Comparative Study of 5G-V2X and 6G-V2X for Intelligent Traffic Signal Control in Urban Environment

Geonmin Kim
Dept. of Software Engineering
Chonnam National University
South Korea
204869@jnu.ac.kr

Yejin Kim
Dept. of Software Engineering
Chonnam National University
South Korea
ye031010@jnu.ac.kr

Eunseong Lee
Dept. of Software Engineering
Chonnam National University
South Korea
200750@jnu.ac.kr

Hyeonji Jang
Dept. of Artificial Intelligence
Chonnam National University
South Korea
gka1225@jnu.ac.kr

Hyukro Park
Dept. of Artificial Intelligence Convergence
Chonnam National University
South Korea
hyukro@jnu.ac.kr

Kyungbaek Kim
Dept. of Artificial Intelligence Convergence
Chonnam National University
South Korea
kyungbaekkim@jnu.ac.kr

ABSTRACT

6G-V2X, a next-generation mobile communication technology, is expected to bring about innovative changes in the implementation of Intelligent Transportation Systems(ITS) by supporting ultra-precise location estimation and ultra-low latency communication using the terahertz(THz) band. Existing 5G-V2X-based systems have limitations in classifying and controlling various traffic subjects (personal mobility, bicycles, pedestrians, etc.) in real time due to limited precision and communication delays. 6G-V2X is expected to overcome the limitations of the existing 5G-V2X by providing ultra-low latency communication of less than ms and ultra-precise positioning of less than cm. Therefore, this study proposes a multi-agent reinforcement learning(MARL)-based intelligent traffic signal control model that aims to optimize real-time traffic flow in a multi-intersection environment based on the 6G-V2X. Each intersection's signal is set as a MARL Agent to communicate in real-time with the signal at the adjacent intersection and the surrounding traffic subjects, and through this obtained traffic flow data, the signal is actively controlled in the direction of increasing the overall traffic flow in the city. The experimental results demonstrated that the multi-agent-based signal control system achieved performance improvement of 23.37% improvement in overall traffic throughput. This study demonstrates that the ultra-low latency characteristics of the 6G-V2X facilitate real-time information sharing in multi-agent systems and accelerate the convergence speed of reinforcement learning, thereby enabling global optimization of traffic flow

KEYWORDS

6G-V2X, Intelligent Transportation System(ITS), Multi-Agent Reinforcement Learning(MARL), Smart City, Real-Time Traffic Optimization

1 INTRODUCTION

The acceleration of urbanization and the rapid increase in traffic volume are causing various social problems such as traffic congestion, air pollution, and energy waste in major cities around the world. Intelligent Transportation System(ITS)[1-2] have been proposed to solve these problems, and technology that detects and optimizes traffic flow in real time has become a key area of ITS. In particular, traffic signal control plays a key role in coordinating traffic flow and alleviating congestion, and the transition to adaptive control and artificial intelligence(AI)-based signal control[3] is taking place away from the existing fixed signal control method.

Recently, signal control methods based on reinforcement learning(RL) technology have attracted attention, and among them, multi-agent reinforcement learning(MARL) techniques[4-6] can model each intersection as an independent agent to optimize traffic flow in a distributed cooperative manner. However, the performance of MARL-based systems depends heavily on the speed and reliability of information exchange between agents, and the limitations of the communication infrastructure related to this are pointed out as major obstacles.

5G-V2X(Vehicle-to-Everything)[7] has enabled data exchange between vehicles and infrastructure (V2I) and between vehicles (V2V), but communication delays of 1 to 10ms and limited precision positioning accuracy have shown limitations in distinguishing and controlling complex and heterogeneous traffic subjects in real time. In particular, in a modern urban environment where various traffic subjects such as personal mobility, bicycles, and pedestrians are mixed, it is difficult to secure sufficient real-time performance and heterogeneous identification of subjects with the performance of 5G-V2X.

The next-generation mobile communication technology, 6G-V2X[8-9], is expected to provide ultra-low latency communication of less than 1ms and ultra-precise position estimation in centimeters (cm) using the terahertz (Thz) band. These characteristics enable real-time cooperative learning of multi-agent based traffic signal control systems, which can bring about fundamental changes in traffic flow optimization across the city. By overcoming the limitations of the existing 5G-V2X, 6G-V2X is attracting attention as a key technology for implementing next-generation intelligent transportation systems that accurately recognize and control the dynamic characteristics of various transportation entities in real time[10].

Based on the 6G-V2X, this study proposes an intelligent traffic signal control model using multi-agent reinforcement learning in a large urban environment where various traffic subjects are mixed. Each traffic signal at intersection is set up as an independent MARL agent to communicate in real time with adjacent intersections and surrounding traffic subjects, exchange information, and perform signal control in the direction of actively adjusting traffic flow.

The proposed model was verified through an experimental environment linked to Simulation of Urban Mobility (SUMO) and ns-3 communication simulator, and the experimental results achieved performance improvement of 33.33% reduction in average latency, 46.11% reduction in queue length, 28.15% reduction in total latency, and 24.58% improvement in overall network throughput compared to 5G-V2X environments. This study empirically demonstrates the positive effects of ultra-low latency characteristics of the 6G-V2X communication infrastructure on real-time information sharing and improving the convergence speed of reinforcement learning in multi-agent systems.

2 Related Works

2.1 6G-V2X Technology: Evolution of Next Generation Vehicle Networks

6G, a next-generation wireless communication technology, is being actively researched with the goal of commercialization in 2030, and aims to improve performance significantly compared to the existing 5G. In particular, 6G-V2X is expected to be a key infrastructure for autonomous driving and smart city implementation in the V2X network. 6G-V2X is expected to provide ultra-low latency communication of up to 1Tbps and ultra-low latency of less than 1ms by utilizing terahertz (THz) frequency bands (0.1 to 10 THz).

Existing 5G-V2X offers communication delays of about 1 to 10ms and transmission speeds of up to several Gbps, but communication interference and coverage problems have limited real-time performance in large-scale, vehicle-intensive or complex urban environments. By providing native AI integration, ultra-precise positioning (1 cm or less), and connectivity density of 10^7/km², 6G-V2X can satisfy various communication requirements such as vehicle-to-vehicle (V2V), vehicle-infrastructure(V2I), vehicle-to-walker(V2P), and vehicle-to-network (V2N).

In particular, the ultra-precision positioning function of 6G-V2X can provide high-trust location information even in a multipath propagation environment, enabling real-time classification and situation recognition of various traffic subjects (personal mobility, bicycles, pedestrians, etc.). In addition, communication delays of less than 1ms are suitable for applications that require ultra-reliable and low-latency communications (URLLC) such as inter-vehicle collision avoidance and real-time traffic control.

6G-V2X includes innovative technology elements such as AI-Native RAN, digital twin-based network optimization, and edge computing integration to comprehensively meet mobility and bandwidth, latency, reliability, and connectivity requirements. These characteristics are essential for traffic signal control systems that require real-time cooperation between agents and quick decision-making, even in complex intersection environments.

2.2 The Theoretical Foundation and Application of Multi-Agent Reinforcement Learning

Reinforcement learning (RL)[11] is a framework in which agents learn optimal policies through interaction with the environment, which is suitable for problems where the environment is dynamic and the state space is vast, such as traffic signal control. In particular, Multi-Agent Reinforcement Learning (MARL) is a system in which multiple agents perform learning independently and cooperatively, and provides a structure suitable for urban transport network optimization problems where multiple intersections interact[12].

MARL is largely divided into cooperative, competitive, and mixed scenarios. The traffic signal control problem in this study is modeled as a typical cooperative MARL problem, and each intersection should learn its signal control policy and promote global optimization in consideration of changes in the state of adjacent intersections. In particular, MARL can solve the problem of scalability of transportation networks. Existing single-agent RL (Single-Agent RL) increases the state space exponentially as the network size increases, while MARL can learn based on intersection-specific regional information to control the learning complexity according to the network size[13].

2.3 Limitations of Traffic Signal Control Research based on 6G-V2X

Existing 5G-V2X-based traffic signal control studies mainly focused on single intersection optimization or considered only vehicle-vehicle(V2V) and vehicle-infrastructure(V2I) communication. Real-time recognition and multi-intersection cooperative control of various traffic subjects remain challenges. In addition, due to communication delays and network bandwidth limitations, there were limitations in real-time information exchange between agents.

6G-V2X-based MARL signal control presents the possibility to overcome this problem. The ultra-low latency communication of 6G enables real-time information sharing among agents, and the ultra-precise positioning function enables accurate identification of location and speed information of various traffic subjects. This allows the MARL model to converge more stably and optimize the traffic flow of the entire network through cooperative control between crossings.

However, the implementation and commercialization of the 6G-V2X communication infrastructure are still in their early stages, and major challenges for practical use include path loss of THz band communication, signal attenuation due to weather conditions, and high communication costs. Therefore, this study intends to make a practical contribution to the design of next-generation smart cities and autonomous vehicle-based transportation systems by designing and experimentally verifying MARL-based traffic signal control models under 6G-V2X communication environments recognizing these limitations.

3 Proposed Traffic Signal Control Methodology

3.1 System Architecture Design

This study proposes a traffic signal control model using multi-agent reinforcement learning(MARL) based on the 6G-V2X communication infrastructure. In the proposed system, each intersection is composed of an independent learning agent to observe the traffic flow by intersection in real time, and based on this, signal phase change and signal period adjustment are performed. Real-time information exchange with adjacent intersections and various traffic subjects(vehicle, bicycle, pedestrian, personal means of transportation) is made through ultra-low latency communication and ultra-precise positioning functions of 6G-V2X, enabling cooperative learning between agents and promoting optimization of the overall traffic flow.

Four traffic subjects were included to increase the reality of traffic flow. Cars, bicycles, pedestrians and personal mobility(PM) participate in this simulation and each traffic subject was defined through an independent route file. This design made it possible to faithfully simulate the complex characteristics of urban transportation, such as traffic congestion, signal waiting and diversity of travel routes.

3.2 State, Action, Reward Function Design

For effective learning of MARL-based traffic signal control models, the definition of state, action and reward functions is designed with the direct goal of traffic flow optimization.

3.2.1 State

Each agent recognizes the environmental state through real-time observation of the intersection it manages and makes a signal control decision based on this. The agent's state is composed of the following items to reflect the characteristics of the traffic flow and the interaction with adjacent intersections.

First, the queue length of each approach to enter an intersection is collected. Second, by calculating the average waiting time of the waiting vehicle, the efficiency of vehicle traffic according to signal control is quantitatively identified. Third, the current control state of the intersection is modeled by including the current signal phase and the remaining time (Remaining Green Time) of the phase. Fourth, by reflecting the queue summary information collected from the adjacent intersection, cooperative decision-making considering the local traffic situation is made possible.

Finally, various traffic subjects around the intersection—Vehicles, Bicycles, Pedestrians, Personal Mobility (PM)—are collected in real time based on ultra-precise positioning data and included in the state vector.

The agent's state S_t can be expressed as follows:

$$S_t = \left\{ \begin{array}{l} q_{i,t}, w_{i,t}, \phi_t, \tau_t, n_{i,t}, (p_{j,t}, v_{j,t}) \\ \mid i \in Approaches, j \in Entities \end{array} \right\} \quad (1)$$

where $q_{i,t}$: Number of waiting vehicles for access road i
$w_{i,t}$: Average stop time for access road i
ϕ_t: Current signal phase
τ_t: Remaining time of signal phase
$n_{i,t}$: Queue summary for Adjacent Intersection i
$p_{j,t}$: Position vector of traffic subject j
$v_{j,t}$: Velocity vector of traffic subject j

All of these state information is converted into a form suitable for neural network input through a normalization process, and the agent learns the optimal signal control policy based on this.

3.2.2 Action

The actions the agent may perform are directly linked to signal control at the intersection. Considering the characteristics of the signal control problem, the action space includes the following two types of control manipulation.

First, it is phase switching. This means selecting one of various signal phase combinations according to the combination of driving directions (straight forward, left, right, etc.) of the intersection. Second, it is green time adjustment. This is a method of extending or shortening the duration of the currently activated signal phase, and enables more sophisticated traffic flow adjustment through detailed control of signal cycles.

The agent's behavior a_t is defined as follows:

$$a_t = (\Delta\phi_t, \Delta\tau_t) \quad (2)$$

where $\Delta\phi_t$: Command change to signal phase
$\Delta\tau_t$: Green signal duration adjustment amount

3.2.3 Reward

The compensation function is set as dual goals of alleviating traffic congestion and improving traffic efficiency. Specifically, by considering the number of vehicles waiting at an intersection and the average waiting time at the same time, the queue minimization and the traveling time reduction are achieved.

The reward R_t at time t is defined as follows:

$$R_t = -\alpha \times Q_t - \beta \times W_t \quad (3)$$

where α, β : Weighting factors for Q_t, W_t
Q_t : Number of waiting vehicles
W_t : Average wait time

The weighting factors α and β are responsible for balancing the congestion minimization of the system and efficiency improvement goals, and the optimal values are selected through experiments.

Such a reward structure contributes to achieving a more complex optimization goal of increasing overall traffic efficiency in a complex traffic environment mixed with various traffic subjects, not just an increase in vehicle passing.

3.3 Learning Algorithm Structure

The training of the proposed model was conducted based on the Deep Deterministic Policy Gradient(DDPG) and Asynchronous Advantage Actor-Critic(A3C) algorithms of reinforcement learning. DDPG utilizes actor-critic structures to effectively address continuous action spaces, and A3C improves learning stability and convergence speed by allowing multiple agents to interact independently with the environment based on parallel learning structures and renewing global neural networks through that experience. Learning takes place under the Centralized Training with Decentralized Execution(CTDE) framework

3.4 Experimental Environment Settings

The experimental environment of this study was constructed by linking simulation of Urban Mobility (SUMO) and ns-3 communication simulator. A large-scale urban transportation network was modeled through SUMO, and ns-3 reflected the communication characteristics by applying the mmWave setting to simulate a 6G communication environment. The transportation network consisted of a 10×10 grid structure, and a total of 100 intersections and 100 MARL agents corresponding thereto were deployed. The transportation entity consisted of vehicles, bicycles, personal means of transportation (PM), and pedestrians, and each movement characteristic was set by reflecting real traffic data. The number of traffic participants input per hour was set to 3,000 to 5,000 vehicles, 3,000 pedestrians, 500 PM, and 1,000 bicycles.

Table 1: Environmental Settings of Different Traffic Participants

Type	MaxSpeed	Acceleration	Deceleration	Length
Car	50km/h	2.0m/s^2	4.5m/s^2	5m
Pedestrian	5km/h	0.5m/s^2	1.0m/s^2	0.5m
PM	20km/h	1.0m/s^2	3.0m/s^2	1.2m
Bicycle	15km/h	1.0m/s^2	3.0m/s^2	1.8m

The communication environment was built under two conditions: 5G-V2X and 6G-V2X, 5G-V2X applied an average delay of 5ms and a packet loss rate of 10^-3 and 6G-V2X applied an average delay of 100μs and a packet loss rate of 10^-6. 100 repetitions of experiments were performed under each condition, and the analysis was conducted centering on the average value to ensure statistical reliability. Table 2 shows the details of communication parameters used in Experiment.

Table 2: Comparative Analysis of Communication Parameters in Experiments for 5G-V2X and 6G-V2X

Parameter	5G-V2X	6G-V2X
Bandwidth	100MHz	100GHz
Packet Transmission Interval	1ms	100μs
Transmission Power	23dBm	30dBm
Packet Size	10KB	100KB
Packet transmission Rate	1,000	10,000

4 Experimental Results and Analysis

4.1 Experimental Results

The experiment compared the performance in 5G-V2X and 6G-V2X environments, focusing on four indicators: average wait time, queue length, total delay, and network throughput.

According to Table 3, the average waiting time in the past 5G-V2X was 7.43 seconds, but in the 6G-V2X, it decreased to 4.99 seconds, showing an improvement effect of about 32.65%. The average queue length was 6.10 vehicles in average in the 5G-V2X, while 48.26% decreased to 3.13 vehicles in the 6G-V2X. The total delay time also decreased from 206.33 seconds in the 5G-V2X to 137.43 seconds in the 6G-V2X by 33.39%, and the network throughput increased from 2400.34 vehicles per hour in the 5G-V2X to 2961.23 vehicles per hour in the 6G-V2X, showing a 23.37% improvement.

Table 3: Performance Comparison of 5G-V2X and 6G-V2X

Metric	5G-V2X	6G-V2X	Change
Average Wait Time(s)	7.43	4.99	-32.65%
Average Queue Length(vehicles)	6.10	3.13	-48.26%
Total Delay Time(s)	206.33	137.43	-33.39%
Total Traffic Throughput(vehicles/h)	2400.50	2961.23	+23.37%

4.2 Analysis of Results

The experimental results in the 6G-V2X environment showed remarkable performance improvement compared to the existing 5G-V2X environment. The ultra-low latency communication characteristics greatly improved the speed of information exchange between agents, enabling cooperative learning between intersections, which led to a decrease in average latency and queue length. As a result of the experiment, it became possible to process real-time information about vehicles approaching intersections and various traffic subjects, which contributed to the optimization of traffic flow at the overall network level.

In addition, the ultra-precise positioning function allowed each traffic subject's location and speed to be accurately recognized in centimeters, which dramatically improved the situational awareness performance in an environment where various traffic subjects, such as small vehicles and pedestrians, are mixed.

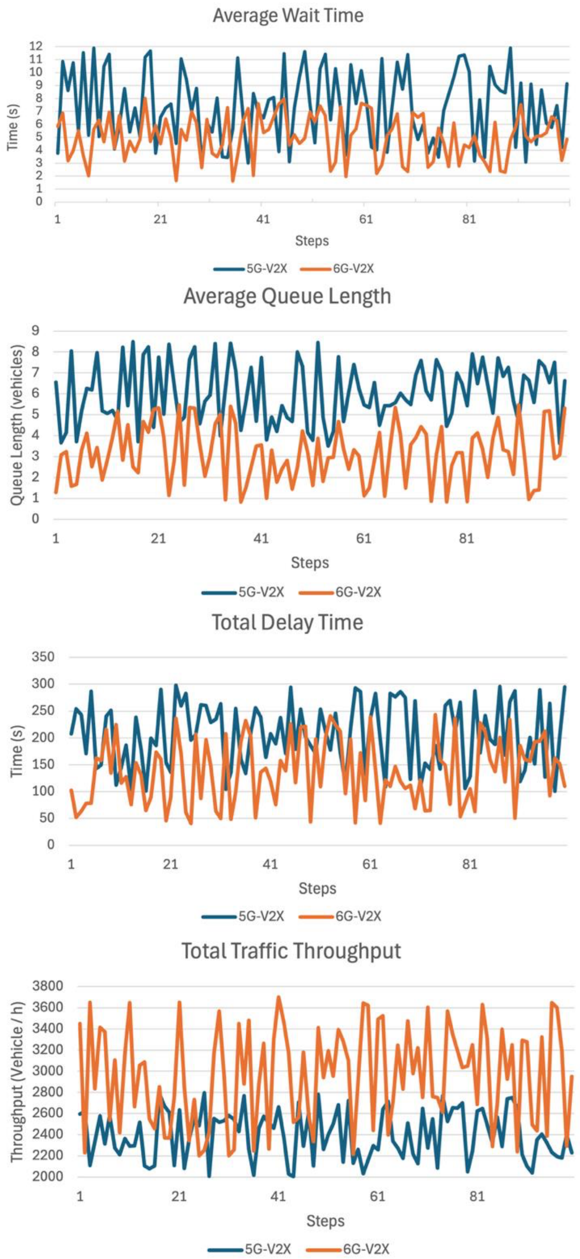

Figure 1: Stepwise Comparison of Traffic Efficiency Metrics between 5G-V2X and 6G-V2X

In Fig. 1, which visualizes the results of 100 experiments, it was confirmed that the 6G-V2X-based control model maintains a consistent performance advantage over time. The trend of decreasing average latency and queue length, shortening total delay time, and increasing traffic throughput was stably observed in all experimental repetitions, which supports that the 6G-V2X communication infrastructure is very effective in meeting the real-time and precision needs of the traffic signal control system.

5 CONCLUSION

In this study, a multi-agent reinforcement learning (MARL)-based traffic signal control model based on the 6G-V2X communication infrastructure was proposed and verified in a large-scale urban transportation network simulation environment. The proposed system established each intersection as an independent learning agent and enabled real-time cooperation between agents through ultra-low latency communication and ultra-precise positioning functions of 6G-V2X. The experiment showed that the 6G-V2X-based model leads to a decrease in average latency, queue length, and total latency, and improvement in overall traffic throughput compared to the 5G-V2X-based system, and significant improvement in traffic flow optimization performance.

In particular, this study demonstrated that the 6G-V2X-based signal control system contributes to the optimization of the overall traffic flow even in a complex traffic environment mixed with multiple traffic subjects (vehicle, pedestrian, bicycle, and personal means of transportation). The ultra-low latency communication characteristics were able to more accurately reflect the real-time state information of various traffic subjects, which simultaneously improved the adaptability and efficiency of the signal control system. In addition, it was experimentally confirmed that real-time cooperation between agents in a multi-agent-based reinforcement learning system accelerates the speed of learning convergence and is directly connected to the improvement of global optimization .

However, this study is limited to simulation-based evaluation, and problems such as path loss, path loss, and communication cost that can occur in the actual commercialization of 6G-V2X network and infrastructure construction are beyond the scope of this study. In addition, the traffic environment considered in this study is limited to normal traffic flow scenarios, and the model's performance evaluation for abnormal situations such as accidents and emergency vehicle passage was not conducted. In future research, it is necessary to conduct empirical verification of this model through actual 6G-V2X network-based real-world tests and evaluate the generalization performance of the model under complex scenarios including various traffic patterns and unexpected situations. In addition, it will be an important follow-up task to conduct an in-depth evaluation of the practical feasibility through economic analysis of the cost and operational efficiency of 6G communication infrastructure construction.

ACKNOWLEDGMENTS

This work was supported by the Institute of Information & Communications Technology Planning & Evaluation(IITP)-Innovative Human Resource Development for Local Intellectualization program grant funded by the Korea government(MSIT)(IITP-2025-RS-2022-00156287, 34%). This work was supported by the Institute of Information & Communications Technology Planning & Evaluation(IITP)- Core Strategic R&D program grant funded by the Korea government(MSIT)(IITP-2025-RS-2025-02219190, 33%). This work was supported by Institute of Information & communications Technology Planning & Evaluation (IITP) under the Artificial Intelligence Convergence Innovation Human Resources Development (IITP-2025-RS-2023-00256629, 33%) grant funded by the Korea government(MSIT).

REFERENCES

[1] X. Che, L. Zhu, L. Wang and X. Li, "Urban Intelligent Transportation System Standards Architecture Research," 2024 9th International Conference on Intelligent Computing and Signal Processing (ICSP), Xian, China, 2024, pp. 1392-1398

[2] L. Dong, "Research on the Industrial Development of Intelligent Transportation System in China," 2020 5th International Conference on Electromechanical Control Technology and Transportation (ICECTT), Nanchang, China, 2020, pp. 622-627

[3] G. V. Priya, B. S. Gowri, B. Rajalakshmi, L. Dilli Kumar, U. Janagan and R. Sudhir, "A Novel Approach to Mitigating Traffic Issues through Advanced Congest Detection and Adaptive Signal Control Using AI," 2024 4th International Conference on Intelligent Technologies (CONIT), Bangalore, India, 2024, pp. 1-5

[4] H. Zafar, Z. Utkovski, M. Kasparick and S. Stanczak, "Transfer Learning in Multi-Agent Reinforcement Learning with Double Q-Networks for Distributed Resource Sharing in V2X Communication," WSA 2021; 25th International ITG Workshop on Smart Antennas, French Riviera, France, 2021, pp. 1-6.

[5] I. Lee and D. K. Kim, "MARL-based Resource Allocation for Heterogeneous Traffic in V2X Communications," 2023 28th Asia Pacific Conference on Communications (APCC), Sydney, Australia, 2023, pp. 61-67

[6] N. Hammami, K. K. Nguyen and H. Purmehdi, "Attentional Communication for Multi-Agent Distributed Resource Allocation in V2X Networks," GLOBECOM 2023 - 2023 IEEE Global Communications Conference, Kuala Lumpur, Malaysia, 2023, pp. 5653-5658

[7] W. Zheng, A. Ali, N. González-Prelcic, R. W. Heath, A. Klautau and E. M. Pari, "5G V2X communication at millimeter wave: rate maps and use cases," 2020 IEEE 91st Vehicular Technology Conference (VTC2020-Spring), Antwerp, Belgium, 2020, pp. 1-5

[8] H. Ouamna, Z. Madini and Y. Zouine, "6G and V2X. Communications: Applications, Features, and Challenges," 2022 8th International Conference on Optimization and Applications (ICOA), Genoa, Italy, 2022, pp. 1-6

[9] D. Wang, Y. N. Nganso and H. D. Schotten, "A Short Overview of 6G V2X Communication Standards," 2023 International Conference on Intelligent Communication and Networking (ICN), Changzhou, China, 2023, pp. 20-26

[10] A. Jouini, H. Dalila and C. Adnen, "ADAS and 5G/6G-V2X Implementation for Sustainable and Intelligent Transport," 2023 22nd Mediterranean Microwave Symposium (MMS), Sousse, Tunisia, 2023, pp. 1-6

[11] J. Jia and W. Wang, "Review of reinforcement learning research," 2020 35th Youth Academic Annual Conference of Chinese Association of Automation (YAC), Zhanjiang, China, 2020, pp. 186-191

[12] C. Shyalika and T. Silva, "Reinforcement learning based an Integrated Approach for Uncertainty Scheduling in Adaptive Environments using MARL," 2021 6th International Conference on Inventive Computation Technologies (ICICT), Coimbatore, India, 2021, pp. 1204-1211

[13] V. Y. Guleva and E. N. Shikov, "Proportion of Similar Neighbours and Optimal Weight of Neighbourhood Contribution in Learning Dynamics of Networked MARL," 2023 7th Scientific School Dynamics of Complex Networks and their Applications (DCNA), Kaliningrad, Russian Federation, 2023, pp. 91-94