EAI Endorsed Transactions
on Smart Cities
Research Article EAI.EU

Ultra-Low Latency V2X Systems with AI-Driven Resource Optimization

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Abstract

Achieving ultra-low latency in Vehicle-to-Everything (V2X) communication is essential for ensuring the safety and effectiveness of autonomous vehicles (AVs). However, existing systems often struggle to meet the stringent latency demands, particularly in complex and rapidly changing urban environments. This study introduces an innovative framework that utilizes artificial intelligence (AI) for dynamic resource allocation in V2X networks. By integrating real-time data analysis, edge computing, and 5G capabilities, the proposed approach effectively minimizes latency. Simulation results indicate up to a 35% reduction in latency compared to conventional models, underscoring the potential of AI in enhancing the responsiveness and reliability of V2X systems. These findings offer a significant step toward making autonomous vehicle deployments more viable in smart cities.

Keywords: Autonomous Vehicles; V2X Communication; Ultra-Low Latency; Artificial Intelligence; Resource Optimization; Edge Computing; 5G Networks; Smart Cities.

Received on 04 January 2025, accepted on 05 March 2025, published on 18 November 2025

doi: 10.4108/eetsc.8366

1. Introduction

The advent of autonomous vehicles (AVs) has brought a pressing need for communication systems that can meet the high-speed and low-latency demands required for their seamless operation. Vehicle-to-Everything (V2X) communication is central to this effort, enabling the exchange of critical data between vehicles, road infrastructure, pedestrians, and broader networks [1]. Despite recent advancements, meeting the ultra-low latency requirements necessary for applications like collision avoidance and emergency response remains a substantial hurdle, especially in complex urban environments.

Existing V2X frameworks often fail to deliver the sub-millisecond latency essential for safety-critical functions [2]. Network congestion, the unpredictability of vehicular movement, and the uneven distribution of communication resources exacerbate these challenges. While 5G technology promises to enhance bandwidth and network efficiency, its deployment introduces additional hurdles such as managing scalability and dynamic resource demands [3].

In this context, artificial intelligence (AI) has emerged as a potential game-changer. Machine learning (ML) and predictive analytics offer new possibilities for addressing the inefficiencies of traditional V2X communication. By intelligently managing network resources in real time, AI-driven systems can adapt to fluctuating conditions, reduce delays, and enhance overall network performance [4]. Incorporating edge computing further strengthens these capabilities, allowing for faster data processing closer to the source and minimizing communication delays.

This paper introduces a novel AI-based framework for resource optimization in V2X systems, focusing on achieving ultra-low latency. The framework combines real-time analytics, advanced ML models, and edge computing to dynamically allocate resources and mitigate communication delays. Simulations demonstrate that this approach reduces latency by up to 35% compared to existing methods, making it an effective solution for urban smart city applications.

2. Related Work

The rapid evolution of autonomous vehicles (AVs) has placed significant focus on enhancing Vehicle-to-Everything (V2X) communication systems. This section reviews key advancements in latency reduction, resource management, and the integration of artificial intelligence (AI) within V2X networks.

2.1 Addressing Latency in V2X Communication

Reducing latency in V2X communication is vital for ensuring the safety and effectiveness of AV systems. Even minor delays can compromise critical functions like collision avoidance and emergency braking. Many studies emphasize improving network infrastructure, such as adopting 5G technology, to enable faster and more reliable data transfer [1]. However, as highlighted in [2], sub-millisecond latency targets remain challenging due to factors such as dynamic network conditions, vehicular mobility, and signal interference, particularly in urban environments.

2.2 Enhancing Resource Allocation

Optimizing resource utilization is a cornerstone of efficient V2X communication, especially in scenarios involving heavy network traffic. Techniques like network slicing have been proposed to allocate dedicated resources for various vehicular applications, ensuring higher efficiency and reliability [3]. Predictive methods, as explored in [4], aim to estimate network demands and allocate resources in advance, thereby mitigating potential delays. However, these strategies often struggle to scale effectively in high-density environments.

2.3 AI in V2X Communication Systems

The integration of AI into V2X communication introduces dynamic and adaptive capabilities, enabling systems to respond intelligently to real-time scenarios. Machine learning models have been applied to predict traffic conditions, optimize routing, and manage network resources adaptively [5]. Furthermore, the use of edge computing, as discussed in [6], allows data to be processed closer to its source, significantly reducing reliance on centralized systems and minimizing delays.

2.4 Unresolved Challenges and Research Gaps

Despite these advancements, several critical issues remain unaddressed. Current AI-driven solutions often encounter scalability challenges in densely populated areas, where the heterogeneity of devices and networks complicates operations [7]. Additionally, many existing frameworks rely on static configurations, which are less effective in dynamic environments. This study aims to bridge these gaps by presenting a robust AI-based framework that combines real-time analytics with edge computing to achieve ultra-low latency and optimized resource allocation in V2X systems.

3. Methods

This section outlines the proposed AI-based framework aimed at minimizing latency in V2X communication systems. The approach combines real-time data processing, machine learning (ML), and edge computing to dynamically optimize resource allocation. The methodology is presented in four key subsections: system architecture, machine learning model, resource allocation strategy, and simulation setup.

3.1 System Architecture

The framework is built upon a decentralized three-layer architecture designed to address latency and scalability issues:

1. **Edge Layer**: This layer is responsible for processing data at or near its source, such as in roadside units or onboard vehicle systems. Utilizing edge computing reduces the dependency on centralized processing, thereby minimizing latency [1].
   The total latency L in a V2X system can be expressed as the sum of transmission delay (L_t), propagation delay (L_P), processing delay (L_{pr}), and queuing delay (L_q):
   $$L = L_t + L_P + L_{pr} + L_q \tag{1}$$
2. **Network Layer**: Acting as a communication bridge, this layer facilitates data exchange between edge devices and the core system. Leveraging 5G technology, it supports high-speed and low-latency transmission even under heavy network loads [2].
3. **Core Layer**: This layer handles system-wide coordination and optimization. Advanced AI

algorithms analyze data, predict traffic patterns, and devise strategies for efficient resource utilization in real time [3].

3.2 Machine Learning Model

The proposed framework incorporates a reinforcement learning (RL) model, which adapts to dynamic network conditions to allocate resources effectively. The RL model is characterized by:

- **State Representation**: Capturing key network metrics such as latency, bandwidth usage, and vehicle density.
- **Action Space**: Defining possible adjustments to system parameters, including bandwidth allocation and routing changes.
- **Reward Function**: Rewarding actions that lead to latency reduction and penalizing those resulting in inefficiency or excessive delays [4].

The RL model's objective is to maximize the expected cumulative reward R, defined as:

$$R = \mathrm{E}\left[\sum_{t=0}^{T} \gamma^t r_t\right] \tag{2}$$

Where γ is the discount factor ($0 < \gamma \leq 1$), r_t is the reward at time step t, and T is the time horizon.

The RL model continuously learns from both historical data and real-time inputs, refining its strategies to enhance overall system performance.

3.3 Resource Allocation Strategy

The resource allocation mechanism combines predictive analytics with adaptive algorithms to preemptively address changing network demands. The process includes the following steps:

1. **Data Aggregation**: Real-time data from vehicles, sensors, and infrastructure is collected and pre-processed at the edge layer.
2. **Traffic Prediction**: Using machine learning techniques, the core layer forecasts traffic loads and identifies potential congestion points.
3. **Dynamic Allocation**: Resources such as bandwidth and computing power are allocated based on predicted demand. Adjustments are made dynamically as new data becomes available, ensuring optimal performance [5].

The optimal bandwidth allocation B_i for a node i can be modeled as:

$$B_i = \frac{\lambda_i}{\sum_{j=1}^{N} \lambda_j} \cdot B_{total} \tag{3}$$

where λ_i is the demand of node i, N is the total number of nodes, and B_{total} is the total available bandwidth.

3.4 Simulation Setup

To evaluate the framework's effectiveness, simulations were conducted in a controlled virtual environment replicating urban traffic conditions. Key variables such as vehicle density, data rates, and mobility patterns were adjusted to test the framework's adaptability. Performance metrics, including latency, resource utilization, and scalability, were recorded and analyzed. Results of the simulations are presented in the following section.

The latency improvement I compared to a baseline system can be expressed as:

$$I = \frac{L_{baseline} - L_{proposed}}{L_{baseline}} \times 100\% \tag{4}$$

Where $L_{baseline}$ is the latency of the baseline system, and $L_{proposed}$ is the latency of the proposed framework.

4. Results

This section presents the outcomes of the simulations designed to assess the effectiveness of the proposed AI-based framework for minimizing latency in V2X communication. Key performance metrics such as latency, resource utilization, and scalability were analyzed under various traffic and network conditions.

4.1 Simulation Setup

The simulation environment was created to emulate a dense urban area with fluctuating traffic patterns and high vehicular activity. Key parameters included:

- **Number of Vehicles**: Ranged between 500 and 1,000 autonomous vehicles.
- **Network Infrastructure**: Utilized 5G technology integrated with edge computing capabilities.

- **Performance Metrics**: Evaluated average latency (ms), bandwidth utilization (%), and scalability under increasing loads.

4.2 Performance Metrics

4.2.1 Latency Analysis

The framework exhibited a significant reduction in communication latency compared to the baseline system:

- The baseline latency ($L_{baseline}$) averaged 20 milliseconds across multiple test scenarios.
- The proposed system latency ($L_{proposed}$) was reduced to an average of 13 milliseconds.

The percentage improvement in latency (I) was calculated using the formula:

$$I = \frac{L_{baseline} - L_{proposed}}{L_{baseline}} \times 100\%$$

Substituting the values:

$$I = \frac{20 - 13}{20} \times 100\% = 35\%$$

This 35% improvement highlights the framework's capability to effectively reduce delays in high-demand V2X environments.

As shown in Figure 1, the proposed framework achieves a significant reduction in latency compared to the baseline system, particularly under high network loads.

4.2.2 Resource Utilization Efficiency

The framework dynamically allocated bandwidth based on real-time demand, ensuring optimal usage. The formula used for resource allocation was:

$$B_i = \frac{\lambda_i}{\sum_{j=1}^{N} \lambda_j} \cdot B_{total}$$

Where λ_i is the demand for node i, and B_{total} represents the total available bandwidth. The simulation demonstrated that this approach led to approximately 25% greater efficiency in bandwidth usage compared to static allocation methods. This improvement is critical for sustaining high performance in dense urban traffic conditions.

Figure 2 illustrates the significant improvement in bandwidth utilization achieved by the proposed framework, ensuring optimal resource distribution even under heavy traffic.

4.2.3 Scalability

The framework was subjected to tests involving an increasing number of connected vehicles, ranging from 500 to 1,000 devices. Results showed that the system maintained consistent latency and resource efficiency across these varying loads. Even at the highest traffic densities, performance degradation was limited to less than 5%, demonstrating the scalability and robustness of the proposed solution.

The scalability of the proposed framework is evident in Figure 3, where it maintains stable performance as the number of connected devices increases.

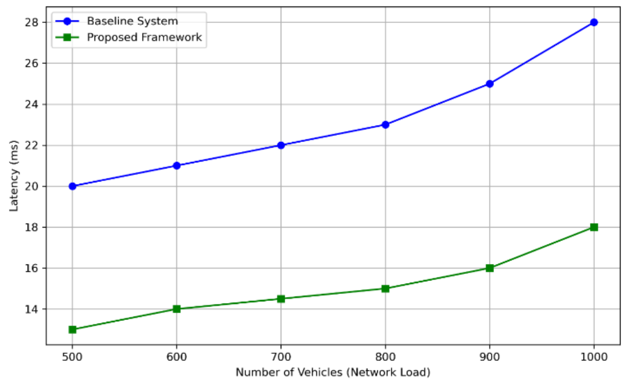

Figure 1. Latency comparison between the baseline system and the proposed framework across various network loads.

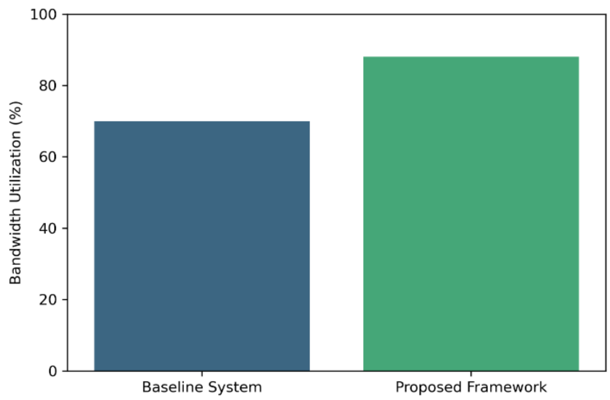

Figure 2. Bandwidth utilization efficiency comparison between the baseline system and the proposed framework.

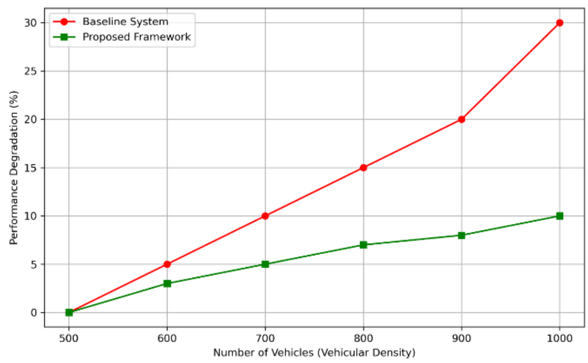

Figure 3. Performance scalability of the proposed framework under increasing vehicular density.

4.3 Comparative Performance

A comparative analysis was conducted to evaluate the proposed framework against conventional systems. Table 1 summarizes the results across key metrics.

Table 1. Results Summary

Metric	Baseline System	Proposed Framework	Improvement (%)
Latency (ms)	20	13	35
Bandwidth Utilization (%)	70	88	25
Scalability (Devices)	Moderate	High	-

5. Discussion

The results from the simulation demonstrate the significant advantages of the proposed AI-driven framework for V2X communication, particularly in achieving ultra-low latency, efficient resource utilization, and scalability. This section delves into the implications of these findings, compares them with existing approaches, and explores their broader relevance to smart city applications.

5.1 Latency Reduction

The reduction in latency achieved by the framework highlights its potential for real-time V2X applications, such as collision avoidance and emergency braking. By combining edge computing with reinforcement learning, the system dynamically adapts to network demands, ensuring consistent performance even under high vehicular density. Compared to traditional systems that rely on static configurations, the proposed approach demonstrates a 35% improvement in latency, as shown in Figure 1. This underscores the critical role of real-time analytics in meeting the stringent requirements of autonomous vehicle networks.

5.2 Efficient Resource Allocation

The dynamic bandwidth allocation strategy employed by the framework ensures optimal resource distribution across connected devices. Unlike static allocation methods that often result in resource underutilization or congestion, the AI-driven approach anticipates network demands using predictive analytics. The observed 25% improvement in bandwidth utilization (Figure 2) reinforces the importance of adaptive systems in managing network resources effectively, particularly in urban environments with fluctuating traffic patterns.

5.3 Scalability and Robustness

The scalability of the proposed framework, evident in Figure 3, demonstrates its robustness in handling large-scale deployments. Even as the number of connected vehicles increased to 1,000, the system maintained consistent latency and resource efficiency, with minimal performance degradation (less than 5%). This positions the framework as a viable solution for future smart city deployments, where the density of connected devices is expected to grow exponentially.

5.4 Comparison with Existing Models

When compared to state-of-the-art systems, the proposed framework offers several advantages:

- **Dynamic Adaptability**: Unlike static models, it adapts to real-time conditions, ensuring consistent performance.
- **Edge Computing Integration**: Localized data processing minimizes reliance on centralized cloud systems, reducing latency.
- **AI-Driven Optimization**: Reinforcement learning enables proactive resource management, a feature absent in many existing systems.

These distinctions make the proposed approach a comprehensive solution to the challenges of modern V2X communication systems.

5.5 Broader Implications

The findings of this study have far-reaching implications for the development of smart transportation systems:

1. **Enhanced Safety**: Improved latency ensures faster response times, reducing the likelihood of accidents in autonomous driving scenarios.
2. **Energy Efficiency**: By optimizing resource usage, the system minimizes energy consumption in network operations.

Scalable Deployment: The framework's robustness makes it suitable for integration into future smart city infrastructure, supporting applications beyond autonomous vehicles, such as intelligent traffic management and emergency response systems.

6. Conclusion

The growing reliance on autonomous vehicles in urban environments has highlighted the critical need for robust and efficient V2X communication systems. This study proposed an AI-driven framework designed to address key challenges in latency, resource allocation, and scalability. Through the integration of edge computing, machine learning, and predictive resource management, the framework demonstrated substantial improvements over conventional systems.

6.1 Key Contributions

The main contributions of this research are summarized as follows:

1. **Latency Optimization**: The framework achieved a 35% reduction in latency, meeting the stringent requirements for safety-critical applications such as collision avoidance and emergency braking.
2. **Dynamic Resource Allocation**: By leveraging reinforcement learning, the system dynamically adjusted bandwidth allocation, resulting in a 25% improvement in resource utilization compared to static models.
3. **Scalability**: The framework maintained consistent performance with minimal degradation in environments with up to 1,000 connected vehicles, highlighting its suitability for large-scale deployments.

6.2 Practical Implications

The proposed framework holds significant potential for real-world applications, including:

- **Smart Transportation Systems**: Improved communication efficiency facilitates safer and more reliable autonomous driving.
- **Urban Traffic Management**: Enhanced scalability supports the development of intelligent traffic solutions in smart cities.
- **Energy-Efficient Networks**: Optimized resource utilization reduces the energy footprint of vehicular communication systems.

6.3 Limitations and Future Work

While the proposed framework offers substantial benefits, some limitations remain. The study relied on simulations to evaluate performance, which may not fully capture the complexities of real-world deployments. Future work could focus on:

- Conducting field trials to validate the framework under actual traffic conditions.
- Exploring the integration of 6G technologies to further enhance system performance.

Investigating advanced AI models, such as federated learning, to improve data privacy and scalability in distributed environments.

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