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# Predicting CAM generation times through machine learning for cellular V2X communication

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**Abstract**

In the narrow Intelligent Transportation System (ITS) band, avoiding wireless channel congestion is essential. Reporting vehicle kinematics in the Cooperative Awareness Message (CAM) only when there are notable changes in vehicle dynamics is a standardized approach to reducing bandwidth usage of periodic CAM messages that are exchanged between vehicles, and is called the CAM generation rule. However, in cellular vehicle-to-everything (V2X) communication, aperiodicity due to frequent omissions of periodic CAM raises problems of resource waste and instability in resource scheduling. The problem can be solved by reserving a resource only for actual CAM transmission times in the future. This article demonstrates that a neural network-based scheme can predict the next CAM generation times at an average accuracy of over 94%, which can be utilized for resource reservation under the CAM generation rule.


*Keywords:* V2X; Cooperative Awareness Message; Congestion control; Machine learning; Prediction

## 1. Introduction

In most countries, the bandwidth allocated for Intelligent Transportation Systems (ITS) is typically no more than 30 MHz. Higher frequency bands such as the millimeter wave band may be added in the future, but their propagation characteristics differ from the currently allocated band at 5.9 GHz. The transmissions in the high frequency bands are more easily blocked and the effective reach is shorter, which raises the question of their suitability for ITS' most fundamental application: safety communication. As it stands, the narrow ITS band is expected to be shared by many different driving safety-related messages such as Cooperative Awareness Message (CAM), Decentralized Environmental Notification Message (DENM), Collective Perception Message (CPM), and Maneuver Coordination Message (MCM) among others. Assuming that the installation of vehicle-to-everything (V2X) communication devices will soon become mandatory in new vehicles, there is a pressing need for further progress to minimize non-essential message transmissions and channel congestion in the ITS band.

Of all V2X messages, continuously transmitted CAM is the most essential for ITS. It lays the foundation for cooperative awareness between vehicles in close proximity and enables a variety of safety-related applications such as Forward Collision Warning (FCW) and Left Turn Assist (LTA). Because CAM is broadcast continuously on all vehicles, it creates a significant channel load. For this reason, congestion control for CAM (or Basic Safety Message (BSM) in the US) has been standardized on the access layer since the early days of V2X communication [1,2], not to mention numerous other congestion control algorithms proposed so far.

In contrast to many congestion control algorithms for the access layer, there is only one that is designed for the facilities layer. It is the *CAM generation rule*, standardized in European Telecommunications Standards Institute (ETSI) National Standards (EN) 302 637-2 [3]. Essentially, the rule allows the vehicle to transmit a CAM only when it is necessary for neighboring vehicles to track its movement by suppressing a periodic CAM that only reports minor vehicle dynamics (moving less than 4 m or turning less than 4° or accelerating less than 0.5 m/s since the last CAM transmission). It can be shown that this facilities layer congestion control mechanism that is more effective than any existing access layer congestion control mechanisms. For instance, McCarthy et al. [4] claim that it maintains the load under 20% in all vehicle densities,

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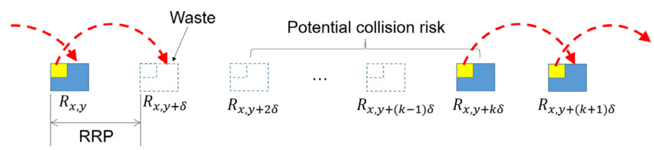



**Fig. 1.** Problems caused by CAM suppression at the facilities layer: dashed arrows are reservations, small box = Sidelink Control Information (SCI), large box = Transport Block (TB), dotted boxes = suppressed packets.

owing to the reduced speed in traffic congestion that leads to less CAM messages generated by the positional change.

Despite the superb channel load suppression performance, the problem of the CAM generation rule is that it does not fit well with the standard cellular V2X resource scheduling algorithm on the access layer. The sensing-based semi-persistent scheduling (SPS) algorithm for New Radio (NR) Sidelink Mode 2 is the standard algorithm to reserve a series of transmission resources for periodic traffic. In the absence of the facilities-layer message suppression, the access layer periodically generates the CAM using the reservations made at predefined resource reservation period (RRP). Even if the CAM generation rule operates on the facilities layer, the SPS algorithm on the access layer still makes periodic reservations for a CAM in case they need to be actually transmitted. Then, when an expected CAM is suppressed, it causes two problems (Fig. 1). First, the reserved CAM transmission resource (e.g. $R_{x,y+\delta}$) is wasted, where $\delta$ = RRP in slots that cannot be used by other vehicles because of the reservation published in $R_{x,y}$. Second, subsequently unused resources (e.g. $R_{x,y+i\delta}$, $2 \leq i \leq k$) will be mistaken by other vehicles as available. In case their (re)selection chooses one of these resources, packet collisions may occur over the next few RRPs. There is a newly added optional feature called *grant breaking* in 3GPP Release 16 [5] that is designed to mitigate the packet collision problem under aperiodic traffic. Unfortunately, its performance can be even lower than the original SPS [4] due to the increased unpredictability from more resource reselections.

In this article, we show that in real-life driving, CAM transmissions could hardly utilize the reservations made by the SPS algorithm and there were as many transmissions without the protection provided by a reservation. It is because most inter-CAM gaps in real-life driving is two or three times wider the original RRP of 100 ms [6]. However, we show that the CAM generation times can be predicted with high precision. Specifically, a Multi-Layer Perceptron (MLP) model that is trained through real-life CAM traces can achieve an average precision of over 94%. We believe that the prediction can be leveraged to make an explicit reservation at the next CAM transmission instant, avoiding resource waste and potential packet collision problems.

The contributions of this paper are as follows. First, a MLP model is developed to only use the dynamics of the ego vehicle as the input features without using those from neighboring vehicles. This increases the robustness of the model because it renders the prediction model independent of the vehicle topology around the ego vehicle. Second, the prediction model provides high accuracy (95%), which can be leveraged to make most transmissions protected by a reservation. It also opens a new possibility that the standard SPS algorithm can minimize costly resource reselections upon the transmission in the absence of a reservation.

## 2. Related work

The inefficiencies due to the newly allowed traffic aperiodicity in 3GPP Release 16 are a major concern in the cellular V2X communication. Bartoletti et al. [7] showed that a resource reselection can be forced, areserved resource can be wasted, or a latency larger than the packet delay budget can occur. If we cannot exploit the underlying message generation dynamics, McCarthy et al. [4] argued that even the random scheduling can outperform SPS as the latter is subject to wasting resources and potential collisions. They show that using Short Term Reservation (STR) [8] that was proposed in 3GPP performs best by reserving a resource just before the aperiodic transmission through a random access procedure. Although these can be valid approaches to pure aperiodic traffic whose packet generation times are unpredictable, the aperiodicity caused by packet-dropping CAM generation rule is not totally unpredictable.

Lusvarghi et al. [9] proposed to predict the CAM generation times under the CAM generation rule. By using the k-nearest neighbor (kNN) and the states of the ego vehicle and the vehicle immediately in front, they show that they can predict the next CAM generation times with more than 90% accuracy. Although their approach is similar to ours, there are differences. First, we only rely on the local information in the ego vehicle. Since there may or may not be a preceding vehicle in proximity of the ego vehicle, relying on other vehicles to define the input to kNN can be less robust. Second, we use a more efficient MLP representation than the kNN that may be difficult to use for real-time prediction.

Saad et al. [10] investigated the impact of sensing window size on the SPS performance for aperiodic traffic as produced by the CAM generation rule. The authors used reinforcement learning to find the optimal value of the sensing window size. Our work parts from this work in that we do not consider the reselections problem due to the untimely transmissions. In fact, we aim to minimize the reselections through accurately predicting the next CAM transmission time and reservating a resource there.

## 3. Machine learning for CAM time prediction

### 3.1. The CAM generation rule

Without the facilities-layer message suppression, the access layer periodically generates a CAM spaced at a resource reservation period (RRP) given by the application. However, it creates heavy channel utilization under high vehicle traffic densities. In Sidelink communication, the channel congestion may lead to packet collisions hence reduced communication reliability. In order to prevent this problem, the standard facilities-layer approach is to suppress the periodically transmitted CAM that reports only minor changes in vehicle kinematics. Only upon major changes that can significantly undermine the tracking of the vehicle, CAM messages are transmitted as planned. Specifically, a CAM is generated by a vehicle if it has changed the heading by more than 4° (e.g. during turning), the position by more than 4 m (e.g. during cruising), the speed by more than 0.5 m/s (e.g. during accelerating), or time elapsed by more than 1 s since the last CAM transmission. The triggering conditions must be checked at least once every 100 ms [3] because a CAM may be transmitted at up to 10 Hz.

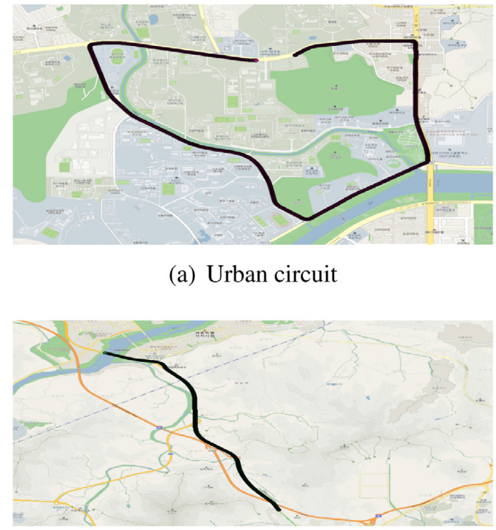
The CAM generation rule significantly reduces the channel utilization. To be shown later, most of the CAM messages are generated when the position changes by more than 4 m (Table 2). Traffic engineering shows that as the traffic density increases, the average vehicle speed decreases [11]. Without the CAM generation rule, increasing vehicle traffic density will proportionally increase the channel utilization. However, as the vehicle movement is limited by the vehicle traffic congestion on the road, the CAM generation rate by the position change condition is reduced. Consequently, McCarthy et al. [4] even showed that at any given vehicle traffic density, the channel utilization under the CAM generation rule stays at less than 20% of channel capacity.

### 3.2. Real-life driving trajectories dataset

In order to accurately predict the next CAM instant, we exploit the current vehicle dynamics information. It is because the next CAM instant depends on which triggering condition applies next. Unfortunately, there are no public CAM traces that record both the CAM type and the time gap between consecutive CAM messages so that we can use them for training the neural network. Therefore, we generated our own CAM traces from real-life driving trajectories so that they contain both the CAM type and the time gap. For the trajectories, we use the high-precision Electronics and Telecommunications Research Institute of Korea (ETRI) dataset that has 10 driving trajectories over two disparate driving paths as shown in Fig. 2 [12]. Each trajectory has the time series of vehicle positions of the data-collecting vehicle. Three of the trajectories were collected on an urban circuit that has multiple turns and traffic lights, whose map is given in Fig. 2(a). The trajectories were produced with different driving directions. The other seven trajectories were collected on a comparatively straight path that spans suburban area, as shown in Fig. 2(b). A Hyundai G80 was equipped with a GPS/IMU device (Spatial FOG Dual) positioned over the center of the rear axel. In order to correct the GPS error, Real-Time Kinematic (RTK) was used with the horizontal and vertical position accuracy of 0.008 m and 0.015 m, respectively. A vehicle position data point was recorded every 100 ms of the driving duration.

### 3.3. Data preprocessing

Since the trace is simply composed of GPS coordinates recorded every 100 ms, we need to process it to obtain the input features. The time and position are given, but we need to compute the heading and speed from two consecutive coordinates. For the former, the two consecutive GPS coordinates are first translated into radian, i.e., $(x_1, y_1)$ and $(x_2, y_2)$. Then, they are used to compute the bearing $h$ as $\operatorname{atan2}(\sin(y_2 - y_1) \cdot \cos x_2, \cos x_1 \cdot \sin x_2 - \sin x_1 \cdot \cos x_2 \cdot \cos(y_2 - y_1))$. To compute the position change $\Delta p$ from $(x_1, y_1)$ and $(x_2, y_2)$, we use the Pythagorean method. The instantaneous speed $s$ is given by dividing $\Delta p$ by the step size, i.e., 100 ms. Then the speed change ($\Delta s$) and heading change ($\Delta h$) for each data point are obtained from the difference from the previous one. Finally, we run the CAM generation rule over the preprocessed entries. If an entry satisfies the CAM generation condition, we assign a label as the time gap between the entry and the next entry that will generate a CAM. We collect only these labeled entries for training the MLP. A snippet from the CAM trace is shown in Table 1. The leftmost column is the check number. The second column is the time gap between the last CAM and the current time, and other columns besides the last track the vehicle kinematics since the last CAM transmission except the last column. The rightmost column is the reason for the CAM transmission. In the example snippet, most CAM messages are triggered by the $\Delta p$ condition and/or the $\Delta s$ condition, but not by $\Delta h$ or by the 1-second timer expiry. Note that multiple triggering conditions can occur at the same time, e.g. check #40 where both $\Delta p$ and $\Delta s$ exceeded their thresholds.



(a) Urban circuit

(b) Suburban road

**Fig. 2.** Driving paths in Daejon, Korea, from where the driving trajectories were collected.

Although not as much as in McCarthy et al. [4], the CAM generation rule suppresses close to 70% of all CAM messages in the ETRI traces. Table 2 shows the composition of CAM types that are produced after the CAM generation rule is applied. In this paper, all CAM messages involving speed changes as well as other triggering conditions are classified as speed-change CAM messages. We notice that most CAM messages are generated by the position change.

**Table 1**
CAM trace generated from the ETRI trace (in part).

| # | $\Delta t$ [ms] | $\Delta p$ [m] | $\Delta s$ [m/s] | $\Delta h$ [°] | Trigger |
|---|---|---|---|---|---|
| ... | | ... | | | ... |
| 40 | 700 | 4.571 | 0.644 | 1.431 | $\Delta p$, $\Delta s$ |
| 45 | 500 | 3.568 | 0.525 | 0.388 | $\Delta s$ |
| 51 | 600 | 4.543 | 0.309 | 0.130 | $\Delta p$ |
| 62 | 500 | 4.194 | 0.421 | 1.086 | $\Delta p$ |
| 66 | 400 | 3.578 | 0.570 | 1.289 | $\Delta s$ |
| ... | | ... | | | ... |

**Table 2**
Five CAM types unfiltered by the CAM generation rule.

| CAM type | $\Delta p$ | $\Delta s$ | $\Delta t$ | $\Delta h$ | Other |
|---|---|---|---|---|---|
| Fraction [%] | 83.27 | 9.51 | 6.32 | 0.89 | 0.01 |

### 3.4. Neural network model

The idea behind the proposed CAM prediction scheme is that the vehicle kinematics is not random, but constrained by the physics of the vehicle movement. The CAM generation rule captures the kinematics and deterministically produces CAM messages. Therefore, there must be an underlying pattern, albeit complex, which a neural network (NN) model can capture. Among NN techniques, we apply Multi-Layer Perceptron (MLP) in this paper to predict the next CAM generation time.

For the MLP model, we define the state of the vehicle at each checkpoint that leads to a CAM generation as:

$$\mathbf{X} = [\Delta t, \Delta p, \Delta s, \Delta h, \gamma_1, \gamma_2, \gamma_3, \gamma_4, \gamma_5]$$

where $\gamma_i$ $(1 \le i \le 5)$ indicates the CAM trigger condition as we saw in Table 1. The triggering condition is represented as a 1-hot vector, where each trigger has a position in the order of $\Delta s, \Delta t, -\Delta s, \Delta h, \Delta p$. For example, a CAM generated for a negative speed change of over $-0.5$ m/s is coded as $(\gamma_1, \gamma_2, \gamma_3, \gamma_4, \gamma_5) = (0, 0, 1, 0, 0)$. On each CAM generation, the vehicle state $\mathbf{X}$ is input to the MLP that outputs a prediction $\mathbf{Y}$. The output $\mathbf{Y}$ is the time prediction of the next CAM where $Y_k$ $(0 \le k \le 9)$ corresponds to $(k+1)\cdot 100$ ms. The MLP model is shown in Fig. 3. It has input, output, and three hidden layers. The employed activation function is ReLU. The size of the model in terms of the occupied memory size is 246 kB. Each classification operation takes approximately 3.9 ms on a PC platform.

### 3.5. Training

To train the MLP model, we merge all entries of the 10 CAM traces produced from the 10 ETRI trajectories. We shuffle the entries and split them into the training, validation, and test sets with ratio 0.7:0.15:0.15. We used a batch size of 40, and stopped training the model at 65th epoch. Adam and cross-entropy are adopted as the optimizer and the loss function, respectively. The initial learning rate was set to 0.001, which decays with $\gamma = 0.8$ at the step size of 10.

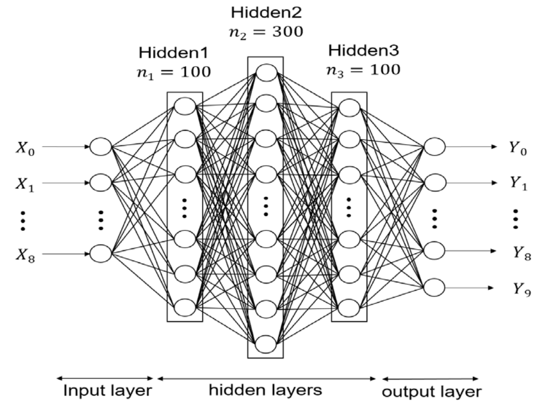



**Fig. 3.** MLP classifier for CAM generation time prediction.

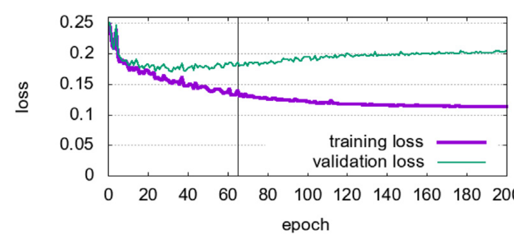



**Fig. 4.** Training and validation losses.

After 65 epochs, the training loss was 0.139 where the training accuracy was 95.1%. The validation loss was 0.186, where the validation accuracy was 94.7%. These losses are depicted in Fig. 4. The early stopping criterion was based on the validation accuracy with the patience set to 30 epochs.

## 4. Performance evaluation

We assume that the standard SPS allocates a transmission resource every 100 ms, some of which will be wasted due to the CAM generation rule. Below, we count wasted resources and unprotected transmissions (see Fig. 1), and compare them in the standard SPS and the proposed scheme.

### 4.1. Prediction accuracy

The overall accuracy of the prediction against the test set was approximately 95%, which is comparable to the training accuracy. The high accuracy means that the resource reservation based on these predictions will be able to cope with most aperiodicity caused by the CAM generation rule. Fig. 5 shows the confusion matrix. Most time gaps between CAM messages are concentrated on 200 ms and 300 ms. This characteristic is also observed in another real-life CAM traces from the CAR-2-CAR consortium [6]. For them, prediction accuracy close to 97% is obtained. Larger time gaps are increasingly difficult to predict. For 400 ms, the accuracy is 85%, and for even larger gaps, they are slightly over 47%. The lower accuracies mainly stem from the scarcity of training samples. At the largest gap of 1000 ms (i.e., CAM generated by the 1-second timer expiry), however, the prediction accuracy is 99.4%.

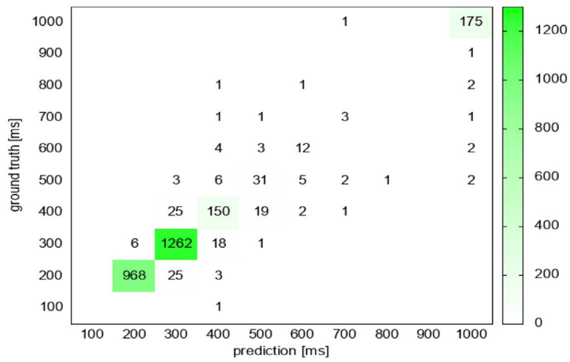



**Fig. 5.** Confusion matrix for the MLP model test result; 0-values are not shown.

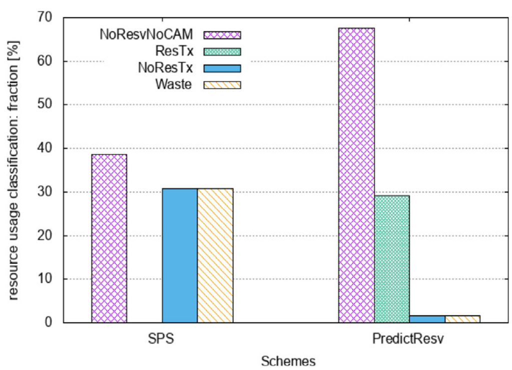



**Fig. 6.** Comparison of SPS and proposed schemes in terms of resource wastes and unprotected transmissions.

### *4.2. Wastes and packet collision-risking transmissions*

Fig. 6 compares SPS with the proposed scheme that we call 'PredictResv' where a resource reservation is made where the MLP model predicts. For each scheme, the figure presents four fractions: (1) suppressed CAM messages at unreserved resource locations ('NoResvNoCAM'), (2) transmissions protected by a reservation ('ResTx'), (3) transmissions not protected by a reservation ('NoResTx') and (4) resource waste by reserving at an unused location. The result shows that few in SPS are transmitted at a reserved location. This is because the inter-CAM gaps are mostly 200 or 300 ms (Fig. 5). Gaps of 100 ms are less than 0.1% in our trace. The small fraction of 100 ms inter-CAM gap is also observed in the CAR-2-CAR traces where it is only 2%–4% [6]. Moreover, for the same reason, these unprotected packets also make as many unused reservations at an RRP of 100 ms. In contrast, 'PredictResv' turns most of the unprotected transmissions into reserved ones, protecting them from potential packet collisions. Only for the small number of prediction errors do the unprotected transmissions occur. Furthermore, resource wastes are all but eliminated.

### *4.3. Discussion*

The high accuracy that we obtain through the neural network model opens a new possibility that SPS can reserve a resource with a dynamically changing time gap. It may well replace the standard procedure that triggers a resource reselection upon a transmission in the absence of a reserved resource, which is known to raise the packet collision probability in SPS due to the lowered predictability of resource use patterns.

We could consider further improving the prediction accuracy by observing the patterns that more than 70% of the prediction errors are either + 100 ms or −100 ms away from the ground truth (Fig. 5) and speed CAM times are most difficult to predict. Considering that the CAM generation rule drastically lowers the channel utilization [4], we could afford to selectively add provisional resource reservations. When the speed CAM transmission takes place, the resource reservations at ±100 ms of the predicted location can be made by using the two resource pointers to reserve future resources as currently studied in Release 17 [13].

## 5. Conclusion

The CAM generation rule on the facilities layer and packet dropping on the access-layer are a promising approach to coping with the channel congestion in future cellular V2X communication. However, its aperiodicity problem must be solved to avoid resource waste and potential packet collisions. This paper shows that for most vehicle movements, prediction accuracy of close to 95% as to the next CAM generation time is possible through machine learning from the real-life vehicle trajectories. Occasional prediction errors mostly stem from vehicle speed changes, off by one check interval. The proposed scheme could be utilized by scheduling so that a resource at the next predicted time of CAM transmission can be made for protected transmission while minimizing resource waste.

## CRediT authorship contribution statement

**Hyeonji Seon:** Data curation, Investigation, Methodology, Software, Visualization, Writing – original draft. **Hojeong Lee:** Investigation, Methodology, Software, Visualization, Writing – original draft. **Hyogon Kim:** Conceptualization, Formal analysis, Funding acquisition, Project administration, Resources, Supervision, Validation, Writing – review & editing.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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