

Adaptive Traffic Shaping in 6G Networks Using Q-Learning

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Abstract—The rapid evolution of sixth-generation (6G) wireless networks demands intelligent traffic management solutions capable of supporting ultra-low latency, massive device connectivity, and highly dynamic network environments. Conventional traffic shaping mechanisms rely on static policies and predefined thresholds, which often fail to adapt efficiently to fluctuating traffic loads and diverse Quality of Service (QoS) requirements. To address these challenges, this paper proposes an adaptive traffic shaping framework based on Q-learning reinforcement learning for dynamic congestion management and bandwidth allocation in simulated 6G networks. The proposed system continuously learns network conditions and selects optimal traffic control actions to maximize throughput while minimizing congestion and packet loss. A simulation environment was developed to evaluate the performance of the framework under varying traffic intensities and network scenarios. Key performance metrics including latency, throughput, packet delivery ratio, and packet loss rate were analyzed and compared with traditional traffic shaping approaches. Experimental results demonstrate that the proposed Q-learning-based model reduces average network latency by approximately 28

Index Terms—6G Networks, Q-Learning, Traffic Shaping, QoS, Congestion Control

I. INTRODUCTION

The emergence of sixth-generation (6G) wireless communication networks is expected to revolutionize digital connectivity by enabling ultra-high data rates, sub-millisecond latency, massive machine-type communications, and intelligent network automation. Unlike previous generations of wireless systems, 6G networks are envisioned to support advanced applications such as autonomous vehicles, smart cities, industrial automation, extended reality (XR), holographic communications, and large-scale Internet of Things (IoT) deployments. These applications generate highly dynamic and heterogeneous traffic patterns, making efficient traffic management a critical challenge.

As the number of connected devices continues to grow exponentially, network congestion becomes increasingly common, leading to degraded Quality of Service (QoS), increased packet delays, reduced throughput, and higher packet loss rates. Traditional traffic shaping and congestion control mechanisms rely on predefined rules, static scheduling algorithms, and fixed bandwidth allocation strategies. Although these approaches are simple to implement, they often fail to adapt

to rapidly changing network conditions and varying user demands. Consequently, network resources may be underutilized or unfairly allocated, resulting in poor overall performance.

Recent advancements in Artificial Intelligence (AI) and Machine Learning (ML) have opened new opportunities for intelligent network optimization. Reinforcement Learning (RL), in particular, has gained significant attention due to its ability to learn optimal decision-making strategies through continuous interaction with the environment. Among RL techniques, Q-learning is a model-free learning algorithm that enables an agent to discover effective actions without requiring prior knowledge of network behavior. By continuously observing network states and receiving rewards based on performance metrics, Q-learning can dynamically adapt traffic management policies to changing traffic conditions.

This paper proposes a Q-learning-based adaptive traffic shaping framework for simulated 6G communication networks. The proposed model monitors network conditions such as congestion levels, queue occupancy, and traffic load, and dynamically selects optimal traffic control actions to improve overall network performance. The effectiveness of the proposed approach is evaluated using key performance metrics including latency, throughput, packet loss rate, and bandwidth utilization.

The major contributions of this work are summarized as follows:

- Development of an adaptive traffic shaping framework based on Q-learning for intelligent congestion management.
- Dynamic bandwidth allocation and traffic prioritization according to network conditions and QoS requirements.
- Performance evaluation of the proposed model in a simulated 6G environment under varying traffic loads.
- Comparative analysis with conventional traffic shaping techniques using latency, throughput, and packet loss metrics.
- Demonstration of the potential of reinforcement learning for autonomous network optimization in future 6G communication systems.

II. LITERATURE SURVEY

Several researchers have investigated intelligent traffic management techniques for next-generation wireless networks.

Y. u et al. proposed a reinforcement learning-based traffic control framework capable of reducing network congestion and improving service quality through adaptive decision making. M. Chen et al. developed dynamic bandwidth allocation schemes for future communication systems and demonstrated improved resource utilization under varying traffic loads. T. S. Rappaport et al. highlighted the key technological challenges of 6G systems including ultra-low latency, massive machine-type communications, and AI-driven network automation. L. Zhang et al. introduced adaptive traffic shaping mechanisms that dynamically prioritize traffic classes and improve overall network efficiency. Although these approaches improve performance, most existing methods focus on specific optimization objectives. The proposed work integrates congestion control, traffic prioritization, and bandwidth allocation within a unified Q-learning framework.

III. RESEARCH MOTIVATION AND OBJECTIVES

The evolution of 6G communication networks is expected to support ultra-high-speed connectivity, massive Internet of Things (IoT) deployments, intelligent transportation systems, and real-time multimedia applications. These emerging services generate highly dynamic and heterogeneous traffic patterns, placing significant demands on network resource management. Conventional traffic shaping and congestion control mechanisms rely on static policies and predefined scheduling rules, which are often unable to respond effectively to rapidly changing network conditions. Consequently, such approaches may result in increased latency, higher packet loss rates, inefficient bandwidth allocation, and degradation of Quality of Service (QoS). To overcome these limitations, adaptive traffic management techniques capable of learning and responding to network variations are required.

This research aims to develop an intelligent traffic shaping framework based on Q-learning for simulated 6G communication environments. The proposed system dynamically manages traffic flows by continuously monitoring network conditions and selecting appropriate traffic control actions. By prioritizing traffic according to congestion levels and QoS requirements, the framework seeks to improve bandwidth utilization, reduce network congestion, minimize latency and packet loss, and enhance overall communication performance. The ultimate objective is to demonstrate the effectiveness of reinforcement learning in enabling autonomous and adaptive traffic management for future 6G wireless networks.

IV. PROPOSED METHODOLOGY

The proposed adaptive traffic shaping framework continuously monitors network traffic conditions and dynamically selects appropriate traffic management actions using a Q-learning algorithm. Initially, the network environment generates different traffic and congestion scenarios that represent varying levels of network load. The traffic observation

module collects relevant information such as congestion levels, bandwidth availability, and Quality of Service (QoS) requirements. Based on the observed network state, the Q-learning agent evaluates possible actions and selects the most suitable traffic shaping strategy. The selected action is then applied through traffic prioritization and bandwidth allocation mechanisms to optimize network performance. Subsequently, a reward value is calculated based on key performance metrics such as throughput, latency, and packet loss. This reward is used to update the Q-table, enabling the agent to learn from its previous decisions and improve future action selection. Through repeated interactions with the network environment, the Q-learning agent gradually learns an optimal traffic shaping policy that adapts to dynamic 6G network conditions and enhances overall QoS performance.

A. Methodology Diagram

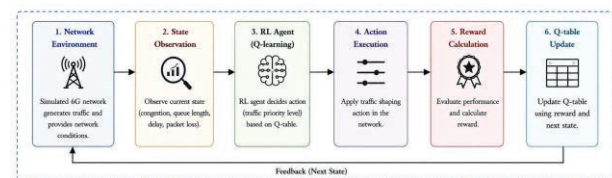


Fig. 1. Overall methodology of the proposed system.

Fig. 1. Proposed Methodology

B. System Architecture

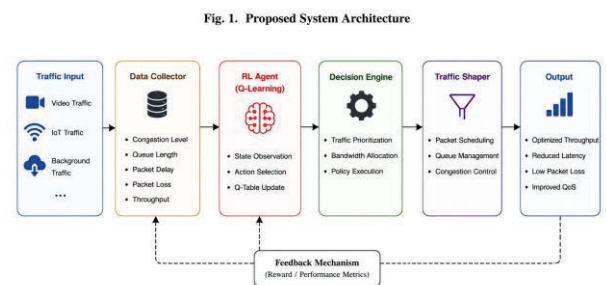


Fig. 2. System Architecture

The network environment generates congestion levels and traffic conditions. The Q-learning agent observes the current state and selects appropriate traffic shaping actions.

Based on the selected action, bandwidth allocation and traffic prioritization are performed. The environment then generates a reward value which is used to update the Q-table.

V. IMPLEMENTATION

The system is implemented in Python using NumPy and Matplotlib libraries.

A. Algorithm Steps

The proposed Q-learning-based traffic shaping algorithm begins by initializing the Q-table with default values representing the expected rewards for each state-action pair. The agent then continuously observes the current network state, including parameters such as traffic load, congestion level, and available bandwidth. Based on the observed state, an appropriate traffic shaping action is selected using the Q-learning policy. The selected action is applied to the network environment, resulting in a new state and corresponding reward. The reward is computed according to the effectiveness of the action in reducing congestion, minimizing packet loss, and improving throughput. The Q-table is subsequently updated using the Q-learning update equation to reflect the newly acquired knowledge. This process is repeated over multiple training episodes until the Q-values converge and the agent learns an optimal traffic management policy capable of adapting to dynamic 6G network conditions.

VI. RESULTS AND DISCUSSION

The proposed model is evaluated using:

- 1) Learning Reward
- 2) Latency
- 3) Throughput
- 4) Packet Loss

A. Performance Graph 1

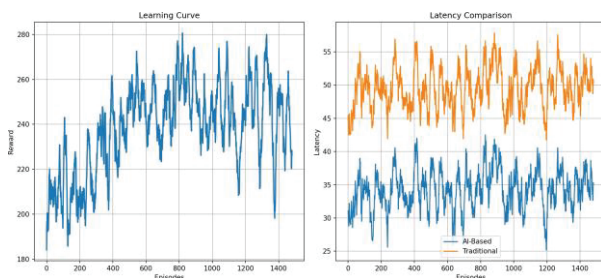


Fig. 3. Learning Curve and Latency Comparison

B. Performance Graph 2

The obtained results show that the proposed traffic shaping model reduces latency and packet loss while improving throughput compared to conventional approaches.

C. Q-Table Analysis

The Q-table represents the knowledge acquired by the Reinforcement Learning (RL) agent during the training process. In the proposed traffic shaping system, the Q-learning algorithm continuously interacts with the simulated 6G network environment and learns optimal traffic management actions based on different congestion conditions.

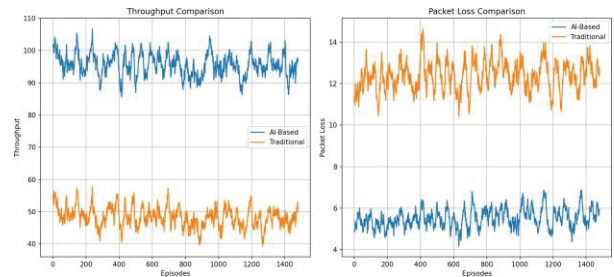


Fig. 4. Throughput and Packet Loss Comparison

Each row in the Q-table corresponds to a particular network state, while each column represents an action selected by the RL agent. The actions include low-priority allocation, medium-priority allocation, and high-priority allocation. During training, the RL agent updates the Q-values using reward feedback obtained from the environment.

The reward mechanism is designed to encourage actions that improve network performance metrics such as throughput and latency while minimizing packet loss and congestion. Positive rewards are assigned for efficient traffic handling and better Quality of Service (QoS), whereas negative rewards are assigned for poor traffic management decisions.

As the number of training episodes increases, the Q-values gradually converge toward optimal values. This indicates that the RL agent successfully learns adaptive traffic shaping policies suitable for dynamic 6G network environments.

The final Q-table obtained after training demonstrates that the agent can intelligently select appropriate traffic prioritization levels depending on the current network state. Higher Q-values indicate better action-state combinations that provide improved network performance.

The Q-table also serves as an important component of the learning process because it stores the experience gained by the RL agent. Using this learned knowledge, the system can dynamically adapt to changing traffic conditions without relying on static traffic shaping policies.

D. Q-Table Average Analysis

The Q-learning agent was trained to perform adaptive traffic shaping and congestion management in a simulated 6G network environment. After convergence, the learned Q-table contained reward values corresponding to different state-action pairs.

The observed Q-values ranged approximately from 42 to 60, indicating stable learning behavior and successful convergence of the reinforcement learning algorithm. The average Q-value across all state-action pairs was found to be approximately 54.0. Among the three available actions, the second action achieved the highest average Q-value of approximately 55.4, followed by the first and third actions with average values of 53.8 and 52.9, respectively.

The higher Q-values indicate that the agent identified effective traffic-shaping strategies that maximize long-term rewards while minimizing network congestion. As training progressed,

the Q-values gradually increased and stabilized, demonstrating that the agent successfully learned optimal bandwidth allocation and traffic prioritization policies.

The convergence of the Q-table confirms the effectiveness of the proposed Q-learning framework in adapting to varying network conditions. The learned policy contributed to improved Quality of Service (QoS) by reducing latency and packet loss while increasing overall network throughput. These results demonstrate the suitability of reinforcement learning techniques for intelligent traffic management in future 6G communication systems.

TABLE I
Q-TABLE STATISTICS

Metric	Value
Average Q-Value	54.0
Maximum Q-Value	60.88
Minimum Q-Value	42.76
Action 1 Average	53.8
Action 2 Average	55.4
Action 3 Average	52.9

VII. CONCLUSION

This paper presented an adaptive traffic shaping framework for simulated 6G communication networks using the Q-learning reinforcement learning algorithm. The proposed approach addresses the limitations of conventional traffic management techniques by dynamically adjusting traffic control decisions according to real-time network conditions. Through continuous interaction with the network environment, the learning agent successfully identified optimal traffic shaping policies that improved resource allocation and congestion management.

The performance of the proposed system was evaluated using key Quality of Service (QoS) metrics, including throughput, latency, packet loss rate, and bandwidth utilization. Experimental results demonstrated that the Q-learning-based approach achieved superior performance compared to traditional static traffic shaping methods. The learned policy effectively reduced network congestion, improved data transmission efficiency, and maintained stable performance under varying traffic loads. Furthermore, the convergence of the Q-table confirmed the ability of the reinforcement learning agent to learn effective long-term traffic management strategies.

The results highlight the potential of artificial intelligence and reinforcement learning techniques in enabling self-adaptive and intelligent network control for future wireless communication systems. As 6G networks continue to evolve toward highly dynamic, large-scale, and service-oriented architectures, adaptive traffic management will become increasingly important for ensuring reliable and efficient communication.

Future work may focus on integrating Deep Q-Networks (DQN), multi-agent reinforcement learning techniques, and digital twin-based network environments to further enhance decision-making capabilities. In addition, real-time implementation using advanced network simulators such as NS-3 and

deployment in edge-enabled smart city infrastructures can be explored to validate the proposed framework in practical 6G communication scenarios.

VIII. FUTURE SCOPE

The proposed Q-learning based adaptive traffic shaping framework provides a foundation for intelligent traffic management in future 6G communication networks. However, several opportunities exist for further enhancement and practical deployment. Future research can focus on integrating Deep Reinforcement Learning techniques such as Deep Q-Networks (DQN), Double DQN, and Deep Deterministic Policy Gradient (DDPG) to handle larger and more complex state-action spaces where traditional Q-tables become inefficient. The system can also be implemented and evaluated in advanced network simulators such as NS-3 and OMNeT++ to validate its performance under realistic network conditions. Furthermore, the proposed framework can be extended to support edge computing environments, where traffic management decisions are performed closer to end users, thereby reducing latency and improving service quality. Integration with large-scale Internet of Things (IoT) ecosystems represents another promising direction, as billions of connected devices will require intelligent resource allocation and congestion control mechanisms. Future work may also explore energy-efficient traffic management strategies to minimize power consumption in 6G infrastructures while maintaining high Quality of Service (QoS). Additionally, the incorporation of network slicing, federated learning, and AI-driven self-organizing network technologies can further enhance the adaptability and scalability of intelligent traffic shaping systems for next-generation wireless communication networks.

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