Packet Delivery Impact of Predictive Resource Allocation for Quasi-Periodic Cellular V2X Communication

Hyeonji Seon, Hojeong Lee and Hyogon Kim

***Abstract*—The channel width for Intelligent Transportation System (ITS) band for vehicle-to-everything (V2X) system is expected to be relatively narrow. It implies that effective congestion control mechanisms will be essential. A well-established standard mechanism is the Cooperative Awareness Message (CAM) generation rule that drops unnecessary periodic beacons. Dropping packets from a periodic packet stream produces a non-periodic traffic. It renders the distributed Semi-Persistent Scheduling (SPS) algorithm exposed to resource waste and packet collision problems. The problems can be tackled by supplementing SPS with machine learning (ML) that predicts the transmission times of non-dropped CAM packets and reserves a transmit resource at the predicted time. The proposed approach is shown to significantly extend the distance up to which the target packet reception ratio (PRR) is met, compared to the current SPS algorithm.**

***Index Terms*—V2X, congestion control, quasi-periodic traffic, prediction, deep learning, packet reception ratio (PRR)**

I. Introduction

In most countries, the bandwidth allocated for Intelligent Transportation Systems (ITS) is typically no more than 30 MHz. A higher frequency band from the millimeter wave range may be added in the future, but its blocking and coverage characteristics make its suitability questionable for ITS' most fundamental application, i.e., 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 vehicle-to-everything (V2X) messages, continuously transmitted Cooperative Awareness Message (CAM) is the most essential one for intelligent transportation systems (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 periodically broadcast by all vehicles (e.g. at 10 Hz), it creates 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 would report only minor vehicle movements (moving less than 4 m or turning less than 4° or accelerating less than 0.5 m/s since the last CAM transmission). In all cases, the CAM should be transmitted at least once every second. It can be shown that this facilities layer congestion control mechanism is more effective than any existing access layer congestion control mechanisms. For instance, McCarthy et al. [4] claims that it maintains the load under 20% in all vehicle densities, owing to the reduced speed in traffic congestion that leads to less CAM messages generated by the positional change.

Access layer or facilities layer, these mechanisms change a periodic packet stream into non-periodic traffic by knocking out some packets. In this article, we will call the resulting traffic *quasi-periodic* because it is not purely non-periodic but retains some residual periodicity information, with inter-packet gaps being multiples of a single period. By breaking the periodic feature of the original CAM traffic, the quasi-periodic traffic negatively affects the standard Sensing-Based Semi-Persistent Scheduling (SPS) algorithm [5] that allocates periodic transmit resources for CAM packets. Fig. 1 provides an illustrative example. Suppose the periodically reserved transmit resources $[R_{x,y+2\delta} : R_{x,y+(k-1)\delta}]$ where x is the frequency index and y is the time slot are not used because the packets scheduled for them were knocked out by the congestion control. Then we face two problems. First, $R_{x,y+2\delta}$ has been explicitly reserved (marked by dotted arrow) by $R_{x,y+\delta}$ that it cannot be used by other vehicles and wasted. Second, $R_{x,y+i\delta}$ $(3 \leq i \leq k)$ apparently look unreserved although they are not. If some other vehicle decides to select one of them and begins a series of CAM transmissions with the same resource reservation period (RRP) δ, they will collide with the ego vehicle transmissions at $R_{x,y+k\delta}$ and on.

In this paper, we show that in real-life driving, CAM

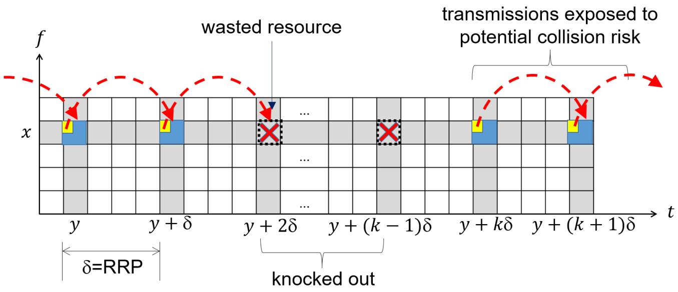


Fig. 1. Problems raised by CAM drops at the facilities layer: dashed arrows = reservations, small box = Sidelink Control Information (SCI) in Physical Sidelink Control Channel (PSCCH), large box = Transport Block (TB) in Physical Sidelink Shared Channel (PSSCH), dotted boxes = dropped packets.

transmissions surviving the CAM generation rule indeed suffer from the resource waste and the increased packet collisions problems. Specifically, the surviving CAM packets can rarely 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, the problems can be solved through precisely predicting the irregular inter-CAM gaps produced by the CAM generation rule. We show in this paper that a Multi-Layer Perceptron (MLP) model that is trained through real-life CAM traces can achieve an average precision of over 94%. We then leverage the prediction 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 summarized as follows.

- A high-precision MLP predictor of inter-CAM gaps is developed to only use the dynamics of the ego vehicle as the input features without using any 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.
- The prediction model is leveraged to make most transmissions protected by a reservation. It raises the packet reception probability (PRR) through reduced packet collisions, and extending the inter-vehicle distance over which a target PRR is satisfied.

The rest of the paper is organized as follows. Section II briefly introduces existing proposals to address the non-periodic traffic. Section III discusses the MLP model that predicts the inter-CAM gaps based on the vehicle movement since the last CAM and the type of the last CAM. It also discusses how the standard SPS algorithm can be modified to use the RRP field in the Sidelink Control Information (SCI) more flexibly, by encoding the next predicted inter-CAM gap in the field instead of the original RRP used for periodic resource scheduling. Section IV conducts simulation experiments based on the real-life driving trajectories to assess the packet reception ratio (PRR) improvement enabled by the proposed predictive resource scheduling. It shows that the communication range over which a target PRR is satisfied is significantly increased under various vehicle traffic densities. Finally, Section V concludes the paper.

II. Related Work

Even for periodic traffic, problems arise when the resource reservation period and packet generation interval are not in sync. Depending on which comes first, a resource reselection can be forced, a reserved resource can be wasted, or a latency larger than the packet delay budget can occur [7]. The inefficient resource utilization further aggravated by the newly allowed traffic aperiodicity in 3GPP Release 16 is a major concern in the cellular V2X communication as duly noticed in recent works. In particular, resource allocation becomes more difficult. If we cannot exploit the underlying message generation dynamics, McCarthy et al. [4] argued that even the random scheduling can outperform SPS. Consequently, there are discussions to upgrade the 3GPP standard, through incorporating such mechanisms as Short Term Reservation (STR) [8] that dynamically reserves resource only shortly before an aperiodic transmission through a random access procedure. When an aperiodic packet is ready, a reservation is transmitted at a random resource location. If it does not collide with other transmissions, the reservation succeeds, and the packet can be transmitted at the reserved resource location without collision. Such proposals could be effective for purely aperiodic traffic. However, the aperiodic traffic caused by the packet drops in the CAM generation rule is not completely unpredictable. In fact, it is produced by the interplay between the vehicle dynamics and the deterministic CAM generation rule that machine learning (ML) can predict the next CAM generation instant with high precision [9], [10]. Our previous work [9] showed that an MLP model can achieve 95% prediction accuracy for the next CAM generation interval, but it did not show how the prediction can be leveraged for resource reservation. Lusvarghi et al. [10] showed that k-nearest neighbor (kNN) can achieve over 90% accuracy in the prediction. By reserving resources at the predicted time, the packet reception ratio (PRR) can be visibly improved over the standard SPS. 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 the 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 deep neural network representation than the kNN that requires heavy computation for distance comparison for every classification operation. The kNN-based approach may be difficult to use for real-time prediction of CAM generation times.

III. Predicting and Reserving for the Next CAM

A. Prediction by machine learning

A solution approach to the resource waste and packet collision problems stated above is to accurately identify the next resource location where a CAM transmission will actually occur (e.g. $R_{x,y+k\delta}$ in Fig. 1), and protect it by explicitly reserving it through the current CAM transmission at the resource $R_{x,y}$. Because an unused resources (e.g. $R_{x,y+2\delta}$) are not reserved, the resource waste is also avoided. In our previous work [9], we showed that the CAM transmission times under the CAM generation rule can indeed be predicted with high precision by using machine learning (ML). In particular, a Multi-Layer Perceptron (MLP) model that is trained through real-life CAM traces can achieve an average precision of over 95%. In this article, we show that if we leverage the prediction in resource scheduling, the packet delivery performance can be significantly improved over the standard SPS due to reduced packet collisions. For instance, on a very congested channel, SPS with the proposed prediction-based resource reservation can more than double the coverage to satisfy a given packet reception ratio (PRR) requirement, compared to the standard SPS algorithm. Under less congestion, the distance gain is decreased, but still remains over 30 meters.

Fig. 2 is the MLP model we train to predict the time of the next non-dropped CAM [9]. It has input, output, and three hidden layers. The employed activation function is Rectified Linear Unit (ReLU). The input to the MLP is the current state that is defined as

$$\mathbf{X} = [x_1, x_1, \ldots, x_9] = [\Delta t, \Delta p, \Delta s, \Delta h, \gamma_1, \gamma_2, \gamma_3, \gamma_4, \gamma_5].$$

Here, $\Delta t, \Delta p, \Delta s, \Delta h$ are respectively the time, position, speed, and heading offsets since the last transmitted CAM, and $\Gamma = [\gamma_1, \gamma_2, \gamma_3, \gamma_4, \gamma_5]$ is the 1-hot vector that indicates which condition ($\Delta t, \Delta p, \Delta s, \Delta h$, or other) caused the generation of the CAM in the CAM generation rule. The MLP model outputs a 1-hot vector $\mathbf{Y} = [y_1, y_2, \ldots, y_{10}]$ where y_j $(1 \leq j \leq 10)$ predicts the next non-dropped CAM at $j \cdot 100$ ms from the current time given that the CAM generation rule checks the CAM triggering conditions every 100 ms [3]. Since the maximum CAM transmission frequency is 10 Hz in the standard [3], smaller inter-CAM gaps need not be predicted by the model.

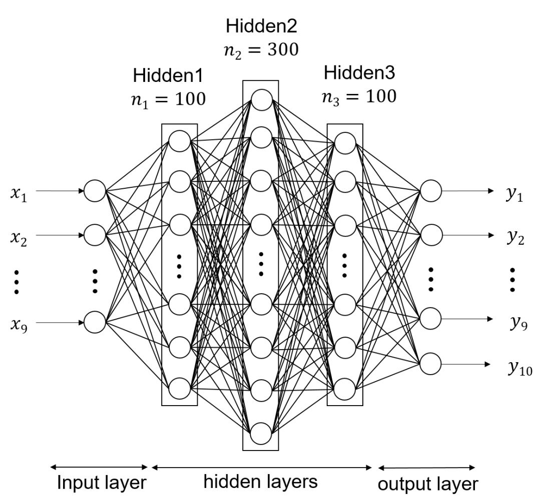
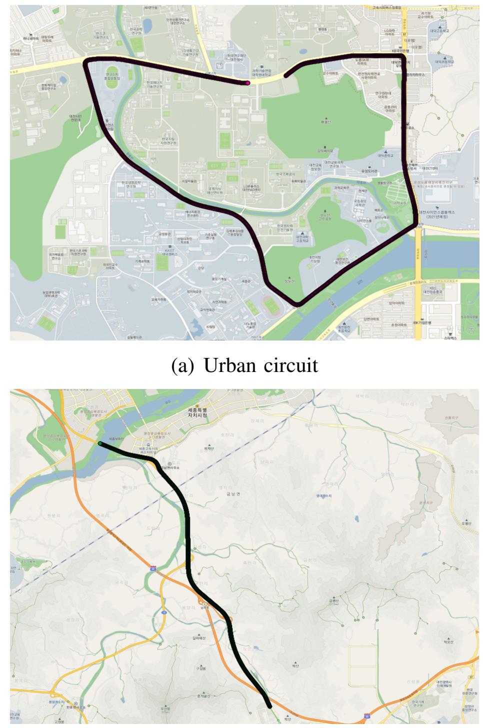


Fig. 2. MLP classifier for CAM generation time prediction.

The intuition 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. The MLP model is trained by the CAM trace that was generated from a real-life driving trajectory dataset [11]. The trajectory dataset was produced by driving on two different types of roads (Fig. 3) ten times.



(a) Urban circuit

(b) Suburban road

Fig. 3. Two types of roads in Daejon, Korea, from where the trajectories were collected.

B. *Predictive resource allocation*

In the current standard, the equally-paced resources are reserved in a daisy-chain manner by using the RRP field in the Sidelink Control Information (SCI). Namely, if the current frequency resource R_x is to be used k times, the RRP field of the CAM transmitted at the current time y is set to point at the next resource at $R_{x,y+\delta}$. When the next CAM is transmitted at $R_{x,y+\delta}$, a resource is in turn reserved at $R_{x,y+2\delta}$ and so on. This way, the reservation daisy chain extends each time a packet is transmitted until the chain reaches the randomly selected Reselection Counter (RC) which is signaled by the RRP value of 0, i.e., $R_{x,y} \rightarrow R_{x,y+\delta} \rightarrow \cdots R_{x,y+(RC-1)\delta} \rightarrow$ null. For RRP = 100 ms, the RC value is chosen in the range [5:15], after which a new frequency resource is reselected. The final RRP value of 0 signifies to other vehicles that R_x will be no longer used by the vehicle that no reservation is made for it. Then, other vehicles can (re)select the resource for their transmissions.

Within the current standard framework, the predictive resource reservation can be readily accommodated by substituting the MLP-predicted value for the original RRP value, in the RRP field of SCI. For instance, if 3δ (e.g. 300 ms) is predicted as the time gap by the MLP, we can code the value in the RRP field instead of the original RRP δ (e.g. 100 ms). Fig. 4 shows the proposed scheme. Notice that there is neither dangling reservation pointerm causing resource waste nor potential risk of consecutive packet collisions due to the vanished daisy chain pointer(s) as discussed in Fig. 1.

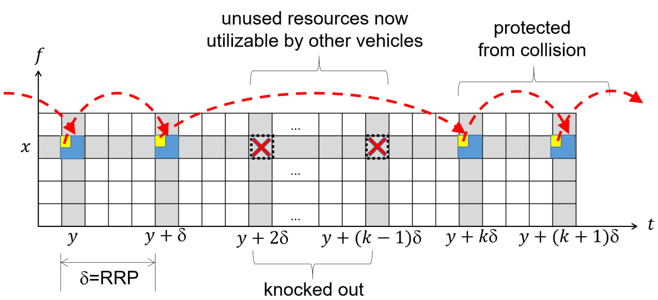


Fig. 4. Predictive resource reservation: RRP at $R_{x,y+\delta}$ is set according to the predicted gap $(k-1)\delta$ instead of δ.

IV. Performance Evaluation

In order to investigate the impact of the proposed scheme on the packet reception ratio (PRR) performance under quasi-periodic CAM traffic load, we conducted a simulation study across different CAM-transmitting vehicle traffic densities. We use LTEV2Vsim, an open source simulator, and Table I summarizes the simulation parameters configuration. We assumed that vehicles move along the multi-lane urban circuit in Fig. 3(a) as given in the trajectory dataset and transmit CAM packets as dictated by the CAM generation rule. We controlled only the inter-vehicle distance, using the exponential distribution with parameter that reflects the investigated traffic density $\rho = 300$, 200, or 100 vehicles/km, respectively. The bandwidth of the ITS channel is 10 MHz that has 5 subchannels. At the Modulation and Channel Coding Scheme (MCS) level of 7 and the CAM size assumed at 190 bytes, each CAM takes two subchannels. It allows two transmit (Tx) resources per time slot. For medium access control (MAC), 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. CAM packets are originally generated at 10 Hz by the basic safety service, but are knocked out by the CAM generation rule according to the vehicle movements.

Fig. 5 presents the packet reception ratio (PRR) values for SPS with ('SPS') and without the predictive reservation ('PredResv') for the quasi-periodic traffic produced by the CAM generation rule. The PRR performance is affected by both the transmitter-receiver (Tx-Rx) distance and the traffic density ρ. For all traffic densities, we notice that the predictive reservation improves the PRR. Moreover, the PRR gap

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)
	Message size	190 bytes
	Max. awareness range	370 m
Road	Topology	Trajectory data (Fig. 3)
	Traffic density	100,200,300 veh./km

between the SPS and PredResv increases in the traffic density.

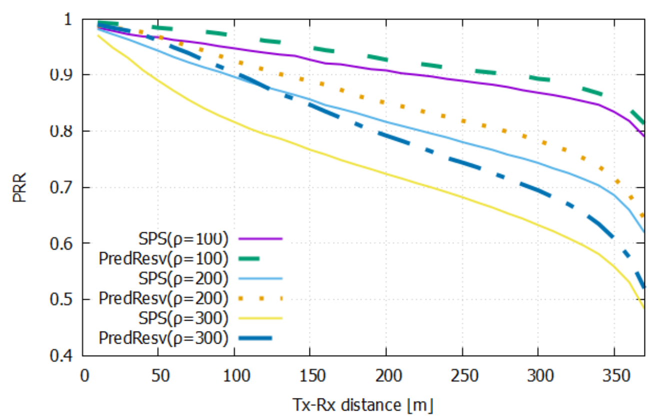


Fig. 5. PRR as a function of Tx-Rx distance.

The PRR gaps shown in Fig. 5 could look deceivingly small, especially when the traffic density is lower, e.g. at $\rho = 100$ veh./km. However, they should not be underestimated, and are illuminated from a different angle in Fig. 6. For V2X safety applications, it is important to deliver messages up to a predefined range at a required delivery probability. The former differs for different applications. For the latter, the minimum delivery probability for any safety application is at least 90%, while higher values such as 99% or 99.99% are required for more critical applications [12]. Fig. 6 compares the range from the transmitter (Tx) within which the given target PRR (ϕ) is satisfied. For $\phi = 99\%$ (98% if 99% not achievable), 95% and 90% we marked the feasible ranges with a circle (PredResv) and a square (standard SPS). We notice that the proposed enhancement supports a larger coverage than the vanilla SPS for any required PRR target. For the traffic density $\rho = 100$ veh./km, SPS cannot satisfy $\phi = 99\%$ at any distance. Even $\phi = 98\%$ can be achieved only at shorter distances than where the PredResv achieves 99%. As we increase ρ, the range gaps between the two compared schemes remain significant. At the most severe traffic congestion level $\rho = 300$ veh./km, the range gap for $\phi = 90\%$ is as large as 60 meters, where SPS achieves just over 40 meters while PredResv, over 100 meters. Neither scheme can satisfy $\phi = 99\%$ at this egregious traffic density, but PredResv can satisfy $\phi = 98\%$ which SPS cannot. This result shows that when the contention for resource rises due to the high traffic density, removing the possibility of packet collisions and resource waste due to "no-shows" contributes to the packet delivery performance. By addressing these two issues, PredResv can contribute to pushing the PRR closer to the required levels [12] although further enhancements must be made to fully accomplish the requirements in all use cases.

V. Conclusion

The CAM generation rule on the facilities layer and packet drop on the access layer are among the most likely approaches to coping with the channel congestion in future cellular V2X communication. However, the resulting aperiodicity must be addressed to avoid resource waste and potential packet collisions. This article shows that by exploiting machine learning, SPS can be improved to cope with a dynamically changing time gap in the quasi-periodic traffic. Extensive simulation study reveals that such enhancement can significantly extend the coverage that satisfies a given reliability requirement in packet delivery.

Acknowledgments

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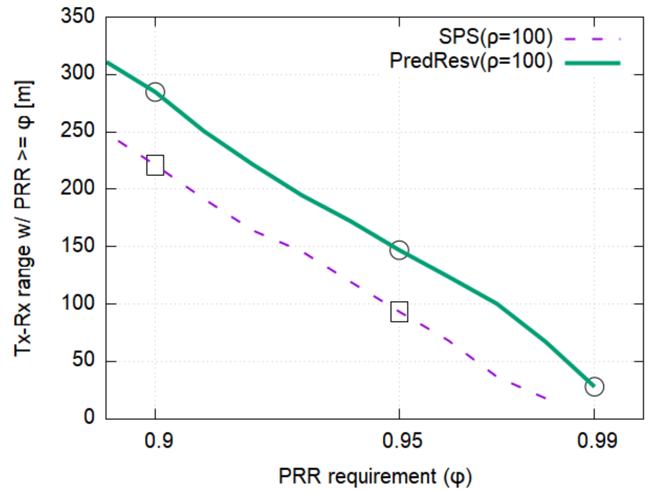
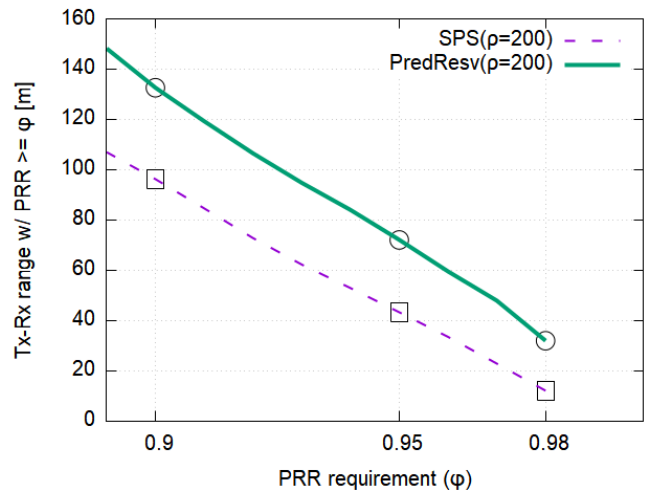
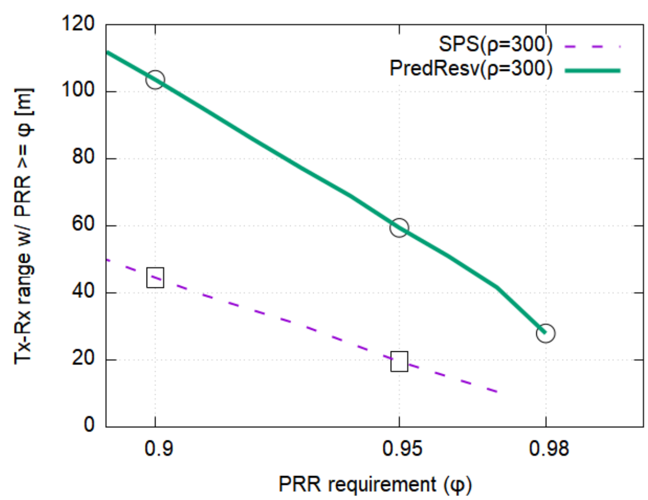


(a) PRR-satisfying range: $\rho = 100$ veh./km



(b) PRR-satisfying range: $\rho = 200$ veh./km



(c) PRR-satisfying range: $\rho = 300$ veh./km

Fig. 6. PRR comparison: with ('PredResv') and without ('SPS') predictive reservation.