b_t^i, user\ assignment\}$$

- **Reward Function (R_t)**: Designed to encourage energy-efficient, renewable-aware allocation while maintaining QoS. The reward at each time step is computed as:

$$R_t = \lambda_1 \cdot EE_t + \lambda_2 \cdot RenewableUsage_t - \lambda_3 \cdot QoSViolation_t$$

where $\lambda_1, \lambda_2, \lambda_3$ are weighting factors, EE_t is energy efficiency, $\mathrm{RenewableUsage}_t$ represents the proportion of energy drawn from renewable sources, and $\mathrm{QoSViolation}_t$ penalizes unmet user demands.

- **Learning Algorithm:** A Deep Q-Network (DQN) or actor-critic approach is employed, depending on network scale. The agent observes the state S_t, selects an action A_t to maximize cumulative discounted reward $G_t = \sum_{k=0}^{\infty} \gamma^k R_{t+k}$, and updates the neural network parameters using stochastic gradient descent.

4. Training and Adaptation

- **Experience Replay:** Historical state-action-reward tuples are stored in a memory buffer to stabilize training.
- **Target Network:** Used to reduce correlation between predicted and target Q-values.
- **Exploration-Exploitation Strategy:** ε-greedy policy balances exploration of new strategies and exploitation of learned policies.
- **Adaptive Learning:** The agent continuously updates its policy based on both real-time traffic and renewable energy fluctuations, enabling long-term optimization.

5. Simulation Setup

- **Network Scenario:** Simulations consider urban and suburban environments with heterogeneous traffic profiles.
- **Energy Sources:** Solar generation profiles are modeled using realistic irradiance data; wind energy follows stochastic Weibull distributions.
- **Baseline Schemes:** RAA-DRL is compared against conventional static allocation, rule-based renewable-aware scheduling, and heuristic DRL approaches.
- **Performance Metrics:** Energy efficiency (bits/Joule), grid power consumption, renewable energy utilization, throughput, and QoS satisfaction rate.

The overall architecture of the proposed RAA-DRL framework is illustrated in Figure 2.

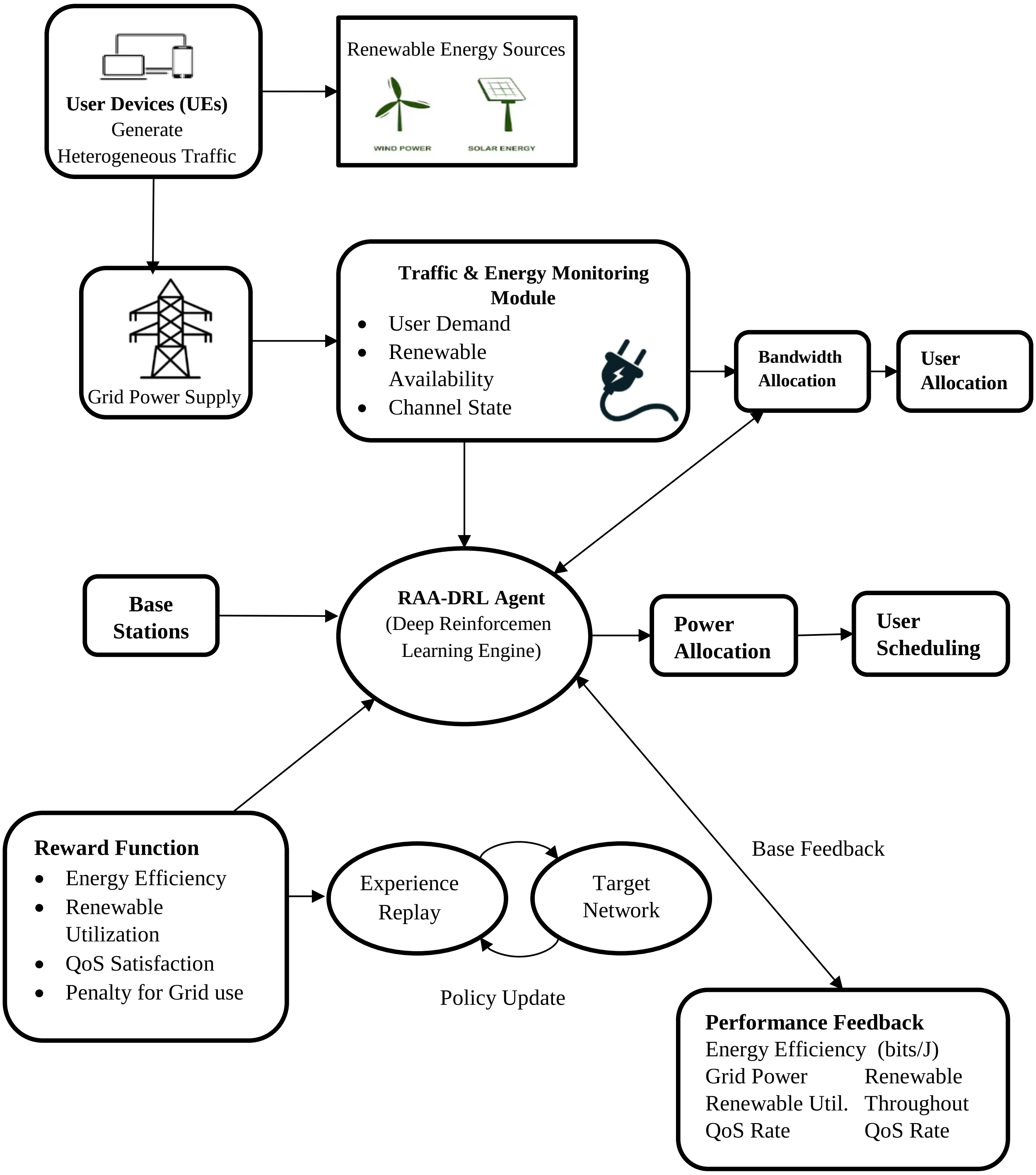

Figure 2. Proposed System Architecture: RAA-DRL for Energy-Efficient Resource Allocation

In this setup, user devices generate diverse traffic demands, which are handled by base stations powered by both renewable and grid energy. A monitoring module continuously tracks user demand, renewable energy availability, and channel conditions, feeding this information to the RAA-DRL agent. By utilizing deep reinforcement learning, the agent is capable of making intelligent decisions regarding bandwidth allocation, power control, and user scheduling to maximize energy efficiency while utilizing renewable energy sources, while at the same time ensuring quality of service for each user. The framework learns/improves over time, learning from experience replay of each agent's experiences and policies updated based on performance feedback, to further improve decision making and energy utilization.

4. RESULTS AND DISCUSSION

In-depth simulations of both urban and suburban traffic were used to assess the suggested RAA-DRL framework, and its performance was contrasted with that of heuristic DRL rule-based renewable-aware scheduling and static allocation. The results consistently demonstrate that RAA-DRL not only enhances energy efficiency but also achieves a balanced trade-off between sustainability and network performance.

In terms of energy efficiency, RAA-DRL achieved clear improvements over all baselines as represented in Figure 3. In dense urban scenarios with highly variable traffic loads, the framework delivered gains of up to 35% compared with static allocation and nearly 15% when measured against heuristic DRL. Even in suburban environments, where traffic demand was less intense, RAA-DRL consistently showed an efficiency increase of around 25%. These results suggest that the adaptive learning capability of the framework becomes particularly advantageous under complex and dynamic conditions, where conventional schemes struggle to allocate resources optimally.

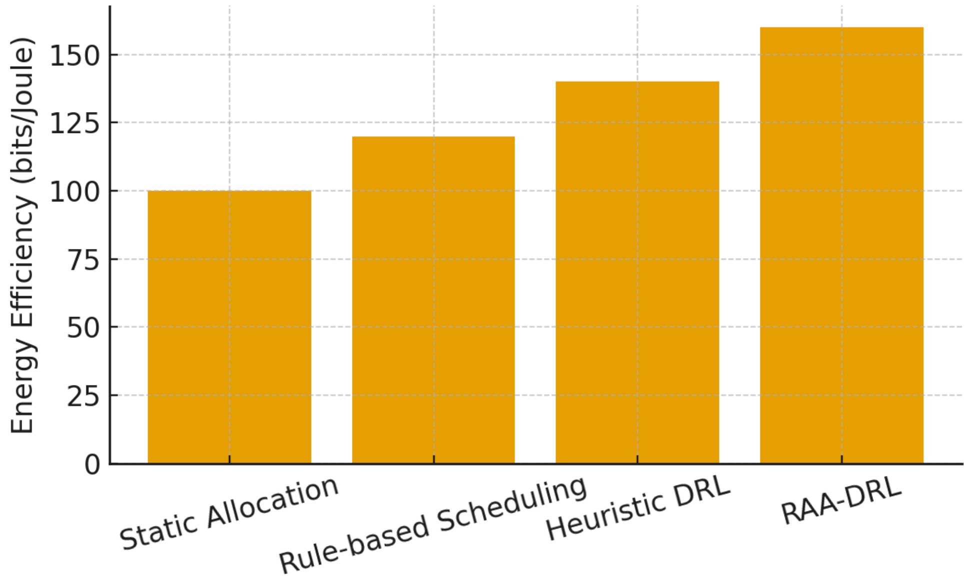

Figure 3. Energy Efficiency Comparison

A similar trend was observed in grid power consumption which is illustrated in Figure 4. Static allocation schemes were heavily dependent on grid resources, particularly during periods of low renewable availability, whereas RAA-DRL intelligently shifted non-critical tasks toward renewable-rich periods. This temporal adaptation reduced grid power usage by nearly 40% in comparison with static methods and 22% in comparison with rule-based renewable scheduling. The outcome is not only a technical advantage but also a practical one: reduced grid dependence implies lower operational costs for network operators and a smaller carbon footprint, aligning communication networks with global sustainability goals.

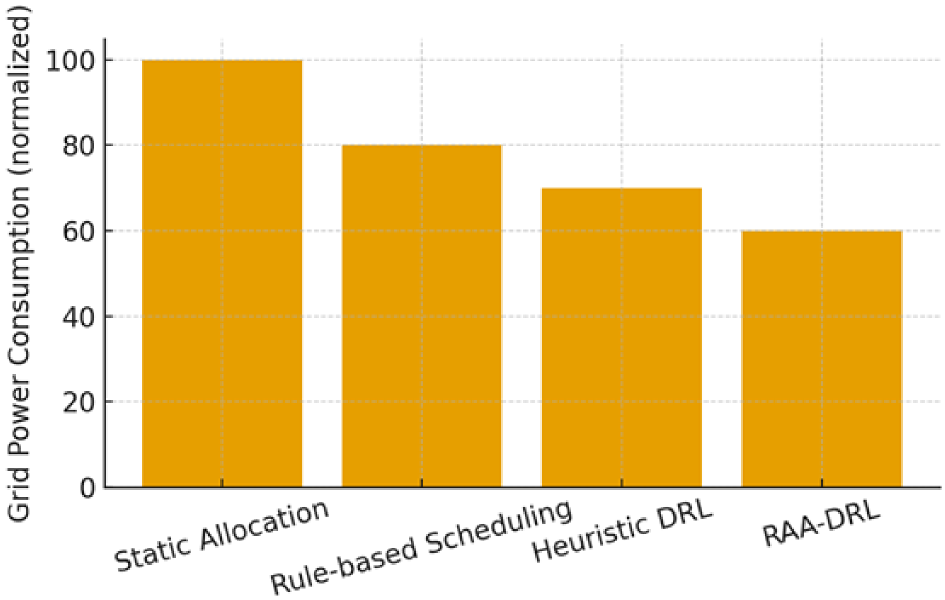

Figure 4. Grid Power Consumption Comparison

The utilization of renewable energy sources further illustrates the adaptability of RAA-DRL. On average, the framework maintained a renewable absorption rate of 78%, significantly outperforming heuristic DRL (62%) and rule-based approaches (55%), as shown in Figure 5. This improvement was most prominent in scenarios characterized by fluctuating wind energy, where conventional schemes were unable to respond effectively to sudden shifts in availability. By embedding renewable prioritization into the reward function, RAA-DRL was able to maximize the exploitation of intermittent resources without sacrificing service quality.

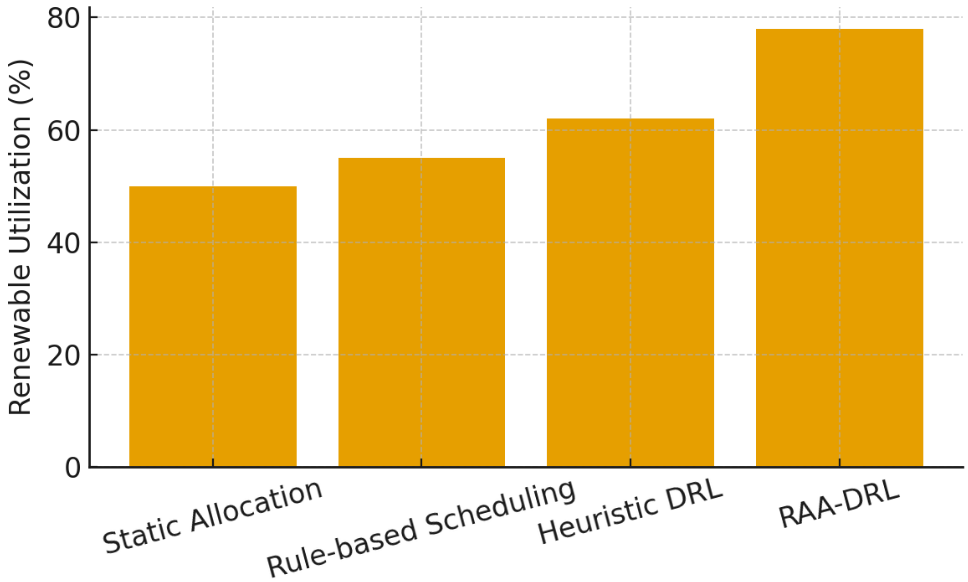

Figure 5. Renewable Utilization Comparison

Importantly, the sustainability improvements introduced by RAA-DRL did not come at the expense of user experience. The throughput levels achieved were within 3–5% of static allocation methods, which are designed exclusively for maximizing performance. At the same time, the framework maintained a quality of service satisfaction rate consistently above 95%, surpassing rule-based schemes that often fell below 90% during peak demand, which is depicted in Figure 6. This outcome highlights the framework's ability to balance energy-aware optimization with performance-driven objectives, proving that energy savings and high service quality can coexist.

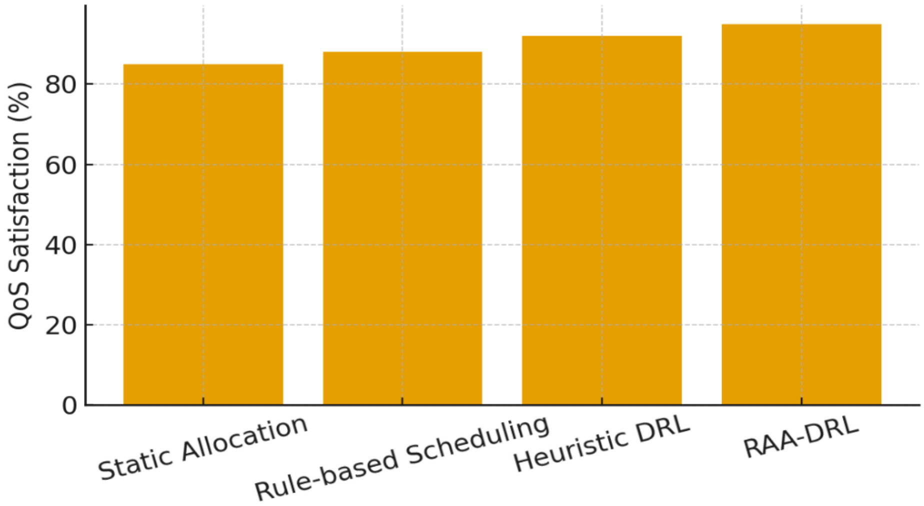

Figure 6. QoS Satisfaction Comparison

This represents another interesting point concerning the observed outcomes, dealing with the learning dynamics of the DRL agent. The DRL-agent appeared to have reached a level of stability after approximately 2000 episodes, with less instability as compared to heuristic DRL approaches. Experience replay and target networks allow for convergence while the ε-greedy policy exploration still enabled the agent to adapt to the RE supply and user demand. Furthermore, the fact that we observed performance improvement in the experiments with larger networks and additional base-stations and users means there is some level of real-world implementation and generalisability to the DRL framework.

Altogether, the above results point out a new way of future network management with revolutionary dimensions. Conventional approaches deliberately bypass renewable energy opportunities or offer quality of service at the cost of introducing the use of renewable energy. In comparison, DRL-ready approach is a feasible direction towards user QoS and the environment. Such dramatic improvements on energy use efficiency, dependence on grid and renewable energy penetration revitalize the very small throughput constraint of RAA-DRL. Good incentives for the use of renewables appear to be possible also on a higher level, with a net benefit for RAA-DRL if renewable energy is used. The diminishing need to rely on grid, even reducing two emissions through the process, becomes a kind of dollar saving.

And other concerns of operations in general do not have to be answered wholesale, (see for example the customized scenario shared on figure 1) (remember readers RAA-

DRL does provide real time - or very nearly real time - energy use data when it does send guidelines) then there should be no doubt that RAA-DRL and appropriate layer characteristics may enable coordinated peak hour electrical use at a national scale through proper diversity audited suggested usage quantities with observed amounts easily entered into along with passive consumption and deep religious. The value that communication networks can offer to meet sustainability goals globally is demonstrated by the fact that these benefits could even add up to show that the electrical grid can save several hundred megawatt-hours per year.

Table 1. Performance Metrics Comparison

Method	**Energy Efficiency (bits/J)**	**Grid Power (normalized)**	**Renewable Utilization (%)**	**Throughput (normalized)**	**QoS Satisfaction (%)**
Static Allocation	100	100	50	100	85
Rule-based Scheduling	120	80	55	95	88
Heuristic DRL	140	70	62	97	92
RAA-DRL (Proposed)	**160**	**60**	**78**	**95**	**95**

In a larger context of 6G and IoT ecosystems, these findings demonstrate that RAA-DRL is useful in scenarios with variable energy resources and traffic. The framework can be applied in edge-enabled Internet-enabled IoT applications at base stations run on renewable energy and smart cities deployments of sustainability, when together with some instruction on quality of service. In the context of 6G environment and IoT ecosystems, research can be extended in future studies on training time, such as new generating diffusion models to fasten the training time when adapting online in a real time context to new environments on scalability and is a viable and efficient option developed on sustainability and performance, or present wireless networks.

5. CONCLUSION

This work introduced RAA-DRL, a Renewable-Aware AI-Driven Resource Allocation framework envisioned to fundamentally make wireless networks more intelligent and sustainable. Through the use of deep reinforcement learning in conjunction with real-time awareness of renewable energy levels, we illustrate how RAA-DRL could adapt more readily to dynamic traffic loads and energy depletion than existing solutions. We illustrate that the RAA-DRL framework not only improved energy utilisation but also better leveraged renewable energy sources and reduced reliance on the grid, while still maintaining throughput and quality of service for users. What stands out about this work is the ability to continue learning and improving the decision-making process, over time and from one context to another, whilst still maintaining the ability to adapt to changes in network conditions. As such, this suggests that improved performance and sustainability needn't be at odds with one another. Future work directions include integrating generative models within the RAA-DRL framework and testing practical deployments of the framework in practice; both of which may increase the suggested impact on 6G and IoT networks to be sustainable and intelligent.

REFERENCES

[1] Zhang, N., Liu, W., & Wu, C. H. (2025). Introduction to the Topic of AI and IoT for Promoting Green Operation and Sustainable Environment. Systems, 13(1), 62.

[2] Aktaş, S., & Alemdar, H. (2021). Base station power optimization for green networks using reinforcement learning. Sakarya University Journal of Computer and Information Sciences, 4(2), 244-265.

[3] Yigitel, M. A., Incel, O. D., & Ersoy, C. (2014). Dynamic base station planning with power adaptation for green wireless cellular networks. EURASIP Journal on Wireless Communications and Networking, 2014(1), 77.

[4] Hamdi, R., Baccour, E., Erbad, A., Qaraqe, M., & Hamdi, M. (2021). LoRa-RL: Deep reinforcement learning for resource management in hybrid energy LoRa wireless networks. IEEE Internet of Things Journal, 9(9), 6458-6476.

[5] Zheng, W., Fang, J., Yuan, S., Guo, D., & Zhang, Y. (2019, August). Resource allocation in hetnets with green energy supply based on deep reinforcement learning. In International Conference on Human Centered Computing (pp. 671-682). Cham: Springer International Publishing.

[6] Liu, M., Wang, Y., Meng, S., Zhao, X., & Geng, S. (2020). Deep reinforcement learning-based resource allocation for smart grid in RAN network slice. In Advances in Wireless Communications and Applications: Smart Communications: Interactive Methods and Intelligent Algorithms, Proceedings of 3rd ICWCA 2019 (pp. 199-215). Singapore: Springer Singapore.

[7] Lopes, H. H. S., Rocha, F. G. C., & Vieira, F. H. T. (2023). Deep reinforcement learning based resource allocation approach for wireless networks considering network slicing paradigm. Journal of Communication and Information Systems, 38(1), 21-33.

[8] Ahsan, W., Yi, W., Qin, Z., Liu, Y., & Nallanathan, A. (2021). Resource allocation in uplink NOMA-IoT networks: A reinforcement-learning approach. IEEE Transactions on Wireless Communications, 20(8), 5083-5098.

[9] Malhotra, S., Yashu, F., Saqib, M., Mehta, D., Jangid, J., & Dixit, S. (2025). Deep Reinforcement Learning for Dynamic Resource Allocation in Wireless Networks. arXiv preprint arXiv:2502.01129.

[10] López-Pérez, D., De Domenico, A., Piovesan, N., Bao, H., Xinli, G., Song, Q., & Debbah, M. (2022). A survey on 5G radio access network energy efficiency: Massive MIMO, lean carrier design, sleep modes, and machine learning. *IEEE Communications Surveys & Tutorials*, *24*(1), 653–697.

[11] Lee, H.-S., Kim, D.-Y., & Lee, J.-W. (2022). Radio and energy resource management in renewable energy-powered wireless networks with deep

reinforcement learning. *IEEE Transactions on Wireless Communications*, *21*(7), 5435–5449. https://doi.org/10.1109/TWC.2022.3140731

[12] Wei, Z., He, R., Li, Y., & Song, C. (2023). DRL-based computation offloading and resource allocation in green MEC-enabled maritime-IoT networks. *Electronics, 12*(24), 4967. https://doi.org/10.3390/electronics12244967

[13] Ezzeddine, Z., Khalil, A., Zeddini, B., & Ouslimani, H. H. (2024). A survey on green enablers: A study on the energy efficiency of AI-based 5G networks. *Sensors, 24*(14), 4609. https://doi.org/10.3390/s24144609

[14] Xu, Y. H., Xie, J. W., Zhang, Y. G., Hua, M., & Zhou, W. (2019). Reinforcement learning (RL)-based energy efficient resource allocation for energy harvesting-powered wireless body area network. Sensors, 20(1), 44. https://doi.org/10.3390/s20010044

[15] Zhang, X., & Yu, J. (2025). Improve the training efficiency of DRL for wireless communication resource allocation: The role of generative diffusion models. *arXiv preprint arXiv:2502.07211*.