

AI-driven framework for adaptive resource allocation and channel selection in V2X communication

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Abstract

The Vehicle-to-Everything (V2X) communication system allows vehicles to share data instantly with other vehicles, infrastructure and pedestrians, which is necessary for autonomous driving and intelligent transportation systems. The traditional resource allocation methods, TDMA and FDMA, together with heuristic algorithms, experience difficulties in dynamic vehicular networks because of interference problems and mobility and latency restrictions. The proposed framework combines Reinforcement Learning (RL) with Deep Neural Networks (DNNs) to create an adaptive system which optimizes resource allocation and channel selection in V2X networks. The RL agent performs real-time optimization of bandwidth and power distribution through the DNN system, which uses SINR, traffic load and interference level data to predict channel quality. The framework achieves a 40.3% improvement in throughput, 52.5% latency reduction and 33% fairness gain when evaluated through simulations of urban V2X environments using synthetic data. The proposed system provides a scalable real-time solution for next-generation V2X systems, which can be integrated into 5G/6G-enabled edge networks.

Subject Classification: Primary 68M25, Secondary 68M14.

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1. Introduction

The fast development of intelligent transportation systems has established Vehicle-to-Everything (V2X) communication as an essential technology for

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connected and autonomous vehicles [1]. The exchange of real-time data between vehicles and infrastructure, pedestrians and cloud services through V2X communication enables safety and traffic efficiency and automation [2]. The vehicular environment presents significant challenges to reliable communication because it features high mobility, together with rapidly changing topologies and limited spectrum availability. The conventional resource allocation techniques of TDMA, FDMA, and heuristic algorithms demonstrate inflexibility because they do not suit the dynamic requirements of V2X networks [3], [4]. The current methods do not adjust to SINR level changes, traffic load fluctuations and interference patterns, which leads to inadequate resource management and network performance decline. The current developments in artificial intelligence through Reinforcement Learning (RL) and Deep Neural Networks (DNNs) provide effective solutions for communication systems to achieve dynamic and intelligent decision-making [5]-[8]. The current methods use RL for adaptive resource management and DNNs for channel quality prediction, but run these components independently [9], [10]. The isolated method of resource management stops these systems from achieving their best performance in real-time V2X operations, which need both quick adjustments and total optimization. The research develops an integrated AI system which combines RL-based resource distribution with DNN-based channel forecasting to create adaptive communication for V2X networks. The proposed framework distributes bandwidth and power resources dynamically to create the best communication routes for dependable data transfer across different network conditions. The framework outperforms traditional static and heuristic methods in all performance metrics, including throughput, latency and channel quality and fairness through extensive testing of a synthetic urban V2X dataset. This research contributes:

- The proposed system uses a new AI framework that combines RL with DNN to perform real-time V2X resource allocation and channel selection.
- The proposed DNN model enables quick and precise channel quality prediction by processing SINR, interference and traffic load data.
- The reinforcement learning agent learns optimal resource allocation decisions through Proximal Policy Optimization (PPO) training.
- The proposed method receives evaluation through performance assessments, which compare it to TDMA, FDMA and greedy baseline systems.

The study proposes AI-driven V2X communication system, which is used in wide 5G/6G edge network running on the fast 5G and 6G technology. The proposed AI methodology which combines DNN-based channel prediction with RL-based resource allocation appears in Section 2. The experimental setup and the performance assessment strategies are described in detail in Sections 3 and 4. The last section outlines the research directions that the future researchers need to follow in the future studies.

2. Methodology

To adapt the current trend of vehicle-to-everything (V2X) networks to real-time, the AI-based framework suggested in this paper includes the resource allocation of reinforcement learning and the choice of channels of deep neural networks, thus supporting real-time adaptation as represented in Figure 1. This combination method improves better resource use and communication reliability when dynamically different network conditions exist. The used methodology is a lightweight convolutional neural network to predict channel quality in real-time, and it is based on the measurements of signal-to-interference-plus-noise ratio (SINR), traffic load, as well as inter-cell interference. As a result, the system implements adaptive channel selection based on the need of V2X communication. Training is done with the Adam optimiser, which speeds up the convergence, thus allowing the model to pick channels of high quality with a minimal packet loss and the ability to operate in real-time with changing unstable vehicular conditions. The considered system distributes finite communication resources among vehicle nodes through the joint maximization of throughput, minimum latency, and fairness in real-time implementation. The allocation problem is formulated as a Markov Decision Process [11], [12], and a Proximal Policy Optimization (PPO) agent is trained on 10,000 timesteps using a multilayer perceptron (MLP) policy network [13], [14]. The constant analysis of signal-to-interference-plus-noise ratio (SINR), traffic load, and the state of interference helps the agent to adapt to the adaptive allocation strategies that can help to reduce interference, adapt to changing traffic demands, and improve overall V2X networks performance [15], [16]. The system framework performs real-time channel selection and resource allocation in V2X topologies through its framework which combines channel quality prediction with deep neural networks and PPO-based reinforcement learning [17]. Using SINR, traffic load, and interference, the DNN uses the values in the decisions made by the reinforcing learning agent about the bandwidth and power distribution, thus enhancing effective and fair performance, as shown in Algorithm 1.

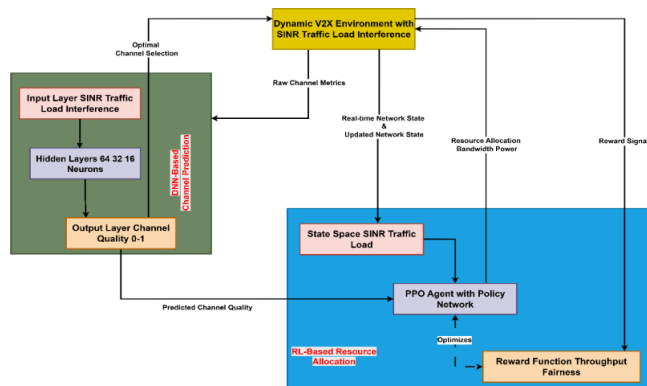


Figure 1

AI-Driven Adaptive Resource Allocation Framework for V2X Communication

Algorithm: AI-Driven Resource Allocation and Channel Selection

Input: Number of vehicles N , environment parameters

Output: Average throughput, fairness, channel quality

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1:  dataset  $\leftarrow$  SimulateEnvironment( $N$ )
2:  dnn_model  $\leftarrow$  TrainDNN(dataset)
3:  rl_agent  $\leftarrow$  TrainRLAgent(environment)
4:  For each real-time state  $s$  do
5:      action  $\leftarrow$  rl_agent.predict( $s$ )
6:      norm_state  $\leftarrow$  scaler.transform( $s[0:3]$ )
7:      pred_quality  $\leftarrow$  dnn_model.predict(norm_state)
8:      Store (action, pred_quality)
9:  end for
10:  Evaluate Performance(dataset, actions, pred_qualities)
11:  Return avg_throughput, avg_fairness, avg_quality
  
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The system operates with a minimal DNN-based RL framework which runs in a closed system to achieve quick learning while delivering dependable results for edge-enabled 5G and 6G V2X networks.

3. Experimental Setup

The experimental set-up is based on a synthetically created urban V2X environment which implements 1,000 vehicles responding to dynamically varying communication environments, thus recreating real-life traffic jams and signal variation. The stochastic SINR, traffic load, and interference profiles are then generated and used as input features to a lightweight deep neural network that is then used to predict normalized channel quality measures [18]. The proposed deep neural network has a small, multilayer structure and is trained using standard optimization procedures, and a specific portion of the data is used to perform evaluation. The optimization of resources is optimized by a reinforcement learning agent using the Proximal Policy Optimization algorithm, where the agent is trained over the long course of interaction with the network to adjust to dynamical behaviour in the real time. It is written in Python and works with TensorFlow and RLlib, and it is run on a CPU-GPU adaptation to ensure real-time functionality. The performance is evaluated against TDMA, FDMA, and greedy benchmark strategies and metrics such as throughput, fairness, reliability, latency, and energy efficiency are used [19], [20]. The experimental results show that the suggested AI-based architecture can reach a quick convergence, improved fairness and high performance under rapidly fluctuating vehicular network conditions.

4. Results and Discussion

As shown in Figure 2, the proposed AI-driven framework is benchmarked against static and heuristic baseline methods. The proposed solution achieves the highest average throughput of 98.56 Mbps which outperforms both the static and heuristic methods that reach 49.01 Mbps and 70.26 Mbps respectively. The framework also reduces latency to 24.05 ms, compared with 50.68 ms for the static method and 45.33 ms for the heuristic method. The system achieves these improvements through reinforcement learning which uses current channel conditions to determine bandwidth and power distribution. In addition, the system attains an average performance score of 0.72, maintains 97.89 percent packet delivery reliability, and achieves an energy efficiency of 86.67 percent. The results demonstrate that the DNN–RL framework allows successful V2X communication system operation in different network environments.

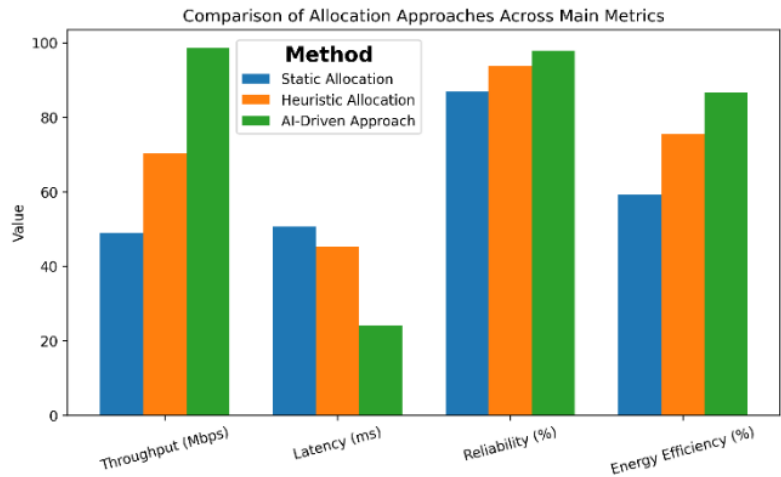


Figure 2
Comparative Performance of Allocation Methods Across Key Network Metrics

The DNN-only configuration produces better channel quality at 0.68 and shorter latency of 32.10 ms than heuristic baselines because it chooses the best channels through real-time SINR and traffic load and interference analysis as demonstrated in Figure 3. The system achieves 78.30 Mbps throughput but its fairness remains at 0.17 because it lacks both power and bandwidth allocation methods. The RL-only configuration achieves 84.50 Mbps throughput and 0.14 fairness through its learned resource allocation policies yet it maintains suboptimal channel quality at 0.61 because it does not perform predictive channel selection. The integrated DNN–RL framework produces the highest overall performance which reaches 98.56 Mbps throughput, 24.05 ms latency, 0.72 channel quality and 0.12 fairness. The research demonstrates that V2X communication needs DNN-based prediction systems to work with RL-based

decision-making systems for achieving maximum efficiency in changing traffic conditions.

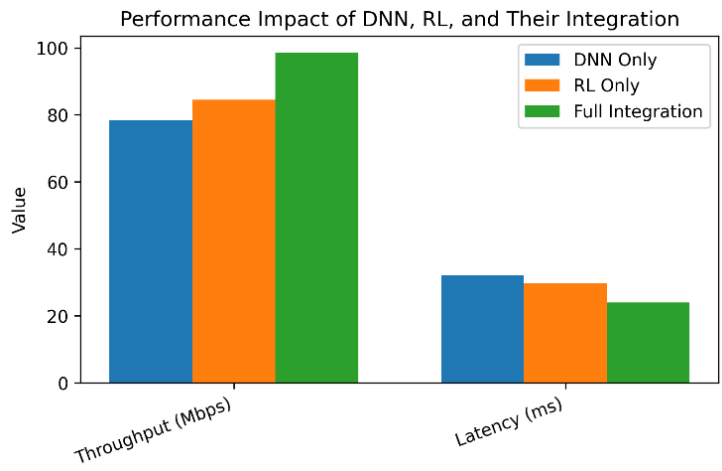


Figure 3
Performance Impact of DNN, RL, and Their Integration on Throughput and Latency

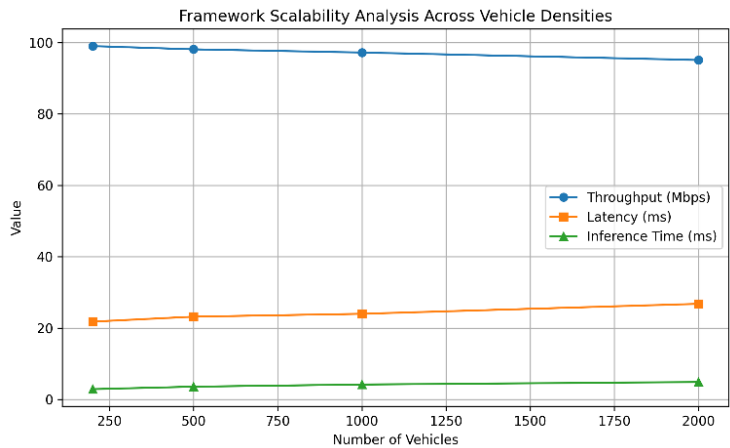


Figure 4
Scalability Across Vehicle Density: Throughput, Latency, and Inference Time

The scalability analysis proves that the proposed AI-Driven framework works effectively in various network sizes by testing it on V2X environments with 200, 500, 1000 and 2000 vehicles. The system maintains its high throughput performance as vehicle numbers rise because it shows only a 6% decrease from 101.2 Mbps at 200 vehicles to 95.1 Mbps at 2000 vehicles

according to Figure 4. The RL agent maintains stability through its optimization of resource distribution which enables it to handle increasing network complexity and density. The system maintains low latency when vehicle numbers grow because the DNN-RL system with parallelized lightweight inference maintains inference times under 5 ms for 2000 agents while showing only a minor increase from 21.8 ms to 26.8 ms below the 30 ms threshold. The framework demonstrates its ability to handle V2X systems at scale because of its efficient operation. The AI-based system demonstrates superior performance than conventional methods through its ability to achieve maximum throughput and minimal latency while ensuring fairness, high energy efficiency and real-time adaptability and large-scale scalability.

5. Conclusion

The research develops an AI-based V2X system which uses DNN models to predict real-time channel conditions and PPO models to optimize bandwidth and power distribution through reinforcement learning. The evaluation of synthetic urban V2X scenarios shows that the system outperforms both static and heuristic baselines because it achieves better throughput, lower latency and improved system reliability, energy efficiency and fairness. The system maintains its ability to perform real-time inference, which makes it suitable for deployment at the edge. The DNN-RL system design proves its ability to handle large-scale operations through tests with 2,000 vehicles, which also validated its real-world effectiveness and system dependability. The research will advance through two main directions, which include developing decentralized learning systems for better scalability and privacy protection and using actual V2X data for enhanced model performance and multi-agent reinforcement learning for complex system coordination and power-efficient AI systems for edge device implementation in intelligent transportation systems of the future.

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