Journal of Infrastructure, Policy and Development 2024, 8(15), 9494.
https://doi.org/10.24294/jipd9494

Article

Deep Q-learning for reducing enhanced distributed channel access collision in IEEE 802.11p of Vehicular Ad Hoc Network

Yongjun Liang[1], Ismail Fauzi Bin Isnin[1,*], Nur Haliza Abdul Wahab[1], Jiafu Su[2]

[1] Faculty of Computing, Universiti Teknologi Malaysia, Johor 81310, Malaysia
[2] International College, Krirk University, Bangkok 10220, Thailand
*** Corresponding author:** Ismail Fauzi Bin Isnin, ismailfauzi@utm.my

CITATION

Liang Y, Isnin IFB, Wahab NHA, Su J. (2024). Deep Q-learning for reducing enhanced distributed channel access collision in IEEE 802.11p of Vehicular Ad Hoc Network. Journal of Infrastructure, Policy and Development. 8(15): 9494.
https://doi.org/10.24294/jipd9494

ARTICLE INFO

Received: 8 October 2024
Accepted: 4 December 2024
Available online: 17 December 2024

Abstract: The purpose of Vehicular Ad Hoc Network (VANET) is to provide users with better information services through effective communication. For this purpose, IEEE 802.11p proposes a protocol standard based on enhanced distributed channel access (EDCA) contention. In this standard, the backoff algorithm randomly adopts a lower bound of the contention window (CW) that is always fixed at zero. The problem that arises is that in severe network congestion, the backoff process will choose a smaller value to start backoff, thereby increasing conflicts and congestion. The objective of this paper is to solve this unbalanced backoff interval problem in saturation vehicles and this paper proposes a method that is a deep neural network Q-learning-based channel access algorithm (DQL-CSCA), which adjusts backoff with a deep neural network Q-learning algorithm according to vehicle density. Network simulation is conducted using NS3, the proposed algorithm is compared with the CSCA algorithm. The find is that DQL-CSCA can better reduce EDCA collisions.

Keywords: Vehicular Ad Hoc Network; enhanced distributed channel access; packet collision; deep neural network Q-learning

1. Introduction

In recent years, the amazing advances in wireless technology and embedded communication systems extend their use to new dimensions so that they can be used anytime, anywhere. Taking advantage of the advancement of wireless communications and the ever-increasing needs of users, the automotive industry and the government have seized the opportunity to use the Vehicle Ad Hoc Network (VANET) to improve the transportation system. Vehicle transportation is the largest transportation sector; however, recently encountered traffic-related problem shave increased significantly, accidents and frequency have become an increasingly serious issue related to vehicles (Mahi et al., 2022). Intelligent Transportation Systems (ITS) have been an active research field for the last few years. As a core element of the next generation ITS, VANETs are intended to provide a low cost, reliable and efficient communication network for transportation systems (Fitah et al., 2018). Vehicle-to-vehicle (V2V) communication is promoted in VANET, which refers to communication between vehicles. In addition, vehicle-to-infrastructure (V2I) communication is used to access infrastructure networks, such as cellular networks or wireless local area networks (WLAN) access points, through network gateways, such as roadside units (RSU) and base stations (BS) (RadhaKrishna, 2021).

IEEE 802.11p is the MAC layer protocol for VANET, which uses the EDCA MAC sublayer protocol to support different types of services. The IEEE 802.11p standard introduced new specifications to the physical layer, as well as the MAC sub-layer, to improve communications in VANETs. It is especially designed for medium range and time-sensitive applications to adapt to vehicle mobility (Harkat et al., 2019). The IEEE 802.11p protocol uses the EDCA method to detect access channels before transmitting data to each vehicle. To resolve data conflicts, EDCA uses Binary Exponential Backoff (BEB) for the backoff process. BEB is the standard algorithm for the collision mitigation mechanism based on EDCA of IEEE 802.11p (Nasir and Albalt, 2009). As a standard algorithm, BEB can usually reduce data collisions effectively.

However, the BEB method is not suitable for vehicular networks, as EDCA packet collisions will increase significantly in density vehicular networks (Gopinath et al., 2020). In this paper, a new method, a deep neural network Q-learning-based channel access algorithm (DQL-CSCA), is proposed. This algorithm adapts the backoff using a deep neural network Q-learning algorithm depending on the number of repetitions and vehicle density. This algorithm has designed a new equation and combined it with the three equations of CSCA algorithm as the four actions for Q-learning. The new equation has a certain degree of flexibility to adapt to various state intervals or dynamically adjust in unstable states, with a certain adaptive mechanism, combined with existing contention windows and collision conditions to further reduce collision probability. The advantage of this algorithm is that the Q-learning algorithm in this paper is based on 7 states and 4 actions, including newly designed formulas, which have a certain degree of flexibility to adapt to various state intervals and have a certain adaptive mechanism. After multiple iterations and training, this algorithm will gradually select the optimal action in each state to reduce data collisions.

This article is organized as follows. Section 1 introduces IEEE 802.11p MAC and EDAC. Section 2 discusses related works. And, section 3 performs an example arithmetic study. Section 4 compares the research methodology of this paper with that of previous literature based on NS3 simulation results. Section 5 discusses the simulation results. Finally, section 6 concludes the paper.

2. Literature review

The most important MAC protocols in the VANET are IEEE 802.11p and IEEE 1609.4. In this article, packet collisions in IEEE 802.11p are examined by literature review.

2.1. IEEE 802.11p EDCA in MAC layer protocols of VANET

To support VANET services, the standard for wireless access in vehicle environments IEEE 802.11p was introduced. The IEEE 802.11p standard offers high data rates through Dedicated Short-range Radio Communication (DSRC) devices, which have a bandwidth of 6 Mbps to 27 Mbps. In VANET, there are two different types of nodes that have DSRC devices. These are: On Board Units (OBUs) and RSUs which are placed at the roadsides (Banda et al., 2012).

In wireless local area network (WLAN), the most basic and widely used access method at the MAC layer is the random contention access method called Distribute

Coordination Function (DCF). The DCF mechanism is the core technology for the MAC layer protocol of IEEE 802.11e, which acts on the basic service group and the basic network structure. IEEE 802.11p is an extended version for IEEE 802.11e (Harkat et al., 2019).

Software defined vehicular network (SDVN) is a new paradigm that enhances the programmability and flexibility of VANETs, but lacks a data collection mechanism. Researchers have proposed a data collection mechanism for this (Wijesekara et al., 2023). The IEEE 802.11P defined the routing capabilities of DSRC devices in VANETs. Routing in vehicular networks is challenging due to the high mobility of nodes leading to a dynamic network topology. Some researchers have conducted research to improve this (Wijesekara and Gunawardena, 2023).

2.2. IEEE 802.11p EDCA channel access method

IEEE 802.11p uses EDCA method to meet the requirements of in vehicle applications. In competition based protocols, each vehicle checks whether the channel is free before transmitting data. Once other adjacent vehicles also detect that they have free lanes, it can lead to collisions between them. To resolve conflicts, the backoff process defined in EDCA uses binary exponential backoff (BEB).

BEB is the standard algorithm for the collision mitigation mechanism based on EDCA according to IEEE 802.11p. It is a binary exponential backoff algorithm used in the backoff process of EDCA (Wang et al., 2023). When the vehicle is ready to access the channel and discovers a busy channel, BEB will select a random value from [0, CW_{UB}] as the backoff value. If no confirmation is received or a conflict occurs within the specified time, CW_{UB} will make modifications according to Equation (1) (Gopinath and Nithya, 2018).

$$CW_{UB^i} = \{ \begin{matrix} 2^i \times CW_{UB^{min}}, failure \\ CW_{UB}{}^{min}, success \end{matrix} \tag{1}$$

BEB includes six backoff stages. Every time there is a packet conflict, CW_{UB} increases exponentially. After successful transmission, it will be reset to the minimum CW value.

2.3. BEB algorithm with dense vehicle population

The BEB algorithm is suitable for environments with few vehicles. If the vehicle density is high, the probability of multiple vehicles choosing the same waiting time will increase. This will lead to more data conflicts in the network (Nasir and Albalt, 2009). The BEB method is not applicable to high-density vehicle networks (Rawat et al., 2011). The number of vehicles within the communication range may increase or decrease due to their mobility. At each backoff stage, regardless of the number of vehicles and traffic conditions, the CW_{LB} value remains at 0.

2.4. Packet collision reduction

BEB is the standard algorithm for the collision mitigation mechanism based on EDCA of IEEE 802.11p. It is a binary exponential backoff algorithm used in the backoff process of EDCA. The standard BEB method is not suitable for vehicular networks because EDCA collisions increase significantly in highly dynamic vehicular networks (Nasir and Albalt, 2009). Researchers have proposed many variants of competitive solutions (Chang et al., 2012; Stanica et al., 2017; Wu and Xu., 2017). Chang et al. (2012) proposed an adaptive EDCA scheme for vehicle communication (A-EDCA). A-EDCA defines a set of CW values for each retransmission attempt. The range of CW values is estimated based on the number of vehicles and collision attempts in the network.

A CW based data distribution protocol for improving vehicle communication was suggested by Arora and Patel (2017). The drawback of this scheme is that as the vehicle density increases, the value of CW may exceed the maximum contention window. Balador et al. (2017) proposed a density based CW scheme. Estimate the vehicle density adjustment CW by maintaining the historical records of the channel. However, maintaining historical records is an additional computational expense. Lei et al. (2021) also pointed out that 802.11p EDCA uses a fixed-size competitive window for secure transmission of messages, which leads to a high probability of collision in a dense environment. To address these shortcomings, a hybrid access method is proposed: the node is configured to reserve time slots for the next transmission round, while the unoccupied time slots are reserved for the nodes with urgent needs. In addition, implicit feedback is used to detect conflicts that occur in reserved time slots during random channel access. Therefore, a mathematical model has been developed to optimize the parameters of our system and minimize the cost caused by unused channels and conflicts. A large number of simulations show that this mechanism can significantly improve the performance of VANET in secure message transmission. Gopinath et al. (2020) proposed improvements to the algorithm of Chang et al. (2012). A channel state based competitive algorithm (CSCA) was suggested by Gopinath et al. (2020), which adjusts the backoff value according to the count of retransmissions attempts and vehicle density of ACK. This algorithm proposes an algorithm that uses equations to calculate the CW_{LB} instead of EDCA, where the CW_{LB} is fixed to 0. This algorithm has been proven effective in NS3 simulation validation when vehicles are dense, but its equation is too fixed and lacks elasticity.

The algorithms discussed above focus on adjusting the CW_{UB}. Moreover, the backoff interval is randomly chosen from the [0, CW_{UB}] interval, so conflicts and repeated retransmissions are inevitable, thereby reducing the performance of the entire network. Although the CSCA algorithm does not start CW_{LB} from zero, but its calculation method is relatively fixed and has not been adjusted according to the actual environmental state. Considering these shortcomings, this paper proposes using deep Q-learning to improve CSCA algorithm in an attempt to optimally adjust the lower bound. In this paper, the CSCA algorithm proposed by Gopinath et al. (2020) is improved.

3. Research methods

Reinforcement learning can be based on the Markov decision process (Gattami et al., 2021). The core idea of the machine learning algorithm of MDP is to imitate the trial and error and exploration mechanism in bionics to seek advantages and avoid disadvantages, according to the interaction between agent and environment, use actions to perform independent training and learning, and optimize the policy and learn the optimal behavior through reward after interaction (Ma et al., 2021). Reinforcement learning aims to find the optimal value function of the value function for all strategies through continuous iteration, including the optimal V function and the optimal Q function (Ernst and Louette, 2024). The reinforcement learning methods are mainly divided into three types: value-based, strategy-based, value-based and strategy-based. Value-based Q-learning is a classical value-based method of reinforcement learning algorithm (Ding et al., 2020). Deep Q-learning can learn from data sets of state-action pairs. The reason is that the neural network can learn to represent the Q-function as a function of state and action. In this work, the DQL algorithm is used to learn and find the optimal CW value to reduce data collisions in vehicle transmission.

This paper aims to address these shortcomings by using deep neural network and Q-learning (DQL), named DQL-CSCA, to calculate CW_{LB} to reduce collision based on retransmission, which corresponds to 7 states from 0 to 6. Q-learning is one classical value method depended on reinforcement learning algorithm. This article improves the CSCA algorithm proposed by Gopinath et al. (2020).

Shown in the following **Figure 1**, in a neural network with 7 inputs and 4 outputs, if input states are specified, the *Q* values of the 4 actions are used as the outputs of the neural network. Among them, state S0 to S6 correspond to retransmission attempts 0 and 6. The three formulas of CSCA (Gopinath et al., 2020) correspond to three actions, plus the default parameters of EDCA as the fourth action, resulting in a total of four actions. Shown as **Figure 1**, a1, a2, a3 and a4 correspond to the following four actions, and VD is vehicle density and Ra is retransmission attempts.

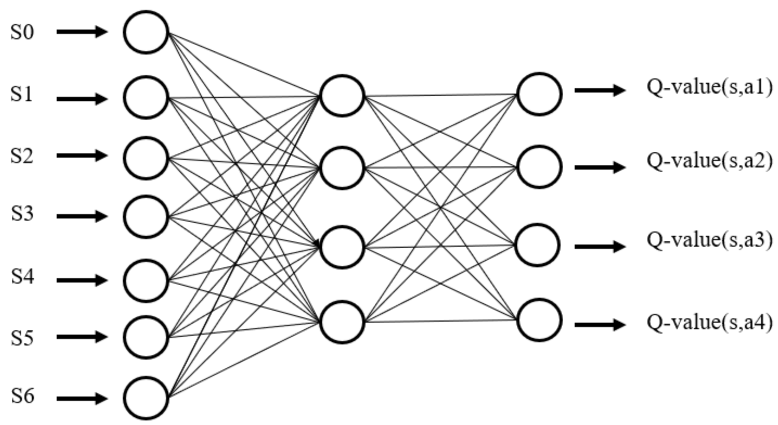

Figure 1. Neural network of DQL-CSCA.

This paper's algorithm is an improvement on CSCA of the Gopinath et al. (2020) algorithm. Gopinath et al. (2020) first proposed an algorithm to reduce EDCA data collisions by adjusting CW_{LB}. Gopinath et al. (2020) proposed three formulas to adjust CW_{LB}. But the three equations of this algorithm are too fixed and lack elasticity, and theoretically they are not the optimal solution for adjusting CW_{LB}. Then, to address these shortcomings, this paper presents a deep neural network Q-learning algorithm that continuously attempts and learns to obtain the optimal solution through reinforcement learning. Based on theoretical calculations of the number of retries and the number of vehicles, the most suitable equation for the current conditions is calculated in real-time according to the three equations of Gopinath et al. (2020).

Action 1, 2 and 3 are based on three equations of CSCA, Equations (2)–(4) (Gopinath et al., 2020). This algorithm designed a new equation as the fourth action for Q-learning. The new Equation (5) has a certain degree of flexibility to adapt to various state intervals.

$$CW_{LB} = \frac{1}{\sqrt{V_D}} \times CW_{UB}{}^{curr} \tag{2}$$

$$CW_{LB} = \sqrt{V_D} \times R_a{}^2 \tag{3}$$

$$CW_{LB} = 2^{R_a - 2} \times CW_{UB}{}^{\min} \tag{4}$$

$$CW_{LB} = \left(1 - \frac{R_a}{6}\right) \times CW_{UB}{}^{curr} + \frac{R_a}{6} \times CW_{UB}{}^{curr} \tag{5}$$

About Q-value (s, a), Q value update method is:

$$Q(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma\, max_{a'} Q\,(s',a') - Q(s,a)] \tag{6}$$

Among them, s is state, and a is action, α is learning coefficient, r is reward received for actions, γ is proportional coefficient, $\max_{a'} Q(s', a')$ is the maximum Q value obtained by the action in the next state. All in all, this section proposes a deep Q-learning algorithm to calculate CW_{LB}, which is a reinforcement learning algorithm based on neural networks.

Showed as **Table 1**, the Q-Table will be a 7 × 4 matrix, where each cell represents the Q value of performing a certain action in a certain state.

Table 1. Q-Table of DQL-CSCA.

State	Action 1	Action 2	Action 3	Action 4
0	0	0	0	0
1	0	0	0	0
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0
5	0	0	0	0
6	0	0	0	0

In the Q-learning algorithm, the Q-Table is a matrix that stores the Q value of each state and action combination to help the agent choose the best action in different states. Then, DQL-CSCA has 7 states (from 0 to 6, state 0 is the best state and state 6 is the worst state) and 4 possible actions. In the initial stage of Q-learning, the Q value is usually set to 0, indicating that the agent has no experience or knowledge of the environment. After multiple iterations and training, the Q value in the Q-Table will gradually reflect the optimal action selection in each state. Q-learning algorithm in this paper is based on 7 states and 4 actions, including newly designed formulas, which have a certain degree of flexibility to adapt to various state intervals and have a certain adaptive mechanism. After multiple iterations and training, this algorithm will gradually select the optimal action in each state to reduce data collisions. The reinforcement learning takes place in node and node is agent.

The proposal model showed as **Figure 2**.

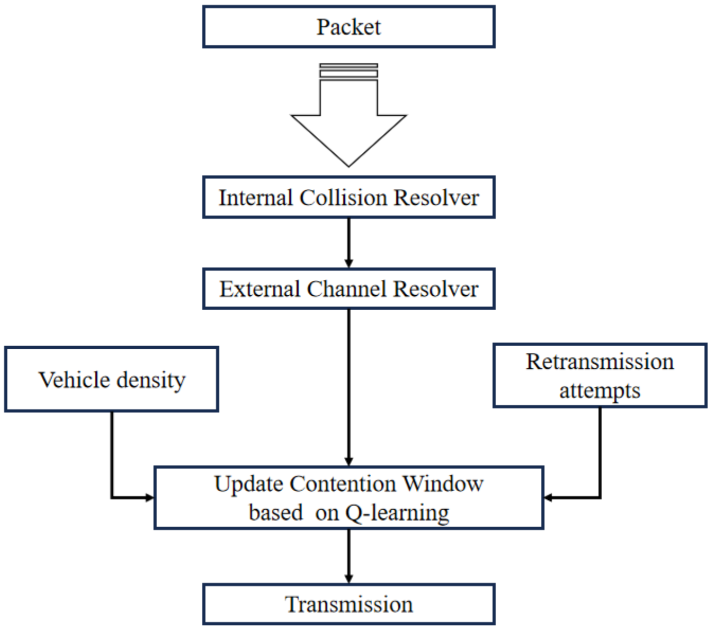

Figure 2. The proposal model.

CW adjustment schemes are described in Algorithm 1.

Algorithm 1 DQL-CSCA algorithm

1: Input: $CW_{UB}curr$—Current CW_{UB}
2: V_D—Vehicle Density
3: R_a—Retransmission Attempt
4: $CW_{UB}min$—Minimum CW_{UB}
5: $CW_{UB}max$—Maximum CW_{UB}
6: *NodeId*—id of each node
7: Output:
8: CW_{LB}—Updated Lower Bound procedure
9: procedure DQL-CSCA(V_D, R_a, $CW_{UB}min$, $CW_{UB}max$, *NodeId*)
10: for each queue do
11: Configure($CW_{UB}min$, $CW_{UB}max$)
12: end for
13: for each arrived packet do
14: Enqueue(packet)
15: end for

Algorithm 1 (*Continued*)

```
CW_UB curr = getCW()
//get action based on Q-value in each node
action = GetActionByQvalue(R_a, NodeId)
//do action to update CW_LB
```
if action = 1 then $CW_{LB} = \frac{1}{\sqrt{V_D}} \times {CW_{UB}}^{curr}$

else if action = 2 then $CW_{LB} = \sqrt{V_D} \times {R_a}^2$

else if action = 3 then $CW_{LB} = 2^{R_a - 2} \times {CW_{UB}}^{min}$

else if action = 4 then $CW_{LB} = \left(1 - \frac{R_a}{6}\right) \times {CW_{UB}}^{curr} + \frac{R_a}{6} \times {CW_{UB}}^{curr}$

$BO_{counter}$ = random(CW_{LB}, $CW_{UB}max$)

BackoffStartedNow($BO_{counter}$)

end procedure

All in all, this section proposes a Q-learning neural networks to calculate CW_{LB}. This algorithm is based on the advantages of Gopinath et al. (2020) algorithm and integrates deep neural network Q-learning algorithm to find the optimal backoff values of each vehicle in dense driving environments, thereby obtaining the optimal value to reduce packet collisions in dense vehicle environments.

4. Result analysis

The data analysis of this paper will refer to the default EDCA conflict avoidance algorithm and CSCA conflict avoidance algorithm in IEEE 802.11p. The simulation will compare data collision rate to evaluate the proposed DQL-CSCA algorithm.

In this study, the network simulator NS-3 is selected because of its availability, simplicity and efficiency. The traditional simulation method usually needs to write program code to implement an algorithm. It may require a lot of machines to test. Some are responsible for making routers, some are responsible for being servers, and some are customers. They even need more equipment laboratories, development and test platforms, etc. NS-3 covers various protocols, traffic models, network types and other network elements. These features make the NS-3 more powerful than other simulators.

The vehicle network has deployed up to 100 cars and range of 350 m. The IEEE 802.11p PHY standard is used for physical layer configuration. Other simulation parameters and their values refer to the IEEE 802.11p PHY/MAC of CSCA paper by Gopinath et al. (2020). This section describes the simulation results of the proposed DQL-CSCA algorithm, default EDCA, and CSCA algorithm. The results are analyzed using the packet collision rate (PCR). PCR is a measure of the number of conflicting packets relative to the number of transmitted packets. The result shown as **Figures 3** and **4**, the proposed DQL-SCA algorithm better controls the packet collision rate than other algorithms.

The proposed DQL-CSCA focuses on changing the appropriate CW_{LB} based on deep neural networks and Q-learning to reduce packet collisions. Therefore, **Figures 3** and **4** witnesses that the proposed DQL-CSCA algorithm performs better message PCR than CSCA and default EDCA. When the density of vehicles increases, such as the number of vehicles ranging from 20 to 100, the proposed DQL-CSCA controls

PCR by 11 to 16 percent. When the vehicle density is 50 vehicles, DQL-CSCA reduces the collision rate by about 5 percent compared to CSCA and about 10 percent compared to the default EDCA. When the vehicle density is 100 vehicles, DQL-CSCA still reduces collision rates by about 5 percent compared to CSCA, but by about 20 percent compared to the default EDCA. This trend indicates that the algorithm proposed in this article is effective in reducing data collisions in situations with high vehicle density. The possible reason for this is that the deep Q-learning algorithm proposed in this article continuously tries and learns through reinforcement learning to obtain the optimal solution. When there are more vehicles and more data transmitted, the more data used for learning is more beneficial for deep Q-learning. Based on more data, the calculation is based on retries and vehicles, The DQL algorithm will better reduce data conflicts in EDCA. In wireless networks, different formulas are adopted to cope with changes in surrounding environmental factors, which is precisely why deep Q-learning can theoretically obtain better solutions, and simulation results also show that this is indeed the case.

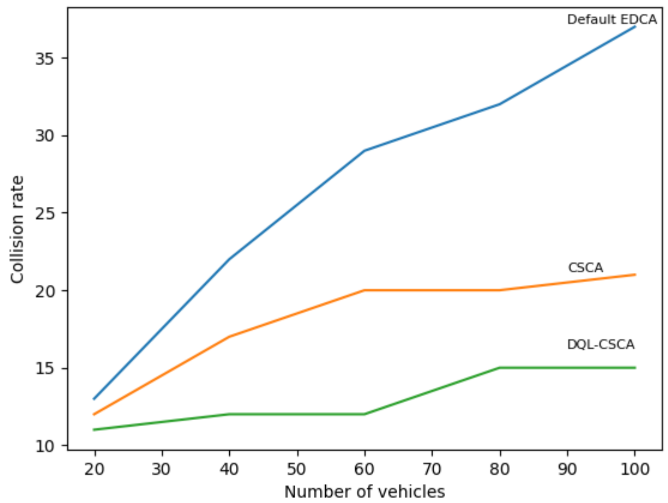

Figure 3. Comparison of packet collision rate (packet size = 100).

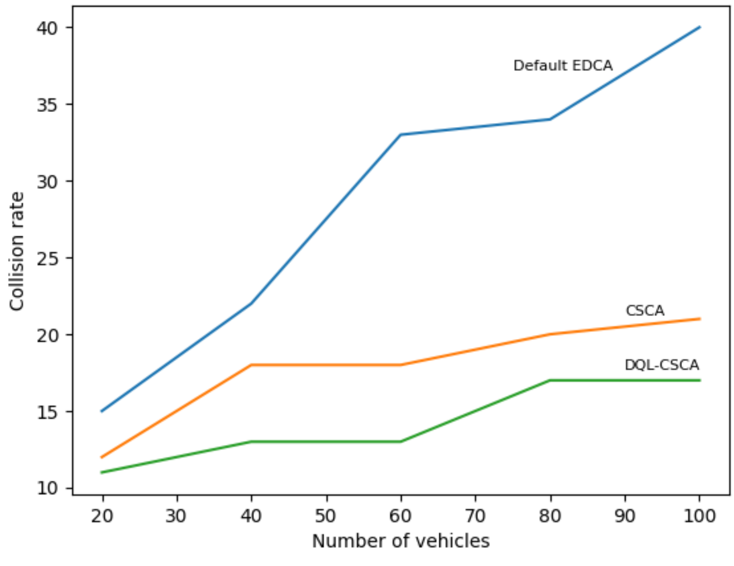

Figure 4. Comparison of packet collision rate (packet size = 200).

5. Discussion

In VANET, the traditional scheme will cause serious data collision when vehicles are dense. Therefore, this study aims to propose a deep reinforcement learning algorithm for data collision, which considers network collision through deep reinforcement learning. The objective of this paper is to solve this unbalanced backoff interval problem in saturation vehicles and this paper proposes a method that is a deep neural network Q-learning-based channel access algorithm (DQL-CSCA), which adjusts backoff with a deep neural network Q-learning algorithm according to the number of retransmissions attempts and vehicle density. The find is that DQL-CSCA can better reduce EDCA collisions. This paper will make a certain contribution to the IEEE 802.11p standard of VANET, because it applies emerging deep neural network algorithm of artificial intelligence to the traditional VANET field.

Based on Gopinath's algorithm, this paper uses the Q-learning algorithm to provide superiority and improvement significance for the backoff window selection strategy. The first is the enhanced adaptability. Compared with traditional algorithms, Q-learning can find the optimal strategy through learning in a constantly changing network environment. Different node densities and collision rates may cause drastic fluctuations in network conditions, and the Q-learning algorithm can adjust the strategy by updating the Q table, so that the agent can choose different actions (equations) to reduce the collision rate. The second is to improve the collision avoidance effect: Gopinath's algorithm is a fixed equation and lacks flexibility. Q-learning can select the optimal formula according to the current collision situation, dynamically adapt to the network load, and reduce the probability of data collision. This makes the network resource utilization higher. Then the Q-learning algorithm accumulates experience, so that the agent can learn the optimal strategy from it, thereby achieving the optimal collision control effect. With the help of Q-learning, the algorithm can select a suitable formula according to the current state, making the adjustment of the backoff window more intelligent, thereby reducing the number of data retransmissions and system overhead.

All in all, this study attempts to design a throughput algorithm in MAC protocol by implementing Q learning of deep reinforcement learning to reduce the frame collision rate due to vehicle density. This paper provided a certain contribution to the algorithm optimization of VANET's IEEE 802.11p EDCA standard in terms of performance and proposed the method DQL-CSCA can solve this problem better.

6. Conclusion

The NS3 simulation results of this paper indicate that the proposed DQL-CSCA algorithm can better reduce EDCA data collisions than the CSCA algorithm and the default EDCA algorithm. This indicates that the DQL-CSCA deep neural network Q-learning algorithm proposed in this paper, based on retransmission attempts and the number of vehicles in saturated vehicle networks, can better reduce conflicts and congestion in VANET networks.

The DQL-CSCA algorithm proposed in this paper, originating from AI, is an improvement on the CSCA algorithm and has been proven to achieve better results.

This theoretically promotes the development of algorithms in the field of IEEE 802.11p EDCA data collision based on adjusting CW_{LB} values, which is conducive to the theoretical development of VANET. It has certain theoretical reference significance for future scholars preparing to apply AI algorithms to the WIFI field. The contribution of the DQL-CSCA algorithm is that this Q-learning backoff window adjustment strategy is not only applicable to existing network environments, but can also be extended to other similar scenarios. For example, in other high-density wireless sensor networks and IoT nodes, Q-learning can help design adaptive backoff mechanisms to effectively reduce interference and collisions, thereby improving communication efficiency.

In short, DQL-SCA can better reduce EDCA collisions in densely populated environments with vehicles. This study did not consider the impact of urban architecture on wireless networks, which can serve as a direction for future research. In addition, TDMA-based MAC protocols and multipath video streaming in VANET will be the next research direction (Aliyu et al., 2020; Emmanuel et al., 2019).

Author contributions: Conceptualization, YL and IFBI; methodology, YL; software, YL; validation, IFBI, NHAW and JS; formal analysis, NHAW; investigation, YL; resources, IFBI; data curation, JS; writing—original draft preparation, YL; writing—review and editing, IFBI; visualization, JS; supervision, IFBI; project administration, NHAW; funding acquisition, JS. All authors have read and agreed to the published version of the manuscript.

Conflict of interest: The authors declare no conflict of interest.

References

Aliyu, A., Abdullah, A. H., Isnin, I. F., Radzi, R. Z. R. M., Kumar, A., Darwish, T. S., & Joda, U. M. (2020). Road-based multi-metric forwarder evaluation for multipath video streaming in urban vehicular communication. Electronics, 9(10), 1663.

Banda, L., Mzyece, M., and Noel, G. (2012). IP mobility support: Solutions for vehicular networks. IEEE Vehicular Technology Magazine. 7(4), 77-87.

Balador, A., Tavares De Araujo Cesariny Calafate, C. M., Cano, J. C., and Manzoni, P. (2017). "A density-based contention window control scheme for unicast communications in vehicular ad hoc networks." International Journal of Ad Hoc and Ubiquitous Computing, 24(1-2),65-75.

Ding, Z., Huang, Y., Yuan, H., & Dong, H. (2020). Introduction to reinforcement learning. Deep reinforcement learning: fundamentals, research and applications, 47-123.

Emmanuel, S. and Isnin, I. F. and Mohamad, M. M. (2019) A survey of TDMA-based MAC protocols for vehicular ad hoc networks. International Journal of Engineering and Advanced Technology, 8 (5). pp. 1247-1259. ISSN 2249-8958.

Ernst, D., & Louette, A. (2024). Introduction to reinforcement learning.

Fitah, A., Badri, A., Moughit, M., & Sahel, A. (2018). Performance of DSRC and WIFI for Intelligent Transport Systems in VANET. Procedia Computer Science, 127, 360-368.

Gopinath, A. J., and Nithya, B. (2018). "Mathematical and simulation analysis of contention resolution mechanism for IEEE 802.11 ah networks." Computer Communications, 124, 87-100.

Gopinath, A. Justin, B. Nithya, Harshit Mogalapalli, and P. Kamalesh Khanna. "Channel Status based Contention Algorithm for Non-safety Applications in IEEE802. 11p Vehicular Network." Procedia Computer Science 171 (2020): 1479-1488. https://doi.org/10.1016/j.procs.2020.04.158.

Harkat, Y., Amrouche, A., Lamini, E. S., & Kechadi, M. T. (2019). Modeling and performance analysis of the IEEE 802.11 p EDCA mechanism for VANET under saturation traffic conditions and error-prone channel. AEU-International Journal of Electronics and Communications, 101, 33-43.

IEEE Standard for Wireless LAN medium access control (MAC) and physical layer (PHY) specifcations. IEEE Std 802.11-1997, pp. 1–445 (2019). https://doi.org/10.1109/IEEESTD.1997.85951.

Lei, Xiaoying, Xiangjin Chen, and Seung Hyong Rhee. "A hybrid access method for broadcasting of safety messages in IEEE 802.11 p VANETs." EURASIP Journal on Wireless Communications and Networking 2021, no. 1 (2021): 118. https://doi.org/10.1186/s13638-021-01933-3.

Ma, X., Yang, Y., Li, C., Lu, Y., Zhao, Q., & Jun, Y. (2021). Modeling the interaction between agents in cooperative multi-agent reinforcement learning. arXiv preprint arXiv:2102.06042.

Mahi, M. J. N., Chaki, S., Ahmed, S., Biswas, M., Kaiser, S., Islam, M. S., ... & Whaiduzzaman, M. (2022). A review on VANET research: Perspective of recent emerging technologies. IEEE Access.

RadhaKrishna Karne, D. T. (2021). Review on vanet architecture and applications. Turkish Journal of Computer and Mathematics Education (TURCOMAT), 12(4), 1745-1749.

Rawat, D. B., Popescu, D. C., Yan, G., and Olariu, S. (2011). "Enhancing VANET performance by joint adaptation of transmission power and contention window size". IEEE Transactions on Parallel and Distributed Systems, 22(9), 1528-1535.

Wang, Y., Shi, J., & Chen, L. (2023). Performance Analysis of IEEE 802.11 p MAC with Considering Capture Effect under Nakagami-m Fading Channel in VANETs. Entropy, 25(2), 218.

Wijesekara, P. A. D. S. N., Sudheera, K. L. K., Sandamali, G. G. N., & Chong, P. H. J. (2023). An Optimization Framework for Data Collection in Software Defined Vehicular Networks. Sensors, 23(3), 1600.

Wu, G., and Xu, P. (2017). "Improving performance by a dynamic adaptive success-collision backoff algorithm for contention-based vehicular network." IEEE Access, 6, 2496-2505.

Nasir, Q., & Albalt, M. (2009, March). Improved backoff algorithm for IEEE 802.11 networks. In 2009 International Conference on Networking, Sensing and Control (pp. 1-6). IEEE.

Stanica, R., Chaput, E., and Beylot, A. L. (2011, September). "Local density estimation for contention window adaptation in vehicular networks." In 2011 IEEE 22nd International Symposium on Personal, Indoor and Mobile Radio Communications (pp. 730-734).

Chang, S. W., Cha, J., & Lee, S. S. (2012, February). Adaptive EDCA mechanism for vehicular ad-hoc network. In The International Conference on Information Network 2012 (pp. 379-383). IEEE.

Arora, P. O., and Patel, A. R. (2017, April). "Contention window based data dissemination in VANETs using roadside segmentation." In 2017 2nd IEEE International Conference for Convergence in Technology (I2CT) (pp. 965-970).

Gattami, A., Bai, Q., & Aggarwal, V. (2021, March). Reinforcement learning for constrained markov decision processes. In International Conference on Artificial Intelligence and Statistics (pp. 2656-2664). PMLR.

Wijesekara, P. A. D. S. N., & Gunawardena, S. (2023, July). A Machine Learning-Aided Network Contention-Aware Link Lifetime-and Delay-Based Hybrid Routing Framework for Software-Defined Vehicular Networks. In Telecom (Vol. 4, No. 3, pp. 393-458). MDPI.