The Upper Bounds of Cellular Vehicle-to-Vehicle Communication Latency for Platoon-based Autonomous Driving

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***Abstract*—Cellular vehicle-to-vehicle (V2V) communications can support advanced cooperative driving applications such as vehicle platooning and extended sensing. As the safety critical applications require ultra-low communication latency and deterministic service guarantee, it is vital to characterize the latency upper bound of cellular V2V communications. However, the contention-based Medium Access Control (MAC) and dynamic vehicular network topology brings many challenges to model the upper bound of cellular V2V communication latency and assess the link capability for quality of service (QoS) guarantee. In this paper, we are motivated to reduce the research gap by modelling the latency upper bound of cellular V2V with network calculus. Based on the theoretical model, the probability distribution of the delay upper bound can be obtained under the given task features and environment conditions. Moreover, we propose an intelligent scheme to reduce upper bound of end-to-end latency in vehicular platoon scenario by adaptively adjusting the V2V communication parameters. In the proposed scheme, a deep reinforcement learning model is trained and implemented to control the time slot selection probability and the number of time slots in each frame. The proposed approaches and the V2V latency upper bound are evaluated by simulation experiments. Simulation results indicate that our network calculus based analytical approach is effective in terms of the latency upper bound estimations. In addition, with fast iterative convergence, the proposed intelligent scheme can significantly reduce the latency by about 80% compared with the conventional V2V communication protocols.**

***Index Terms*—Autonomous Driving, Broadcasting, C-V2X, Reinforcement Learning, Stochastic Network Calculus.**

I. Introduction

VEHICULAR platoons show promising potentials to enhance driving safety and road traffic efficiency. By exchanging messages with neighbour vehicles via Internet of Vehicles (IoV), autonomous vehicles in the same platoon can maintain stable driving states and conduct cooperative driving, which provides superior on-road experience than conventional individual autonomous driving technologies [1]. There are two mainstream vehicle communication technologies, IEEE 802.11p based Dedicated Short Range Communication (DSRC) and 3rd Generation Partnership Project (3GPP) cellular vehicle-to-everything (C-V2X). The latter can support both traditional cellular network based communication and direct communication between vehicles (V2V) through the so-called PC5 interface [2]. With the advanced features including resource reservation and slotted frame structures, cellular V2V can provide better spectrum efficiency, higher packet delivery ratio and wider communication range [3]–[5] than DSRC. Through instant V2V communications, it enables many very useful road safety applications, such as collision warning, blind spot warning and lane change warning. Moreover, C-V2V developed by 3GPP is capable of supporting advanced cooperative driving applications such as vehicle platooning and extended sensing.

The platoon-based autonomous driving applications require much lower communication latency (e.g., one millisecond) than the traditional cellular V2X applications (100 milliseconds) [6], [7]. Moreover, to ensure safety and platoon stability, vehicles need to periodically broadcast their driving states to other vehicles, which will significantly increase the network traffic loads compared to the traditional vehicular networks [8]–[10]. However, whether the existing protocols can meet the ultra-low latency requirement in this scenario still lacks study. For example, considering a platoon whose inter-vehicle distance is 10 m and the distance error needs to be less than 1%, i.e., 0.1 m. If the speed of this platoon is 100 km/h, each vehicle should broadcast its driving state within about 3.7 ms. As the single time slot length of C-V2X mode 4 protocol is already 1 ms, this distributed access protocol cannot be directly used in platoon-based autonomous driving scenarios because it cannot guarantee that vehicles access the channel within several time slots. Based on our analysis results, it is recommended to further reduce the length of time slots or add more frequency resources for autonomous driving applications.

In a practical IoV, V2V communications often adopt the random access MAC protocol for short message delivery, such as DSRC and C-V2X mode 4 protocol [2]. The contention-based MAC protocol and dynamic vehicular network topology present many challenges to analyse the upper bound of V2V latency. On the other hand, most existing analytical methods for V2V communications assume saturated Poisson arrival traffic, which does not match the actual V2V message traffic in the cellular V2V channels as the transmissions of cellular V2V messages follow the MAC protocol and the slotted frame structure. To the best of our knowledge, there is a lack of research studies on the upper bound of unsaturated C-V2V

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communication latency. New analytical and control approaches are needed to model and control the cellular V2V latency in a unsaturated traffic environment with the framed structure based MAC protocol.

To fill the gaps mentioned above, we are motivated to theoretically analyse the upper bound of cellular V2V communication latency and reduce the latency through intelligent configuration of the MAC protocol parameters. Network calculus provides a new method to analyse the lower bound of system performance under a specified protocol and traffic flow condition [11], [12]. The probability upper bound provides a guarantee that the probability of the delay being longer than a given value is not higher than the analytical result of the theoretical model. Consequently, the upper bound cannot be used as an accurate probabilistic mathematical description of the transmission delays. Existing analysis work based on network calculus mainly consider the traditional contention-based MAC protocols without frame structure, such as IEEE 802.11 MAC protocol [13], [14]. We design a new analytical method for C-V2V communications in vehicular platoon scenarios to model the performance of the frame-based time division MAC protocols [15]. In addition, an intelligent control scheme is proposed to reduce the upper bound of C-V2V communications. In the proposed scheme, a deep reinforcement learning model is applied to adjust the time slot re-selection probability and the number of time slots in each frame. The proposed model is trained and implemented in the platoon head vehicle. Simulation experiments are conducted to evaluate the proposed approaches and their impact on road safety. The main contributions of this paper can be summarized as follows.

- We propose a theoretical approach to analyse the upper bound of cellular V2V communication latency by using stochastic network calculus. It can be adopted as an efficient tool to evaluate and optimize the performance of corresponding protocols, and assess the deterministic latency for many advanced safety applications. To the best of our knowledge, this is the first work on modelling the transmission delay upper bound for platoon-based autonomous driving through cellular V2V communications.
- With the stochastic network calculus based analysis model, we design an intelligent C-V2V communication optimization scheme with our proposed Smart Protocol Optimization (SPO) algorithm which is performed by the head vehicle in a platoon. SPO can adaptively adjust the system parameters of the MAC protocol using deep reinforcement learning technology. Simulation results show that the proposed scheme is able to reduce the end-to-end message delivery latency by approximately 80%.
- Based on the simulation experiments, it can be observed that the end-to-end latency of the cellular V2V communication defined by the 3GPP standard [16] cannot meet the latency requirement (one millisecond) of platoon-based autonomous driving. To enhance the standard protocol to support these delay sensitive advanced driving applications, we provide the optimal system parameter configuration of the MAC protocol.

The rest of this paper is organized as follows. Section II introduces the related work on the analysis and optimization of distributed MAC for vehicular networks. Section III presents an overview of the cellular V2V and system settings. In Section IV network calculus is applied to develop the analytical approach to stochastic delay upper bound. The intelligent MAC parameter control scheme for platooning driving application is presented in section V. Numerical simulation results are presented and discussed in section VI. Finally, section VII concludes this paper.

II. Related Work

There are two branches of distributed and contention-based MAC protocols for V2V communications, IEEE 802.11p and C-V2X. Performance analysis of distributed MAC for vehicular networks is an important research issue. More importantly, V2V communication performance guarantee in the vehicular networks has significant impact on the road traffic safety and efficiency. Although the modern V2V communications mainly consider the C-V2X protocol stack, which is a natural evolution from the Long-Term-Evolution-Vehicle (LTE-V) standard [4], some theoretical analysis models of both protocols are similar. Therefore, it is worth to present related literatures of both two protocol branches.

The analysis of contention-based MAC protocols for vehicular networks has two main kinds of models, i.e., Markov-based models and network-calculus based models. As the first performance analysis using Markov-based models, G. Bianch [17] analysed the saturation throughput of the IEEE 802.11 Distributed Coordination Function (DCF). Some critical simplification is used to obtain the collision probability and became a critical method adopted in many following works. F. Cali *et al.* proposed a novel analysis model for the IEEE 802.11 protocol in [18]. The authors found that the throughput of the exponential back-off algorithm is equivalent to p-persistent protocol. Moreover, they also proposed an adaptive optimization algorithm for the IEEE 802.11 protocol. Unsaturated throughput of IEEE 802.11 protocol is analysed in [19], but it only consider the Poisson arrival process, other applications such as periodic broadcasting applications are not considered in the analysis model.

The other analyse approaches are network calculus based models [20]. In [13], J. Xie and Y. Jiang obtained the stochastic delay upper bound of IEEE 802.11 DCF, which laid the foundation for many subsequent works. K. Konstantinos *et al.* analysed the end to end delay of hybrid vehicular networks with stochastic network calculus theory in [14].

The performance of IEEE 802.11p and LTE-V2X was compared in [2]. It was concluded in [2] that the LTE-V2X protocols are more suitable for periodical messages. In [21], Q. Ding *et al.* investigated the existing LTE-V direct protocol resource allocation schemes. T. Maruko *et al.* proposed a collision reduction scheme for LTE-V2X communications in [22]. The sidelink communication in [22] uses the LTE-V direction protocol, with packet reception rate increased by about 5% with the proposed scheme. H. Chihi *et al.* analysed the latency of LTE-V mode 4 protocol and proposed an optimization algorithm. However, the analysis is a little bit too simple to provide a reliable delay upper bound guarantee. K. Xiong *et al.* optimised the communication and computation resources for autonomous driving applications in [23]. But they also did not consider the end-to-end delay analysis and optimization.

The influence of the network performance on the platoon traffics has been analysed. In [24], authors use PLEXE, an open source simulator built based on Veins [25], to analysis the platoon behaviours in a heterogeneous scenario with co-operative driving and manual driving.

It is noted that the above mentioned work has analysed some random channel access protocols with the Markov chain model or network calculus theory. However, the network calculus-based performance analysis and optimization for cellular V2V remain a challenging problem. To the best of our knowledge, there is no report on the theoretic modelling of the latency upper bounds for the cellular V2V MAC protocol. The level of deterministic latency guarantee and the enhancement with cellular V2V have not been studied for advanced cooperative driving applications.

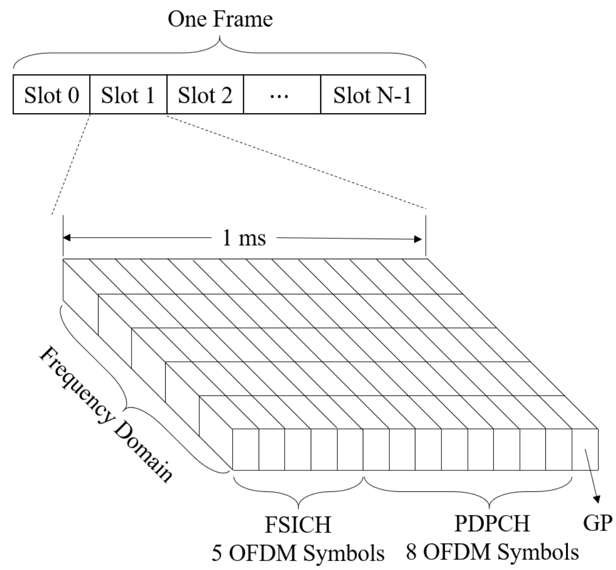

Fig. 1. Frame structure of C-V2X mode 4 standard.

III. System Model

In this section we will present the basics of the cellular V2V MAC protocol, which is to be analysed later. Some critical symbols are summarized in Table I.

According to [4], the C-V2X mode 4 is based on the Time-Divided LTE (TD-LTE) protocol, whose time domain is divided into time slots. Time is divided into frames, and one frame is composed of several time slots. One time slot is the essential unity which cannot be divided furthermore. The duration of each time slot is 1 ms.

TABLE I
Notations of some critical parameters

Parameter	Description
p_{rs}	Re-select probability in C-V2X mode 4 standard.
T	Generation duration for awareness messages.
T_s	Translation time for a single awareness message.
N	Number of vehicles connected to the V2V network.
N_f	Number of time slots in a frame.
p_i	Channel free probability.
p_c	Collision probability.
p_s	Transmission probability for one node in one frame.
$\otimes$	Min-plus convolution of two functions
$h(\alpha, \beta)$	Maximum horizontal distance between two functions

One time slot is further divided into two periods, Frame Information (FI) and Physical Data Payload Channel (PDPCH). The FI includes the slots occupy information. The PDPCH includes the transmission data. The channel that transmits FI is called Physical Slot Information Channel (PSICH), consisting of five Orthogonal Frequency Division Multiplexing (OFDM) symbols. The PDPCH channel has eight OFDM symbols. In addition, an OFDM symbol called Guard Period (GP) also exists at the last time slot in a frame for synchronization between transmitter and receiver. The structure of one C-V2X mode 4 frame is shown in Fig. 1.

Each node needs to monitor the channel for one frame duration before trying to occupy time slots. Once one node finds some free time slots in a frame, it will occupy a time slot in a p-persistent-like manner. As described in [27], in C-V2X mode 4 standard, each node has a probability p_{rs}, which stands for the reselect probability. It will occupy a particular time slot in each frame for a duration T_s with probability p_{rs}. In the original protocol, T_s is a random variable that equals sums of random variable which is uniformly distributed between $[5, 15]$, and the number of summed-up random variable satisfied geometry distribution with parameter $1 - p_{rs}$. The original protocol can be found in [27]. However, this paper only considers the awareness message broadcasting, which is often supposed to have constant data size, and data is generated with fixed duration. Consequently, we think T_s is a constant value. But if we set p_{rs} equals 0, all vehicles will transmit at the beginning of a period, as a result, we use p_{rs} to select the transmission frame.

Each node can only select at most one time slot in each frame. The whole channel access process is illustrated in Fig. 2. rand (0, 1) in Fig. 2 means generating a real number with equal probability in interval $[0, 1]$.

Because each time slot has FI, collisions can be detected within one frame, much faster than the CSMA/CA protocols. Furthermore, with the FI enhancement, the C-V2X mode 4 standard provides an efficient way to exchange the resource allocation information between access nodes, preventing the hidden terminal problem. Consequently, the vehicular network investigated in this paper is considered as a complete graph, which means every pair of nodes can communicate with each other in one hop.

Besides the pre-mentioned benefits, networks in the C-V2X mode 4 standard ask for accurate synchronisation between nodes in high dynamic on-road scenarios. In engineering, nodes in the base station coverage can synchronise from the Coordinated Universal Time signalling (UTC) module, such as Global Positioning System (GPS) or Beidou. Nodes out of the base station need to take a self-synchronisation procedure,

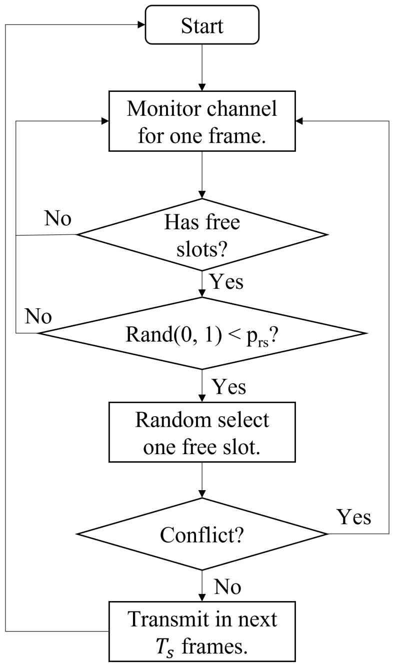

Fig. 2. Channel access process of C-V2X mode 4 standard.

which may be more inaccurate than the UTC module.

IV. Performance Analysis

This section will analyse the performance of the C-V2X mode 4 standard with stochastic network calculus theory. We will first analyse some critical probabilities according to the protocol details. Based on these probabilities, the stochastic delay upper bound is obtained with the network calculus theory. The basic knowledge of the stochastic network calculus theory used in this section is presented in Appendix A. The analysing results will be further used for the system optimization in the next section.

A. Critical Probabilities

First, we need to calculate the collision probability. To simplify the problem, in the C-V2X mode 4 standard service curve calculation, we assume that each node always has some packets in the transmitting queue to send. Based on this assumption, the calculated collision probability will be higher than practice. But when we calculate the end-to-end delay bound in the next sub-section, the flows will be modelled as a non-saturated arrival process with constant rate and fixed generate duration, which can make the upper bound tight even if the probability is calculated in the saturation scenario. There are N_f time slots in one frame and N vehicles connected to the V2V network.

Inspired by the ideas in [19], to simplify the question, we assume that each node has the same probability of sending on any time slot in any frame and the same probability of collision, which is named p_s and p_c, respectively. Moreover, the sending probability p_s is related to the probability that the current frame has some free time slots to use, named p_i.

According to the protocol, we can list following equations,

$$p_i = \begin{cases} 1, & N \le N_f \\ \displaystyle\sum_{k=0}^{N_f-1} \binom{N}{k} p_s^k (1-p_s)^{N_f-k}, & N > N_f \end{cases}, \tag{1}$$

$$p_s = \frac{p_i \cdot p_{rs} \cdot (p_c + (1-p_c)\cdot T_s)}{N_f + T_s}. \tag{2}$$

$$p_c = p_s \sum_{k=1}^{N-1} \binom{N-1}{k} p_s^k (1-p_s)^{N-k}. \tag{3}$$

Notice Eq. (3) is a binomial distribution, so it can be further simplified to

$$p_c = p_s \left(1 - (1-p_s)^{N-1}\right). \tag{4}$$

As a result, we can obtain the collision probability p_s and p_c by solving the non-linear equation system consisted of (1), (2) and (4). This equation system can be solved in a very fast speed with numerical methods.

Considering the vehicular awareness message are generated in a fixed duration and a constant data size, we use two constants, T and T_s, to denote the generating duration and transmitting frames for a single vehicular awareness message, respectively. C-V2X mode 4 standard has a maximum try duration called T_m. If a vehicle cannot access the channel after T_m time, it will give up the current message. In [15], $T_m = 1500ms$. However, we think it is reasonable to assume $T_m = T$ in the vehicular awareness broadcasting scenario because old messages should be given up after new vehicular state messages are generated.

As for each frame has N_f time slots and each time slot is 1 ms, the maximum frame for a vehicle tries to access channel is $\left\lfloor \frac{T_m}{N_f} \right\rfloor$. At each frame, we can simplify the access process as a Bernoulli distribution with probability $p = p_i \cdot p_{rs} \cdot (1-p_c)$. The first success access frame is a Geometry Distribution with p as its parameter. With the maximum frame constraint, we can obtain the mean time for a vehicle accessing the channel as following,

$$\begin{aligned} \bar{t}_{\text{serv}} = \quad & N_f \cdot \left[\sum_{k=0}^{\left\lfloor \frac{T_m}{N_f} \right\rfloor} (1-p)^k pk + \right. \\ & \left. \left\lceil \frac{T_m}{N_f} \right\rceil \left(1 - \sum_{k=0}^{\left\lfloor \frac{T_m}{N_f} \right\rfloor} (1-p)^k p \right) \right] + D_r, \end{aligned} \tag{5}$$

where $\lfloor x \rfloor$ and $\lceil x \rceil$ are maximum integer less or equal to x and minimum integer greater or equal to x, respectively. D_r is the radio transmission delay, which can be found in [28]. And the unit of $\bar{t}_{\text{serv}}$ is in millisecond. In addition, because each time slot only has eight of fourteen symbols are used to transmit the awareness data, which means effective duration of one time slot is $\frac{4}{7}$ ms, and the actual channel rate can written as

$$r = \frac{4C}{7N_f}, \tag{6}$$

where C is the channel capacity.

Furthermore, the packet loss rate can also be obtained by p_c. In each back-off stage, the transmitter will try to send at each slot with equal probability. Consequently, the conflict probability in a stage is equal to conflict probability of a time slot, *i.e.* p_c. As we clarified before, for the vehicular awareness message, vehicle will not retransmit if the current back-off stage exceeds the maximum back-off limit. As a result, we can obtain the packet loss rate as following,

$$P_L = p_c^{\left\lfloor \frac{T_m}{N_f} \right\rfloor}, \tag{7}$$

where P_L is the packet loss rate. Because p_c is related to the vehicle number N, we can consider this is a theoretical analysis result of the interference caused by the competition between vehicles.

B. Service Curve and Delay Upper Bound

After obtaining the critical probabilities in the previous section, we can further get the C-V2X mode 4 standard service curve. The stochastic network calculus related symbols, operators and theorems used in this section can be found in the Appendix of this paper.

We will first obtain the service time for each packet based on a similar method to [13], which is used to analyse the IEEE 802.11 DCF protocol. Let t_{serv} be the delay for each packet that from preparing to be transmitted to finished transmitted, which is called per-packet service delay. The Chernoff bound is heavily used here, which is presented as follows,

$$P(X \geq x) = P\left(e^{\theta \cdot X} \geq e^{\theta \cdot x}\right) \leq e^{-\theta x} E\left[e^{\theta X}\right] \tag{8}$$

where X is a non-negative random variable. Notice e^x is a convex function. The following state is always true:

$$e^{\theta X} \leq 1 - X + X e^{\theta} \tag{9}$$

for any $0 \leq X \leq 1$. Consequently, we can say that

$$E\left[e^{\theta X}\right] \leq 1 - q + q e^{\theta} \tag{10}$$

where $q = E[X]$ and X is a random variable in interval $[0, 1]$.

To use Eq. (10), we need to scale the delay random variant into $[0, 1]$. There are two extreme states give the range of t_{serv}. One is that a vehicle monitors the state for one frame, than find the channel is free and transmits its awareness message. At this state, $t_{\text{serv}} = N_f + T_s$. Another one is the waiting time exceeds the maximum time and the vehicle gives up. At this state, $t_{\text{serv}} = T_m + T_s$. Notice that the unit of t_{serv} here is in milliseconds. So we can define the following variables,

$$Y = \frac{t_{\text{serv}} - (N_f + T_s)}{T_m + T_s - (N_f + T_s)} = \frac{t_{\text{serv}} - (N_f + T_s)}{T_m - N_f} \tag{11}$$

$$q = \frac{\bar{t}_{\text{serv}} - (N_f + T_s)}{T_m - N_f} \tag{12}$$

$$y = \frac{x - (N_f + T_s)}{T_m - N_f} \tag{13}$$

then Y will be a random variable between $[0, 1]$ and with q as its mean value. Combining Eq. (8), (10), (11), (12), (13), we can get

$$\begin{aligned} P\left(t_{\text{serv}} > x\right) &= P\left(Y > y\right) \\ \leq e^{-\theta y} E\left[e^{\theta Y}\right] &\leq e^{-\theta y}\left(1 - q + q e^{\theta}\right) \end{aligned} \tag{14}$$

Let $e^{\theta} = \frac{y(1-q)}{q(1-y)}$, we can obtain the per-packet service time:

$$P(t_{\text{serv}} > x) \leq \left(\frac{q}{y}\right)^{y} \left(\frac{1-q}{1-y}\right)^{1-y}. \tag{15}$$

Notice that θ need to be greater then 0, so y needs to be greater than q, otherwise Eq. (15) will be false.

According to Eq. (15) and the constant generated duration of awareness messages, the C-V2X mode 4 standard has the following weak service curve when $\bar{t}_{\text{serv}} \leq T$:

$$\beta(t) = \frac{L}{T_s + \bar{t}_{\text{serv}}} t \tag{16}$$

$$g(x) = \left(\frac{q}{y}\right)^{y} \left(\frac{1-q}{1-y}\right)^{1-y} \tag{17}$$

The vehicular awareness messages are generated in a constant interval, according to [14], its arrival curve is:

$$\alpha_a(t) = \frac{L}{T} \cdot t \tag{18}$$

$$f_a(x) = 0 \tag{19}$$

where L is the packet size. Moreover, some safety related messages to show the emergent accidents also need to be transmitted. We assume these messages are generated in Poisson arrival process. According to Example 3.9 in [29], the arrival curve is

$$\alpha_e(t) = \lambda \cdot t \tag{20}$$

$$f_e(x) = \sum_{k=\lceil x + \lambda t \rceil}^{\infty} \left\{ \frac{e^{-\lambda t} [\lambda t]^k}{k!} \right\} \tag{21}$$

According to Theorem 2 in the appendix A, the total arrival curve except the awareness message of current vehicle is:

$$\alpha'(t) = (N-1)\alpha_a(t) + \alpha_e(t) \tag{22}$$

$$f'(x) = \left(f_e \otimes \underbrace{f_a \otimes f_a \cdots \otimes f_a}_{N-1 \text{ times}} \right)(x) \tag{23}$$

Based on the properties of min-plus convolution in Chapter 1 of [29], we can simplify

$$f'(x) = f_e(x) \tag{24}$$

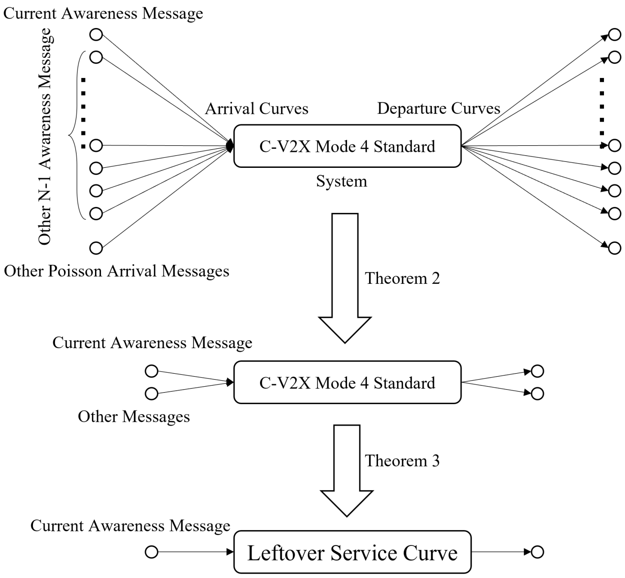

Fig. 3. Stochastic network calculus analyse process.

According to Theorem 3, the service curve of the current awareness message is

$$\beta'(t) = \left[\beta(t) - \alpha'^{\theta}(t)\right]^{+}, \tag{25}$$

$$g'(t) = \left(g \otimes f'^{\theta}\right)(x) \tag{26}$$

where

$$\alpha'^{\theta}(t) = \alpha'(t) + \theta \cdot t, \tag{27}$$

and

$$f'^{\theta}(x) = \left[f_e(x) + \frac{1}{\theta}\int_x^{\infty} f_e(y)dy\right]_1. \tag{28}$$

Based on Theorem 1, we can obtain the delay upper bound for C-V2X mode 4 standard for vehicular awareness messages:

$$P[D > h(\alpha_a(t) + x, \beta'(t))] \leq (f_a \otimes g')(x) \tag{29}$$

And finally we can obtain the simplified stochastic delay upper bound:

$$P(D > x) \leq g'\left(\frac{(T_s + \bar{t}_{\text{serv}})Tx}{TL - (T_s + \bar{t}_{\text{serv}})(N-1)L - \lambda - \theta}\right) \tag{30}$$

According to Eq. (30), we can derive the delay upper bound in different scenarios for C-V2X mode 4 standard. The total analyse process can be summarized in Fig. 3.

The upper bound of the end-to-end delay for the C-V2X mode 4 protocol is not a mathematical model to describe the probability distribution of the delay. The network calculus-based delay upper bound can be used to make sure that the timeout probability is less than the theoretically analysed results under any circumstance. As a result, it considers the worst communication cases to ensure on-road safety. In this case, it is not tight enough for the simulation results. If we consider an extreme case that all vehicles choose not to send packets until reach the maximum retrial times (the reselect probability p_{rs} is set to 1), we can obtain much tighter results compared to the current simulation results. The results of this extreme case are shown in Fig. 9. We can find that the upper bounds of the extreme cases are much tighter than the original network calculus-based analysed results. As a result, the theory we use to analyze the delay upper bounds of the C-V2X mode 4 protocol is appropriate.

However, to guarantee the analysis results are the end-to-end delay upper bound, in Eq. (11) to Eq. (13), we use the extreme cases to normalize the stochastic variables, which will increase the gaps between analysis results and the realistic delays. As a result, we can use the average delay, *i.e.*, $\bar{t}_{\text{serv}}$, to replace the extreme cases. In this manner, these normalized variables will be followings.

$$\bar{Y} = \frac{t_{\text{serv}} - (N_f + T_s)}{\bar{t}_{\text{serv}}} \tag{31}$$

$$\bar{q} = \frac{\bar{t}_{\text{serv}} - (N_f + T_s)}{\bar{t}_{\text{serv}}} \tag{32}$$

$$\bar{y} = \frac{x - (N_f + T_s)}{\bar{t}_{\text{serv}}} \tag{33}$$

From the simulation results, we can find with these modified variables, more compact upper bounds compared to the original network calculus-based results can be obtained, which is valuable in engineering applications. We call this new proposed mathematical model as Network Calculus Model based on Average Service Time (NCMAS).

V. Intelligent Optimization Scheme

Based on the theoretical analysed results of the system performance lower bounds, we propose a centralized intelligent protocol adjust scheme in the vehicular platoon scenarios. The intelligent algorithm called Smart Protocol Optimization (SPO) algorithm is periodically performed by the head vehicle in a centralized manner. As a result, the kernel of the proposed algorithm is head vehicle selection and intelligent algorithm design.

A. Platoon-based Smart Framework

The awareness messages are generated in a fixed duration, which is used to inform other vehicles of the state of the current vehicle, including position, speed and other factors. This application often occurs in vehicular platoon scenario. Moreover, the MAC protocol parameters can be easily synchronized in the same vehicular platoon, which is the basic assumption of the previous theoretical analysis. Therefore, we design a centralized vehicular platoon based framework to implement the smart algorithm in this paper. The vehicular platoon scenario is illustrated in Fig 4.

Each vehicle in the same platoon should generate awareness messages to inform other vehicles periodically. In addition, some other safety-related messages will also be generated,

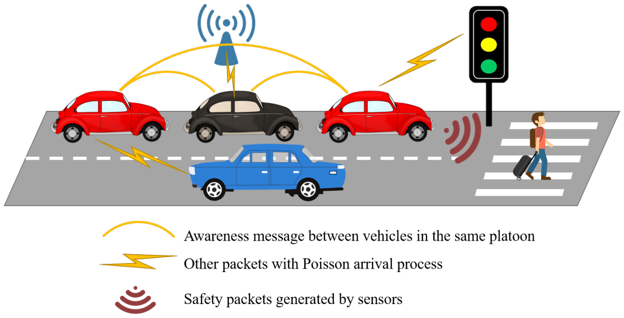

Fig. 4. Vehicular platoon scenario.

such as passing through vehicles, roadside units and sensor data. All of these messages are together assumed to have a Poisson arrival process. The arrival curve is defined in Eq. (20) and (21). It is noticeable that other messages may not use the C-V2X sidelink. Consequently, according to the practice, we only consider the messages also use the same communication resource, which will influence the performance of the awareness message broadcasting.

To adjust the MAC protocol parameters in a centralized way, a vehicular platoon should select a head vehicle to perform the optimization algorithm. Although the intelligent algorithms can be conducted by the edge computing servers [30]–[33], we only consider the platoon to process the algorithm to ensure the proposed algorithm can work without the infrastructure support. Because the neural network in the proposed algorithm is not very large (limited input and output scale), the computation time and the communication time play equal roles in the head vehicle selection. When the platoon is initially formed, all vehicles have the same protocol parameters with default values. And with these default configurations, vehicles can build basic V2V communication links. Therefore, each vehicle can broadcast its state with the default vehicular network. After receiving all states in the same platoon, each vehicle can be compared to determine the head vehicle.

To determine the head vehicle, we need to build a compare method of different vehicles. Each vehicle has some available CPU and memory resources for the intelligent algorithms. Consequently, we use a ordered pair (c_i, m_i) to represent the effective CPU frequency and memory size of vehicle i. The compare method is illustrated as follows,

$$f_c(v_i, v_j) = \begin{cases} \text{LT}, & \begin{array}{l} c_j - c_i > c_t \text{ or} \\ |c_i - c_j| < c_t \text{ and } m_i < m_j \end{array} \\ \text{EQ}, & |c_i - c_j| \leq c_t \text{ and } m_i = m_j \\ \text{GT}, & \begin{array}{l} c_i - c_j > c_t \text{ or} \\ |c_i - c_j| < c_t \text{ and } m_i > m_j \end{array} \end{cases} \tag{34}$$

where f_c is the compare function. LT, EQ and GT represents $v_i < v_j$, $v_i = v_j$ and $v_i > v_j$, respectively. c_t is the CPU frequency compare threshold to balance the compare priority of CPU frequency and memory size.

When each vehicle calculates all scores of the vehicles in the same platoon, vehicles can know which vehicle is the head vehicle. After determining the head vehicle, the chosen head vehicle will gather the environment information and perform the intelligent algorithm. Furthermore, the head vehicle will periodically request the computation resources of other vehicles. When the head vehicle computes better parameter values of the MAC protocol in current environment, it will broadcast the optimized parameters to other vehicles. And the whole platoon will use the same optimized MAC protocol parameters in the platoon.

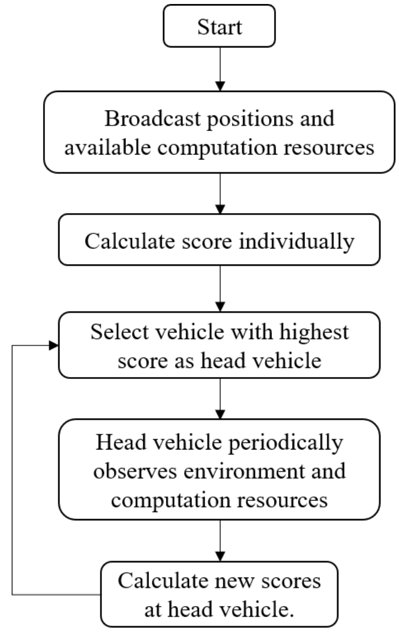

Fig. 5. Flowchart of AHVSA.

Sometimes the head vehicle needs to be altered caused by certain reasons. For example, the environment changes caused by a new vehicle entering the platoon or computation resource changes. At this moment, the platoon will re-select a new head vehicle with the pre-mentioned process. The flow of the head vehicle maintenance is summarized in Fig. 5. We call the head vehicle maintenance algorithm as Automatic Head Vehicle Selection Algorithm (AHVSA).

B. Smart Delay Upper Bound Reduction Algorithm

The analysed end-to-end delay results in Eq. (30) has lots of calculations or operations defined in stochastic network calculus theory, which are not conventional mathematical calculations, such as min-plus convolution and horizontal distance. As a result, it is impossible to optimization the end-to-end delay with conventional mathematical tools, such as convex optimization.

Fortunately, artificial intelligent technology provides general-purpose methods to solve optimization problems in complex or even unknown scenarios. The essential idea of the proposed MAC protocol parameter adjusting method is treating the network calculus analysed results as a black box. All we know is the input-output corresponding pairs. We can train the agent by studying from the tests. After training the intelligent agent, we can put it in the on-line scenes to choose the best solution according to the current environment. With the trained agent, we can use reinforcement learning algorithm to optimize the network performance.

The main motivation for applying RL in this problem is that RL has proven superior performances demonstrated for many other research works, such as high accuracy, fast computation, strong adaptability and generalization, and small memory requirement [34]. The strong performance of RL technology makes it an excellent candidate for safety-critical autonomous driving applications [35] including the platooning application studied in this paper. While RL has been widely used for many system optimization problems, to our best knowledge, it has not been applied to optimize the network calculus-based analysed results. Simulation results show that significant performance improvement can be achieved with RL-based algorithms over the baseline methods. Moreover, we developed a new framework for applying the RL models to solve the delay reduction problem, under which other existing learning-based models can be also applied. Due to the time limitation, these investigations are left for our future work.

To set up a reinforcement learning algorithm, we need to clarify the actions, states and rewards. The awareness message generation duration T should be a controllable parameter. It should be in a particular range, denoted by $[T_l, T_u]$, to ensure road traffic safety and control the network loads. Furthermore, the re-select probability p_{rs} in C-V2X mode 4 standard also can be specified. Because 3GPP releases do not fix the number of time slots in each frame, N_f is also a controllable parameter. The actions of the proposed smart algorithm can be summarized by the following equation:

$$\begin{gathered}\mathcal{A} = \{(T_\Delta, N_\Delta, p_\Delta)| \\ T_\Delta \in \{-T_p, 0, T_p\}, \\ N_\Delta \in \{-1, 0, 1\}, \\ p_\Delta \in \{-p_p, 0, p_p\}\}\end{gathered} \tag{35}$$

where T_p and p_p is the change precision for T and p_{rs}, respectively.

The states of the proposed algorithm should contain the controllable parameters. Moreover, the states have additional two parameters: the number of connected vehicles N and the arrival rate of the safety-related packets λ. It is noticeable that λ can only be measured or observed in practice and is usually related to the on-road environment. The states can be summarized as:

$$\mathcal{T} = \{(T, N_f, p_{rs}, N, \lambda)\}, \tag{36}$$

where each parameter should stay in its effective range.

The rewards R have a straightforward definition, the successful transmission probability (i.e. no time-out probability) divided by the duration T. The result for state $S \in \mathcal{T}$ should be the following equation,

$$R(S) = \frac{P\left(d < T \,|S(T, N_f, p_{rs}, N, \lambda)\right)}{T} \tag{37}$$

We can run simulations to obtain some observations, which is some sets of (a, s) pairs, where a and s are action and state, respectively. We adopt policy gradient reinforcement learning

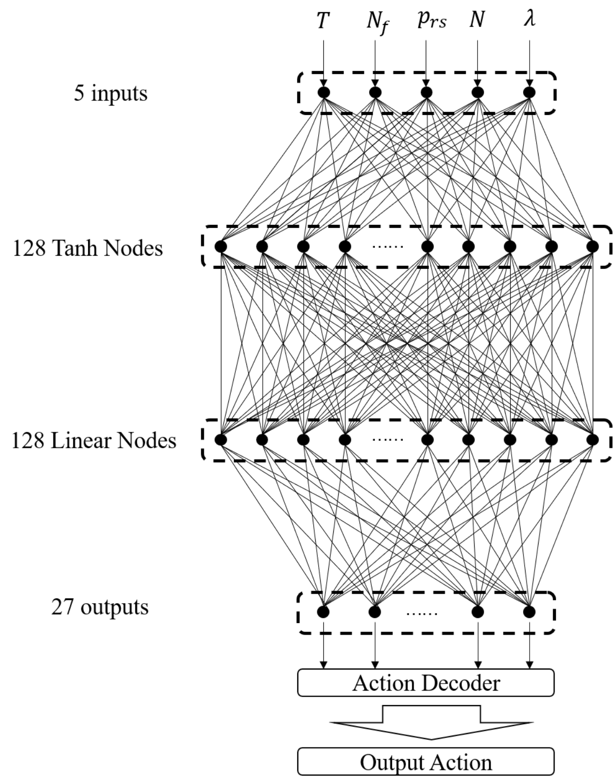

Fig. 6. Structure of the neural network.

algorithm in this paper. The structure of the designed neural network is illustrated in Fig. 6. We train the neural network with the loss function

$$L(\theta) = \sum \log \pi(a|s, \theta) R(s, a), \tag{38}$$

where θ is the parameter of the neural network, π is the action probability under the given state and neural network. And the input of the neural network is a 5-length vector and the size of its output is $3^3 = 27$.

In summary, we can use network calculus results to obtain the reward for a certain state with Eq. (37), and use the rewards to train a neural network with Eq. (38). After training the smart agent, head vehicle can decide how to adjust platoon MAC protocol parameters according to the current environment. The pseudo-code of the proposed RL-based algorithm is shown in Algorithm 1.

Algorithm 1 Smart Delay Upper Bound Reduction Algorithm

Select a head vehicle by AHVSA.
Initialize each parameters of the neural network with normal distribution initializer.
repeat
  Get probabilities of all possible actions of current state with neural network θ
  Update the neural network by maximizing Eq. (38).
until Neural network parameter θ converges.
Determine actions according to different on-line scenarios with the trained neural network.

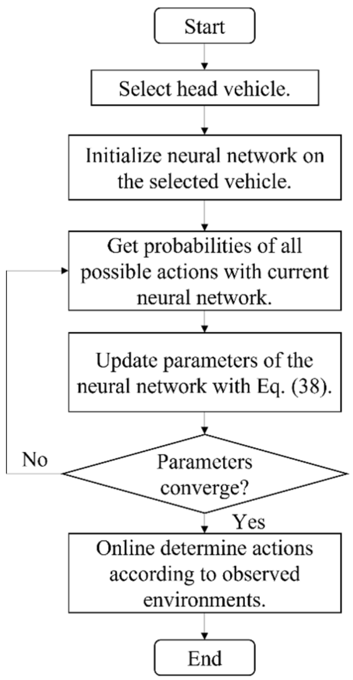

Fig. 7. The flowchart of smart delay upper bound reduction algorithm.

TABLE II
VALUES OF SOME CRITICAL PARAMETERS IN SIMULATION

Parameter	Value
Reselect probability p_{rs}	0.4
Generation duration T	100 ms
Transmission time T_s	10 ms
Number of vehicles N	30
Number of time slots in a frame N_f	50
Other flows' arrival rate λ	1 bits/ms
Simulation Times	20000

The flowchart of the smart delay upper bound reduction algorithm is shown in Fig. 7. The proposed algorithm will train a neural network on the selected head vehicle. To update the parameters of the neural network, we need to calculate the reward, which include the network calculus-based analysed results. Consequently, we use network calculus theory to train the off-line neural network and put the trained network to the on-line environment.

VI. Performance Evaluation

This section will present the numerical simulation results of the network calculus-based analysis results and the proposed smart optimization algorithm results. The parameters of the simulations which are not specified will be set as the values in Table II.

We use Wolfram Mathematica to evaluate the performance of the proposed algorithms and the correctness of the analysis results. Although there exist some professional numerical simulation tools, such as NS3 and OMNET++, we use a general-purpose computing platform with a functional programming language to implement the sophisticated network calculus-related computing. As for the platoon simulation, the PLEXE [25] software can combine the platooning scenario with the communication network to simulate the platoon traffic behaviors. However, this paper mainly considers communication performance without need of detailed simulation of platoon dynamics. Consequently, we choose the simulation tool according to the communication performance evaluation, intelligent algorithms function and complex mathematics supports.

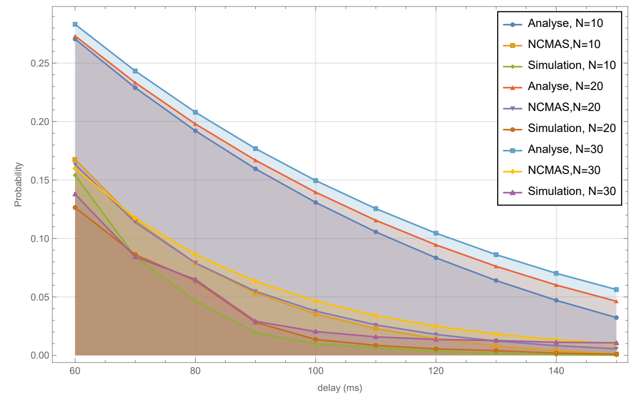

Fig. 8. Per-packet service time

Because the vehicular awareness message is short enough, the transmission delay can be ignored compared to the channel access latency. Therefore, in the experiments, this paper does not consider the the simulation of physical channels. Moreover, for training the neural network, we adopt the ADAM optimizer. Each episode only has five tries for fast iteration, max training rounds are set to 100.

Fig. 8 shows the simulation results of per-packet service time, which can verify the correctness of Eq. (15). The analyse results mean the delay upper bound calculated by the theoretical analysed results. The NCMAS mean the results obtained according to the network calculus theory, but use the average variable showed in Eq. (31), Eq. (32) and Eq. (33). The simulated distributions are obtained by performing 20000 times simulations. Because we use a linear function to fit the experimental function, there has some gas between the simulation and the analysis results. Nevertheless, we can find that the analysis results can accurately show the relation between delay upper bound distributions in different scenarios. As the analysis results indicate, the delays become greater as the vehicle number increases, and the difference between the distributions are accurate enough to be used in the optimization algorithms. We can find the NCMAS is much more compact to the simulated results compared to the analyse results. However, it is not guaranteed that all the simulation results are less than the average results. Consequently, it is not advised to use the average results in safety-related applications.

To verify the correctness of the Network Calculus theory, we compare the theoretical delay upper bounds and the simulation results in extreme cases in Fig. 9. In the extreme cases, we set the re-select probability p_{rs} to 1, which means vehicles always choose not to send packets until reach the maximum retrial times. We can find in these extreme cases, the theoretical delay upper bounds become tight. As a result, the network calculus-based analysed results can guarantee that, in each situation,

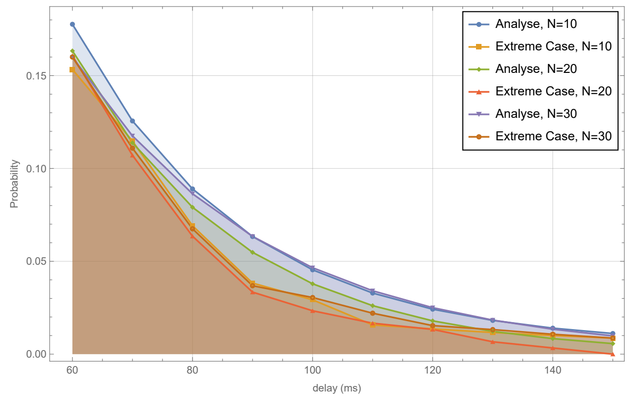

Fig. 9. Delay upper bound vs. extreme cases

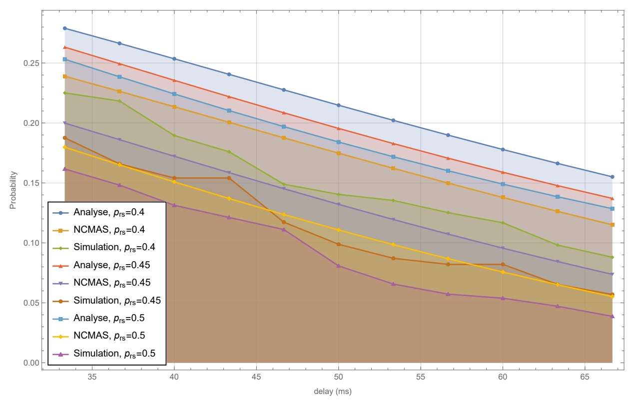

Fig. 10. Delay upper bound vs. $p_{\rm rs}$

the probability that the delay exceeds a specific value is lower than the theoretical model.

The effects of reselect probability, i.e. p_{rs}, is showed in Fig. 10. In these scenarios, increasing the reselect probability can improve the network performance. Because the communication resource of the C-V2X mode 4 protocol is not efficiently used in the default scenarios and standard parameters. Consequently, if vehicles can more aggressively try to access the channel, the total delays will be decreased. If we increase the p_{rs} from 0.4 to 0.5, observed from both simulation and analysis, the delay upper bound corresponding probabilities can decrease about 1/10, which is a substantial performance improvement.

Fig. 11 verifies the correctness of the Poisson arrival flows related analysis. The unit of the Poisson arrival rate is one bit per millisecond. As the Poisson arrival rate increases, the other flows will occupy more communication resources, which leads to performance reduction of the vehicular awareness messages. In addition, we can find to distinguish between different arrival rates by simulation, we need to have hundreds of thousands of simulations, and the analysis method can calculate the probability in a much faster way, which can support the proposed optimization algorithms.

We present the loss values and the rewards values of the training process in Fig. 12 and Fig. 13, respectively. The neural network is not well trained at the early training period and is almost in a stochastic search scheme. Therefore, the rewards

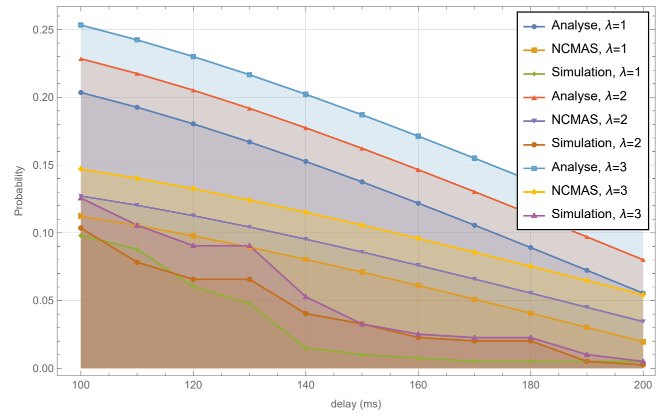

Fig. 11. Delay upper bound vs. poisson arrival rate

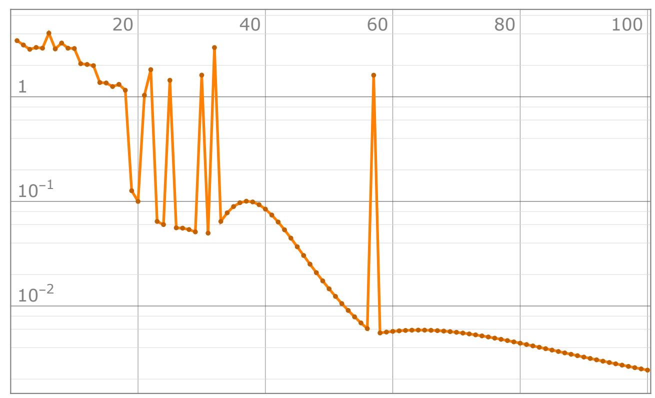

Fig. 12. Training loss

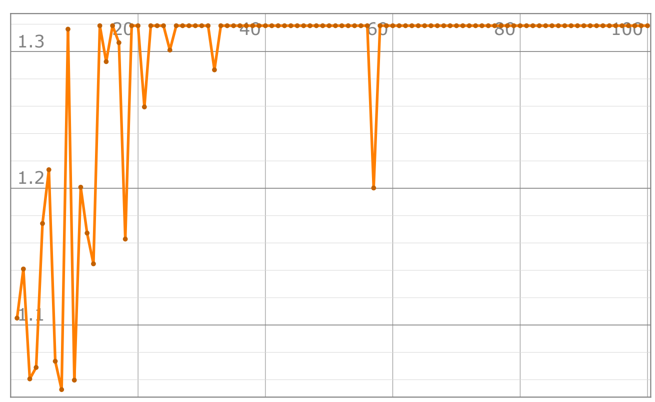

Fig. 13. Training reward

are very unstable, and the loss is not reduced. After 20 training rounds, the loss value starts to reduce. In this period, which is in training rounds 20 to 40, the neural network has found an excellent search direction but is still not converges. After 40 training rounds, the neural network converges in the right direction. At about the 57th training rounds, the optimizer searches the solution in a new direction, which leads to high loss value and low reward. As a result, the neural network comes back in the next iteration. And then, the loss values decrease at a slow speed, and the reward stays unchanged.

We can see that the proposed algorithm can converge in

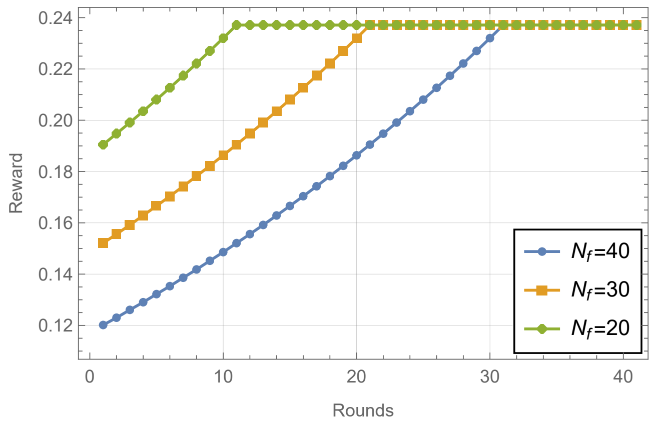

Fig. 14. Take action based on training network on different initial frame slot numbers

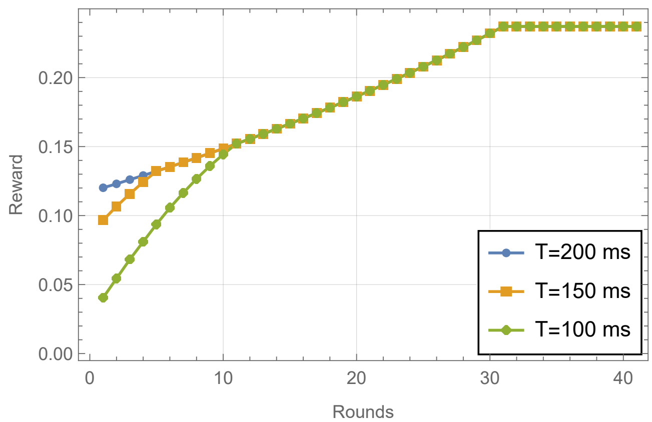

Fig. 15. Take action based on training network on different initial generated durations

100 training rounds, which is fast enough compared to most other smart applications. Nevertheless, the network calculus-based analysis results need many computation resources. As a result, the simulations are performed on a computer with a 2.90G Hz CPU and 16G memory (we do not use GPU to perform the neural network training) and need about 5 minutes to finish 100 training rounds. Consequently, we cannot run the proposed algorithm in an online scenario. Fortunately, the number of related parameters are not too high, and we can off-line calculate all of the possible situations.

We apply the proposed smart algorithm to different scenarios and measure the rewords in each iteration. Fig. 14 shows the algorithm results of scenarios with different number of time slots in each frame, i.e. N_f. Because there remain many available communication resources, the smart algorithm decides to reduce the number of time slots in each frame, which means a more aggressive scheme to use the channel. As a result, the protocol will reduce N_f at each iteration. When N_f reducing to about 10, the system stays stable and has a higher performance than the initial state.

The rewards of each iteration for the proposed smart algorithm in scenarios with different initial awareness generation duration is illustrated in Fig. 15. The generation time has a complex effect on the system performance. On the one

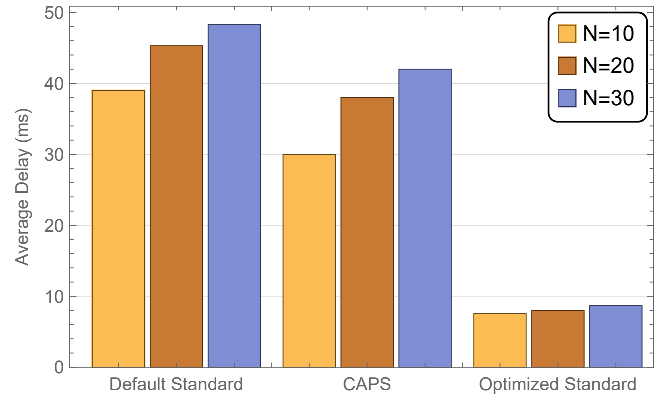

Fig. 16. Average transmission delays of default C-V2X mode 4 standard, CAPS, and the protocol with optimized parameters

hand, longer generation time will make the system try to transmit less messages. On the other hand, a shorter generation time will increase the traffic load and reduce the system performance. Furthermore, because all vehicles share the same generation time, decreasing the generation time will cause much traffic and quickly run out the communication resources. Consequently, the intelligent algorithm slowly increases the generation time to reduce the system traffic until the generation time reaches its maximum value.

We calculate the average delays in different scenarios, which is presented in Fig. 16. We further compared our algorithm with Collision Avoidance based Persistent Scheduling (CAPS) algorithm [36]. CAPS has a piggyback-based collaboration method for collision avoidance that can decrease the channel busy ratio. However, this method tries to optimize the existing protocol with fixed protocol parameters. the performance of CAPS is poor compared to our proposed smart algorithm. The performance can be improved by about 80% only by adaptively adjusting the parameters according to the environment. With the default C-V2X standard, the number of time slots in a frame is fixed but unspecified by 3GPP. However, it can dramatically influence the system performance. For example, if each frame has 50 time slots, one frame will take 50 milliseconds. Then, only two frames will exceed 100 milliseconds, which is time-bound for conventional safety-related applications. Consequently, adjusting the parameters of the C-V2X standard according to the environment can significantly improve the system performance.

However, from Fig. 16 we can find that the C-V2X mode 4 standard cannot meet the one millisecond delay requirement of the platoon-based autonomous driving scenarios even with the proposed intelligent algorithm. It is because the length of each time slot is specified by 3GPP, which is one millisecond. One frame contains several time-slots, and nodes need to monitor the channel for one frame duration before transmitting. As a result, the transmission delay will exceed one millisecond, whatever the optimization algorithms do. To satisfy the autonomous driving requirement, the length of time slots should be further decreased.

We compare some other algorithms with our proposed algorithm in Fig. 17. We implement the DDPG and Trust

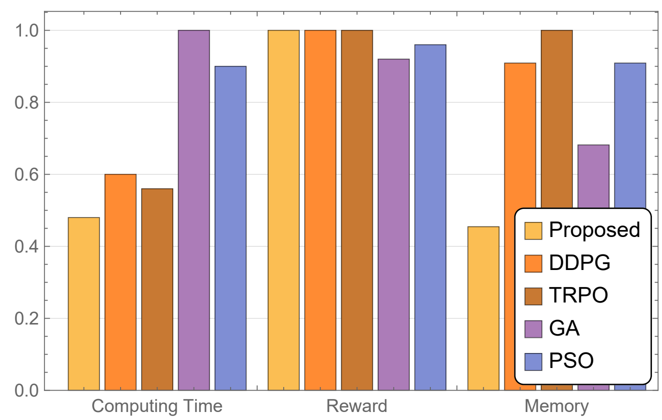

Fig. 17. Normalized performance for different algorithms

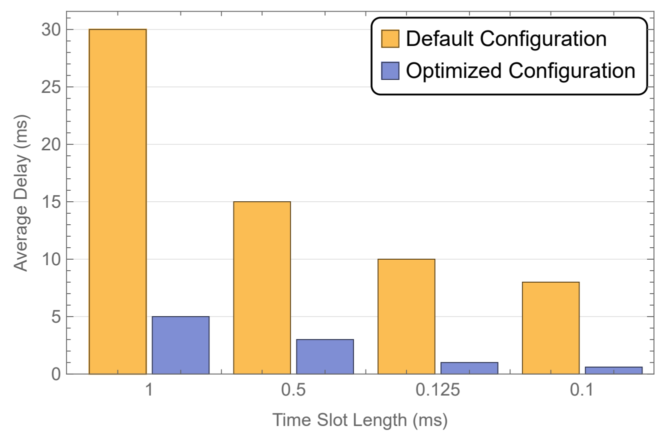

Fig. 18. Average end-to-end delays with different time slot lengths

Region Policy Optimization (TRPO) version of the proposed algorithm. The simulation results are normalized into range [0, 1]. We can find because these algorithms need to train two neural networks, it will cost more memory and computing time. But for this optimization question with theoretical analysis results, the optimized rewards are similar. Two non-learning algorithms are compared to the RL-based algorithm, which are the Genetic Algorithm (GA) and Particle Swarm Optimization (PSO), respectively. As for computing time, these heuristic algorithms have low convergence speeds, which makes the computation delay longer than intelligent algorithms such as the RL-based approaches. The heuristic algorithms obtain worse results than the intelligent algorithms due to the lack of advanced neural network structure. Furthermore, these algorithms also need a lot of memory. For example, GA needs to store lots of results in a population to get the fitness and generate new populations, and PSO needs to store many particles to track their search paths. Representative results are presented in Fig. 3, from which we can find the RL-based algorithm has a much shorter computational time and smaller memory requirement, and higher rewards compared to other intelligent algorithms. The added comparison and corresponding results indicate the advantage of the RL-based algorithm over the existing non-learning baselines. Consequently, the proposed algorithm is efficient enough for the protocol performance optimization problem.

It is clear that the one millisecond time slot configuration cannot satisfy the 1ms delay requirement of autonomous driving. It is reasonable to reduce the time slot length. We compare the average end-to-end delays of different time slot length in Fig. 18. In this figure, the default configuration means the protocol parameters, such as the frame length, the re-select probability, etc., specified by the standard without optimization. The optimized configuration means the protocol parameters that are optimized by our proposed intelligent algorithm. The values of some critical parameters in the optimized configuration are shown in Table III. It can be found that the end-to-end delay is roughly proportional to the time slot length. To satisfy the 1ms requirement for autonomous driving, we should decrease the time slot length to no more than 0.125ms and optimize the protocol by using our proposed algorithm.

TABLE III
KEY PARAMETERS IN OPTIMIZED CONFIGURATION

Parameter	Value
Reselect probability	0.57
Number of time slots in a frame	8
Time slot length	0.125ms
Number of vehicles	30

From the simulation results, we can confirm that the smart algorithms can make reasonable decisions to adjust the C-V2X mode 4 standard parameters in the right direction based on the network calculus analysis results with enough accuracy. With off-line trained neural networks, the smart online vehicular networks in C-V2X mode 4 standard can self-optimize in different scenarios. [37]

VII. Conclusion

This paper analyses the delay upper bound of C-V2X mode 4 standard for vehicular awareness message broadcasting with stochastic network calculus theory. We obtain the probability distribution of the awareness message broadcasting latency in a vehicular platoon under the given conditions. With the obtained upper bound of the communication latency, we proposed a smart scheme to improve the system performance by adjusting the behaviours of the awareness message generation and the C-V2X mode 4 standard. An implemented framework of the proposed smart scheme is also presented in this paper.

The simulation experiments indicated the correctness of the theoretical analysis results and the effectiveness of the proposed scheme. Moreover, the intelligent algorithm can converge in less than 100 iterations, making the proposed scheme feasible for a practical environment. In addition, we conclude that the current C-V2X mode 4 standard is impossible to meet the 1-millisecond delay requirement of the platoon-based autonomous driving applications. In order to reduce the end-to-end delay, the length of time slot in the standard should be decreased at least to 10^{-4} second.

APPENDIX A
STOCHASTIC NETWORK CALCULUS OVERVIEW

Some basics of stochastic network calculus theory will be presented here, including the notations, definitions and some basic conclusions.

In the network calculus theory, elements in networks are modelled as two types of abstract elements: flows and servers, which are described by arrival curves and service curves, respectively [38]. $A(t)$ and $A^*(t)$ are arrival (or input) and departure (or output) flows, respectively. $S(t)$ is an element that deals with flows, which can be a router, a channel, and other things.

Definition 1: $A(t)$ and $A^*(t)$ are total cumulative number of bits of arrival and departure flow in time interval $[0, t)$, respectively. Furthermore, $A(s,t) = A(t) - A(s), \forall t > s$.

Definition 2: A flow $A(t)$ has a traffic-amount-centric (t.a.c) stochastic arrival curve $\alpha(t)$ with bounding function $f(x)$, if for all $0 \leq s \leq t$ and $\forall x \geq 0$ there holds

$$P\left(A(s,t) - \alpha(t-s) > x\right) \leq f(x), \tag{39}$$

which is denoted as $A \sim_{ta} \langle f, \alpha \rangle$.

Definition 3: A server $S(t)$ provides a weak stochastic curve $\beta(t)$ with bounding function $g(x)$, denoted by $S \sim_{ws} \langle g, \beta \rangle$ if, for all $t \geq 0$ and $\forall x \geq 0$, there holds

$$P\left((A \otimes \beta)(t) - A^*(t) > x\right) \leq g(x) \tag{40}$$

where $\otimes$ denotes the min-plus convolution in network calculus, which is defined as follows:

$$(f \otimes g)(x) = \inf_{0 \leq y \leq x} \left[f(y) + g(x-y)\right] \tag{41}$$

Definition 4: The delay in network calculus for a bit arriving at time t means the duration that all bits received before it are served, which can be expressed as follows,

$$d(t) = \inf\left[\tau : A(t) \leq A^*(t+\tau)\right] \tag{42}$$

Theorem 1: If a system has an arrival flow characterized by $\langle f, \alpha \rangle$ and a server characterized by $\langle g, \beta, \rangle$, then the delay $d(t)$ satisfies the inequality

$$P\left(d(t) > h(\alpha(t) + x, \beta(t))\right) \leq (f \otimes g)(x) \tag{43}$$

where $h(a,b)$ is the maximum horizontal distance between functions a and b, which is defined as

$$h(a,b) = \sup_{s \geq 0}\left\{\inf\left[\tau \geq 0 : a(s) \leq b(s+\tau)\right]\right\}. \tag{44}$$

Theorem 2: N flows with arrival processes $A_i(t) \sim_{ta} \langle f_i, \alpha_i \rangle, \forall i = 1, \ldots, N$ can be aggregated into single flow, with the following arrival curve:

$$\alpha(t) = \sum_{i=1}^{N} \alpha_i(t) \tag{45}$$

$$f(x) = f_1 \otimes f_2 \otimes \cdots \otimes f_N(x). \tag{46}$$

Theorem 3: Consider two flows $A_1(t)$ and $A_2(t)$ pass through system S, the service curve of S is $S \sim_{sc} \langle g, \beta \rangle$, the arrival curve fo $A_2(t)$ is $A_2 \sim_{ta} \langle f_2, \alpha_2 \rangle$, then the service curve that the system offers to A_1 can be characterized by

$$\beta_1(t) = \left[\beta(t) - \alpha_2^{\theta}(t)\right]^{+} \tag{47}$$

$$g_1(t) = \left(g \otimes f_2^{\theta}\right)(x) \tag{48}$$

where

$$\alpha_2^{\theta}(t) = \alpha_2(t) + \theta \cdot t \tag{49}$$

and

$$f_2^{\theta} = \left[f_2(x) + \frac{1}{\theta}\int_x^{\infty} f_2(y)dy\right]_1, \tag{50}$$

for any $\theta > 0$. And $[x]_1 = \min\{x, 1\}$.

ACKNOWLEDGEMENT

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