Age-of-Information Aware Intelligent MAC for Congestion Control in NR-V2X

Malik Muhammad Saad, Muhammad Ashar Tariq, Junho Seo, Mahnoor Ajmal, Dongkyun Kim
School of Computer Science and Engineering, Kyungpook National University, Daegu, Republic of Korea
Emails: {maliksaad,tariqashar,jhseo,mahnoor.ajmal,dongkyun}@knu.ac.kr

***Abstract*—The third-generation partnership project (3GPP) introduces the 5G NR-V2X to supplement the C-V2X to support advanced applications. 3GPP defines the semi-persistent scheduling for distributed resource scheduling likewise in C-V2X, however new medium access control (MAC) features are introduced in NR-V2X mode 2. Re-evaluation mechanism is added in semi-persistent scheduling to reduce resource contention. Despite with new MAC feature, NR-V2X mode 2 cannot handle the scheduling of aperiodic packets efficiently. With the increase in vehicular density, channel congestion occurs leading to packet collision. 3GPP defines the channel congestion control mechanism based on two metrics; channel busy ratio (CBR) and channel occupancy ratio (CR). These metrics, however, have considered the system-level requirements but ignore the application-level requirements such as age-of-information (AoI) associated with the message packet. In this paper, we proposed a deep reinforcement learning-based congestion control mechanism to support both system and application requirements. The performance of the proposed scheme is evaluated and compared with the conventional decentralized congestion control mechanism in a simulator designed inline with the 3GPP specifications.**

***Index Terms*—Age-of-Information, NR-V2X, Congestion Control, Semi-peristent Scheduling, MAC**

I. Introduction

The Third Generation Partnership Project (3GPP) introduced Long Term Evolution (LTE) based Cellular vehicle-to-everything (C-V2X) in Release 14 for advanced traffic safety and management services. C-V2X, enabled with two transmission modes (mode 3 and mode 4), employs periodic transmission of cooperative awareness messages (CAMs) between vehicles. The CAMs transmitted between vehicles contain the location and speed information of a vehicle for critical applications. Further enhancements by 3GPP led to the development of new radio V2X or NR-V2X [1]. Like C-V2X, NR-V2X contains two transmission modes: mode 1 and mode 2. In mode 1, the base station schedules the resources for vehicles within the coverage area, whereas, in mode 2, the vehicles perform the reservation by themselves when out-of-coverage. With the increasing density of vehicles in a network, high channel load causes packet losses and hence leads to increased latency in communication [2]. To avoid this, 3GPP defined a congestion control mechanism called distributed congestion control (DCC) based on two parameters: i) channel busy ratio (CBR) and ii) channel occupancy ratio (CR).

Although 3GPP introduced the DCC mechanism, however, it is not mature. Numerous researches are ongoing to analyze and enhance the performance of DCC. In terms of analysis, the authors in [3] analyzed the effectiveness of DCC for C-V2X. Another analysis is presented in [3] where the performance of packet transmission was evaluated for several parameters such as transmission rate, transmission power, and modulation and coding scheme in Wi-Fi and CV2X. An evaluation is performed in [4] and [5] to assess the implementation of the DSRC-based DCC mechanism for the C-V2X stack. Some relevant metrics and potential mechanisms were highlighted by 3GPP to reduce congestion in the channel; however, no specific algorithm is defined by the standard.

Deep Reinforcement Learning (DRL) based solutions have been exhibiting quite adequate performance improvements in mobile networks. Given the high number of tunable metrics in DCC, DRL is a suitable method to design a congestion control mechanism with balanced metrics. In [6], the focus on DCC is with respect to the transmission rate control of the packet. The authors proposed an algorithm to determine the transmission time interval (TTI) of packets using the packet-dropping information. However, they have not considered the age-of-information (AoI) associated with the message packet. Till to date, state-of-the-art enhancements have not considered the application level metrics i.e., AoI, and introduced the mechanisms to control the congestion by adjusting the packet transmission rate and transmission power. To this end, in this paper, we proposed a mechanism to convert aperiodic CAMs to periodic CAM transmission and have proposed deep reinforcement learning for congestion control while considering the AoI metric for the timely transmission of message packets. The rest of the paper is structured as follows. Section II provides the overview of the semi-persistent scheduling and re-evaluation mechanism. Section III presents the standard format of CAMs. In section IV, impact of CAM generation on channel congestion is presented. In section V and VI proposed scheme and performance evaluation is discussed. Finally conclusions are drawn in section VII.

II. NR-V2X Semi-persistent Scheduling

3GGP introduced the semi-persistent scheduling for NR-V2X mode 2 with the added novelty of a re-evaluation mechanism compared to C-V2X mode 4 [7], [8]. The semi-persistent scheduling comprises three steps as follows, also shown in Fig. 1.

Step: 1 Whenever a message packet reaches the vehicle from the application layer for transmission. The vehicle will

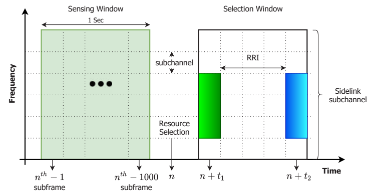

Fig. 1. Semi-persistent Scheduling

look for reserve resources if the resources are preserved for persistent periodic transmission. If no resources have been preserved, then the vehicle will select the new resources for its transmission and reserve the resources for its future periodic transmission. To make the resource selection, the vehicle scans the last 1000 subframes which constitute a sensing window size of 1 sec. While scanning the resources, the vehicle fetches the information that indicates the busy resources and potential candidate resources that could be reserved based on the sidelink control information received. Each participating vehicle receives the SCI. The SCI contains the following fields; resource reservation interval (RRI), Received signal strength information (RSSI), and retransmission counter (RC). RRI indicates the transmission interval for the periodic transmission of message packets for RC times. The RC is depleted after every transmission. When the RC reaches zero, the vehicle selects the new resources with a probability P_b (1-P) where 0.2 $\leq$ P $\leq$ 0.8. P_b represents the resource kept probability, usually, a vehicle keeps the 20% of the resources from the previous selection. After performing the sensing, the vehicle identifies the potential resources from the selection window that could be reserved. The length of the selection window is between $(n + t_1)$ to $(n + t_2)$, where $0 \leq t_1 \leq 4$ ms and t_2 depends on the latency of the message packet.

Step 2: The vehicle creates a list of available resources (L_A). The L_A contains all the resources as identified in step 1 except those which met the following conditions simultaneously.

(a) The resources are already reserved based on RRI.

(b) The RSSI received is greater than the threshold defined.

Step 3: From L_A, the vehicle sorts the potential candidate resources into a list L_C in ascending order based on the least average RSSI. The L_C must contain at least 20% of the resources identified in step 1. If the 20% criteria are not met, then the RSSI threshold is increased by 3 dB until the criteria is met. From L_C the vehicle selects randomly the resources for its transmission ad reserve the resources for its periodic transmission.

Re-evaluation mechanism is also added to make the resource reservation process smooth and reduce resource contention due to aperiodic transmissions. The CAM generation process is aperiodic as discussed in section III. The already reserved resources remained unused due to the reselection of resources because of the aperiodic CAM generation process this led to unutilized resources and increased resource contention. The vehicle if selects the resource at slot m, re-evaluates and execute the step 1 to check if the resource is still available or not. The vehicle executes the re-evaluation mechanism at slot m-T3. T3 is the maximum time vehicle takes to complete the resource selection process. If the resource is not identified idle in the re-evaluation of step 1, then, the vehicle will re-execute the step 2 over the new selection window to select the resources else the vehicle will proceed to the step 3 without re-execution of step 2. The length of the $SW\prime$ is defined as $(n\prime + T1)$ to $(n\prime + T2\prime)$ where, $T2\prime \leq (PDB–(n\prime–n)$. PDB represents the latency associated with the packet and $(n\prime–n)$ represents the time elapsed from the generation of message packet to the execution of the re-evaluation mechanism). The re-evaluation mechanism is left up to the vehicle application and processing capacity, that if it could finish the re-execution before the tolerable latency associated with the message packet. Fig. 2 shows the re-evaluation mechanism. However, despite the new features of NR-V2X mode 2, it still faces challenges in handling variable size packets.

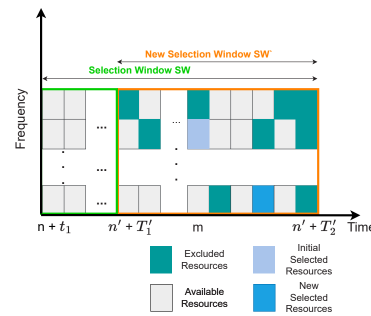

Fig. 2. Re-evaluation Mechanism

III. ETSI Standard Format for CAM

The European Telecommunication Institute (ETSI) rules imply that the generation of CAM depends on the heading, speed, and acceleration. The CAM is generated if any of the following condition is met.

Heading: Change in angle +/- 4 degrees.

Speed: Change in position of $\geq$ 4 m.

Acceleration: change in speed of +/- 0.5 $msec^{-1}$.

From this, it is concluded that CAMs are no more periodic. Moreover, the CAM packet size is also not fixed and it varies. ETSI defines the format of CAM as depicted in Fig. 3. The CAM packet comprises three containers as; a basic container, a high-frequency container, and a special container. The basic container includes the location coordinates and speed of the vehicle, the high-frequency container contains the dynamic data such as change of lane and the special container includes information such as traffic conditions or any hazard reporting. The size of the CAM depends on the latter two containers whereas the former container includes the mandatory information.

IV. Impact of CAM Generation on the Channel Congestion

According to the ETSI CAM generation is aperiodic which affects the resource reservation semi-persistent scheduling

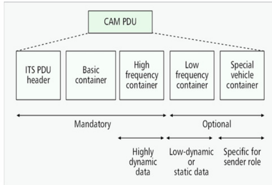

Fig. 3. CAM packet standard format

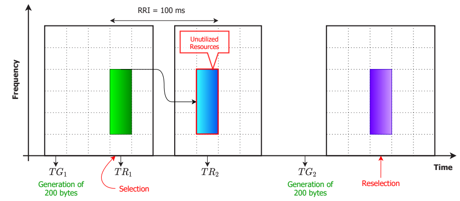

Fig. 5. Channel Congestion due to aperiodic generation of CAM

mechanism and in turn, increased the resource contention [9]. The three cases are discussed below which show the aperiodic CAM generation impact on channel congestion.

A. Channel congestion due to variable size packet

Whenever a vehicle selects a resource for its transmission, it reserves the resources periodically for RC times after every RRI. The resource reservation information is broadcast to neighboring vehicles over the physical sidelink control channel (PSCCH). The other vehicles while reserving the resources consider the resource reservation by other vehicles and selects the free resources. Let a vehicle V_a generate 200 bytes packet at TG_1 and selects the resource at TR_1 as shown in Fig. 4. The vehicle V_a reserves the resource at TR_2 for future 200 bytes message packet transmission. However, if a message packet generated is of a different size i.e.$\geq$ 200 bytes, the V_a requires to reserve another resource for the transmission of $\geq$ 200 bytes. Therefore, the already reserved resource at TR_2 remains unused which increased the overall resource contention resulting in increase in channel congestion.

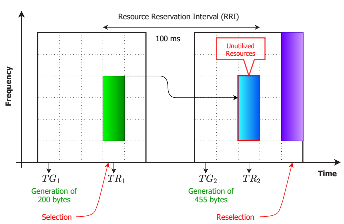

Fig. 4. Channel congestion due to variable size packet

B. Channel Congestion due to aperiodic generation of CAM

Similar to the above case discussed, let a vehicle V_a selects and reserve the resource at TR_1 and TR_2 respectively as shown in Fig. 5. However, if the message packet is generated at TG_2 such that $TG_2 > (TR_1$ + RRI). The resource reserved at TR_2 would be unutilized. This will affect the semi-persistent scheduling and increase the resource collision probability since the available resources would be reduced from the perspective of other neighboring vehicles.

C. Channel Congestion due to latency associated with the message packet

Alternative to case 2 discussed above, in this case, let a vehicle V_a select and reserve the resource at TR_1 and TR_2 respectively as shown in Fig. 6. However, if the message packet is generated at TG_2 and the latency associated with the message packet is $<$ $(TR_1$ + RRI), the V_a has to reselect a new resource for its packet transmission such that the interval between the message generation (TG_2) and selected slot $\leq$ PDB i.e., packet delay budget of the associated message packet.

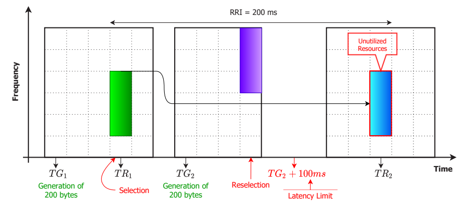

Fig. 6. Channel Congestion due to latency associated with the message packet

V. Two-folded Proposed Approach

In this section, we proposed a two-folded solution to reduce channel congestion in V2X. Since aperiodic CAM generation adversely affects the semi-persistent scheduling mechanism and increased the resource collision probability. The unutilized resources reduce the number of available resources to the neighboring vehicles virtually depicting that the channel is busy. Since the 3GPP defines the two metrics for channel congestion. The first metric is the channel busy ratio (CBR), which is a measure of the number of subchannels that a vehicle can occupy in its previous 100 subframes. The second metric is the channel occupancy ratio (CR), which is a measure of the number of resources that a vehicle reserved over the two-dimensional frequency and time grid in the last 1000 subframes. This mechanism does not take into account the various requirements of an application, such as the impact of AoI associated with the packet. To overcome the virtual channel congestion and to preserve the timely transmission of the message packet, the proposed scheme is discussed in two parts as follows.

A. Split and Tranmist the Aperiodic CAMs into Periodic CAMS

In NR-V2X, the resources are distributed over the two-dimensional frequency and time domain. In the frequency domain there are subchannels wherein time domain there are subframes. Corresponding to the message packet size, vehicle reserves the subchannels within the subframe for the message packet transmission. For 190, 200, 400, 600, 800, 1000 and

1200 bytes to transmit requires 1 ,1, 2 , 3, 3, 4 and 4 subchannels. If a message packet is reserved corresponding to the 190 bytes and in the next interval a message packet is generated of a different size other than 190 or 200 bytes will affect the resource reservation and a new reservation is required for its transmission. As discussed in section III (a), this in turn results in resource unutilization leading to virtual channel congestion. Therefore to keep the periodicity, we forced the message packet transmission over the single subchannel. For a message packet size $\geq$ 400 bytes, we propose to split the message packet into two parts each of 200 bytes, and increase the transmission rate λ by two times. This will keep the message packet periodicity and to cope with the updated transmission rate the new RRI is broadcasted to the neighboring vehicles over the SCI. This will mitigate the channel unutilization however, this might increase the CR. The increase in CR possibly increases the channel congestion, the following section explains the proposed scheme to reduce the channel congestion.

B. Deep Reinforcement Learning based Channel Congestion Control considering the AoI Metric

The 3GPP defined the two metrics CBR and CR to measure channel congestion. Vehicle V_a calculates the CBR and CR at the subframe m^{th} where the transmission is scheduled as given in equations (1) & (2). To determined the CBR and CR, V_a considers the last 100 and 1000 subframes respectively.

$$CBR = \frac{\sum_{i=1}^{100} m'_i}{100} \tag{1}$$

$$CR = \frac{\sum_{i=1}^{1000} k'}{1000.(k)} \tag{2}$$

In eq (1), m' represents the occupied subframe i.e., the measured RSSI in m_i subframe is greater than the threshold. In eq (2), k' represents the subchannels in m_i subframe occupied by the vehicle V_a, where k represents the total number of subchannels in m_{th} subframe.

3GPP and ETSI define the corresponding CR limit against the CBR as given in Table 1. If the measured CR is greater than the corresponding CR limit defined against the determined CBR from (1), then the vehicle will adjust its packet transmission rate as defined in lookup Table 2.

TABLE I
CR LIMIT CORRESPONDING TO THE CBR MEASURED

CBR	**CR limit**
0 $\leq$ CBR $\leq$ 0.3	No limit
0.3 <CBR $\leq$ 0.65	0.03
0.65 <CBR $\leq$ 0.8	0.006
0.8 <CBR $\leq$ 1	0.003

Adjusting the packet transmission rate to lower rate results in packet dropping which would reduce the throughput. In order to support the NR-V2X advanced applications, high throughput and timely transmission of exchange of message packets are required. Therefore, we formulated the problem as follows.

TABLE II
PACKET TX RATE CORRESPONDING TO THE CBR MEASURED

CBR measured	Packet Rate	RRI
0 $\leq$ CBR $\leq$ 0.3	10 Hz	100 ms
0.3 <CBR $\leq$ 0.4	5 Hz	200 ms
0.4 <CBR $\leq$ 0.5	2.5 Hz	400 ms
0.5 <CBR $\leq$ 0.6	2 Hz	500 ms
CBR >0.6	1 Hz	1 sec

$$\begin{aligned} P1: \max PDR &= \frac{\frac{\sum_{j=1}^{J} V_j[m,k]}{V_a[m,k]}}{J} \\ \text{s.t.} \quad & C1: CBR_T \leq CBR_M \\ & C2: (\tau - T_0) \leq PDB \end{aligned} \tag{3}$$

In equation (3), CBR_M and CBR_T shows the measured CBR at m_th subframe and target CBR respectively. τ represents the maximum tolerable delay and T_0 represents the time left for transmission. We aim at to maximize the packet delivery ratio (PDR) with the constraints to utilize the channel maximum i.e., to keep the throughput high and packet should be transmitted before the packet delay budget (PDB) i.e., AoI associated with the packet. To this end, we proposed deep reinforcement learning based channel congestion control while adjusting the transmission power and packet transmission rate while considering the AoI.

The main components of deep reinforcement learning are as follows.

Agent: The vehicle V_a is an agent that observes the current state of an environment and performs the action from the action space.

State: The consists of measured CBR and CR at the m^{th} subframe.

$$S_t = \{CBR[m_{th}], CR[m_{th}]\} \tag{4}$$

Action: The aim is to increase the throughput without channel congestion. Therefore the action is determined over two dimensions i.e., power level and the transmission rate. The Tx rate is chosen between $\{10, 5, 3.33, 1\}$ Hz and the power level to be selected is from $\{5, 10, 23\}$ dBm. With a high transmission rate, the power level is adjusted such that to reduce channel congestion. Despite the low transmission power if the channel congestion is still high then the agent reduces the transmission rate due to the implicit relationship between the action and reward.

Reward: The conventional congestion control algorithm defined by the 3GPP adjusts the transmission rate control and only considers the system-level metrics however, it ignores the QoS-related application requirements i.e., AoI associated with the message packet. Adjusting the transmission rate to lowered values by dropping the packets violates the application requirements, and would also result in stale packets. Therefore the reward is designed, given in equation (4), in such a way to cater the stale packet transmission and considers the latency associated with the message packet for timely transmission.

$$R_t = PDR–(CBR_T–CBR_M)–(\tau–t_0) \quad (5)$$

The fraction $(CBR_T–CBR_M)$, encourages the agent to increase the packet transmission rate and the fraction $(\tau–t_0)$ shows the time taken for the transmission. Plenty will be given if the vehicle takes more time to transmit a packet.

Fig. 7 shows the deep reinforcement learning-based architecture. Each agent has its deep Q network (DQN). DQN is made up of a target network, replay memory, and the main network, which approximates the Q-value of the state-action pair. The network is composed of fully connected layers consisting of two hidden layers each with 100 neurons. The weight θ of the neurons is updated while minimizing the loss $L = E[(y_j - Q(s, a; \theta))^2]$, where y_j is the target value. To improve performance, the replay memory and the target network are used to stabilize the learning. The Q-value of the target network is computed by taking into account the weight of the various experiences in the replay memory. Each experience is stored in a buffer, and a minibatch is randomly sampled at each step. The minibatch data is then used to determine the target value.

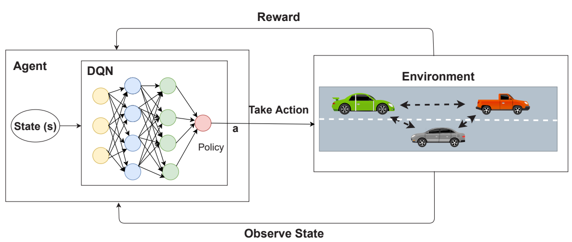

Fig. 7. Deep reinforcement learning based congestion control architecture considering AoI

VI. Performance Evaluation

We consider a Manhattan grid scenario of 750 x 500 m^2. The vehicles considered in a scenario are moving at an average speed of 60 km/h. The simulator is designed inline with the 3GPP specifications defined for NR-V2X mode 2 [10]. The vehicles reserve the resources semi-persistently before transmitting a packet. The winner + B1 channel model is considered for realistic evaluation [11]. The 3GPP DCC is modified utilizing deep reinforcement learning with the simulation parameters as defined in Table 3.

Fig. 8 shows the average throughput with density β 0.2 and 0.3 $vehm^{-1}$. Since NR-V2X advanced applications require high throughput to meet the user satisfaction level, however with the increase in the number of vehicles the throughput degrades with the conventional DCC mechanism defined by the 3GPP. The throughput degrades with the increase in the number of vehicles because of a busy channel. To overcome the channel congestion, the 3GPP defines the MAC layer mechanism for congestion control as to drop the packets i.e.,

TABLE III
Simulation Parameters

Transmission power	{5, 15, 23} dBm
No of subchannels	5
channel	Winner + B1
CBR_T	0.6
Packet transmission rate	{10, 5, 3.33, 1} Hz
Number of hidden layers	2
Number of layers in each layer	100
CAM size	{190, 200, 400, 800, 1000, 1200} bytes
τ	100 ms
β	0.2,0.3

lowering the packet transmission rate. This can overcome the channel congestion but will also reduce the throughput. From Fig. 8, it is clearly shown that the throughput in the proposed deep reinforcement learning based decentralized congestion control (DRL DCC) case is higher compared to conventional DCC. In DRL DCC based scheme the packet transmission rate is aimed to keep high while controlling the transmission power to control the channel congestion.

Fig. 9 shows the average CBR over the simulation time of

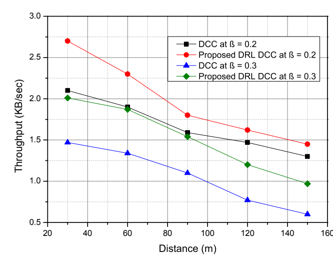

Fig. 8. Average Throughput

5000 ms. From Fig. 9 it is shown that the CBR in DRL DCC based mechanism is on average close to the target CBR. We aim to keep the packet transmission rate high while controlling the channel congestion by lowering the transmission power. Fig. 10 shows the average PDR with respect to the number of vehicles. With the increase in the number of vehicles, the PDR degrades in both cases because of channel congestion could occur. However, DRL DCC handles the channel congestion efficiently as evident from Fig. 10 that the PDR is quite higher as compared to conventional DCC.

Fig. 11, shows the average AoI. The tolerable latency associated with the message CAM is set to 100 ms. The average AoI is evaluated with the increase in the number of vehicles. With the increase in the number of vehicles the channel congestion increased, therefore, vehicles defer the channel access and reduce the packet transmission rate while the RRI is increased. The message packets are transmitted after a newly set RRI interval which might affect the age of information. From Fig. 11, it is shown that AoI is least affected in DRL DCC based mechanism compared to conventional DCC.

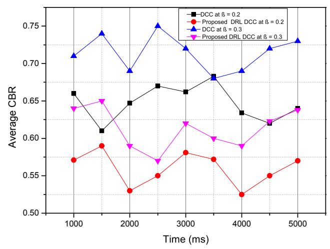

Fig. 9. Average CBR

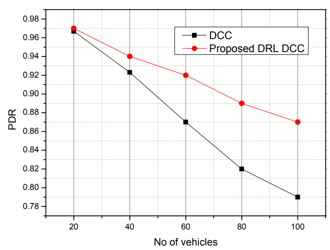

Fig. 10. Average PDR with respect to number of vehicles

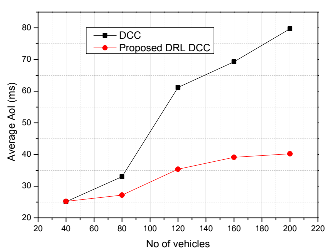

Fig. 11. Average AoI

VII. Conclusion

In this paper, we have optimized the medium access control (MAC) layer in NR-V2X for congestion control. We have utilized the deep reinforcement learning to control the packet transmission rate and transmission power while maintaining the throughput high. The conventional decentralized congestion control algorithm (DCC) including the standard 3GPP DCC and state-of-the-art enhancements has not considered the age-of-information (AoI) metric while controlling the congestion. In our proposed work, we considered the both system level i.e., channel busy ratio (CBR) and channel occupancy ratio (CR) and application level i.e., AoI metric to find the optimal packet transmission rate, transmission power, and resource reservation interval (RRI) utilizing the deep reinforcement learning. From, the simulation results, it has shown that our proposed scheme surpasses the standard DCC scheme. The proposed scheme has shown better performance in terms of packet delivery ratio (PDR), timeliness of message packet transmission, throughput, and average CBR.

Acknowledgment

This research has been supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government(MSIT), (NRF-2022R1A2C1003620); and supported by the MSIT (Ministry of Science and ICT), Korea, under the Innovative Human Resource Development for Local Intellectualization support program (IITP-2023-RS-2022-00156389) supervised by the IITP (Institute for Information & communications Technology Planning & Evaluation). In addition, this research was supported by the 2021 Kyungpook National University BK21 FOUR Graduate Innovation Project (International Joint Research Project for Graduate Students).

References

[1] M. H. C. Garcia, A. Molina-Galan, M. Boban, J. Gozalvez, B. Coll-Perales, T. Şahin, and A. Kousaridas, "A tutorial on 5G NR V2X communications," *IEEE Communications Surveys & Tutorials*, vol. 23, no. 3, pp. 1972–2026, 2021.

[2] A. Molina-Galan, B. Coll-Perales, L. Lusvarghi, J. Gozalvez, and M. L. Merani, "How does 5G NR V2X Mode 2 Handle Aperiodic Packets and Variable Packet Sizes?," in *2022 IEEE 23rd International Conference on High Performance Switching and Routing (HPSR)*, pp. 183–188, IEEE, 2022.

[3] A. Mansouri, V. Martinez, and J. Härri, "A first investigation of congestion control for LTE-V2X mode 4," in *2019 15th Annual Conference on Wireless On-demand Network Systems and Services (WONS)*, pp. 56–63, IEEE, 2019.

[4] B. Toghi, M. Saifuddin, Y. P. Fallah, and M. O. Mughal, "Analysis of distributed congestion control in cellular vehicle-to-everything networks," in *2019 IEEE 90th Vehicular Technology Conference (VTC2019-Fall)*, pp. 1–7, IEEE, 2019.

[5] Y. Yoon and H. Kim, "Balancing power and rate control for improved congestion control in cellular V2X communication environments," *IEEE Access*, vol. 8, pp. 105071–105081, 2020.

[6] J.-Y. Choi, H.-S. Jo, C. Mun, and J.-G. Yook, "Deep reinforcement learning-based distributed congestion control in cellular V2X networks," *IEEE Wireless Communications Letters*, vol. 10, no. 11, pp. 2582–2586, 2021.

[7] M. M. Saad, M. T. R. Khan, S. H. A. Shah, and D. Kim, "Advancements in Vehicular Communication Technologies: C-V2X and NR-V2X Comparison," *IEEE Communications Magazine*, vol. 59, no. 8, pp. 107–113, 2021.

[8] M. Muhammad Saad, M. Ashar Tariq, M. Mahmudul Islam, M. Toaha Raza Khan, J. Seo, and D. Kim, "Enhanced Semi-persistent scheduling (e-SPS) for Aperiodic Traffic in NR-V2X," in *2022 International Conference on Artificial Intelligence in Information and Communication (ICAIIC)*, pp. 171–175, 2022.

[9] S. Bartoletti, B. M. Masini, V. Martinez, I. Sarris, and A. Bazzi, "Impact of the Generation Interval on the Performance of Sidelink C-V2X Autonomous Mode," *IEEE Access*, vol. 9, pp. 35121–35135, 2021.

[10] 3GPP, "Technical Specification Group Services And System Aspects; Study on Architecture Enhancements for the Evolved Packet System (EPS) and the 5G System (5GS) to Support Advanced V2X services," Tech. Rep. TR 23.786, 3GPP Rel. 16, 16, June 2019.

[11] 3GPP, "Technical Specification Group Radio Access Network; Study LTE-Based V2X Services," Tech. Rep. TR 36.885, 3GPP Rel. 14, June 2016.