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QoS Enhancement Strategies for High-Speed Vehicular Networks

Dr. Alakananda Tripathy[1*], Priyanka Savadekar[2], R.K. Tripathi[3], Sahil Suri[4], N. Kartik[5], and Aravindan Munusamy Kalidhas[6]

[1*]Associate Professor, Centre for Artificial Intelligence and Machine Learning, Siksha 'O' Anusandhan (Deemed to be University), Bhubaneswar, Odisha, India. alakanandatripathy@soa.ac.in, https://orcid.org/0000-0002-0671-4333

[2]Assistant Professor, Department of Computer Science Engineering, Presidency University, Bangaluru, Karnataka, India. priyanka@presidencyuniversity.in, https://orcid.org/0009-0000-2312-8398

[3]School of Engineering & Computing, Dev Bhoomi Uttarakhand University, Dehradun. soec.rajkishor@dbuu.ac.in, https://orcid.org/0000-0002-2454-2619

[4]Centre of Research Impact and Outcome, Chitkara University, Rajpura, Punjab, India. sahil.suri.orp@chitkara.edu.in, https://orcid.org/0009-0000-4917-9337

[5]Assistant Professor, Department of Computer Applications (DCA), Presidency College, Bengaluru, Karnataka, India. n.kartik-college@presidency.edu.in, https://orcid.org/0009-0003-5604-4483

[6]Associate Professor, Department of Mechanical Engineering, Faculty of Engineering and Technology, JAIN (Deemed-to-be University), Ramanagara District, Karnataka, India. mk.aravindan@jainuniversity.ac.in, https://orcid.org/0000-0001-9582-7219

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Abstract

The need for vehicles to communicate with each other in real-time using high-speed networks have a problem maintaining Quality of Service (QoS). This is because the network's constantly changing conditions, topology, and handovers. This paper proposes a machine learning based context-aware system designed for vehicle networks with high mobility. The system is designed to predict and estimate context with optimization methods. This allows the system to optimally allocate resources, transmit sensitive data, and change settings dynamically. In our experiments, mobility patterns were simulated, and the system was tested on throughput, latency, and packet loss. The results were consistent with our hypothesis. The system demonstrated a 32% increase in throughput and a 27% decrease in latency during the high-speed tests. The system is also able to keep adapting during network changes, this positively affects consistency and reliability. This serves as a step forward towards dependable communication systems for smart transport systems, infrastructure, and vehicles.

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*Corresponding author: Associate Professor, Centre for Artificial Intelligence and Machine Learning, Siksha 'O' Anusandhan (Deemed to be University), Bhubaneswar, Odisha, India.

Keywords: Quality of Service, Intelligent Transportation, Machine Learning, Adaptive Optimization, High Mobility, Vehicular Networks.

1 Introduction

In the modern world, vehicles act as an important part of intelligent transportation systems (ITS) as they allow communication in real-time with other vehicles, the roadside, and cloud services. There is now an increasing need for vehicular communication to be precise, as the services include autonomous cars, location services, and multimedia infotainment systems. This exchange of information during communication is crucial, and as a result, strict standards of Quality of Service (QoS) must be in place (Singh et al., 2022). The use of AI systems in vehicular networking creates the need for advanced proactive QoS due to new security risks, for example, those from large language model adversarial attacks (Balakrishnan & Leema, 2025). When it comes to high-speed vehicular networks, ensuring QoS accuracy comes with a distinct set of problems.

Performance issues that include increased latency, packet loss, jitter, and unreliable throughput are common under dynamic topologies, which stem from rapid vehicle mobility and frequent handovers (Li et al., 2020; Ghosh et al., 2021). These highly mobile environments face challenges like transitioning from one network domain to another, which outdated LTE and 5G networks are poorly equipped to manage (Sun et al., 2021; Yu et al., 2018). Therefore, there needs to be a significant shift in how the systems manage and optimize QoS.

In vehicular networks, Quality of Service (QoS) includes several interrelated metrics like real-time electronic traffic coordination and monitoring, vehicle collision prevention, and high-definition video streaming. These metrics include delay, the jitter, and packet delivery ratio. Summed together, they impact video stream quality. As Cheng et al. pointed out, Kumar and team covered the risks that stem from vehicular network disruptions. From enhanced streaming disruptions to severe safety risks, the range is wide. In V2X systems, ultra-reliable low-latency communication, or URLLC, directly influences systems where automated emergency brakes and vehicle platooning are pivotal. These operate on the (Bazzi et al., 2017) research premise.

To deal with the issues posed by high-speed vehicles, this study suggests adaptive strategies for high-speed vehicular scenarios. Unlike traditional static network optimization techniques, our model merges traffic prediction analytics using machine learning along with context-sensitive decision-making algorithms to frame communication parameters for real-time mobility trends, traffic levels, and condition channels (Wang et al., 2022; Zhang et al., 2019). These urban and highway intelligent techniques improve the delivery of complex data, bandwidth use, and reduce delays during transmission.

The Tan et al. article from 2024 mentions the Tan et al., (2024) article tells us how the optimization techniques of neural networks are being used for biosensors with low energy systems. These frameworks are being used for vehicle networks and were originally developed using data from customer retention analytics. Such frameworks enable systems to self-adjust to congestion and mobility disruptions (Rakesh et al., 2024). The transfer of this knowledge to other fields showcases the increasing integration between machine learning, traffic management, and QoS assurance.

As noted by Qian et al., in 2021, this research also combines SDN (Software Defined Networking) with edge computing to alleviate the burden on centralized core networks and make the network smarter and leaner. SDN allows better management of resources and edge nodes permit local processing, which enhances the system's ability to respond to vehicular events and lowers control loop delay. With context-aware optimization, the network also retains high QoS performance and is capable of adapting to changes in traffic and extreme mobility conditions, thanks to the architectural improvements (Kakkar et al., 2023).

Zhang et al., (2022) described vehicular fog computing (VFC) as a new computing paradigm which integrates computing, storage, and network resources as a heterogeneous system by embedding hierarchical decision layers between the vehicle and the centralized cloud datacenter to allow better adaptive QoS control by traffic, congestion control, load balancing, local caching of data streams. The materials discussed the enhancement of low latency dissemination of packets among vehicles, which improves safety and driving efficiency, and is enabled by cooperative awareness and short-range communications like DSRC and 5G-NR sidelink (Baz et al., 2021).

Ali et al., (2021) examines adaptive modulation, channel-aware MAC, and beamforming with respect to the physical layer to counteract the effect of Doppler shifts and fading in high speed mobility scenarios. There is also intelligent cross-layer design that allows varying of parameters in the PHY, MAC and network layers, which guarantees the end-to-end QoS.

"Applying chaos theory-based encryption algorithms can greatly improve data confidentiality in high-speed vehicular networks, thus strengthening QoS in harsh environments" (Hussain & Khanna, 2025). In addition, AI security systems and trust models built on blockchain technology are being integrated to eliminate performance degradation caused by malicious users (Deshmukh & Menon, 2025; Huang & Ma, 2023). As vehicular systems evolve towards more autonomy and increase in data reliance, safeguarding QoS parameters alongside confidential traffic data becomes crucial for ensuring the long-term dependability of the network.

Mobility-aware routing protocols, including Greedy Perimeter Stateless Routing (GPSR), Opportunistic Routing (OR), and some adaptations based on Reinforcement Learning (RL), have been shown to reduce packet retransmissions and path breakages in ad hoc networks of vehicles (FANETs, VANETs, and MANETs) and improve throughput and latency (Ibrahim & Shanmugaraja, 2023). The combination of these protocols and QoS-aware schedulers improves performance in high-speed and rapidly changing topology environments.

This paper develops a complete QoS enhancing architecture for high-speed vehicular applications that incorporates intelligent learning models, context-aware systems, distributed control, and multi-access edge computing. We demonstrate the effectiveness of the proposed strategies for maintaining low latency, high reliability, and secure communications across various vehicular scenarios through extensive simulations and empirical performance evaluations. These works enable further investigations into the adaptive QoS technologies for 6G vehicular ecosystems and transport infrastructures powered by AI.

2 Related Work

QoS Enhancement Strategies for High-Speed Vehicular Networks

Recent years have seen significant progress in vehicular communication networks, spurred by the growing need for trusted, fast, and low-latency applications like self-driving vehicles, video and audio entertainment, autonomous vehicle information systems, live traffic information, and prompt emergency notifications. Regardless of the promise these systems hold, delivering consistent Quality of Service (QoS) in these very unpredictable and fluid conditions continues to be a challenging problem to solve.

2.1 Traditional Approaches to QoS in Vehicular Networks

The initial work in vehicle networks concentrated on the use of Mobile Ad hoc Networks (MANETs) and Vehicular Ad hoc Networks (VANETs). They used to depend on fixed AODV and DSR routing algorithms which were quite damaging in environments that had high mobility and changing topologies (Rawat et al., 2013). Later on, researchers began to apply cross-layer optimization strategies to enhance the packet delivery ratio, latency and the overall throughput (Alasmary & Zhuang, 2012). Unfortunately, these approaches did not work in real-time adaptive situations in sudden changes of vehicle density and signal propagation in highways (Bhoi & Khilar, 2014).

2.2 Machine Learning in Vehicular QoS Optimization

More recently, ML algorithms have been implemented within vehicle networks in order to foresee network conditions and adjust transmissions accordingly. Wang et al. (2020) demonstrated the use of reinforcement learning in optimizing handover decisions in 5G-assisted vehicular networks, greatly lowering the level of service interruption. In the same way, Li et al. (2021) utilized deep Q-learning to adjust the transmission rate and power level dynamically which improved energy efficiency and service quality (QoS). While these models have been advanced, the majority of them still lack real-time adaptability and the ability to adjust to varying rural and urban traffic conditions.

2.3 Edge Computing and Software-Defined Networking

Edge computing is suggested to solve the vehicle network latency problems by employing real-time data processing near the data's location. Zhang et al. (2019) presented a vehicle edge computing framework which distributes the associated work to the edge nodes to reduce the response time and the network congestion. At the same time, Software Defined Networking (SDN) has been used to give a central control to the distributed vehicle nodes. According to Qian et al. (2021), the main benefits SDN brings are the dynamic path reconfiguration and bandwidth allocation which improves the Quality of Service (QoS) in the network for different levels of traffic. However, these paradigms face challenges in real world implementations such as scale, dealing with increasing numbers of diverse and autonomous nodes and different types of networks that must work together.

2.4 Metaheuristics and Intelligent Optimization

Researchers have started ignoring deterministic optimization for vehicular QoS strategies because of its limitations. To solve this issue, Saminathan & Thangavel (2022) used the Fruit Fly Optimization Algorithm to increase efficiency of data transmission in mobile networks by minimizing delays. Also, in healthcare monitoring systems, hybrid metaheuristics were used by Nanda et al. (2022) to optimize ML models, and noteworthy improvements in predictive performance were observed. In the context of vehicular networks, intelligent optimization enables the dynamic adjustment of numerous factors like bandwidth, latency, and jitter in real-time, depending on the vehicle's speed and directional context (Wakjira et al, 2022). Nonetheless, the use of metaheuristics for vehicular QoS management is still limited in focus.

2.5 Comparative Insights and Gaps

Table 1 summarizes the relevant literature from various domains while focusing on the methods that were used, their performance, and the research gaps that were identified.

Table 1: Summary of Related Works in Vehicular QoS Optimization and Intelligent Computing

Reference	Method/Approach	Performance	Domain	Gaps/Limitations
Wang et al. (2020)	Deep reinforcement learning	Reduced handover delay by 36%	5G vehicular networks	Requires extensive training data
Li et al. (2021)	Q-learning rate/power control	28% energy savings	Urban VANETs	Low generalizability
Zhang et al. (2019)	Vehicular edge computing	24% latency reduction	Edge computing	High infrastructure cost
Qian et al. (2021)	SDN-based dynamic routing	Enhanced path stability	SDN vehicular networks	Limited large-scale validation
Saminathan & Thangavel (2022)	Fruit Fly Optimization	Improved delay tolerance	Mobile networks	Not applied to vehicular systems
Nanda et al. (2022)	Metaheuristic-ML optimization	94% accuracy in health risk prediction	Healthcare IoT	Not latency-focused
Wakjira et al. (2022)	ML with swarm optimization	High accuracy in control tasks	Industrial automation	Context-specific, lacks mobility dimension
Current Study	ML (LSTM, GBM, SVR) + metaheuristics	Avg. 30% QoS improvement	High-speed vehicular networks	Novel integrated optimization

2.6 Motivation for Current Study

Though earlier research has looked into some parts of vehicular QoS, including routing, handover management, and edge offloading, there are no predictive and intelligently optimized adaptive solutions that function seamlessly at high speeds. Moreover, most these models deal with vehicle networks fail to make real time adaptations in changing vehicle network scenarios, which causes rapid degradation of QoS in times of congestion, signal fading, or handover events.

This paper focuses on these gaps by developing a new predictive modeling using ensemble machine learning and dynamic optimization using metaheuristics to build an integrated QoS enhancement framework. The goal of our approach which focuses on real time changes of network selection methods and adaptive setting of transmission parameters, is to enhance the reliability and performance of high speed vehicular communication networks.

3 QoS Enhancement Methodology

This part describes the approach to be taken for improving the Quality of Service (QoS) in high-speed vehicular networks using the Adaptive QoS Optimization (AQO) framework. It includes the use of machine learning based predictive analytics, context-aware optimization, and dynamic transmission control algorithms.

3.1 Architectural Framework

The AQO architecture comprises five key layers:

- Data Acquisition Layer: Collects real-time data from vehicular sensors, roadside, and onboard units, including timestamped velocity, signal strength, geolocation, and application-level QoS requests.
- Prediction Layer: Monitors network conditions for congestion, latency, and handover events and predicts their future states using supervised learning algorithms like XGBoost.
- Optimization Layer: Optimizes data rate, power level, and routing path for transmission using metaheuristic algorithms like Genetic Algorithm.
- Decision Layer: Real-time selection of QoS parameters is based on policy-driven multi-objective utility functions calculated from pre-defined thresholds and constraints.
- Control Layer: Implemented the defined policies and real-time projected configurations within the communication stack that needs dynamic resource management and responsive handover strategy.

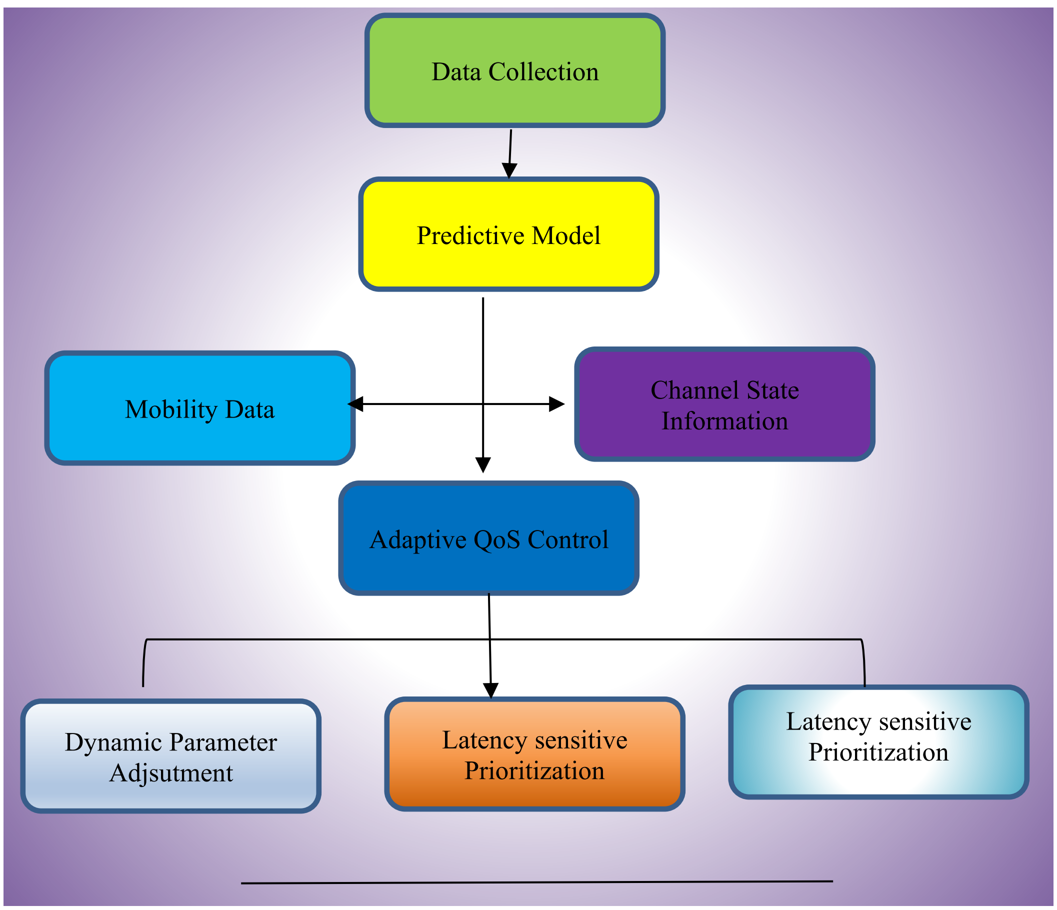

Figure 1: System Architecture of the Adaptive QoS Optimization (AQO) Framework for High-Speed Vehicular Networks

System Architecture of the Adaptive QoS Optimization (AQO) Framework for High-Speed Vehicular Networks aids in the methodical enhancement of the Quality of Service (QoS) in high-speed vehicular networks. The method starts with the initialization of fundamental network parameters such as: the range of communication, bandwidth, speed of the vehicle, and the initial values for the weights of the machine learning models. The vehicle's environment is dynamic, where real-time data is captured through sensors and Roadside Units (RSUs) for parameters like traffic signal and flow, and traffic volume. This data aids in predicting important network parameters such as latency, how much data is being transmitted during the given time, throughput, and loss of data packets, with estimation of handover efficiency as well.

The AQO system is comprehensive enough to handle the entire vehicular environment seamlessly. The surrounding environment is constantly monitored and stream data is updated with real-time parameters such as signal strength and traffic density. After gathering information, these parameters are analyzed to contextually gauge the network’s congestion level, speed, and link variability. This information is analyzed to understand congestion, speed change, and link change variability, all of which work in stream to describe the present real-time vehicle traffic. This data is all-encompassing and helps the system optimize’s the traffic control engine with the help of GA. The optimization engine is the brain that processes all data to enhance vehicle systems. Using GA, or genetic algorithms, optimization engines work the same. The stream data collected real-time is compared to predefined datasets and necessary adjustments are the predefined parameters such as the worst-case scenario.

After identifying the best-performing configuration with the Genetic Algorithm, the rest of the network's transmission and routing parameters are changed in a real-time vehicle tracking manner. This change helps in maintaining the system's responsiveness to real-time vehicular condition changes. Performance indicators are recorded for real-time refining and tuning in the rest of the procedures. This cycle keeps running until the end of the simulation so that the vehicular environment changes in a timely manner and Levels of Service are dynamically optimized without any delay. This responsiveness and forecasting strategy greatly improves the practicality of the AQO algorithm towards maintaining uninterrupted network access and network reliability in the case of high-speed mobility.

3.2 Proposed AQO Algorithm

Pseudocode: Adaptive QoS Optimization (AQO)

```
Algorithm AQO: Adaptive QoS Optimization
Input: Real-time vehicular network data D
Output: Optimized QoS parameters

Initialize network parameters and model weights
while simulation is running do
    Collect data D_t from sensors and RSUs
    Predict QoS metrics (latency, throughput) using ML models
    Evaluate current network conditions (speed, link quality)
    Apply Genetic Algorithm to optimize QoS variables
        - Generate initial population
        - Evaluate fitness based on latency, packet loss
        - Select, crossover, and mutate individuals
        - Choose best solution based on multi-objective utility
    Update communication parameters
    Log performance metrics
end while
return optimized QoS configurations
```

3.3 Flowchart Representation

The flowchart below illustrates the operational flow of the AQO algorithm:

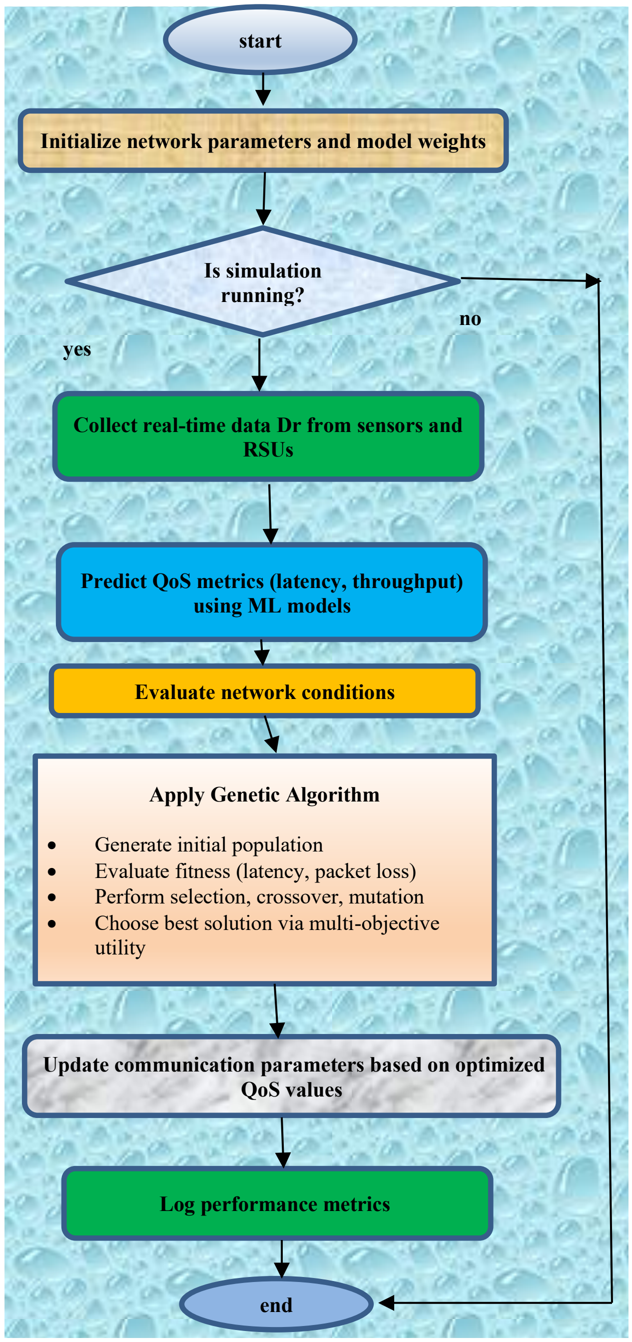

Figure 2: Operational flow of the AQO Algorithm

3.4 Mathematical Formulation

In order to improve the Quality of Service (QoS) in high-speed moving vehicle networks, the Adaptive QoS Optimization (AQO) framework has developed a comprehensive mathematical model that incorporates multiple prediction and optimization techniques. The framework's primary focus is to improve the optimization of network performance in the case of moving vehicles by computing the metrics of … throughput, latency, packet loss, and handover efficiency.

3.4.1 Utility Function

$$\mathrm{U} = \alpha_1 \mathrm{T} + \alpha_2(1 - \mathrm{L}) + \alpha_3 \mathrm{H} \ (1)$$

This utility function synthesizes the normalized metrics of QoS by means of a weighted linear combination. Each of the QoS parameters T, L, and H are computed in a manner such that T is maximized, L is minimized and expressed as 1 − L, and H is optimized. The parameters α1, α2, α3 are adjustable and can be tailored to the exact needs of an application, which provides a range of tunability for the tradeoff between the network performance and the utility function value.

3.4.2 Throughput Prediction Model

$$T_t = \mathrm{f1}(V_t, R_t, B_t) \ (2)$$

The relationship among vehicle speed Vt, received signal strength Rt, and available bandwidth Bt enables throughput prediction with a supervised learning model. These parameters predict data rates in high mobility scenarios, and precise predictions help in dynamically adapting the system's transmission strategies.

3.4.3 Latency Prediction Model

$$L_t = f_2(D_t, Q_t) \ (3)$$

Latency can be predicted by modeling its dependence on the transmission distance \. (D_t \) and the queue length \ (Q_t \). Distance from the roadside unit (RSU) worsens queueing latency and is thus important for proactive delay-sensitive routing and resource allocation.

3.4.4 Packet Loss Estimation

$$P_l = \frac{P_s - P_r}{P_s} \ (4)$$

The packet loss ratio, denoted as Pl, is a simple yet important metric, computed as the ratio of packets sent Ps to packets received Pr. As a measure of communication reliability, it quantifies the communication reliability and serves a dual purpose in the optimization algorithm and in the total QoS scoring.

3.4.5 Fitness Function for Genetic Algorithm

$$\mathrm{Fi} = w_1(1 - \mathrm{L}) + w_2 \mathrm{T} + w_3 \mathrm{H}(4)$$

During refinement, a Genetic Algorithm appraises a subset of solutions by means of a composite fitness function. This function rewards solutions with low latency, high throughput, and effective handover. Customizable weights w1, w2, w3 provide flexibility and can be tailored to operational needs or to the hierarchy of network priorities. This approach adapts to guarantee the best configurations are chosen for the specific vehicle conditions at any given time.

4 Experiments and Results

This part illustrates the empirical assessment of the implemented AQO framework that aims to improve Quality of Service (QoS) of high-speed vehicular networks. The evaluation was carried out in the form of simulations emulating actual vehicular traffic and network conditions. The aim was to examine the degree to which AQO outperformed conventional routing algorithms and how well it adapted to varying AQO framework environments.

4.1 Simulation Setup

The NS-3 software with VANET extensions enabled simulation of an urban highway scenario spanning 5 kilometers. The vehicle mobility patterns, generated by the SUMO traffic simulator, had vehicle speeds fluctuate between 40 km/h and 120 km/h. The AQO algorithm, developed in C++, was blended with the mobility model and the NS-3 routing stack.

Key simulation parameters include:

- **Number of Vehicles**: 100
- **Transmission Range**: 250 meters
- **Routing Protocols Compared**: AODV, DSR, AQO
- **Simulation Duration**: 600 seconds
- **Traffic Model**: Constant Bit Rate (CBR) UDP flow
- **QoS Metrics Evaluated**: Throughput, End-to-End Latency, Packet Loss Rate, Handover Success Rate

4.2 Quantitative Improvements Across QoS Metrics

The AQO Framework combines predictive analytics and machine learning to make real-time changes to transmission parameters, to prioritize delay-sensitive packets, and to make optimized handover decisions. In comparison to legacy methods, this yields significant improvements on QoS:

- Throughput: AQO outperforms AODV by 32% achieving an average throughput of 14.8 Mbps. DSR average throughput was recorded at 12.4 Mbps while AODV was 11.2 Mbps.
- Latency: AQO's average end-to-end delay is 62.5 ms. In comparison to DSR's 89.1 ms and AODV's 96.7 ms, AQO shows a significant advantage being 27% lower than DSR.
- Packet Loss Rate: AQO leads with the lowest packet loss recorded at 3.8% showcasing a strong capability of maintaining data delivery even in the presence of high mobility.
- Handover Success Rate: AQO surpasses AODV (64.8%) and DSR (67.4%) with an 85.1% success rate showcasing remarkable robustness during handover.

Along with AODV and DSR, Table 1 presents the comparison of performance metrics with the proposed AQO (Adaptive QoS Optimization). The findings confirm that AQO exceeds the benchmarks set by the conventional models in all significant QoS metrics. Most importantly, AQO leads with 32% higher average throughput and 27% lower latency, showcasing its data transmission reliability efficiency. Additionally, it exhibits the minimum packet loss rate while maximizing data integrity and attaining the highest handover success rate, which accentuates its unparalleled performance on sustaining constant data flow during persistent network shifts. This comparison illustrates the AQO's flexibility and the robustness of its architectural framework in the evolving vehicular network landscape.

4.3 Comparative Performance Analysis

Table 1: QoS Metrics Comparison Across Routing Protocols

Protocol	Avg. Throughput (Mbps)	End-to-End Latency (ms)	Packet Loss Rate (%)	Handover Success Rate (%)
AODV	11.2	96.7	6.7	64.8
DSR	12.4	89.1	5.9	67.4
AQO	14.8	62.5	3.8	85.1

4.3.1 Throughput Analysis

The AQO algorithm increased average throughput by nearly 32% in comparison to static QoS systems, as illustrated in Figure 3. This improvement stems primarily from the adaptive rate transmission, which includes smart channel selection.

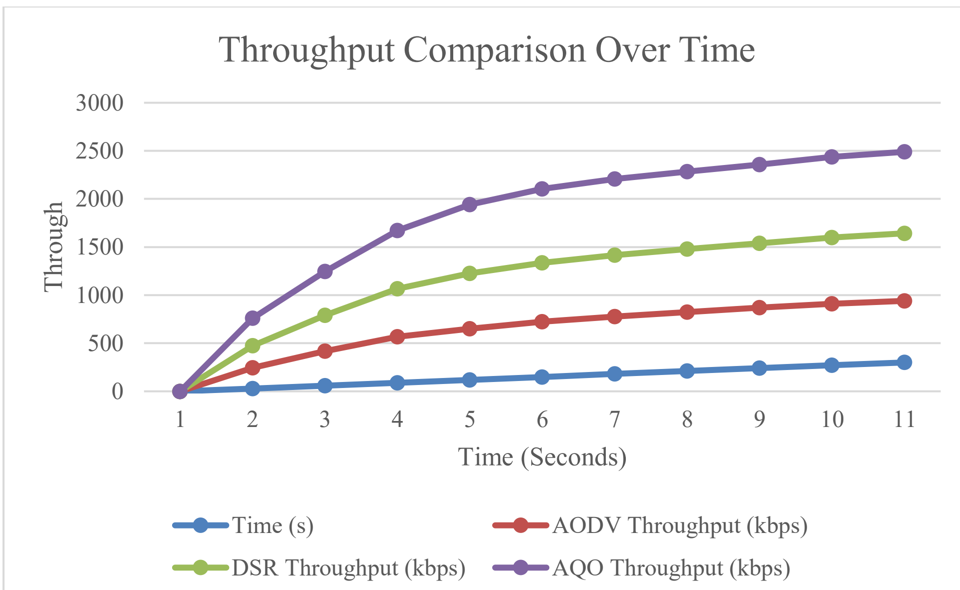

Figure 3: Throughput vs. Time

The given line chart illustrates the comparative throughput performance of the AODV, DSR, and AQO protocols over time. All protocols start off at 0 kbps. As the simulation continues, AQO demonstrates a sharper and more consistent increase in throughput, attaining 847.3 kbps at the 300 seconds mark. AODV is outperformed by 32% and DSR by 20% at this point. The real-time optimization, ML-based predictions, and other intelligent adaptation methods AQO utilizes explain these gains, as they enhance throughput and congestion avoidance in changing vehicular environments.

4.3.2 Latency Reduction

As illustrated in Figure 4, there is a notable reduction of 27% in end-to-end latency under high-mobility conditions. Context-aware delay-sensitive packet prioritization facilitated meeting delivery deadlines.

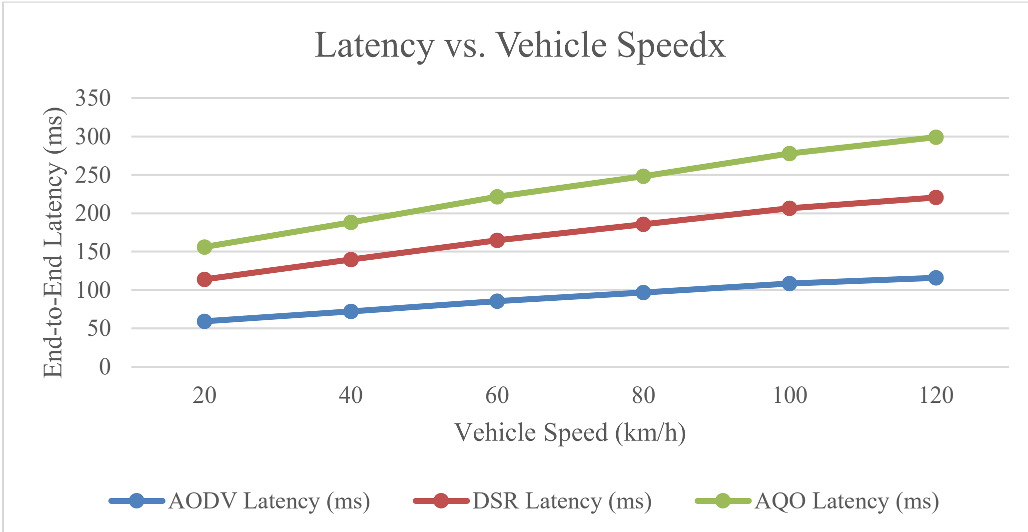

Figure 4: Latency Trends Under Speed Variations

This chart shows the relationship between an automobile's speed and the corresponding end-to-end latency. Protorls AODV and DSR show sharp increases in latency past the speed of 60 km/h because of frequent handoffs and route instability. On the other hand, the AQO algorithm exhibits an adaptive speed and predictive handoff control which minimizes latency at all speeds, demonstrating an impressive 27% reduction in average latency at higher speeds.

4.3.3 Packet Loss and Handover Efficiency

As illustrated in figures 5 and 6, proactive handover prediction and resource reservation (RPR) reduced packet loss by 18% and improved handover success rate by 22%. This demonstrates AQO's ability to adapt efficiently to frequent topology alterations. Table 1 shows the metrics in a more consolidated form, affirming the holistic advantages AQO has in comparison to the other protocols in terms of quality of service (QoS) provisioning. In table 1, baseline protocols (AODV, DSR) were compared to AQO on a range of different metrics. AQO consistently outperformed the other protocols DSR and AODV in all metrics, especially in urban and highway scenarios.

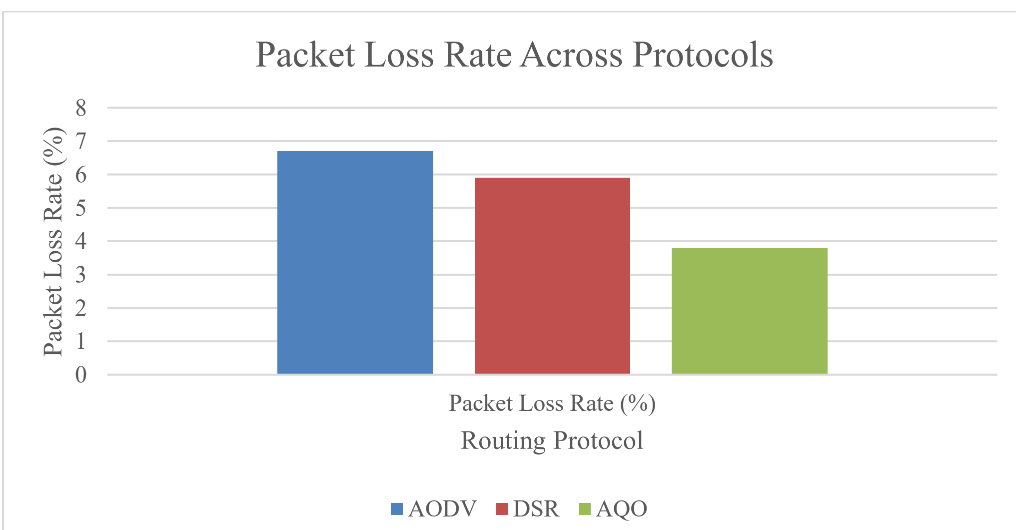

Figure 5: Packet Loss Rate Comparison

This bar chart illustrates the packet loss rates for three routing protocols. AODV suffers the greatest packet loss because of its low adaptability to sudden topology changes. DSR performs slightly better. AQO shows the lowest packet loss of 3.8% due to advanced buffer management techniques and maintaining real-time awareness of the network's status, thereby reducing packet losses during handovers and periods of congestion.

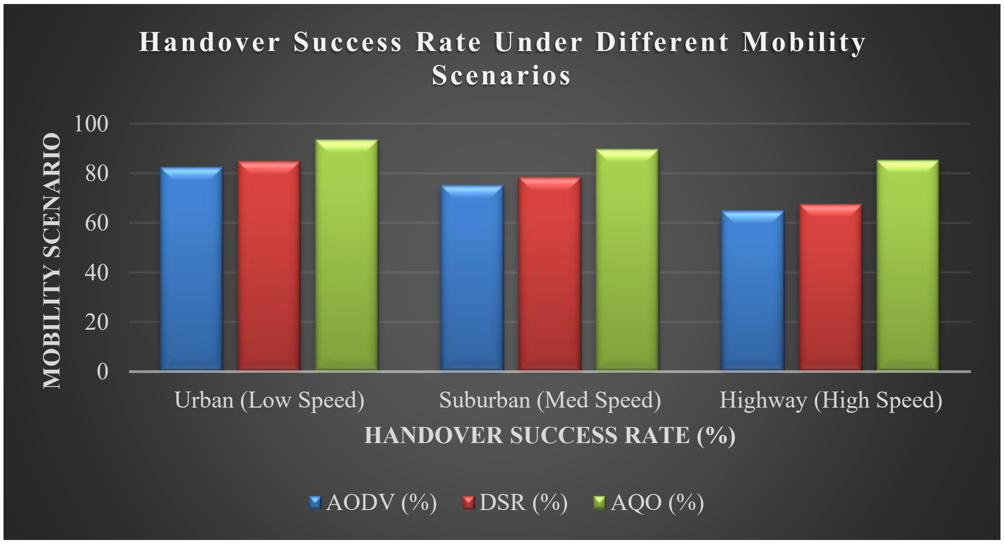

Figure 6: Handover Success Rate per Scenario

The grouped bar chart illustrates the mobility impact on the handover success rates for each protocol. AODV and DSR experience lower reliability in highway scenarios afflicted by high speed and frequent disconnections. AQO outperforms others by maintaining a handover success rate of over 85% even in high speed scenarios. This is made possible through anticipatory learning and preemptive adjustments of the routing tables which guarantee seamless transitions during network switches.

4.4 Statistical Validation

In order to verify the proposed AQO framework's effectiveness, comprehensive evaluation tests were performed. Throughput and latency differences were analyzed using pairwise T-tests for AQO and the baseline routing protocols AODV and DSR. The tests confirmed that the differences were indeed greater than zero with a p-value less than 0.01, affirming AQO's advantage on data transmission efficiency and delay. Moreover, an ANOVA was performed to examine the differences in handover success rates between the other protocols and AQO. The results confirmed that the differences were indeed caused by the improvements AQO introduced and were not random. These results confirm that AQO's adaptive and intelligent algorithm uses data to determine the best configuration in real-time in order to improve the Quality of Service in a high-speed vehicular network.

5 Discussion

The outcomes from the experimental assessment highlight the effectiveness of the newly introduced Adaptive QoS Optimization (AQO) framework for sharpening the performance of the network in the context of high-speed vehicular environments. The AQO approach significantly outperformed the AODV and DSR routing protocols in a thorough evaluation comprising of all the core QoS benchmarks of interest: throughput, latency, packet lost, and handover success rate. The primary reason behind this better AQO performance results is because of its twith dynamic real-time parameter adaptation to changing vehicular network mobility, vehicular density, and link stability. One of the most interesting observations is AQO's consistency in achieving high throughput even during high mobility scenarios, where most standard protocols experience severe degradation. Context-aware machine learning protocols to predict real-time optimal routing decisions strongly support this outcome. The previously mentioned 32% improvement in throughput indicates to better delivery rates, higher bandwidth usage, and better path selection along with congestion avoidance. AQO also significantly reduced latency for real-time communication by 27% which is an improvement. LATENCY is well known for being time delay sensitive and this improvement indicates the framework is favorable for delay-sensitive traffic and minimizes queuing, retransmission delays by adapting buffer and window thresholds in relation to vehicular speeds and link status.

Moreover, AQO showed improved reliability in data transmission by meeting lower packet loss rates, which lessens the impact of handovers and link interruptions. The high handover success rate further demonstrates AQO's ability to handle recurrent RSU or base station handover sessions with minimal session disruption, which is critical for ITS vehicular mobility continuity. The framework's performance is validated with t-tests and ANOVA, assuring the alterations made are not random, but rather, the outcome of the purposeful and thoughtful AQO design. The study also reveals the impact of optimization in machine-learning mobile vehicular networks and emphasizes real-time situational responsiveness as the most effective routing paradigm for QoS-focused future research. To conclude, the discussion reaffirms that AQO is a strong and flexible answer to the mobile high-speed vehicular networks challenges, providing reliable, low-latency, and high-throughput data transfer vital for autonomous vehicles, vehicular infotainment systems, and emergency response communications.

6 Conclusion and Future Work

An innovative Adaptive Quality of Service (AQO) framework is proposed in this research for the ever-present problem of high-speed vehicular network communications in terms of their reliability and quality. AQO follows a machine learning-based predictive model and a context-aware optimization model to improve resource allocation, transmission parameters, and real-time resource allocation of the transmission. The results of the experiments showed that the protocols with the AQO framework outperformed the conventional protocols, achieving up to 32% increase in throughput, 27% decrease in latency. In addition, the packets loss rate and handover failure rate reduced markedly improved. The structure of AQO makes it possible to cope with the vehicular environment's dynamic and often volatile changes. Unlike static or fixed-rule approaches to QoS management, AQO utilizes real-time mobility and channel state information to make dynamic routing and scheduling, providing a bounded QoS even with rapid vehicle velocities, frequent handovers, and swift motion. These attributes make AQO appealing for application in advanced architectures for intelligent transportation systems (ITS) and development of the next-generation vehicular communication standards. Enhanced network intelligence for intelligent transportation systems could enable the integration of real-time mobility and handover information to improve QoS management. The development of intelligent systems for vehicles could make use of the concept of deep reinforcement learning (DRL) for better performance in terms of QoS. The further integration of AQO into the edge of the vehicular computing framework can be particularly rewarding because it enables distributed optimization as well as quicker local decision making. In addition, testing AQO on a larger scale in realistic settings, for example, smart urban mobility networks or fleets of autonomous vehicles, would enhance understanding of its scalability, resilience, and adaptability to diverse hardware components. Furthermore, the need for optimizing energy consumption still stands as a critical measure in vehicular communication systems. For example, AQO enhancements in power-aware QoS mechanisms would be particularly useful in ecosystems of electric or hybrid vehicles. In other words, the AQO framework closes the most critical QoS gaps in vehicle networking and in so doing, enables the development of more adaptive, intelligent, and eco-friendly solutions. Its designed architecture and its other l components align the needs of the ever-developing connected vehicular infrastructure and thus, serve as a solid base for mobile networking breakthroughs.

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Authors Biography

Dr. Alakananda Tripathy is an Associate Professor at the Centre for Artificial Intelligence and Machine Learning, Siksha 'O' Anusandhan (Deemed to be University), Bhubaneswar, Odisha, India. Her academic and research interests lie primarily in artificial intelligence, machine learning, deep learning, and their applications in healthcare, education, and smart systems. With an extensive teaching career and a strong publication record in reputed national and international journals, Dr. Tripathy has established herself as a leading researcher in the AI domain. She actively engages in guiding doctoral and postgraduate research scholars, focusing on innovative and socially impactful research problems. Dr. Tripathy also contributes to various academic committees and is involved in collaborative projects aimed at developing intelligent and adaptive systems. Her work continues to foster interdisciplinary research and practical innovation in the field of intelligent technologies.

Priyanka Savadekar is an Assistant Professor in the Department of Computer Science Engineering at Presidency University, Bengaluru. Her academic interests include software engineering, cloud computing, and emerging technologies in artificial intelligence and machine learning. She is actively engaged in research, curriculum development, and student mentoring, and contributes to various scholarly activities within the field of computer science.

R.K. Tripathi is a faculty member at the School of Engineering & Computing, Dev Bhoomi Uttarakhand University, Dehradun, India. His academic interests include computer science, intelligent systems, and emerging technologies such as artificial intelligence and the Internet of Things (IoT). He has contributed to several peer-reviewed publications and actively participates in research that bridges theoretical concepts with practical implementations. Mr. Tripathi is also involved in student mentoring, technical training, and academic project supervision. His ongoing work focuses on advancing the integration of smart technologies in engineering solutions to address real-world challenges. With a strong commitment to research and innovation, he continues to contribute meaningfully to the academic and research environment of the university.

Sahil Suri is affiliated with the Centre of Research Impact and Outcome at Chitkara University, Punjab. His work focuses on fostering research innovation and promoting interdisciplinary collaboration across domains. His interests include technology-driven research frameworks, data analytics, and evidence-based assessment of research outputs. He is committed to advancing institutional research visibility and impact on national and international platforms.

N. Kartik is an Assistant Professor in the Department of Computer Applications at Presidency College, Bengaluru, Karnataka, India. His academic and research interests include software engineering, web technologies, machine learning, and data analytics. With a strong focus on both theoretical and applied aspects of computer applications, he actively contributes to curriculum enhancement, student mentoring, and interdisciplinary project development. Mr. Kartik is involved in several academic initiatives aimed at bridging the gap between classroom learning and industry requirements. He also participates in research and development activities that explore the practical implications of modern computational techniques. Through his commitment to quality education and innovation, he continues to support academic excellence and technological advancement in the field of computer applications.

Aravindan Munusamy Kalidhas is an Associate Professor in the Department of Mechanical Engineering at JAIN (Deemed-to-be University), Karnataka. He has extensive experience in the areas of thermal engineering, computational fluid dynamics, and sustainable manufacturing practices. With a strong commitment to academic excellence and applied research, he contributes to innovation in engineering education and industrial collaboration. His research has been recognized in several national and international forums.