Mitigating Packet Collisions by Predicting Collective Perception Message Transmissions in Cellular V2X Environment

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***Abstract*—Collective perception is known to effectively boost awareness in vehicle-to-everything (V2X) environment. However, the Intelligent Transportation System (ITS) frequency band is narrow, and channel congestion may occur due to frequent exchange of Collective Perception Messages (CPM). For this reason, European Telecommunications Standards Institute (ETSI) is standardizing a facilities-layer congestion control for CPM traffic, called the CPM generation rule. Unfortunately, it changes the periodic CPM traffic into an aperiodic one, causing disruption for the Sensing-based Semi-Persistent Scheduling (SPS) algorithm used in New Radio (NR) Sidelink Mode 2 that reserves periodic transmit resources. Therefore, to solve this problem, this paper proposes a deep learning-based scheme that predicts when the sensed vehicles will qualify to be included in the CPM. Based on the prediction, the proposed scheme reserves transmit resource where there will be vehicles to report about. It shows that the number of wasted resources and packet collisions can be greatly reduced compared to using standard SPS. Consequently, the packet reception ratio (PRR) is increased and the target PRR for safety applications can be achieved at much longer distances.**

***Index Terms*—Cellular V2X, collective perception, CPM generation rule, prediction, deep learning, packet reception ratio (PRR)**

I. Introduction

TODAY, vehicles use on-board sensors such as cameras, lidars, and radars to obtain awareness of the driving environment. In order to supplement these line-of-sight (LoS) sensors, vehicle-to-everything (V2X) communication can be used to expand the awareness to non-LoS areas. For this purpose, Collective Perception Message (CPM) has been standardized by European Telecommunications Standards Institute (ETSI) [1]. It can be used by vehicles to exchange road objects information from the on-board sensors and expand each other's perception. The use of CPM can be highly effective in raising the awareness level of the driving situation [2].

Despite the usefulness of CPM exchanges, the CPM traffic can be a significant burden on the narrow Intelligent Transport System (ITS) band. The frequency resource for dedicated ITS use in most countries is limited to 20 to 40 MHz in 5.9 GHz band. Furthermore, it is to be shared by many driving safety-related messages such as Cooperative Awareness Message (CAM) [3], Decentralized Environmental Notification Message (DENM) [4], and Maneuver Coordination Message (MCM) [5] among many others [6] and the ones that will arise in the future. Assuming that the installation of vehicle-to-everything (V2X) communication devices will soon become mandatory in new vehicles, there is a pressing need to minimize non-essential message transmissions and suppress consequent channel congestion in the ITS band. As an effort, ETSI is standardizing a facilities-layer congestion control method for the CPM traffic, called the CPM generation rule [7] that suppresses less essential CPM packets. It can significantly reduce the CPM traffic [8].

Unfortunately, the CPM generation rule on the facilities layer changes the periodic CPM traffic into an aperiodic one, causing difficulty in resource allocation on the access layer in the cellular V2X environment. As the Sensing-based Semi-Persistent Scheduling (SPS) algorithm [9] is used to reserve periodic transmit resources in New Radio (NR) Sidelink Mode 2, the CPM suppression in the facilities layer disrupts the SPS operation. It leads to resource waste by suppressing a CPM in a reserved resource as well as potential packet collisions due to the loss of reservation. The latter problem arises because the CPM suppression breaks the daisy chain of reservation for the next periodic transmission that would have continued if not suppressed. The apparently unclaimed resource looks available to other vehicles and they may begin to use it, causing packet collisions thereafter.

To solve the resource waste and the potential packet collision problems, this paper proposes a deep learning-based scheme that predicts when each neighbor vehicle will be included to be reported in a CPM message. It leads to the prediction of the time instant the next CPM will occur and enables reserving the resource for it. The simulation experiment of the proposed enhancement shows that the number of the wasted resources and packet collisions can be greatly reduced compared to using standard SPS. Consequently, the packet reception ratio (PRR) is increased and the target PRR for safety applications can be achieved at much longer distances.

II. Related work

Seon et al. [10] showed that when the facilities layer suppression of Cooperative Awareness Message (CAM) packets called the CAM generation is active, the resulting non-periodic traffic can cause resource waste and increased packet collisions in the SPS algorithm. They showed that the next CAM transmission instant can be predicted by recent ego vehicle dynamics and the CAM generation condition that allowed the previous CAM transmission. Lusvarghi et al. [11] solved the same problem, but using not only the ego vehicle dynamics but also the immediately preceding vehicle's. Also it uses the kNN classifier instead of a neural network. Our work is an extension of Seon et al. [10] to CPM traffic, but there are differences. First, the input data is not the ego vehicle dynamics but the neighboring vehicle movements captured by a camera sensor. Second, the prediction targets are both CPM message times and the number of object containers in the next predicted CPM transmission. Third, the neural network model uses less input features.

Thandavarayan et al. [12] proposed an improvement for the CPM generation rule itself in the 802.11p environment, which looks ahead and predicts if any of the detected objects that are not included in the current CPM would be included in the following CPM. It reduces the packetization and channel access overhead by including such objects in the current CPM, and saves the bandwidth so that the packet collisions are reduced and packet delivery probability is improved. Unlike Thandavarayan et al. [12], our work assumes the cellular V2X environment. Moreover, our work is orthogognal to it because the prediction in our work is utilized for managing reservations, not for packetization.

III. Problem definition

In SPS, the resource allocation for future periodic transmissions is done in a daisy-chain manner. In the Orthogonal Frequency Division Multiple Access (OFDMA) used in the Sidelink communication between vehicles, a transmit resource $R_{x,y}$ is defined by a frequency range x and a time slot y. Periodic transmission is reserved by allocating n resources at an interval called Resource Reservation Period (RRP), where n is randomly determined in the range $[5, 15]$ if RRP ≥ 100 ms or $[5 \times \lceil \frac{100}{max(20,RRP)} \rceil, 15 \times \lceil \frac{100}{max(20,RRP)} \rceil]$ otherwise [13]. Note that the only way to keep the reservation is to reserve the next resource in the daisy chain every time a CPM is transmitted, through the RRP field in the Sidelink Control Information (SCI) that is transmitted along with the payload. If any transmission is suppressed among the n transmissions, therefore, the daisy chain is cut. Therefore, the facilities layer CPM suppression performed in the ignorance of the access layer does not fit well with SPS in the cellular V2X environment and cause confusion to other vehicles about the resource use of the ego vehicle. Specifically, it causes resource waste and potential packet collisions. Figure 1 illustrates the problems.

Suppose the RRP for an ego vehicle is δ and the vehicle reserves periodic resources when the CPM generation rule knocks out the CPMs supposed to be transmitted in $R_{x,y+i\delta},\ 2 \leq i \leq k-1$. First, since $R_{x,y+2\delta}$ is explicitly reserved by $R_{x,y+\delta}$ (dotted arrow), other vehicles cannot use it, so it is bound to be wasted. Second, $R_{x,y+i\delta},\ (2 < i \leq k-1)$ appear to be available for other vehicles because they are not being claimed by a daisy chain reservation. If another vehicle decides to select one of these "idle" resources and starts a series of CPM transmissions with the same period δ, some of them may suffer collisions with the transmissions from the ego vehicle that considers the resources to still belong to it.

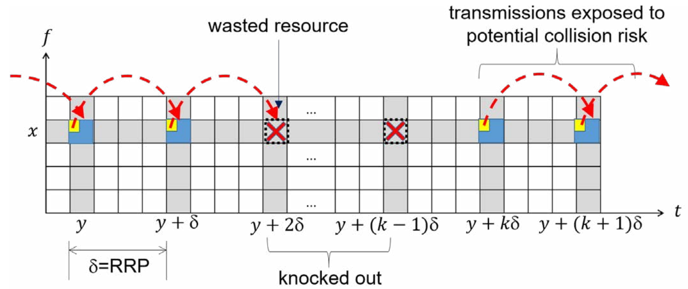


Fig. 1. Problems raised by CPM drops at the facilities layer: dashed arrows = reservations, small box = Sidelink Control Information (SCI) in Physical Sidelink Control Channel (PSCCH), large box = Transport Block (TB) in Physical Sidelink Shared Channel (PSSCH), dotted boxes = dropped packets

A solution to the two problems illustrated in Fig. 1 is to reserve the location of the next resource where the next CPM transmission will actually occur (i.e., $R_{x,y+k\delta}$). Namely, the current CPM transmission at $R_{x,y}$ can explicitly reserve it instead of $R_{x,y+\delta}$ by pointing the RRP field at $R_{x,y+k\delta}$. Fig. 2 shows the proposed idea. Resources that will not be used (e.g. $R_{x,y+2\delta}$) are not reserved anymore, so resource waste can be prevented because other vehicles can utilize them. Moreover, other vehicles that may want to use the unclaimed resources knows that only $R_{x,y+i\delta},\ (2 < i \leq k-1)$ are safe to use. They can avoid starting a reservation chain that overlaps with the rest of the ego vehicle's chain resuming at $R_{y+k\delta}$, thereby avoiding packet collisions.

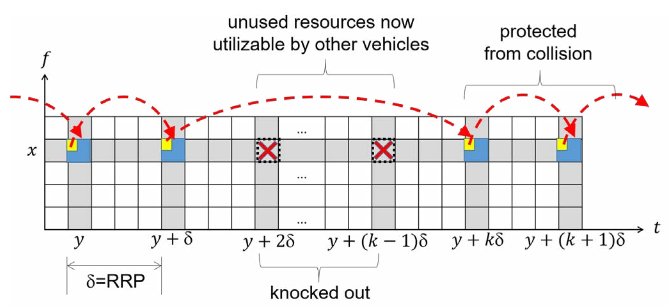


Fig. 2. Predictive resource reservation: RRP at $R_{x,y+\delta}$ is set according to the predicted gap $(k-1)\delta$ instead of δ.

IV. Predicting SPS timing and size

The difficulty in realizing the proposal in Fig. 2 for the ego vehicle is in accurately predicting the timing and the duration of the suppression of CPM packets because they depend on the neighbor vehicles' movements. In this section, we show how the next CPM timing and the size of the CPM message can be predicted from the camera sensor data of neighbor vehicles' movements. Below, we start the discussion by first describing the CPM generation rule and the real-life driving data we used to train our prediction model.

A. CPM generation rule

A CPM consists of five types of containers: Management Container (MC), Station Data Container (SDC), Sensor Information Containers (SIC), Perceived Object Containers (POC), and Free Space Addendum Container (FSAC). MC is the only mandatory container and includes basic information such as the type and position of the ego vehicle. SDC can further describe other properties of the ego vehicle such as size, heading, and speed. SICs contain information about sensing capabilities for each on-board sensor, such as the detection area. POCs contain information about dynamic state and properties of the sensed objects, such as other vehicles, up to 128 objects. FSAC describes the free space areas within the sensor detection areas.

Whenever the time elapsed since the previous CPM is equal to or greater than T_GenCPM (100 ms $\leq$ T_GenCPM $\leq$ 1000 ms), a check is performed. First of all, if the neighbor vehicle is discovered for the first time, it should be reported in the current CPM, contained in a POC. Otherwise, if any of the conditions arises for a neighbor vehicle since the last CPM transmission that reported it, the event is considered significant, and the vehicle is included as a POC in the current CPM.

- Its Euclidean absolute distance between the previous and the current positions exceeds 4 m.
- The difference between the previous and the current speed of the vehicle exceeds 0.5 m/s.
- Its angle between the previous and the current direction vector of the absolute speed exceeds $4°$.

Otherwise, if T_GenCpmMax (= 1000 ms) has elapsed since the vehicle was last included in a CPM, the vehicle is reported anyway. This is the CPM generation rule [7]. Note that if no POC is produced after the check, the CPM message itself is suppressed unless the SIC has to be transmitted. This causes the aperiodic traffic pattern that gives difficulty for SPS. Finally, the SIC transmission must happen every 1000 ms anyway [7], so that a CPM with zero POC can be transmitted.

B. Data

The proposed method in this paper utilizes the sensed information about surrounding vehicles to predict the time of their inclusion in one of the *subsequent* CPMs (not the current one as dictated by the CPM generation rule above). Unfortunately, there is a dearth of public CPM traces available for our prediction model training, which document both the time interval between successive CPM messages and the number of POCs included therein. Therefore, we created our own CPM trace from actual driving trajectories publicly available from Electronics and Telecommunications Research Institute of Korea (ETRI) data set [14]. The dataset records a total of 10 trajectories produced by driving on two different driving routes, urban and suburban.

Each trajectory has vehicle location information of the data-collecting vehicle (Hyundai G80). In addition, the position information of the neighboring vehicles sensed by a Mobileye device attached in front of the windshield inside the G80 is also recorded. Three trajectories out of ten were collected on an urban circuit with multiple turns and traffic lights. The other seven trajectories were collected on a relatively straight route across a suburban area. Since the Mobileye sensor measures the position relative to the position of the data-collecting vehicle, a GPS/IMU device (Spatial FOG Dual) mounted on the center of the rear axle was used to precisely measure the position of G80. To compensate for the GPS error, Real-Time Kinematic (RTK) with horizontal and vertical position accuracy of 0.008 m and 0.015 m, respectively, was used. Computed neighboring vehicles' positions were recorded every 100 ms. From this, we derived the CPM trace.

For the CPM trace obtained from above, Fig. 3 shows the distribution of the number of POCs (i.e., reported neighbor vehicles) under the CPM generation rule ('CPMgen') and fixed CPM transmission rates (2 – 10 Hz) for all trajectories. It shows that the CPM generation rule significantly reduces the CPMs transmitted with no POC. Specifically, it halves them from more than 40% to less than 20%. It also reduces the fraction of 2 or more POCs, as the CPM generation rule intends. On the other hand, the total number of CPM transmissions in each case is 11905 (2 Hz), 22042 (CPM generation rule), 29754 (5 Hz), and 59503 (10 Hz). It shows that the CPM generation rule parsimoniously controls the CPM traffic, second only to 2 Hz. In exchange, however, the time instant and duration of the resulting CPM suppression becomes unpredictable to the access layer and it can cause disruption in the resource allocation performed by the SPS algorithm.

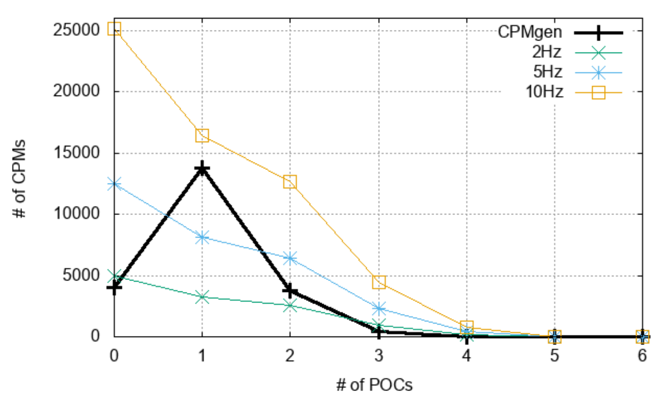


Fig. 3. POC number distribution in the ETRI trace

C. CPM time and size prediction

For each vehicle i that the Mobileye sensor reports, we extract two features and classify the time t_i the vehicle will qualify as a POC to be included in the CPM. The two features are the speed of the vehicle i and the time since the last CPM where i was represented as an object. For the prediction of the time t_i at which a given neighbor vehicle i satisfies one of the enabling conditions in the CPM generation rule, we use a simple neural network model. Then, for all sensed neighbor vehicles $N = \{i\}$, we compute $t_M = \min_{i \in N} t_i$ and count the vehicles that has the CPM time at t_M. This is the predicted size of the next CPM.

The CPM suppression behavior is not completely random but is governed by the physical dynamics of vehicles. Therefore, patterns exist which deep learning models may capture. In this paper, we use the simplest yet effective model, the Multi-Layer Perceptron (MLP). The simplicity matters for the model size, because the classifier has to work on resource-limited embedded platforms on vehicles. The input vector $X = [v_i, \Delta t_i]$ contains the speed of the sensed vehicle i and the time since the last CPM where i to be classified was last listed as an object. The output $Y = [y_1, y_2, \ldots, y_{10}]$ is a vector whose maximum valued entry predicts one of 10 time gaps from 100 ms (y_1) to 1 s (y_{10}). Between the input and the output layer, there are three fully connected hidden layers with $[100, 300, 100]$ nodes, respectively. Rectified Linear Unit (ReLU) is used as the activation function. The MLP model size is 243 KB, and is small enough to operate in the resource-limited computing environment of the vehicle.

Although the neural network model may look excessive for only two simple features (e.g. compared to Thandavarayan et al. [12]), it is first due to the limitation of the currently used trace data. The ETRI dataset has only position data for the neighboring vehicles, lacking heading, acceleration or speed for the sensed vehicles. We find that extracting the heading and acceleration features from the position data involves large errors. Therefore, we only extract the speed data from it, and limit the features to the aforementioned two. However, if other datasets become available with tolerable errors for other features, the neural network model can be more easily extended to accommodate them than other models. Also, there is another reason that we focus on the distance change triggered POC generation in the CPM generation rule. Under the rule, the distance change of 4 m will be exceeded every 200 ms of 300 ms in most speed-regulated roads, unless the vehicle can travel at high speeds over 144 km/h. Then, the POC generation due to speed change of 0.5 m/s or more since the last CPM amounts to upwards of 2.5 m/s^2 of acceleration if CPMs are generated every 200 ms [10]. If the gap is 300 ms, the acceleration should be even higher to generate a POC. According to Jurecki et al. [15] that analyzed real driving traces, such large acceleration rarely happens during driving. Also, Ramyar et al. [16] showed that 4° change in the 200 ms CPM gap can rarely happen unless the car is turning at an intersection. Therefore, we argue that most POC generations during driving are triggered by distance changes. For this reason, we focus on the prediction of CPM timing and size triggered by the distance change in this paper.

D. Model training

To train the deep learning model, 8 out of 10 trajectories of the ETRI data set were combined and processed to produce a single CPM trace. Then, the entries in the CPM trace were randomly mixed and split into training and validation data at the ratio of 0.75:0.25. For training, three data items in the derived CPM traces are used: speed (v), elapsed time (Δt) since last time of POC generation, and the time to the next POC generation as the label. The hyperparameters are as follows:

- batch size: 80
- learning rate: 0.01
- decay: 0.8 per 10 steps
- optimizer: Adam
- loss function: cross entropy
- patience: 20 epochs

In order to prevent overfitting, the training was stopped at 65$^{\mathrm{th}}$ epoch (Fig. 4).

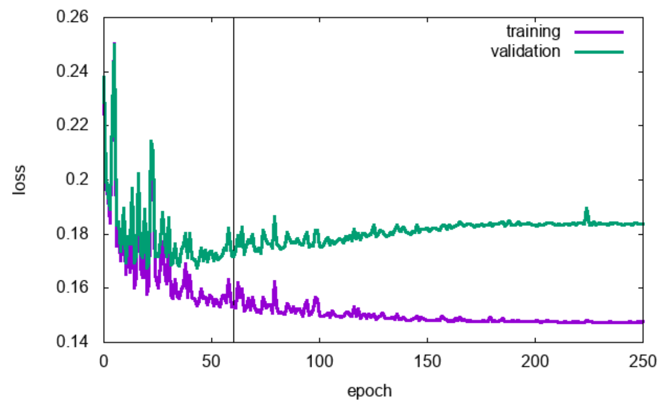


Fig. 4. Training and validation losses

V. Performance Evaluation

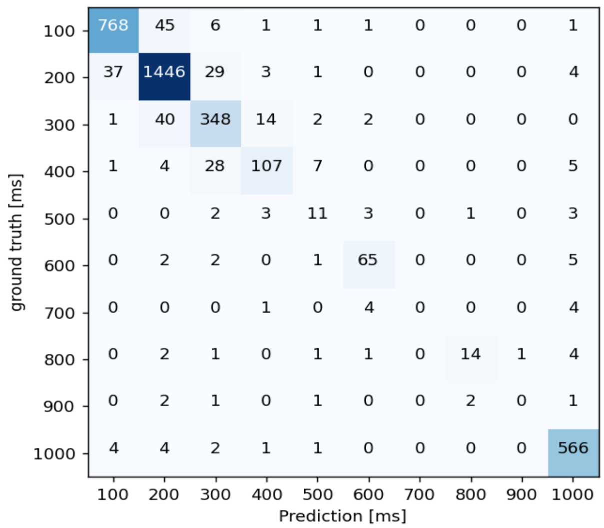
This section first evaluates the prediction accuracy of the proposed algorithm to be used for resource reservation at correct times, and then compares its packet delivery performance with the standard SPS that allocates transmission resources every 100 ms. Simulations were conducted at various traffic densities to measure the performance as a function of the channel congestion.

A. Prediction accuracy

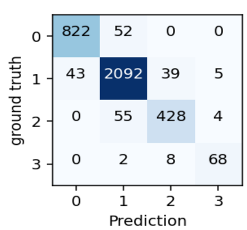
Two trajectories (#6 and #8) set aside during training are used for testing. Recollect that the CPM generation rule is run once every T_GenCPM. It may or may not result in the actual CPM generation. Also, the SIC transmission may happen even if the CPM generation rule fails to produce any POC. Either way, whenever an actual CPM transmission happens, our prediction model is executed for all neighboring vehicles $i \in N$. Namely, the trained model is given an input $(v_i,\ \Delta t_i)$ for vehicle i from the test trajectories for which it outputs the predicted time of the next POC generation for i. As discussed above, $t_M = \min_i t_i$ is computed, and a resource is reserved by setting the value of the RRP field in the SCI to t_M (see Fig. 2). Note that the SCI is associated with the Transport Block (TB) carrying the *current* CPM triggered by the CPM generation rule.

We obtain the prediction results as shown in the confusion matrices for the prediction of the next CPM transmission time

t_M and of the number of POCs included in the CPM, respectively (Fig. 5). The accuracy of the proposed scheme was approximately 92% for CPM time prediction. Most inter-CPM gaps are concentrated on small values below 500 ms, with the exception of the 1,000 ms resulting from the T_GenCpmMax condition in the CPM generation rule and the SIC generation constraint. The accuracy for the number of POCs was higher at approximately 94%.



(a) CPM time prediction



(b) POC number prediction

Fig. 5. Confusion matrices for CPM time gap and POC number predictions

B. V2X communication performance

A simulation study across different CPM-transmitting vehicle traffic densities were performed by using LTEV2Vsim [17], an open source simulator. Table I summarizes the simulation parameters configuration. The bandwidth of the ITS channel is 10 MHz and has 5 subchannels. At the Modulation and Channel Coding Scheme (MCS) level of 7, up to 309 bytes of data can be carried by each transport block (TB). The space can accommodate four POCs in addition to the CPM header overhead and the SIC [7]. A larger number of POCs included in a CPM will require fragmentation, but we do not consider fragmentation in this paper, because the effect of CPM sizes requires a further study *a la* Thandavarayan [8] in the context of cellular V2X. Each TB takes two subchannels, so it allows two transmit (Tx) resources per time slot. We set the SPS parameters for the resource counter (RC) and the selection window size to [5:15] and 100 ms, respectively. Each Tx resource can be retained with probability P_{keep}=0.8 after RC is reached. CPM packets are assumed to be generated at 10 Hz, but can be knocked out by the CPM generation rule according to the neighbor vehicle movements. The only controllable parameter in the simulation is the inter-vehicle distance that follows the exponential distribution with parameter that reflects the investigated traffic density $\rho = 100$, 200, or 300 vehicles/km.

TABLE I
SIMULATION PARAMETER CONFIGURATION

Category	Parameter	Setting
PHY	Carrier frequency	5.9 GHz
	Bandwidth	10 MHz
	No. of Tx resources / subfr.	2
	Antenna gain	3 dB
	Max. Tx power	23 dBm
	Noise figure of receiver	9 dB
	Pathloss model	WINNER+B1
	Shadowing distribution	Log-normal
	Shadowing std. dev.	0 (LOS), 4 (NLOS) dB
	MCS level	7
MAC	Resource counter	[C1, C2] = [5,15]
	Selection window	[T1, T2] = [1,100]
	Resource keep prob.	0.8
Application	Messaging rate	10 Hz (before knockout)
	CPM size	300 bytes
	Max. awareness range	370 m
Vehicles	Traffic density	100,200,300 veh./km

Fig. 6 compares the number of packet collisions in the proposed predictive resource reservation enhancement to SPS ('prop.') and the original SPS scheme for Trajectories #6 and #8. We can observe that the proposed scheme drastically reduces the number of packet collisions compared to the original SPS (note that the y-axis in log scale).

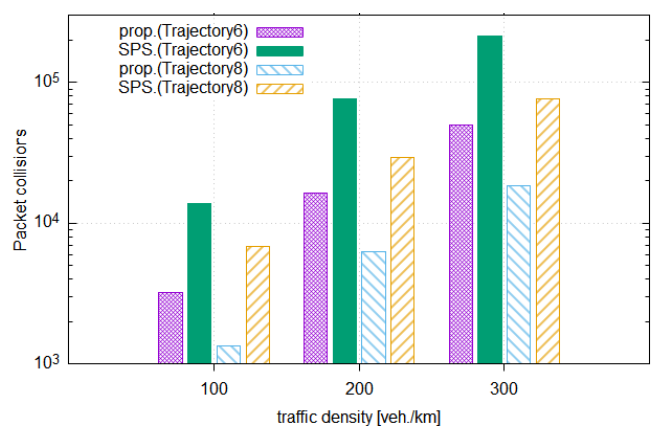
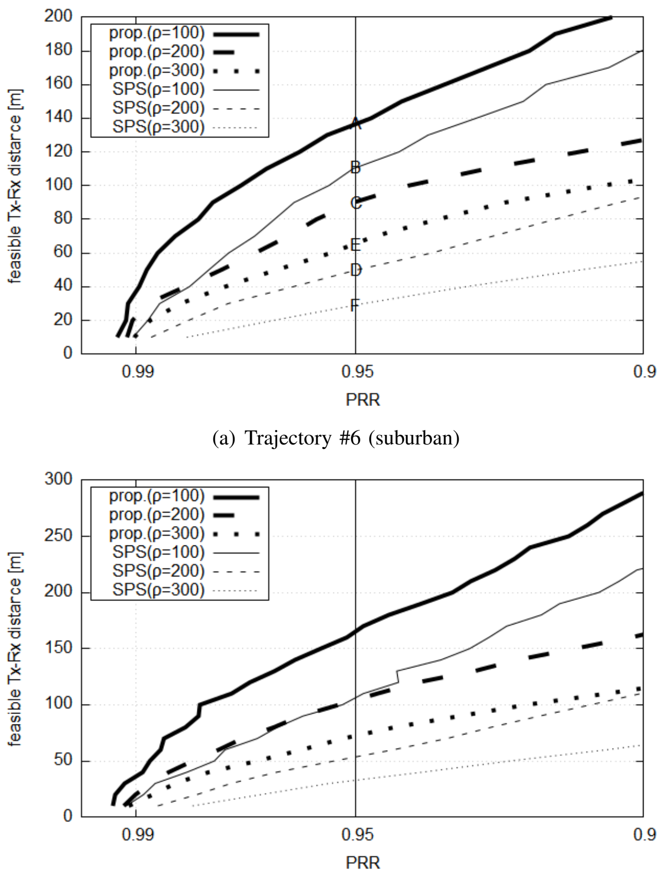


Fig. 6. Comparison of packet collisions.

For V2X-based driving safety applications, it is important to deliver messages to a specific range with high probability. This specific range is application-dependent, but the minimum Packet Reception Ratio (PRR) required for safety applications typically requires at least 90%, with more critical applications requiring 99% or higher. For Trajectories #6 and #8, Fig. 7 plots the transmitter-receiver (Tx-Rx) distance within which a given PRR is satisfied, for each experimented traffic density. It can be seen that the maximum PRR-satisfying Tx-Rx distance can be significantly extended by using the proposed scheme. For instance in the suburban Trajectory #6, at $\rho = 100$ veh./km, the proposed scheme can guarantee 95% packet reception up to 135 meters from the transmitter (marked 'A'), whereas SPS can guarantee it only up to 110 meters (marked 'B'). For $\rho = 200$ and $\rho = 300$ veh./km, 'C' vs. 'D' and 'E' vs. 'F' similarly show the range gaps. The same tendency persists for the urban Trajectory #8. Also, in either case, SPS cannot achieve 99% for $\rho = 200$ and 300 veh./km whereas the proposed scheme does.



(a) Trajectory #6 (suburban)

(b) Trajectory #8 (urban)

Fig. 7. Tx-Rx range that satisfies the given target PRR

From the experiments above, we can conclude that the predictive resource reservation scheme that supplements the standard SPS algorithm in the cellular V2X environment that predicts the next CPM messaging instant based on the neighbor vehicles' movements can be conducive to reducing packet collisions and extending feasible communication range to satisfy the stringent reliability requirements given by driving safety applications.

VI. Conclusion

For reliable vehicular communication in the narrow ITS band, both the CPM generation rule in the facilities layer and the packet dropping in the access layer can significantly reduce the number of CPM packets, effectively dealing with channel congestion. However, the resulting aperiodic traffic causes resource waste and potential packet collisions in the standard SPS algorithm. This paper shows that a prediction-based packet reservation scheme can mitigate this problem. A deep learning model can predict the next CPM time with 92% accuracy and the consequent resource reservation boosts the packet reception rate and greatly extends the range that meets the given communication reliability requirement in cellular V2X environment.

Acknowledgments

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