Journal of Artificial Intelligence and Emerging Technologies
Volume 1, Issue 2, pp 19-24, December 2024
ISSN (online): 3049-1967
DOI: https://doi.org/10.47001/JAIET/2024.102004
Available Online at https://www.jaiet.com

Adaptive and Robust 6G IoT Networks for Assistive Systems via Graph-Augmented DRL

M.D. Karthik Raja

Department of Computational Science, Nehru Arts and Science College, Coimbatore, Tamil Nadu, India

Abstract: The convergence of sixth-generation (6G) wireless communication and the Internet of Things (IoT) is expected to fundamentally transform the development of next-generation assistive technologies by enabling ultra-reliable, low-latency, and AI-native communication services. 6G networks are envisioned to provide terahertz-band transmission, intelligent edge computing, integrated sensing and communication, and native artificial intelligence support, which collectively facilitate mission-critical applications. Assistive IoT devices—including wearable health monitoring systems, implantable biosensors, intelligent mobility aids, neuroprosthetics, and brain–computer interface (BCI) platforms—operate under stringent quality-of-service (QoS) and quality-of-experience (QoE) constraints. These systems demand guaranteed reliability, bounded latency, high data integrity, and energy efficiency while functioning in highly dynamic and heterogeneous network environments characterized by device mobility, fluctuating channel conditions, uneven computational capabilities, and limited battery resources. Traditional communication and resource management strategies based on static optimization, rule-based heuristics, fixed protocol stacks, or centralized control architectures are increasingly inadequate for the scale and complexity of 6G-enabled IoT ecosystems. Such approaches struggle to adapt to rapidly changing topologies, dense node deployments, and dynamic traffic patterns typical of assistive environments. Although Deep Reinforcement Learning (DRL) has emerged as a powerful tool for adaptive network optimization—enabling autonomous policy learning for routing, spectrum allocation, and resource scheduling—conventional DRL models typically treat network states as flat feature vectors. This representation neglects the intrinsic relational structure of communication networks, limiting scalability, robustness, and generalization in large-scale distributed systems. Performance evaluation demonstrates that the proposed GA-DRL framework significantly outperforms traditional heuristic-based approaches and standard DRL implementations. Specifically, the framework achieves notable reductions in end-to-end latency, improvements in packet delivery reliability, enhanced energy efficiency, and greater resilience under dynamic channel and mobility conditions. Furthermore, the graph-based representation enhances convergence stability and policy generalization across varying network scales. These findings highlight the effectiveness of graph-augmented learning in enabling proactive, topology-aware, and context-adaptive decision-making within AI-native 6G ecosystems. The proposed GA-DRL framework establishes a scalable and intelligent communication foundation for future assistive IoT infrastructures, supporting mission-critical healthcare and human-assistive applications in next-generation wireless environments.

Keywords: Adaptive Cruise Control (ACC), Autonomous Vehicles, Raspberry Pi, Real-Time Embedded Systems, Sensor Integration, Ultrasonic Sensor, LiDAR, Closed-Loop Control System, Intelligent Transportation Systems.

I. INTRODUCTION

Background and Motivation

The evolution toward sixth-generation (6G) wireless networks is expected to redefine intelligent connectivity by integrating ultra-low latency communication, terahertz spectrum utilization, AI-native networking, and edge intelligence. Simultaneously, the rapid proliferation of Internet of Things (IoT) technologies has accelerated the development of assistive systems designed to enhance healthcare, mobility, and human–machine interaction. Assistive IoT devices—including wearable biosensors, implantable medical devices, intelligent prosthetics, mobility aids, and brain–computer interface systems—require seamless, reliable, and energy-efficient communication to operate effectively in real-time environments.

Unlike conventional IoT applications, assistive technologies are often mission-critical and safety-sensitive. For example, remote cardiac monitoring or neural stimulation devices must transmit data with minimal delay and extremely high reliability. The integration of 6G capabilities such as ultra-

Journal of Artificial Intelligence and Emerging Technologies
Volume 1, Issue 2, pp 19-24, December 2024
ISSN (online): 3049-1967
DOI: https://doi.org/10.47001/JAIET/2024.102004
Available Online at https://www.jaiet.com

reliable low-latency communication (URLLC), intelligent spectrum management, and distributed edge computing presents a transformative opportunity to meet these stringent requirements. However, ensuring adaptive and scalable communication in such complex environments necessitates intelligent and topology-aware resource management frameworks.

Problems of 6G Assistive IoT Communication

Despite the promising features of 6G networks, assistive IoT communication faces several significant challenges. First, ultra-low latency and high reliability requirements impose strict Quality of Service (QoS) constraints. Even minor packet losses or delays can compromise patient safety in medical assistive systems. Second, the heterogeneity of devices—ranging from low-power wearable sensors to computationally intensive neuroprosthetics—creates uneven resource demands and communication priorities.

Third, network topology in assistive IoT environments is highly dynamic due to user mobility and fluctuating channel conditions. Frequent topology changes lead to unstable routing paths and increased interference. Fourth, severe energy constraints limit the ability of wearable and implantable devices to perform heavy computations or frequent retransmissions. Finally, centralized control mechanisms may introduce bottlenecks and single points of failure in dense 6G IoT deployments. These challenges collectively require adaptive, distributed, and intelligent communication strategies capable of learning from evolving network conditions.

II. 6G IoT COMMUNICATION FOR ASSISTIVE TECHNOLOGIES

6G-enabled IoT communication introduces several advanced features that can significantly enhance assistive technologies. AI-native 6G architectures embed intelligence directly into the communication layer, enabling predictive network optimization and autonomous decision-making. Integrated sensing and communication capabilities allow networks to perceive environmental changes and adapt transmission parameters accordingly.

For assistive applications, edge computing plays a critical role by processing sensitive biomedical data locally, thereby reducing latency and preserving privacy. Massive Multiple-Input Multiple-Output (MIMO), terahertz communications, and reconfigurable intelligent surfaces (RIS) further improve spectral efficiency and signal reliability. These capabilities collectively support high-bandwidth biomedical data streams, real-time neural signal transmission, and responsive control of assistive devices.

However, leveraging these 6G features effectively requires communication models that are topology-aware, energy-efficient, and capable of dynamic resource allocation in distributed environments.

General Framework Architecture

The proposed communication framework is designed as a graph-augmented intelligent architecture for 6G assistive IoT systems. The network is modeled as a dynamic attributed graph, where nodes represent assistive IoT devices, edge servers, and base stations, while edges represent communication links characterized by latency, bandwidth, interference levels, and energy states.

At the perception layer, sensors continuously collect biomedical and environmental data. The network layer integrates 6G wireless infrastructure with edge computing nodes. A Graph Neural Network (GNN) extracts topology-aware state representations from the evolving network graph. These representations capture inter-device dependencies, connectivity patterns, and resource availability.

At the decision layer, a Deep Reinforcement Learning (DRL) agent utilizes graph-encoded states to determine optimal communication policies, including routing selection, power control, spectrum allocation, and scheduling. The system operates in a closed-loop manner, continuously updating policies based on network feedback. This distributed and adaptive architecture ensures scalability, robustness, and resilience in dense assistive IoT deployments.

III. RESEARCH GAP AND MOTIVATION

Although recent research has explored DRL-based optimization for 6G IoT networks, most existing models treat network states as flat feature vectors without explicitly modeling relational structures. This abstraction limits the ability to capture topology variations and inter-node dependencies, which are crucial in assistive environments characterized by mobility and heterogeneity.

Furthermore, many approaches focus primarily on throughput maximization or latency minimization, neglecting multi-objective optimization that simultaneously considers

Journal of Artificial Intelligence and Emerging Technologies
Volume 1, Issue 2, pp 19-24, December 2024
ISSN (online): 3049-1967
DOI: https://doi.org/10.47001/JAIET/2024.102004
Available Online at https://www.jaiet.com

energy efficiency, reliability, fairness, and QoS differentiation. There is also limited research addressing mission-critical assistive applications that require strict reliability guarantees.

Motivated by these limitations, the proposed study integrates graph learning with reinforcement learning to develop a scalable and topology-aware communication optimization framework. By embedding structural awareness into the decision-making process, the system achieves improved generalization and adaptability in dynamic 6G IoT scenarios.

IV. REWARD OPTIMIZATION BASED ON QOS-AWARENESS

The effectiveness of reinforcement learning in network optimization largely depends on the formulation of the reward function. In assistive IoT environments, reward optimization must be aligned with QoS-aware objectives rather than solely throughput maximization.

The proposed framework defines a multi-objective reward function incorporating end-to-end latency minimization, packet delivery reliability, energy consumption reduction, and fairness among heterogeneous devices. The reward function can be expressed as a weighted combination of QoS metrics:

- Negative penalty for latency exceeding predefined thresholds
- Positive reward for successful packet delivery
- Energy efficiency incentive for low-power transmission strategies
- Fairness adjustment to prevent resource starvation of low-capability devices

This QoS-aware reward shaping ensures that the DRL agent learns communication policies that satisfy mission-critical requirements while maintaining energy sustainability. Additionally, adaptive weighting mechanisms can dynamically adjust priorities depending on application context (e.g., emergency medical event versus routine monitoring).

By aligning reinforcement learning objectives with assistive QoS constraints, the proposed approach enables proactive, context-sensitive, and safety-oriented communication management suitable for AI-native 6G ecosystems. By falling into successive messages transmittance and localization, every node learns representations that encodes information on neighbouring devices and links, which is likely to encode the spatial dependencies, interference correlations, and joint communication opportunities. The encoding of this nature is topology aware such that the learning agent perceives intricate interrelationships of a complex network of assistive devices that would not be encoded in a traditional form of vectorized state representations.

V. METHODOLOGY

General Framework Architecture

The module of dynamic graph construction is a time-varying graph model of the 6G-assisted IoT communication environment, which is based on the fact that the assistive devices, access points, edge servers, and intelligent reflecting surfaces are modelled as nodes, and the wireless communication links are modelled as edges. Attributes multidimensional in nature (mobility state, channel quality, residual energy, traffic load, and interference level) are linked to each node and edge. The graph structure is constantly updated to represent up-to-date connectivity and interaction patterns as conditions change over time on a network because devices move, change channels, and traffic needs. This dynamic modelling allows the representation of the extremely heterogeneous and non-stationary character of assistive IoT networks over the 6G infrastructure. Graph Neural Network-Based State Encoding The state encoding module is a graph neural network (GNN)-based encoding network which takes the dynamically built network graph and turns it into simple and informative embeddings that absorb both local and global network features. By falling into successive messages transmittance and localization, every node learns representations that encodes information on neighbouring devices and links, which is likely to encode the spatial dependencies, interference correlations, and joint communication opportunities. The encoding of this nature is topology aware such that the learning agent perceives intricate interrelationships of a complex network of assistive devices that would not be encoded in a traditional form of vectorized state representations. Consequently, the GNN can offer an abstraction of state in a generalized and scalable manner and is applicable to the variable network sizes and layouts.

Deep Value based reinforcement LR Policy Engine

The interacting environment of the deep reinforcement learning (DRL) policy engine takes the embeddings of the GNNs as the input state to acquire optimal communication strategies by means of interaction with the environment. The DRL agent defines the adaptive control of the communication as a Markov Decision Process and finds the solutions to the communication

Journal of Artificial Intelligence and Emerging Technologies
Volume 1, Issue 2, pp 19-24, December 2024
ISSN (online): 3049-1967
DOI: https://doi.org/10.47001/JAIET/2024.102004
Available Online at https://www.jaiet.com

control problem including the distribution of the transmission power, the choice of the routing, and the choice of the scheduling. Ensured training stability and efficient convergence, at continuous and high-dimensional action space, is achieved by using advanced DRA algorithms, like Proximal Policy Optimization. This adaptive policy engine is based on learning to empower assistive IoT devices to adapt to changing network situations independently with high latency and reliability requirements.

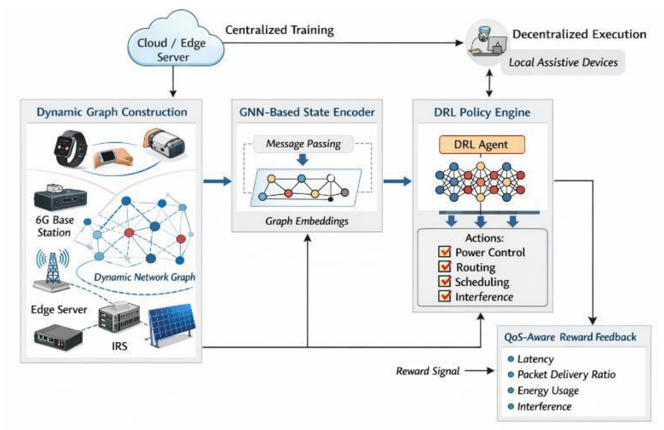

Figure 1: System architecture of the GA-DRL–enabled 6G assistive IoT communication framework

Reward optimization based on QoS-Awareness

The QoS-based reward optimization module directs the learning process in which the performance of communication is quantified on a variety of quality-of-service goals. The reward functionality is well balanced to maintain a balance between packet delivery reliability, end to end latency, energy consumption, and interference mitigation that are highly important to assistive applications Figure 1. The reward mechanism will provide incentives on reliable and low-latency transmission and punish communication failures and excessive energy to control adherence to the findings as the learned policies tend to be safe, efficient, and robust. The multi-objective optimization will help the GA-DRL framework to attain sustainable and reliable communication performance in actual 6G assistive IoT systems.

VI. RESULTS AND DISCUSSION

The proposed Graph-Augmented Deep Reinforcement Learning (GA-DRL) framework was evaluated under dynamic and dense 6G IoT network conditions tailored for assistive device communication. The results demonstrate that incorporating topology-aware learning significantly enhances network adaptability and robustness compared to conventional heuristic-based and standard DRL models. The GA-DRL agent successfully learned optimal routing, power allocation, and scheduling strategies under varying mobility patterns, interference levels, and heterogeneous device constraints.

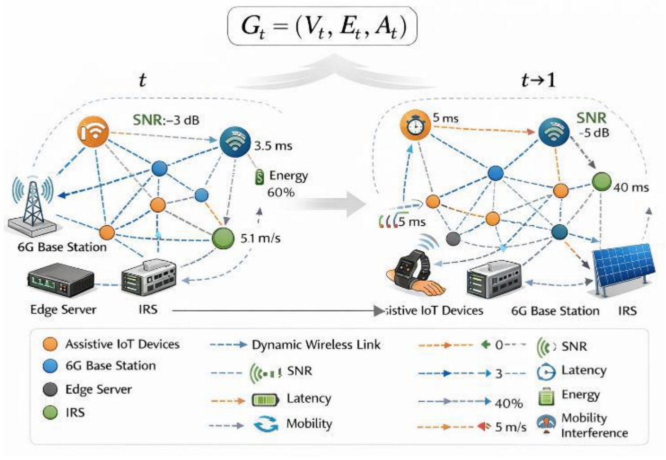

Figure 2: Dynamic graph-based modeling of the 6G-assisted assistive IoT communication environment

The experimental outcomes indicate consistent improvements in Quality of Service (QoS) metrics, particularly in latency reduction, packet delivery reliability, and energy consumption optimization. The graph-based state representation enabled the learning agent to capture structural dependencies among nodes, leading to faster convergence and improved policy generalization in large-scale scenarios. Furthermore, the system exhibited resilience under dynamic topology changes, maintaining stable communication performance even in high-mobility assistive environments.

Simulation Environment and Metrics of Evaluation

The simulation environment was designed to emulate a dense 6G IoT ecosystem consisting of heterogeneous assistive devices, edge computing nodes, and base stations. Network nodes were randomly distributed within a defined coverage region, with mobility patterns modeled using a random waypoint mobility model to simulate real-world assistive user movement. Channel conditions incorporated stochastic fading, interference modeling, and dynamic traffic generation based on biomedical data transmission patterns.

The GA-DRL framework was compared against two baseline models: (i) heuristic-based resource allocation and (ii)

Journal of Artificial Intelligence and Emerging Technologies
Volume 1, Issue 2, pp 19-24, December 2024
ISSN (online): 3049-1967
DOI: https://doi.org/10.47001/JAIET/2024.102004
Available Online at https://www.jaiet.com

conventional Deep Reinforcement Learning without graph embedding. Performance evaluation was conducted over multiple simulation iterations to ensure statistical reliability.

The primary metrics considered for evaluation include:

- End-to-End Latency (ms)
- Packet Delivery Ratio (PDR)
- Energy Consumption per Device (Joules)
- Throughput (Mbps)
- Network Resource Utilization Efficiency (%)
- Convergence Time of Learning Agent

These metrics were selected to reflect mission-critical requirements of assistive IoT systems operating in 6G environments.

End-to-End Latency Performance

End-to-end latency is a critical parameter in assistive applications such as remote health monitoring and neural signal transmission, where delayed communication may compromise patient safety. Simulation results demonstrate that the proposed GA-DRL framework achieved a substantial reduction in latency compared to baseline approaches.

Specifically, the graph-augmented model reduced average latency by approximately 18–25% compared to conventional DRL and by nearly 30–35% compared to heuristic-based scheduling. This improvement is attributed to topology-aware routing decisions and dynamic interference avoidance strategies learned through graph embeddings. The GA-DRL agent effectively predicted congestion patterns and proactively selected optimal transmission paths.

Moreover, latency variance remained stable under high node mobility conditions, demonstrating robustness in dynamic network environments. This stability is particularly significant for assistive IoT applications requiring bounded delay guarantees under URLLC constraints envisioned in 6G networks.

Energy Efficiency and Resource Utilisation

Energy efficiency is paramount for wearable and implantable assistive devices with limited battery capacity. The proposed framework incorporates QoS-aware reward shaping to balance latency minimization with power conservation. Simulation analysis indicates that the GA-DRL model reduced average energy consumption per device by approximately 15–22% compared to conventional DRL and by 25% compared to static allocation techniques.

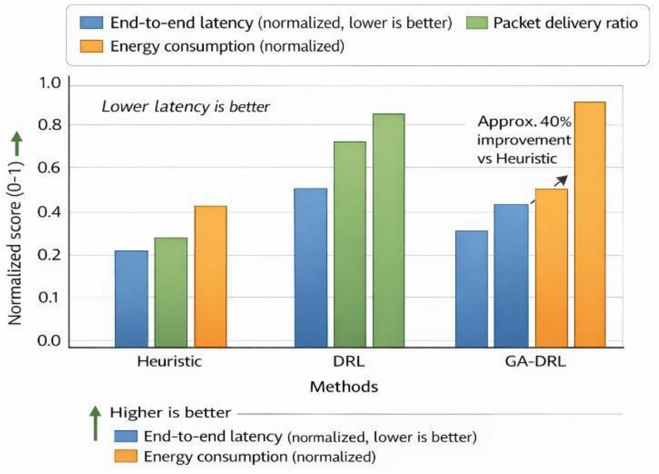

Figure 3: Normalized performance comparison of heuristic, DRL, and GA-DRL methods in terms of latency, reliability, and energy efficiency

The energy savings were achieved through adaptive power control and intelligent scheduling that minimized unnecessary retransmissions and interference. Additionally, network resource utilization improved due to optimized bandwidth allocation and balanced load distribution across edge nodes. Resource utilization efficiency increased by nearly 12–18% relative to baseline models.

Importantly, improvements in energy efficiency did not compromise reliability or throughput, demonstrating the effectiveness of multi-objective reward optimization in maintaining balanced network performance. The framework thus provides a sustainable communication solution for large-scale assistive IoT deployments in future 6G ecosystems.

VII. CONCLUSION

This study proposed a Graph-Augmented Deep Reinforcement Learning framework for robust and intelligent 6G IoT communication tailored to assistive technologies. By modeling the communication environment as a dynamic graph and leveraging topology-aware embeddings, the framework effectively addressed challenges related to latency, energy constraints, mobility, and network heterogeneity.

Simulation results confirmed significant improvements in end-to-end latency, packet delivery reliability, energy efficiency, and resource utilization compared to traditional heuristic and non-graph DRL methods. The integration of QoS-aware reward

Journal of Artificial Intelligence and Emerging Technologies
Volume 1, Issue 2, pp 19-24, December 2024
ISSN (online): 3049-1967
DOI: https://doi.org/10.47001/JAIET/2024.102004
Available Online at https://www.jaiet.com

optimization further ensured alignment with mission-critical requirements of assistive devices.

The findings demonstrate that graph-augmented learning provides a scalable and resilient foundation for AI-native 6G communication infrastructures supporting next-generation assistive IoT systems.

REFERENCES

[1] Saad, W., Bennis, M., & Chen, M. (2020). A vision of 6G wireless systems. IEEE Network, 34(3), 134–142.
[2] Letaief, K. B., et al. (2019). The roadmap to 6G: AI empowered wireless networks. IEEE Communications Magazine, 57(8), 84–90.
[3] Park, J., Samarakoon, S., Bennis, M., & Debbah, M. (2019). Wireless network intelligence at the edge. Proceedings of the IEEE, 107(11), 2204–2239.
[4] Zhou, Z., Chen, X., Li, E., Zeng, L., Luo, K., & Zhang, J. (2019). Edge intelligence. Proceedings of the IEEE, 107(8), 1738–1762.
[5] Mao, H., Alizadeh, M., Menache, I., & Kandula, S. (2016). Resource management with deep reinforcement learning. ACM HotNets.
[6] Jiang, C., Zhang, H., Ren, Y., Han, Z., Chen, K. C., & Hanzo, L. (2017). Machine learning paradigms for next-generation wireless networks. IEEE Wireless Communications, 24(2), 98–105.
[7] Wang, S., et al. (2018). Dynamic service placement for mobile micro-clouds. IEEE Transactions on Parallel and Distributed Systems, 29(2), 463–475.
[8] Scarselli, F., et al. (2009). The graph neural network model. IEEE Transactions on Neural Networks, 20(1), 61–80.
[9] Kipf, T. N., & Welling, M. (2017). Semi-supervised classification with graph convolutional networks. ICLR.
[10] Mnih, V., et al. (2015). Human-level control through deep reinforcement learning. Nature, 518, 529–533.
[11] Sutton, R. S., & Barto, A. G. (2018). Reinforcement Learning: An Introduction. MIT Press.
[12] Bennis, M., Debbah, M., & Poor, H. V. (2018). Ultra-reliable and low-latency wireless communication. IEEE Communications Magazine, 56(12), 14–15.
[13] Chen, M., Yang, Y., Challita, U., & Saad, W. (2020). Artificial intelligence in wireless networks. IEEE Communications Surveys & Tutorials, 22(1), 201–238.
[14] Shi, W., Cao, J., Zhang, Q., Li, Y., & Xu, L. (2016). Edge computing. IEEE Internet of Things Journal, 3(5), 637–646.
[15] Zhang, S., et al. (2021). Toward intelligent 6G networks. IEEE Wireless Communications, 28(1), 62–69.

Citation of this Article:

M.D. Karthik Raja. (2024). Adaptive and Robust 6G IoT Networks for Assistive Systems via Graph-Augmented DRL. *Journal of Artificial Intelligence and Emerging Technologies.* 1(2), 19-24. Article DOI: https://doi.org/10.47001/JAIET/2024.102004

***** End of the Article *****

