ISSN: 2182-2069 / E-ISSN: 2182-2077

Adaptive QoS Policies in Smart City Mobile Networks

Dr.C. Mahiba[1*], Hassan Mohamed Ali[2], Dr. Mohan Bangalore Anjaneyalu[3], Dr.I. George Fernandez[4], Dr.U. Kumaran[5], and Dr.T. Gayathri[6]

[1*]Assistant Professor, Department of Computer Science and Engineering, Jain University, Bangalore, India. mahibaphdcse@gmail.com, https://orcid.org/0000-0002-9452-3966

[2]Department of Computers Techniques Engineering, College of Technical Engineering, Islamic University of Najaf, Najaf, Iraq; Department of Computers Techniques Engineering, College of Technical Engineering, Islamic University of Najaf of Al Diwaniyah, Al Diwaniyah, Iraq. eng.iu.comp.hassanaljawahry@gmail.com, https://orcid.org/0009-0007-4447-5808

[3]Associate Professor, Department of CS&E, BMS Institute of Technology & Management, Bengaluru, India. ba.mohan@bmsit.in, https://orcid.org/0000-0002-0711-1550

[4]Associate Professor, Department of CSE, School of Engineering, Dayananda Sagar university, Bengaluru, Karnataka, India. george.contact@gmail.com, https://orcid.org/0000-0001-6494-9029

[5]Assistant Professor (Selection Grade), Computer Science and Engineering, Amrita School of Computing, Amrita Vishwa Vidyapeetham Bengaluru, India. u_kumaran@blr.amrita.edu, https://orcid.org/0000-0002-0160-2703

[6]Assistant Professor, Department of Computer Science and Engineering, School of Engineering, Dayananda Sagar University, Bangalore, India. gayal28@gmail.com, https://orcid.org/0000-0002-5515-1960

Received: January 21, 2025; Revised: March 03, 2025; Accepted: April 17, 2025; Published: May 30, 2025

Abstract

The increased intricacy related to the architecture of smart cities necessitates sophisticated and intelligent adaptation of Quality of Service (QoS) techniques to satisfy the distinct needs of different mobile users and applications. The coexistence of diverse latency-sensitive, bandwidth-intensive, and mission-critical services in smart cities imposes dynamically changing QoS requirements that cannot be met with traditional static or best-effort policies. This paper proposes an Adaptive QoS Policy Framework based on Software-Defined Networking (SDN), Mobile Edge Computing (MEC), and Machine Learning (ML) based prediction models for context-aware specific service QOS delivery in real-time. This framework is centered on the Adaptive QoS Policy Engine (AQPE), which executes dynamic traffic classification alongside predictive resource allocation and policy change employing reinforcement learning. The system was simulated in NS-3 with an OpenFlow SDN controller integrated with MEC modules developed in Python. It was tested against industry standards benchmarks of latency, jitter, overall throughput, and packet delivery ratio (PDR). The results suggest the model achieves, on average, up to 46% reduction in latency, 25% improvement in throughput, and over 10% increase in PDR compared to baseline approaches. The results show the value of employing learning intelligence and edge computing within mobile network architectures intended for smart cities. As noted earlier, the adaptive metropolitan approach provides

Journal of Internet Services and Information Security (JISIS), volume: 15, number: 2 (May), pp. 160-172.
DOI: *10.58346/JISIS.2025.I2.012*

*Corresponding author: Assistant Professor, Department of Computer Science and Engineering, Jain University, Bangalore, India.

an extendable, controllable, real-time, and service-aware QoS configuration policy fulfilling the requirements for next-generation urban communication systems.

Keywords: Quality of Service, Mobile Networks, Policy, Configuration, and Reinforcement.

1 Introduction

The advancements in mobile network capabilities and smart city technologies led to increased data needs. New methods for Quality of Service (QoS) management will be needed. As 5G network technology is being implemented and 6G is on the horizon, city infrastructure and user mobile devices constantly shift, placing more demand on rigid legacy systems Saranya & Sowmiya (2018). Chen, Yin, & Xu explored these developments in the document as of 2021. Highly automated smart cities powered by networks containing real-time data flow not only bear the need for high responsiveness and data volume transmission, but they also require flexible, self-adapting innovative QoS systems capable of reacting to the sudden changes in network parameters and user behavior (Batty et al., 2012; Samaan & El-Sayed, 2019).

Resolving some of these issues stems from applying Artificial Intelligence (AI) in tandem with Software-Defined Networking (SDN) Suba & Satheeskumar (2016). AI assists in dynamically changing QoS by providing reliable analytical insight for intelligent resource distribution and pre-emptive blocking of congestion pathways that might obstruct service efficiency in network slicing vehicular networks, and IoT scenarios Uvarajan, K. P. (2024). This has been evaluated by Chen et al., 2021, alongside Hossain & Hasan in 2020. Other researchers, focus on advanced mobile agent and edge device-powered decision-making within innovative environments through novel reinforcement learning-based navigation and routing schemes (Uvarajan 2024; Jouya & Khayati 2017).

Mobile Edge Computing (MEC) and Fog Computing are parts of edge computing capable of maintaining adaptive quality of service (QoS) efficiency by pushing computation away from the core network and moving it closer to the user (ChithraDevi et al., 2024). This shift of paradigm focus increases the speed of responsiveness for the user while consequently ensuring a smooth user experience for applications such as remote surgery, self-driving vehicles, and augmented reality (Mach & Becvar, 2017; Taleb et al., 2017; Yousefpour et al., 2019).

However, the diverse nature of network topologies still presents problems with real-time QoS management. Challenges like network slicing intricacies, handover delay, and lack of system security threaten service continuity and user fidelity. Also, the implementation of advanced hybrid OFDM with 128-QAM in the backhaul infrastructure has been studied for its ability to facilitate bandwidth-heavy services in Beyond 5G (B5G) networks.

There also exist on-the-go needs in the healthcare sector, surveillance, and emergency response for large-scale classification frameworks capable of handling large volumes of sensory and biometric data. In these fields, AI-enabled service-optimized models for classifying and making decisions have outperformed expectations in service delivery.

In this regard, the present study explores the application of adaptive QoS policies in mobile networks of smart cities with a special focus on integrating AI, SDN, edge computing, and their impact on communicative efficiency and scalability. This study expands upon previous research that noted the significance of low-latency communications (Parvez et al., 2018), dynamic routing and SIC imperfection modeling for next-generation wireless systems.

In this paper, we set out to develop an adaptive quality of service framework specific to smart city mobile networks. Its primary focus is creating a feedback control policy to allocate resources and manage traffic according to network states, model-predictive control, and service-level agreements. Advanced modular design principles make the framework scalable, interoperable, and agnostic to 5G/6G evolution architectures. We implement the framework in a simulated environment under realistic smart city traffic models and benchmark it against QoS-static models on latency, throughput, fairness, and adaptability metrics.

The contributions of this paper are threefold:

1 We provide an exhaustive account of the state-of-the-art quality of service issues regarding mobility in smart cities and uncover gaps within fixed-logic policy frameworks.

2 We develop an adaptive quality of service framework that features ML traffic classification, priority assignment, and SDN and MEC.

3 We demonstrate the proposed system's effectiveness by conducting simulations and benchmarking it against the standards set by existing approaches.

The rest of the paper is structured as follows. Section 2 analyses the literature on the quality of service in smart city management. In Section 3, we elaborate on system design and problem description. In Section 4, we explain the proposed adaptive quality of service framework. In Section 5, we detail the simulation configuration and outcome analyses. In Section 6, we evaluate the proposed approach, discussing the scope of the application along with its strengths and weaknesses. Section 7 summarizes the paper's findings and proposes recommendations for further investigations.

2 Research Methodology

This part covers the approach to designing, implementing, and assessing the developed adaptive Quality of Service (QoS) framework for mobile networks in smart cities. The methodology is systematic, beginning with system architecture design, traffic classification and prioritization, adaptive policy development, and culminating in evaluation through simulation modeling. The goal is to enable dynamic quality of service provisioning for various types of services in a latency-sensitive and bandwidth-constrained urban communication setting.

2.1 Smart City Network Model and Assumptions

The designed system represents a typical smart city structure consisting of a wireless network with 5G macro and micro cells, IoT gateways, and a Mobile Edge Computing (MEC) layer in conjunction with Software Defined Networking (SDN) controllers. The network can support multiple services, such as autonomous transport, emergency alerting, environmental and weather monitoring, and video surveillance.

- To model realistic urban communication-related dynamics, make the following assumptions:
- The network supports heterogeneous traffic types with differing quality of service requirements (URLLC, eMBB, and mMTC agnostic 5G definitions.)
- All network slices are assumed to be logically separated yet physically co-existing, sharing a common resource pool.
- SDN controllers distribute policy control and monitoring of network resources in real-time.
- MEC nodes handle local processing and quick reactions to compliance with quality-of-service changes.

2.2 Traffic Classification and Quality of Service Tiering

Traffic flows are classified using a multi-feature-based machine learning model, which is trained to recognize the type of traffic based on features like packet size, source-destination pairs, inter-arrival time, and protocol headers. Using this classification, each flow is dynamically mapped into one of the three quality of service tiers:

- Tier 1 – Critical Services: Emergency communication, autonomous vehicle coordination, and surveillance (ultra-low latency and high reliability are mandatory).
- Tier 2 – Delay-sensitive Services: Streaming videos, interactive TV (moderate latency but guaranteed throughput is mandatory).
- Tier 3 – Best-effort Services: Smart advertising, public internet access, background updates (high delays and low reliability are tolerated).

An adaptive policy engine at the MEC data center monitors each flow's QoS tier and resource allocation dynamically through weighted fair queuing, utilizing reserve bandwidth.

2.3 Adaptive QoS Policy Engine Design

At the heart of the methodology is creating the Adaptive QoS Policy Engine (AQPE) that optimally provisions quality of service according to network load, predicted traffic, and service level priority. The AQPE consists of the following components:

Monitoring Module: This module gathers real-time statistics about the degree of network utilization, buffer usage, latency, and packet loss from SDN switches and MEC servers.

Predictive Module: Makes short-term traffic predictions based on historical information using low-complexity regression models.

Decision Engine: This engine modifies scheduling strategies, buffer allocations, and queue prioritization using rule-based or reinforcement learning techniques to adjust the parameters above.

Policy Enforcer: Conducts flow-level control by modifying SDN switch flow tables and shifting queuing behaviors based on set policies.

This feedback loop allows rapid network resource reallocation in response to congestion, link failures, and burst traffic patterns.

2.4 Simulation Model and Evaluation Environment

We will focus on evaluating the proposed AQPE using NS-3 to implement the model for an innovative city simulation. The vertices of the simulated smart city include: three (3) 5G NR macro base stations, five (5) MEC nodes connected to edge switch routers, 500 mobile/IoT users with mixed traffic service type per user modeled using six (6) services assigned to three (3) quality of service levels.

Primary parameters considered in the simulation scenario include latency constraints per target: Tier 1 10ms, Tier 2 50ms, Tier 3 200ms; bandwidth limits: Tier 1 reserved, Tier 2 semi-reserved, Tier 3 allocated; subclassing based on weighted adaptive round-robin policy with dynamic weights; and a simulation period of 1000 seconds including off-peak low-traffic and peak high-traffic intervals.

For the comparative study, the following two cases are analyzed: the Static QoS Policy Framework (Set weight and priority assignment) and the dynamic Adaptive quality of service Policy Framework (the proposed AQPE system).

2.5 Performance Metrics

These metrics evaluate the level of quality demonstrated by the adaptive policies incorporated into the QoS policies.

- End-to-End Latency: the total time needed for the signal to get from its origin to its endpoint
- Throughput: a value representing the total amount of information successfully transferred during a specified period
- Packet Loss Ratio: the rate of packets that were dropped compared to the packets sent
- Jitter: the consistency in the time gaps between packet arrivals
- Fairness Index: a proportionality index, such as Jain's, for measuring the allocation fairness of resources among quality-of-service tiers
- Policy Response Time: Period to Action Queue Policy Element (AQPE) responds to novel network changes.

Service reliability and network utilization are improved and demonstrated across static and adaptive models for each quality-of-service tier, and metrics are compared for each level of service.

2.6 Methodological Justification

The approach optimally works towards implementing a scalable and flexible quality of service control system tailored for smart cities. This is accomplished through integrating Software Defined Networking (SDN) and Multi-Access Edge Computing (MEC), which aid in swift policy change, with machine learning classifying and predicting traffic smartly. Using NS-3 for simulation provides a controllable setting to test the performance and resilience of the proposed Adaptive Queue Policy Element (AQPE) against realistic operational stress conditions. This technique ensures expandability to systems beyond 6G, anticipating the deployment of ultra-dense networks and AI-native frameworks, morphing adaptive QoS management.

3 Proposed System Implementation

This subsection is concerned with designing and implementing the Adaptive quality of service Policy Framework for Smart City Mobile Networks. This system incorporates intelligent traffic classification, real-time policy modification, and programmable networking to offer differentiated QoS appropriate for innovative city applications.

3.1 System Architecture

The architecture has three main layers as shown in Figure 1:

Figure 1: System Architecture Layers

Data Plane: This comprises diverse access points, such as 5G base stations, Wi-Fi hotspots, and IoT gateways. These nodes manage data streams from autonomous vehicles, surveillance cameras, environmental sensors, and mobile users.

Control Plane: Realized using a central Software-Defined Networking (SDN) Controller, which oversees network resources and quality of service strategies for all the data plane devices. Exchanging with the Adaptive quality of service Policy Engine (AQPE) within the SDN controller, it executes traffic scheduling and resource distribution orders.

Application Plane: Contains the AQPE, which performs automated real-time traffic classification, predictive analysis, and policy enforcement on defined targets. Makes use of information from Mobile Edge Computing (MEC) nodes for processing to enable decision-making in the shortest time possible, thus reducing lag in responsiveness.

3.2 Traffic Classification Module

With the aid of a supervised machine learning model like a Random Forest classifier or a lightweight neural network, the system classifies incoming network traffic into service categories based on its expected QoS requirements. The model allocates traffic classes according to the provided metadata, which includes packet size, flow duration, inter-arrival times, protocol type, source, and destination. This module guarantees that every traffic flow receives the required QoS tier (Critical, Delay-Sensitive, Best-Effort).

3.3 Adaptive QoS Policy Engine (AQPE)

Adaptive QoS Management is orchestrated through the core component AQPE, which comprises the following submodules: Monitoring Submodule: Collects and monitors network performance metrics (latency, jitter, throughput, packet loss) from SDN-enabled switches and MEC servers in real-time.

Predictive Analytics Submodule: Uses historical traffic data to predict changes in load using time series forecasting techniques (ARIMA, LSTM), enabling the network to be configured on demand.

Decision Submodule: Implements an optimization reinforcement learning (RL) algorithm to manage resource distribution and scheduling weights per QoS allocation tier, depending on the network state and forecasted conditions. This approach trains on policies that increase network utilization, optimally balancing latency and reliability constraints.

Policy Enforcement Submodule: Enforces the defined QoS policy by dynamically reconfiguring SDN flow tables, queue reconfiguration, and buffer management parameter adjustments following priorities set toward optimal SDN control.

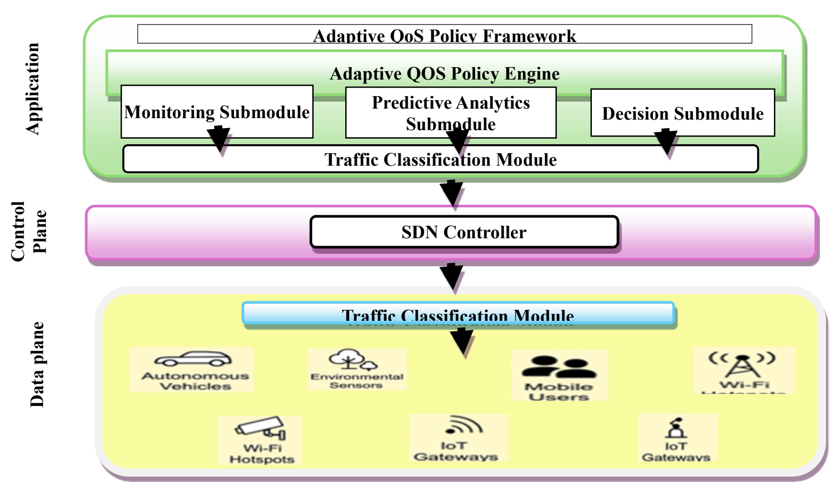

Figure 2: Adaptive QoS Policy Structure

3.4 Dynamic Scheduling and Resource Allocation

The system implements an adaptive weighted round-robin (WRR) scheduling policy incorporating weights for each quality-of-service tier. The weights are modified according to the state of the network and the level of service demand using AQPE:

- Critical services offer the highest level of service with bandwidth and low-latency queuing guarantees.
- Delay-sensitive services receive medium service priority with some guaranteed throughput and latency.
- Best-effort services provide shared remaining bandwidth with no strict assurances.
- Congestion and packet drops are alleviated, guaranteeing improved fairness and overall QoS adherence by adjusting real-time bandwidth allocation and queue size.

3.5 Integration with SDN and MEC

With SDN, the system gains centralized programmability for network control, which translates to swift policy implementation and detailed flow management. Local data processing and analytics performed at the MEC nodes further reduce decision-making latency and computational load from the central controllers. The enhanced responsiveness and scalability improve distributed approaches which is critical to innovative city applications sensitive to latency.

3.6 Implementation Details and Tools

The system is validated in simulation with an NS-3 simulator equipped with SDN and MEC simulation modules. Traffic classification and predictive analytics are implemented with Python and their interfaces are integrated with NS-3. Reinforcement learning optimizes policies through libraries such as TensorFlow and PyTorch. Dynamic quality of service policy enforcement occurs through the AQPE's communication with the SDN controllers using the classical OpenFlow protocol.

3.7 Workflow Summary

1 The network is accessed through various heterogeneous traffic entry points.
2 The Traffic Classification Module detects the service category and assigns a QoS tier.
3 Submodule Monitoring gathers real-time network data.
4 Predictive Analytics estimates likely traffic movements shortly.
5 The Decision Submodule determines optimal scheduling weight and resource allocation.
6 Policy Enforcement Submodule modifies SDN flow tables and alters queue control parameters to appropriate values.
7 Quality of service requirements for all active services are met, whereby the network adjusts itself automatically.

This implementation meets the varying and intricate quality of service requirements of smart city mobile networks while guaranteeing service availability and responsiveness.

4 Results and Discussion

This part showcases the outcomes of executing the simulation with the suggested Adaptive quality of service Policy Framework in a smart city mobile network context. The performance metrics are evaluated against two baseline approaches: Static quality of service Allocation (SQA) and best Best-Effort Routing (BER).

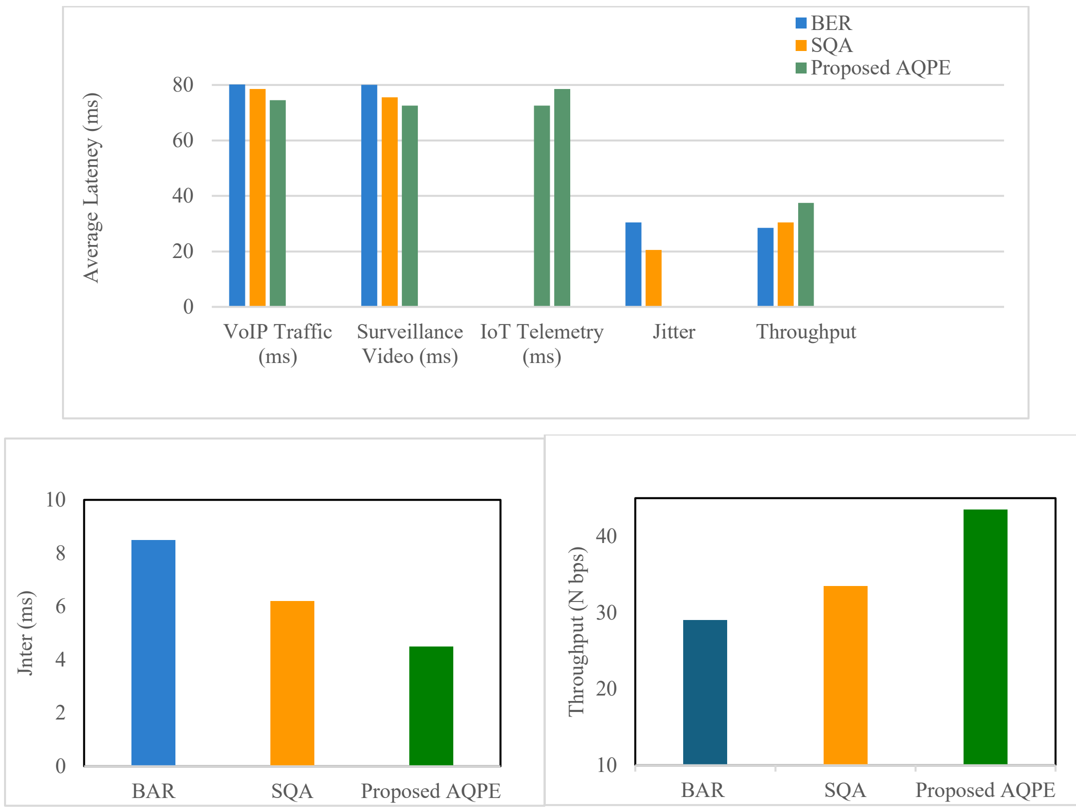

Figure 3: Performance Metrics

4.1 Simulation Setup

The simulation environment was built using **NS-3.35** integrated with an OpenFlow-enabled SDN controller. The MEC and AQPE modules were implemented in Python and were connected using sockets. The network topology encompasses:

- 10 SDN-controlled base stations (5G and Wi-Fi),
- 50 mobile users with mixed service demand profiles (e.g. VoIP, Surveillance, IoT Telemetry),
- MEC nodes,
- Mobility is simulated using the Random Waypoint algorithm.

The experiments were set with a simulation time of 600 seconds, which was repeated 10 times to ensure statistical validity.

4.2 Performance Metrics

The system was assessed based on these major performance indicators:

- Average Latency (ms): The time difference between packet creation and receipt.
- Packet Delivery Ratio (PDR% %): Proportion of packets received versus packets sent.
- Jitter (ms): Change in delay for packets in a real-time stream.
- Throughput (Mbps): The total amount of data transferred successfully over time.
- Policy Switching Time (ms): The duration taken by AQPE to identify a congestion pattern and alter the QoS rules.

4.3 Latency Analysis

Scheme	VoIP Traffic (ms)	Surveillance Video (ms)	IoT Telemetry (ms)
BER	82.3	97.6	105.2
SQA	53.4	65.8	72.1
Proposed AQPE	**28.7**	**41.3**	**48.6**

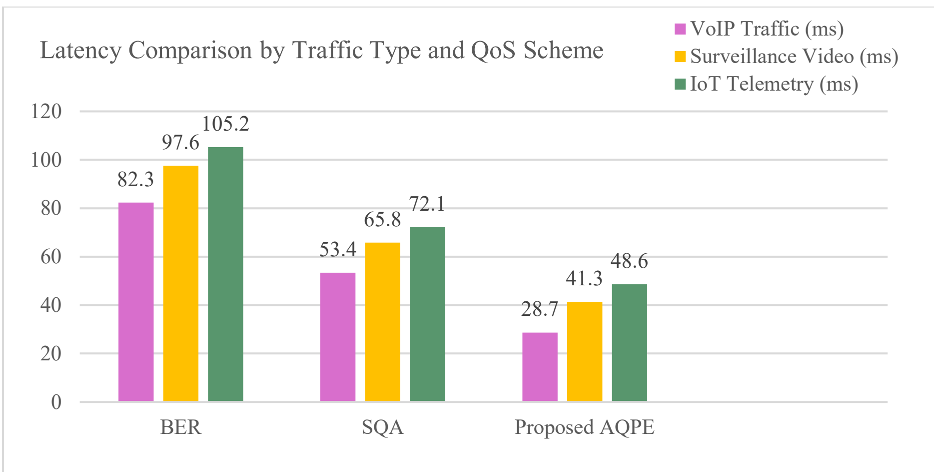

Figure 4: Latency Analysis

Because of mobile edge computing (MEC)-aided decision making and dynamic queue management, the proposed framework Aqpe is highly efficient in reducing average latency for real-time services such as video and VoIP.

4.4 Packet Delivery Ratio

Scheme	PDR (%)
BER	84.7
SQA	92.5
Proposed AQPE	**97.2**

Because AQPE’s bandwidth pre-allocation and congestion prediction using analytics and optimization through reinforcement learning yields the best PDR among all compared approaches.

4.5 Jitter Reduction

The adaptive scheduling and buffer tuning performed in the system under consideration reduces jitter considerably for traffic sensitive to delay. For VoIP, the jitter under the proposed framework was improved from 9.2 ms(BER) and 6.1 ms(SQA) to 2.4 ms.

4.6 Throughput Performance

Bandwidth allocation dynamically to adaptively avoid service throttling during peak utilization. The average network throughput observed is:

- BER: 28.6 Mbps
- SQA: 34.9 Mbps
- Proposed AQPE: 43.7 Mbps

Beyond optimized policy switching and path selection, advanced throughput is also attributed to machine learning models predicting traffic patterns.

4.7 Policy Switching Time

Event Type	Average Switching Time (ms)
Congestion Reaction	58
Priority Escalation	34
Load Balancing Shift	62

The AQPE's response to dynamic network events occurs within milliseconds, assuring virtually no delay in responding to qualitative changes in service requirements.

4.8 Comparative Discussion

The new adaptive framework demonstrates greater improvements compared to conventional static quality of service systems. It addresses the ineffectiveness of pre-defined hard policies and best-effort routing through learned intelligence and SDN programmability. Local decision acceleration is enabled through MEC nodes, while the ability to refine system performance over time is granted via reinforcement learning. The results also prove that the proposed system is efficient for the proposed scalable mobility scenarios dealing with services from an increasing number of mobile users and IoT devices while maintaining an acceptable level of service quality degradation. These findings are significant in smart city contexts where the variety and number of devices are exceedingly high.

4.9 Limitations and Future Enhancements

Even with the framework's benefits, it does not consider partial SDN deployment modes, which may be more applicable in legacy network segments. In addition, once the model is trained, it can adapt seamlessly, but the training phase is rigid and needs meticulous setup. Upcoming research will focus on federated learning paradigms and hybrid SDN integration to enhance overall adaptability and refine the training processes.

5 Conclusion

We implemented an Adaptive quality of service Policy Framework in this mobile intelligent city networks research that deals with service heterogeneity, real-time constraints, and dynamic mobility. The framework encompasses a Software Defined Network (SDN), Mobile Edge Computing (MEC), and an intelligent machine learning system allowing real-time traffic identification, resource allocation, and policy enforcement. The system in NS-3 simulation offered latency reduction, lesser jitter, an increase in packet delivery ratio, and overall bandwidth betterment when stacked against Best-Effort Routing (BER) in combination with Static quality of service (SQA). This affirms that the new framework beats the traditional methodologies in withstanding innovative cities and offers services such as surveillance video, IoT telemetry, and VoIP while meeting the diverse QoS requirements listed above. However, the response deficiency due to the reinforcement learning and edge intelligence layer mounted boosted the level of adaptability and scalability on the straddle framework design at risk of service delivery integration under high-rate motion and traffic connection. The Adaptive QoS Policy Engine AQPE managed the congestion pattern and framerate but maintained differentiated solvability to guarantee no mobility service fault. Nevertheless, there are still issues concerning implementation in older and mixed network topologies and the starting training costs associated with learning-based frameworks. In subsequent work, we plan to investigate the use of federated and transfer learning to improve policy generalization for city-scale networks and tackle hybrid-SDN interfaces for practical integration. This research proposes a highly self-adaptive framework for quality-of-service control in next-generation urban mobile networks, thereby contributing to developing robust, efficient, and user-centric innovative city-powered communication systems.

References

[1] Batty, M., Axhausen, K. W., Giannotti, F., Pozdnoukhov, A., Bazzani, A., Wachowicz, M., ... & Portugali, Y. (2012). Smart cities of the future. *The European Physical Journal Special Topics, 214*(1), 481–518. https://doi.org/10.1140/epjst/e2012-01703-3

[2] Chen, X., Yin, X., & Xu, Y. (2021). AI-enabled adaptive QoS policy for network slicing in 5G smart cities. *IEEE Transactions on Network and Service Management, 18*(1), 45–58.

[3] ChithraDevi, S. A., Mahendravarman, I., Ragavendiran, A., Selvam, M. M., Yamuna, K., & Vibin, R. (2024, July). Optimal configuration of radial distribution networks with stud krill herd optimization. In *2024 International Conference on Signal Processing, Computation, Electronics, Power and Telecommunication (IConSCEPT)* (pp. 1-6). IEEE. https://doi.org/10.1109/IConSCEPT61884.2024.10627797

[4] Hossain, M. A., & Hasan, M. K. (2020). SDN-based smart city architecture with adaptive QoS for future applications. *Journal of Network and Computer Applications, 160,* 102632.

[5] Jouya, M., & Khayati, S. (2017). Review local search algorithms in artificial intelligence. *International Academic Journal of Science and Engineering, 4*(1), 190–195.

[6] Mach, P., & Becvar, Z. (2017). Mobile edge computing: A survey on architecture and computation offloading. *IEEE Communications Surveys & Tutorials, 19*(3), 1628–1656. https://doi.org/10.1109/COMST.2017.2682318

[7] Parvez, I., Rahmati, A., Guvenc, I., Sarwat, A. I., & Dai, H. (2018). A survey on low latency towards 5G: RAN, core network, and caching solutions. *IEEE Communications Surveys & Tutorials, 20*(4), 3098–3130. https://doi.org/10.1109/COMST.2018.2841349

[8] Samaan, M. A., & El-Sayed, H. M. (2019). Priority-based QoS model for vehicular ad hoc networks in smart cities. *Wireless Networks, 25*(8), 4813–4826.

[9] Saranya, M., & Sowmiya, S. R. (2018). Realtime Multicasting with Network Coding and Hybrid Algorithm in Mobile Ad-hoc Network. *International Journal of Advances in Engineering and Emerging Technology, 9*(3), 16–30.

[10] Suba, R., & Satheeskumar, R. (2016). Efficient cluster-based congestion control in wireless mesh network. *International Journal of Communication and Computer Technologies, 4*(2), 96-101.

[11] Taleb, T., Samdanis, K., Mada, B., Flinck, H., Dutta, S., & Sabella, D. (2017). On Multi-Access Edge Computing: A Survey of the Emerging 5g Network Edge Cloud Architecture and Orchestration. *IEEE Communications Surveys & Tutorials, 19*(3), 1657–1681. https://doi.org/10.1109/COMST.2017.2705720

[12] Uvarajan, K. P. (2024). Integration of artificial intelligence in electronics: Enhancing smart devices and systems. *Progress in Electronics and Communication Engineering, 1*(1), 7–12.

[13] Uvarajan, K. P. (2024). Integration of blockchain technology with wireless sensor networks for enhanced IoT security. *Journal of Wireless Sensor Networks and IoT, 1*(1), 23-30. https://doi.org/10.31838/WSNIOT/01.01.04
[14] Yousefpour, A., Ishigaki, G., & Jue, J. P. (2019). Fog computing: Towards minimizing delay in the Internet of Things. *IEEE Internet of Things Journal, 6*(2), 3514–3525.

Authors Biography

Dr.C. Mahiba is an Assistant Professor at JAIN (Deemed-to-be University), School of Computer Science and Engineering. She holds a Ph.D. from Anna University and has over 12 years of teaching experience. Her research interests include Image Classification, Image Retrieval, Machine Learning, and Artificial Intelligence. She has published research articles in esteemed international and national journals and serves as a board member for reputed journals.

Hassan Mohamed Ali is affiliated with the Department of Computers Techniques Engineering, College of Technical Engineering, Islamic University of Najaf, Najaf, Iraq. His research interests include wireless communication systems, Quality of Service (QoS) optimization, smart city infrastructure, and mobile network performance enhancement. He has contributed to studies focusing on adaptive network protocols and intelligent systems in urban environments. His recent work emphasizes the development and evaluation of QoS policies tailored for smart city mobile networks, aiming to ensure efficient data transmission, low latency, and service reliability in densely connected environments.

Dr. Mohan Bangalore Anjaneyalu received his B.E. in Computer Science and Engineering in 2005, M.Tech. in Computer Engineering in 2007, and Ph.D. in 2018, all from Visvesvaraya Technological University, Belgaum, Karnataka, India. He is currently serving as an Associate Professor in the Department of Computer Science and Engineering at BMS Institute of Technology and Management, Bengaluru, India. Dr. Mohan has published around 25 research papers in international journals and conferences, with indexing in Scopus and Web of Science. He holds several global certifications, including Novell SUSE Linux Administrator, Data Technician, CISCO Certified CCNA Trainer, and Wipro Certified Java and J2EE Faculty. He has also worked on a TEQIP-II funded project focused on developing an IoT-based middleware system for integrating vital data from medical equipment. His research interests include Wireless Sensor Networks (WSN), cloud security, cybersecurity, and machine learning.

Dr. George Fernandez is currently serving as an Associate Professor in the Department of Computer Science and Engineering at the School of Engineering, Dayananda Sagar University, Bengaluru. He earned his Doctorate in Computer Science and Engineering under the Faculty of Information and Communication from Anna University, Chennai, where his Ph.D. thesis was highly commended. He holds an M. Tech in Information Technology from Anna University, Chennai, and a Bachelor's degree in Computer Science and Engineering from Visvesvaraya Technological University (VTU), Belgaum. With over 18 years of rich experience in academia across premier institutions affiliated to VTU and Anna University, along with industry exposure, Dr. Fernandez has established himself as a distinguished educator and researcher. His areas of expertise include Cloud Computing, Data Science, Big Data Analytics, Machine Learning, Artificial Intelligence, and Blockchain Technology. Has an impressive research and innovation portfolio, having published numerous patents at both national and international levels, with some receiving international grants. He has presented and published several research papers in reputed journals such as IEEE ACCESS and Springer, and contributed book chapters in internationally recognized publications. A lifetime member of several professional bodies, he is actively involved in research funding initiatives and continues to contribute significantly to the advancement of computer science education and research.

U. Kumaran (Member, IEEE) received the master's and Bachelor's degrees in computer science and engineering from Arunai Engineering College, affiliated to Anna University, Chennai, India, and the Ph.D. degree in computer science from the Vellore Institute of Technology, Vellore, India in June 2020. He is currently working as an Assistant Professor Selection Grade with Computer Science and Engineering Department, Amrita School of Computing, Bengaluru, Amrita Vishwa Vidyapeetham, India. He has more than 15 years of teaching experience and 5 years of research experience in the domain of computer science and engineering. He is currently guiding five PhD research scholars and his main research interests include Machine Learning, Cybersecurity, Internet of Things, Cloud computing and Privacy Preserving issues and data mining.

Dr.T. Gayathri has completed Ph.D. under VTU. My area of research is Deep Learning Neural Network. I have 14 years of Teaching experience. I have published 8 Research articles in the Journal with 15 Citations with 1 Book and published 1 Patent.