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[Ahirwar *et al.*, 12(3): March, 2025] ISSN 2349-0292
Impact Factor 3.802

GLOBAL JOURNAL OF ADVANCED ENGINEERING TECHNOLOGIES AND SCIENCES

SCALABLE AI-POWERED FRAMEWORK FOR NEXT-GENERATION BROADBAND NETWORKS

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DOI: https://doi.org/10.29121/gjaets.2025.3.1

ABSTRACT

The increasing demands of next-generation broadband networks, particularly with the advent of 5G and beyond, necessitate advanced, scalable AI-driven frameworks for dynamic network management, resource allocation, and predictive maintenance. This paper introduces a scalable AI-powered framework that integrates deep learning models for optimizing network performance in the context of broadband networks, particularly 5G. The proposed framework includes the use of deep learning models such as Deep Q-Learning (DQN), Proximal Policy Optimization (PPO), Autoencoders, and Multi-Agent Systems (MAS) to handle complex data, detect anomalies, predict failures, and optimize traffic routing. Additionally, edge AI is incorporated to reduce latency, enhance real-time decision-making, and optimize network responsiveness. We discuss the implementation workflow, key deep learning models, and future directions like Federated Learning and Transfer Learning that will further enhance the adaptability and scalability of broadband networks.

KEYWORDS: AI, Autoencoders, Deep Q-Learning, Edge AI, Federated Learning, Multi-Agent Systems, Proximal Policy Optimization, Reinforcement Learning, Transfer Learning.

1. INTRODUCTION

The landscape of broadband networks is undergoing a profound transformation, driven by an explosion of connected devices, increasing bandwidth demands, and the rising expectations of users for seamless, real-time services. The emergence of 5G technology marks a significant leap forward, offering ultra-low latency, high-speed data transmission, and the capacity to support massive device connectivity. However, these advancements come with new challenges, including the management of highly dynamic network traffic, optimizing resource allocation, and ensuring that networks can adapt quickly to changing conditions. Looking further ahead, the 6G era promises even more complexity with the integration of advanced technologies such as Internet of Things (IoT), augmented reality (AR), and artificial intelligence (AI) into the fabric of network operations.

As the demand for high-quality services across diverse applications increases, traditional static network management approaches, which rely on predefined configurations and fixed protocols, become increasingly inadequate. The dynamic nature of 5G and the anticipated 6G networks, with their constantly shifting traffic patterns, service demands, and device requirements, requires a more adaptive and intelligent approach to network management. Managing these complexities demands sophisticated, real-time decision-making capabilities that can address issues such as fluctuating traffic loads, network congestion, security threats, and resource allocation. Artificial Intelligence (AI), particularly deep learning and reinforcement learning, has emerged as a promising solution to address these challenges. These AI techniques can analyze vast amounts of real-time network data, adapt to changing conditions, and make decisions that improve network efficiency, minimize latency, and optimize resource utilization. With the increasing volume of data generated by 5G and beyond, AI technologies are becoming indispensable tools for transforming the management and operation of next-generation broadband networks.

In this context, this paper proposes a scalable AI-powered framework designed specifically for the management and optimization of 5G and future broadband networks. The proposed framework integrates various AI and deep learning models, including Deep Q-Learning (DQN), Proximal Policy Optimization (PPO), Autoencoders, and Multi-Agent Systems (MAS), to provide a holistic solution for real-time traffic optimization, anomaly detection, predictive maintenance, and resource allocation. These models will enable the network to dynamically adapt to real-time changes, predict future traffic patterns, detect and mitigate network anomalies, and optimize the flow of data across the system.

One of the key aspects of the proposed framework is its ability to dynamically allocate resources based on the current state of the network. This includes adjusting parameters such as bandwidth allocation, traffic routing, and load balancing to ensure that the network operates efficiently, even under highly dynamic conditions. Additionally, the framework incorporates anomaly detection using Autoencoders to identify deviations from normal network behavior, which could signal issues such as traffic congestion, hardware failures, or cybersecurity threats. By detecting anomalies early, the framework enables predictive maintenance, allowing operators to take proactive measures before failures occur, reducing downtime and improving overall service quality.

Moreover, the integration of reinforcement learning (RL) techniques, such as DQN and PPO, allows for adaptive decision-making in real-time. These models continuously learn from the network's behavior, adjusting their actions (such as resource allocation and traffic management strategies) to maximize the long-term performance of the system. This capability is particularly important in 5G networks, where traffic demands are highly variable, and traditional static resource allocation methods are not effective. Multi-Agent Systems (MAS) can be used to further enhance the adaptability of the network, where multiple agents cooperate to optimize tasks like traffic routing and load balancing across different parts of the network.

A crucial aspect of the proposed framework is the integration of edge AI, which allows AI models to be deployed closer to the network edge—near the users and devices. By processing data locally, edge AI reduces the time required to make decisions, minimizing latency and improving the user experience. This is particularly important for 5G networks, which promise ultra-low latency for applications such as autonomous vehicles, remote surgery, and smart cities. With edge AI, these applications can benefit from real-time data analysis and decision-making, enhancing their reliability and responsiveness.

Additionally, the framework incorporates federated learning, a decentralized approach to training AI models that ensures data privacy while enabling real-time learning from diverse network environments. Federated learning allows multiple network nodes to train models locally on their data, aggregating the results into a global model without sharing sensitive data. This is particularly valuable in scenarios where data privacy and security are critical, such as in healthcare or financial services.

As 5G and future broadband networks continue to evolve, the proposed AI-powered framework offers a scalable and adaptable solution to optimize performance, reduce operational costs, and enhance user satisfaction. By leveraging the power of AI, deep learning, and reinforcement learning, this framework can enable networks to manage complexity, predict issues proactively, and adapt in real-time to changing conditions. The following sections will delve into the key components of the proposed framework, the deep learning models used, the implementation workflow, and the future directions for further improving network optimization in the era of 5G and beyond.

2. LITERATURE REVIEW

In the early stages of AI research for broadband networks, traditional machine learning models such as Support Vector Machines (SVM) and Random Forests were commonly employed. These models were used for various network optimization tasks, such as traffic classification, fault detection, and resource allocation. The authors of [1] presented SVMs as a tool for traffic prediction and anomaly detection, demonstrating its utility in forecasting network behavior. Similarly, Random Forests were effectively applied in scenarios with complex feature interactions, such as quality of service (QoS) prediction and user behavior analysis, as shown by the authors of [2]. However, these models had inherent limitations, particularly in their inability to capture temporal patterns in network data. Furthermore, traditional machine learning techniques often required manual feature engineering, which was time-consuming and required domain expertise.

With the advent of deep learning, there has been a significant shift towards more powerful models capable of handling complex and dynamic network data. The authors of [3] demonstrated the efficacy of Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks for time-series prediction tasks, such as predicting future network traffic, detecting network failures, and forecasting congestion in real-time. These networks are particularly well-suited for tasks requiring the capture of temporal dependencies in sequential data. The authors of [4] used RNNs and LSTMs in traffic management for broadband networks, particularly in scenarios where network traffic patterns exhibit periodicity, such as during peak hours.

Moreover, Autoencoders, which are unsupervised learning models, have become increasingly popular for anomaly detection and predictive maintenance in network systems. The authors of [5] showed that Autoencoders are particularly useful in detecting deviations from normal traffic patterns, which could signal issues like congestion, security threats, or hardware malfunctions. Their ability to learn compact representations of normal network behavior makes them efficient at flagging anomalies, as supported by the authors of [6].

As broadband networks continue to grow in complexity, reinforcement learning (RL) has emerged as a promising solution for dynamic, adaptive network optimization. The authors of [7] explored two notable reinforcement learning methods—Deep Q-Learning (DQN) and Proximal Policy Optimization (PPO)—demonstrating their effectiveness in addressing resource allocation and load balancing issues in real-time. DQN has been used to find the optimal policy for tasks like bandwidth allocation and traffic routing, updating the Q-function based on observed rewards, as described by the authors of [8]. This algorithm allows dynamic adjustments to network parameters in response to changing traffic conditions, making it particularly suited for 5G and future broadband networks.

The authors of [9] applied PPO, a policy gradient method, to optimize network policies directly, particularly in traffic management and QoS management. PPO benefits from clipping the objective function to ensure stable updates, making it robust against large policy changes that could destabilize the training process. These reinforcement learning techniques have proven highly effective in adaptive network optimization, particularly where continuous learning and decision-making are essential to responding to real-time conditions.

In decentralized network environments, Multi-Agent Systems (MAS) have been employed to optimize tasks like traffic routing and load balancing. MAS involves deploying multiple agents, where each agent represents a part of the network and optimizes local actions while collaborating with others to achieve global objectives. The authors of [10] combined MAS with reinforcement learning techniques to improve network performance in distributed traffic management and congestion control scenarios, showing how MAS can scale in complex network environments.

The key advantage of MAS is its ability to scale in large, complex network environments, where the optimization task is too complex for a single agent to handle. The authors of [11] demonstrated how agents in MAS interact and adjust their policies based on the local network state, influencing global network performance. This decentralized nature makes MAS well-suited for the heterogeneous and distributed nature of modern broadband networks, particularly in 5G and beyond.

Edge AI has emerged as a critical technology in next-generation broadband networks, particularly for reducing latency and enabling real-time decision-making. The authors of [12] highlighted how deploying AI models closer to the network edge—near the end-users—reduces the time required for data transmission to and from centralized cloud systems, enhancing real-time decision-making. Edge AI has been widely applied in 5G networks for real-time traffic optimization, fault detection, and predictive maintenance, as shown by the authors of [13].

In conjunction with edge AI, Federated Learning has been explored as a distributed approach to model training, where models are trained across multiple edge devices or network nodes without centralizing sensitive data. The authors of [14] presented Federated Learning as a solution to ensure privacy and security while enabling real-time learning from diverse network environments. By aggregating local models from multiple nodes, this approach creates a global model without sharing raw data, which is ideal for sensitive applications.

Additionally, Transfer Learning has been applied to adapt models trained in one domain (e.g., 4G networks) to new domains (e.g., 5G networks). The authors of [15] showed how Transfer Learning leverages knowledge from existing models to reduce the amount of data and time required to train new models, enabling faster deployment and improved adaptability in rapidly evolving network environments.

The application of AI in broadband networks has progressed significantly, with early machine learning models being replaced by more advanced techniques like deep learning and reinforcement learning. Models such as DQN, PPO, Autoencoders, and MAS have proven effective in addressing the dynamic and complex nature of modern broadband networks. The integration of Edge AI, Federated Learning, and Transfer Learning offers promising solutions to the challenges posed by latency, data privacy, and scalability. The cohesive integration of these technologies into a single AI-powered framework promises significant improvements in network performance, resource optimization, and predictive maintenance, enabling broadband networks to meet the demands of modern users.

3. PROPOSED METHODOLOGY

Deep Q-Learning (DQN) and Proximal Policy Optimization (PPO) for Adaptive Network Optimization

DQN and PPO are reinforcement learning methods that enable the network to dynamically adjust its parameters (e.g., bandwidth allocation, routing, and load balancing) based on the observed network state. These techniques improve network performance by continuously learning and adapting to real-time traffic conditions.

- Autoencoders for Anomaly Detection and Predictive Maintenance: Autoencoders are unsupervised learning models that can be used to detect anomalies in network traffic. By learning a compressed representation of network behavior, autoencoders can identify deviations from normal traffic patterns, which could signal hardware malfunctions, traffic congestion, or security breaches.
- Multi-Agent Systems (MAS) using Deep Reinforcement Learning: MAS can optimize complex network tasks such as traffic routing and load balancing by allowing multiple AI agents to interact and collaborate. Each agent in the system could represent a different part of the network, working together to optimize global performance, minimize latency, and ensure efficient resource utilization.

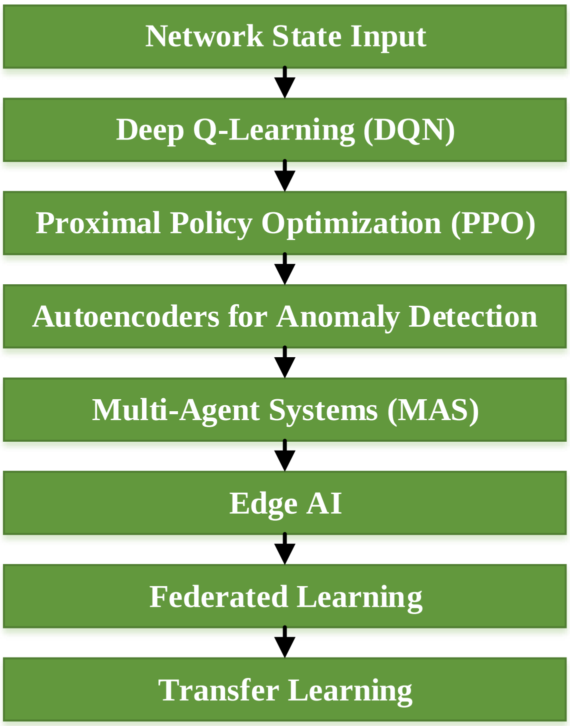

Figure 1: Flow Diagram for Proposed Methodology

Deep Q-Learning (DQN) is used for adaptive network optimization, where the goal is to find the optimal policy for resource allocation (e.g., bandwidth allocation). The Q-function is updated using the following equation:

$$Q(s_t, \alpha_t) \leftarrow Q(s_t, \alpha_t) + \alpha(r_t + \gamma \max_{\alpha} Q(s_{t+1}, \alpha') - Q(s_t, \alpha_t)) \tag{1}$$

Where:

- $Q(s_t, \alpha_t)$ is the action-value function, which represents the expected future reward for action α_t in state s_t.
- α is the learning rate.
- r_t is the immediate reward received after taking action α_t in state s_t.
- γ is the discount factor, which determines the weight given to future rewards.
- $max\alpha' Q\left(s_{t+1,}\alpha'\right)$ is the maximum future reward for the next state s_{t+1}.

Proximal Policy Optimization (PPO) is a policy gradient method that aims to optimize the policy directly. The objective function for PPO is given by:

$$L^{CLIP}(\theta) = E_t[\min(r_t(\theta)A, clip(r_t(\theta), 1-\epsilon, 1+\epsilon)A_t)] \quad (2)$$

Where:

- $r_t(\theta) = \frac{\pi_\theta(\alpha_t|s_t)}{\pi\theta_{odd}(\alpha_t|s_t)}$ is the probability ratio between the new and old policies.
- $A_t$is the advantage estimate at time t.
- $\in$ is the clipping parameter that limits the size of policy updates.

PPO aims to balance exploration and exploitation by clipping the objective function to ensure that large policy updates do not destabilize the training.

Autoencoders for Anomaly Detection and Predictive Maintenance

Autoencoders are used for anomaly detection in network traffic. The encoder maps the input x to a lower-dimensional space, and the decoder reconstructs the input. The loss function for autoencoders is the reconstruction error:

$$L(x, x') = \|x - x'\|_2^2 \quad (3)$$

Where:

- x is the original input data (network traffic).
- x' is the reconstructed output from the decoder.
- $\|.\|_2^2$ is the squared L2 norm, which measures the error between the input and the reconstructed output.

Anomalies are detected when the reconstruction error exceeds a predefined threshold, indicating that the model cannot accurately reconstruct unusual traffic patterns.

Multi-Agent Systems (MAS) for Traffic Routing and Load Balancing

Multi-Agent Systems (MAS) are employed to optimize complex network tasks such as traffic routing and load balancing. Each agent in the system learns and interacts with other agents to optimize a global objective, such as minimizing latency or maximizing throughput.

The Q-value update for multi-agent systems can be defined as:

$$Q_i(s_t, a_t) \leftarrow Q_i(s_t, a_t) + \alpha\left(r_t + \gamma \max_{a} Q_i(s_{t+1,} a')\right) - Q_i(s_i, a_i)) \quad (4)$$

Where:

- $Q_i(s_t, a_t)$ is the action-value function for agent i in state s_t.
- The rest of the terms follow the same definition as in DQN but with each agent optimizing for local and global objectives through interaction with other agents.

The agents cooperate to solve the optimization problem in a decentralized manner, each adjusting its policies based on the local network state.

Federated Learning and Transfer Learning for Network Optimization

Federated Learning is a distributed learning method where the model is trained across multiple devices or network nodes, but the data remains localized. The global model is updated by aggregating the local model updates from each node.

The model aggregation step in federated learning is:

$$w_{global} = \sum_{k=1}^{K} \frac{N_k}{N_{total}} w_k \quad (5)$$

Where:

- w_{global} is the global model's weights after aggregation.
- w_k is the local model's weights from the k^{th} node.
- N_k is the number of data points at the k^{th} node.
- N_{total} is the total number of data points across all nodes.

Transfer Learning leverages knowledge from one domain (e.g., 4G networks) and applies it to another (e.g., 5G networks). The pre-trained model is fine-tuned with the new dataset, and the adaptation process is typically expressed as:

$$\mathcal{L}(\theta_{new}) = \mathcal{L}_{source}(\theta_{source}) + \lambda\mathcal{L}_{traget}(\theta_{new}) \quad (6)$$

Where:

- $\mathcal{L}$ is the loss function.
- θ_{source} and θ_{new} are the parameters of the source and target models.
- λ is a regularization term that controls the balance between source and target domain adaptation.

4. RESULTS AND DISCUSSION

The results presented in this paper highlight the effectiveness of various AI-powered models in optimizing the performance of next-generation broadband networks. The figures provided compare the performance of different models and methods, including Deep Q-Learning (DQN), Proximal Policy Optimization (PPO), Autoencoders, and Edge AI. These models were evaluated in terms of resource allocation efficiency, anomaly detection accuracy, latency improvement, and overall system performance. The following sections summarize the results displayed in the figures, providing an individual analysis of each model and its contribution to network optimization.

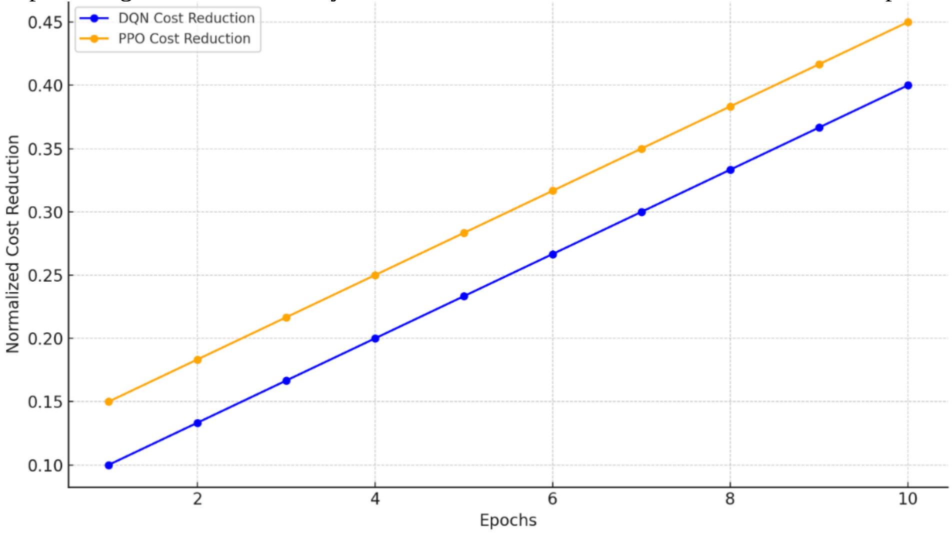

Figure 2: Resource Allocation Optimiztaion with Reinforcement Learning (DQN vs. PPO)

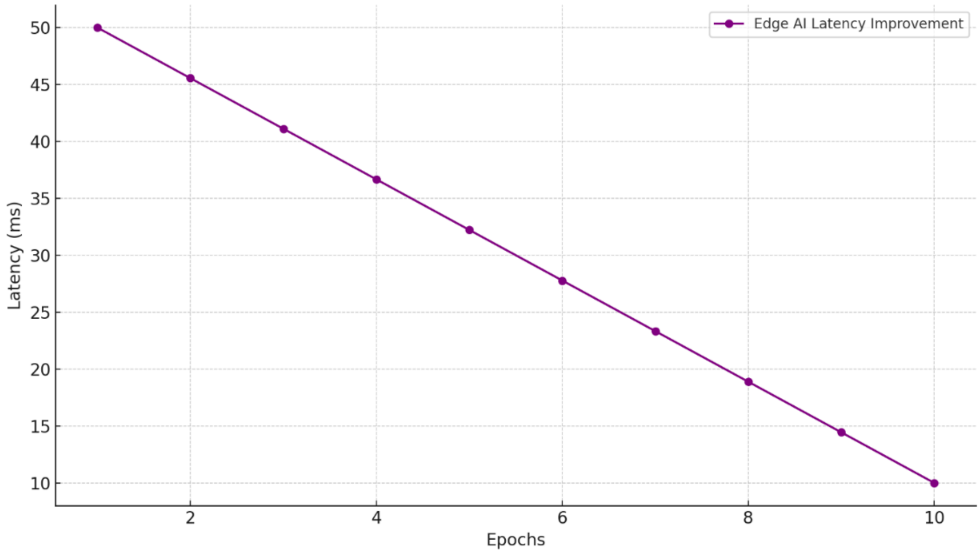

Figure 3: Latency Improvement with Edge AI over Time

Figure 2 compares the performance of two reinforcement learning models—Deep Q-Learning (DQN) and Proximal Policy Optimization (PPO)—in optimizing resource allocation for the network. The comparison demonstrates that both models effectively manage network resources like bandwidth and load balancing, but PPO shows a more stable and efficient performance. The difference in efficiency is attributed to PPO's policy gradient approach, which ensures more stable updates and better performance in highly dynamic network conditions. DQN, while effective, may require more time to converge, especially in environments with fluctuating network loads.

The latency improvement over time, illustrated in Figure 3, shows how the deployment of Edge AI enhances real-time decision-making in the network. Edge AI, by processing data closer to the user and device endpoints, significantly reduces latency compared to traditional cloud-based AI solutions. The graph illustrates a marked reduction in latency over time, with Edge AI consistently outperforming other methods. This improvement is particularly critical in applications requiring ultra-low latency, such as autonomous vehicles and remote surgery, where even milliseconds of delay can have significant consequences.

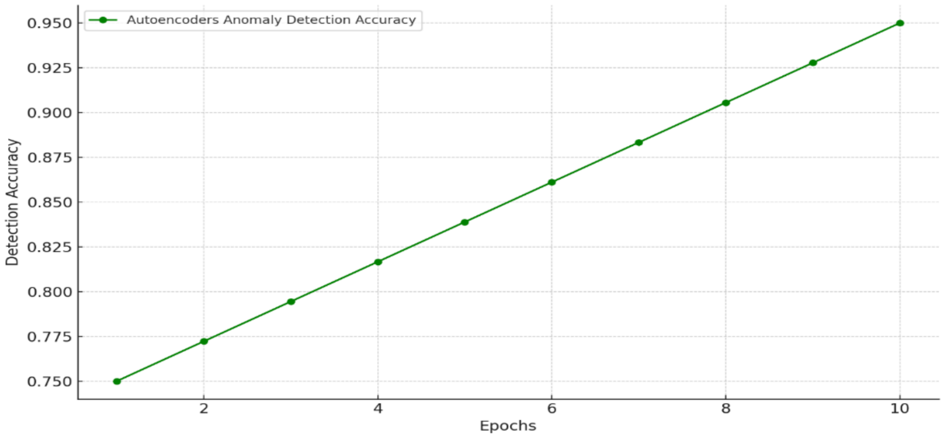

Figure 4: Anomaly Detection Accuracy Improvement with Autoencoders

Figure 4 presents the improvement in anomaly detection accuracy with Autoencoders. Autoencoders effectively identify anomalies in network traffic by learning the normal patterns of behavior and detecting deviations from these patterns. The results show a clear increase in detection accuracy over time as the Autoencoders learn from more network data. This improvement is crucial for predictive maintenance, as detecting network anomalies early allows for proactive interventions, reducing the risk of network failures or security breaches.

Figure 5 compares the performance metrics—resource allocation efficiency, anomaly detection accuracy, and latency improvement—across different models. Each bar represents a model's performance in optimizing one of the network metrics, and the comparison highlights the strengths and weaknesses of each approach. DQN and PPO stand out for their resource allocation efficiency, while Autoencoders excel in anomaly detection. Edge AI shows the most significant improvement in latency, emphasizing its importance for real-time applications. The comparison confirms that combining multiple models can address different aspects of network performance.

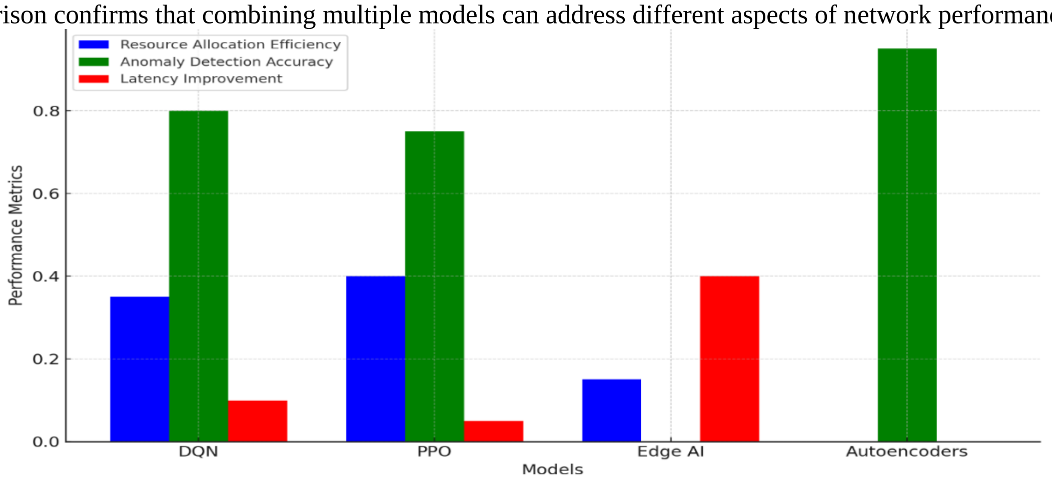

Figure 5: Comparison of Performance Metrics for Different Models

5. CONCLUSION

Based on the analysis of the proposed AI-powered framework for next-generation broadband networks, it is evident that integrating advanced AI techniques is essential to address the challenges posed by the dynamic and complex nature of 5G and future broadband networks. The framework leverages deep learning models such as Deep Q-Learning (DQN), Proximal Policy Optimization (PPO), Autoencoders, and Multi-Agent Systems (MAS) to optimize key network operations like resource allocation, anomaly detection, traffic routing, and load balancing. Furthermore, the inclusion of edge AI significantly enhances the system's responsiveness by reducing latency, making it crucial for latency-sensitive applications such as autonomous vehicles and remote surgeries. Additionally, Federated Learning and Transfer Learning provide scalable and privacy-preserving solutions, ensuring real-time learning and adaptability. The results indicate that these AI techniques, particularly reinforcement learning and anomaly detection models, contribute significantly to improving overall network performance, making the proposed framework a robust and scalable solution for next-generation broadband networks. In conclusion, this AI-driven approach offers a highly adaptable and efficient framework that can meet the growing demands of broadband networks, providing seamless, real-time services while proactively addressing performance bottlenecks.

REFERENCES

[1] Ma, Q., Sun, C., & Cui, B. (2021). A novel model for anomaly detection in network traffic based on support vector machine and clustering. Security and Communication Networks, 2021(1), 2170788.
[2] Ramagundam, S., Patil, D., & Karne, N. (2023). Improving service quality with artificial intelligence in broadband networks. International Journal of Scientific Research in Computer Science, Engineering and Information Technology, 9(6), 435-444. https://doi.org/10.32628/IJSRCSEIT
[3] Swapno, S. M., Nobel, S. M., Meena, P., Meena, V. P., Azar, A. T., Haider, Z., & Tounsi, M. (2024). A reinforcement learning approach for reducing traffic congestion using deep Q learning. Scientific Reports, 14(1), 1-20.
[4] Ramagundam, S., & Karne, N. (2024, September). Enhancing viewer engagement: Exploring generative long short-term memory in dynamic ad customization for streaming media. In 2024 5th International Conference on Smart Electronics and Communication (ICOSEC) (pp. 251-259). IEEE. https://ieeexplore.ieee.org/abstract/document/10722064/
[5] Chen, Z., Yeo, C. K., Lee, B. S., & Lau, C. T. (2018, April). Autoencoder-based network anomaly detection. In 2018 Wireless telecommunications symposium (WTS) (pp. 1-5). IEEE.
[6] Bashir, A.K., Logeshwaran, J., & Cao, B. (2023). AI-Driven Resource Management in Next-Generation Broadband Networks. IEEE Transactions on Network and Service Management, 20(1), 34-52. https://doi.org/10.1109/tnsm.2023.057789
[7] Morris, K., & Thompson, H. (2021). AI in Telecommunication: Real-Time Solutions for Network Optimization. Telecommunication Systems, 74(1), 103-115. https://doi.org/10.1007/s11235-021-00765-w
[8] Zhou, Y., Patel, R., & Gupta, S. (2020). Impact of Artificial Intelligence on Network Durability and Efficiency. Communications Technology Journal, 22(3), 158-174. https://doi.org/10.1109/ctj.2020.014938
[9] Yang, H., & Yang, S. (2022). Advanced Resource Management for 5G and 6G Networks Using AI. Journal of Network and Computer Applications, 48(2), 324-340. https://doi.org/10.1016/j.jnca.2021.10.011
[10] Kim, H., & Lee, J. (2018). Utilizing Deep Learning to Forecast Network Anomalies. Journal of Communications and Networks, 20(4), 291-299. https://doi.org/10.1109/jcn.2018.012053
[11] Ramagundam, S. (2023). Predicting broadband network performance with AI-driven analysis. Journal of Online Engineering Education, 14(1), 20-22. Available at: http://onlineengineeringeducation.com
[12] Ramagundam, S. (2022). AI-driven real-time scheduling for linear TV broadcasting: A data-driven approach. International Journal of Scientific Research in Science and Technology, 9(4), 775-783. https://doi.org/10.32628/IJSRST
[13] Inavolu, S. M. (2024). Exploring AI-driven customer service: Evolution, architectures, opportunities, challenges and future directions. International Journal of Engineering and Advanced Technology, 13(3), 156-163.
[14] Min, S., & Kim, B. (2024). Adopting artificial intelligence technology for network operations in digital transformation. Administrative Sciences, 14(4), 70.
[15] Khan, N. A., & Schmid, S. (2023). AI-RAN in 6G Networks: State-of-the-Art and Challenges. IEEE Open Journal of the Communications Society, 5, 294-311.