Deep Learning-aided Resource Orchestration for Vehicular Safety Communication

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***Abstract*—IEEE 802.11p based V2X communication uses stochastic medium access control, which cannot prevent broadcast packet collision, in particular during high channel load. Wireless congestion control has been designed to keep the channel load at an optimal point. However, vehicles' lack of precise and granular knowledge about true channel activity, in time and space, makes it impossible to fully avoid packet collisions. In this paper, we propose a machine learning approach using deep neural network for learning vehicles' transmit patterns, and as such predicting future channel activity in space and time. We evaluate the performance of our proposal via simulation considering multiple safety-related V2X services involving heterogeneous transmit patterns. Our results show that predicting channel activity, and transmitting accordingly, reduces collisions and significantly improves communication performance.**

I. Introduction

Vehicle to Vehicle (V2V) and Vehicle to Infrastructure (V2I) communications are being deployed with a goal to improve traffic safety and transport efficiency. Initially a majority of the vehicular safety applications were only based on improving a vehicle's awareness of its vicinity by exchanging with its neighbors its position, speed, heading through periodically broadcasting Cooperative Awareness Messages (CAM) or Basic Safety Messages (BSM). Further along the road, V2X communication will be used for cooperative driving and navigation, when a variety of messages will be transmitted, as intelligent vehicles will negotiate and coordinate their maneuvers. This will require more reliable V2X communication mechanisms.

Among several potential wireless communication technologies, the technology being currently commercially available is called ITS-G5 in Europe and DRSC in the USA, with standardized PHY and MAC layers based on IEEE 802.11p.[1] In the ad-hoc mode of IEEE 802.11p, no centralized channel resource management is available. Each node is granted access in a stochastic way using a CSMA/CA mechanism. However, advanced applications such as Autonomous Driving and other Safety-V2X services will need highly reliable communication, which CSMA/CA-based medium access of IEEE 802.11p is not capable of providing. As the channel load increases, the communication performance of CSMA/CA also rapidly degrades, further affecting the performance of critical V2X services.

Wireless congestion control has been designed to prevent channel saturation, enabling each node to periodically monitor the channel load and adjust its transmit rate and power. However, collisions still occur due to the stochastic nature of CSMA/CA and near-far effects. As safety-V2X services mostly rely on broadcast traffic, packet collisions due to probabilistic channel access or due to hidden terminals can neither be detected nor fully avoided. Yet, what if an intelligent vehicle could precisely anticipate and predict neighboring vehicles' transmission, and accordingly orchestrate its own transmissions?

We address the possibility for a vehicle to learn, predict and transmit channel activities in order to avoid packet collisions. Assuming a vehicle can learn the transmit patters from 1-hop neighbors, it can precisely know the channel activity rather than sensing it. Thus, each node will know much better when to transmit and to avoid collisions with its neighbors. Moreover, if such a vehicle further shares such predicted channel activity with its 1-hop neighbors, it would enable farther away vehicles to learn the transmit patterns of hidden nodes. Accordingly, this would let each vehicle better orchestrate its transmissions, not only based on the slots used by its 1-hop neighbors, but also considering slots initially sensed 'idle' via carrier sense, but actually being occupied by hidden neighbors.

In a static and highly synchronous system, this can be easily optimized by coordinating the transmissions from different nodes. However, safety V2X communication scenarios are far from synchronous. They are rather highly dynamic, with aggressive node mobility, a varying neighbor density, a fluctuating channel load and subject to events triggered packet transmissions. In this regard, machine learning can be a useful tool for an intelligent vehicle to learn and predict its neighbors' transmit patterns for an optimized resource orchestration.

In this paper, we propose a novel approach to avoid packet collisions by learning and predicting neighboring transmissions using Recurrent Neural Networks (RNN) with Long and Short Term Memory (LSTM). Our contributions are threefold: (i) we highlight the challenges of ITS-G5 to sense

[1]The 3GPP LTE-V2X mode 4 is a promising alternative technology. Due to its ad-hoc nature, it bears similarities regarding the challenges discussed in this paper, and is expected also to benefit from the approach proposed in this paper.

idle resources in time and space. (ii) we propose a machine learning mechanism using deep neural network for learning and predicting neighbors' transmissions. (iii) using simulation based evaluation, we demonstrate that resource orchestration according to predicted channel activities can significantly reduce packet collisions and improve communication performance of safety V2X applications.

The rest of the paper is organized as follows: Section II discusses resource management and corresponding issues in IEEE 802.11p based vehicular networks. Section III presents our intelligent orchestration via machine learning. Section IV provides performance evaluation results, followed by a brief review of the state of the art in Section V. The conclusion and future work are discussed in Section VI.

II. Resource Management in IEEE 802.11p based Vehicular Network

Medium Access: The medium access of ITS-G5 and DSRC is based on IEEE 802.11 standards, where there is no centralized channel resource scheduler and each node acts in a decentralized way to contend for channel access. It employs a CSMA/CA listen before talk approach, i.e. if the channel is sensed free for a certain time the node transmits directly, otherwise the node chooses a random back-off window, which decreases each time the channel is sensed free. Transmission occurs when the countdown reaches zero. The random back-off value between 0 and CW is chosen to avoid simultaneous channel access by multiple nodes.

Transmit Rate Control: In CSMA/CA, when a unicast packet in not acknowledged, the contention window is increased. This reduces channel congestion by distributing the transmission attempts over a longer period. However, safety related vehicular communications involve packet broadcast without acknowledgments, so this contention window increase mechanism is not possible. To counter this problem, on top of CSMA/CA, there is additional flow control to limit the transmit rate of each node and reduce channel congestion. This mechanism is also known as Decentralized Congestion Control, or DCC in European Standards. Similarly in the USA, SAE has standardized a channel congestion control algorithm in SAE J2945/1 [1].

A. Issues with existing Approaches

Stochastic Medium Access: CSMA/CA attempts to minimize concurrent channel access by several nodes using a random back-off window, usually of a size between 0 to 15 slots. However, it is still probable for two nodes to obtain the same back-off window or same remaining back-off. Identical back-off results in simultaneous transmissions and collisions.

Lack of Spatial Resource Reuse: The presence of hidden nodes beyond the Carrier Sense range cannot be detected via Carrier Sense. This results in packet collisions and significantly deteriorates the communication performance as the node density increases. CSMA/CA cannot rely on spatial channel usage information beyond the Carrier Sense range. For example, if hidden nodes could transmit during different time slots, it could mitigate the problem of hidden node collisions.

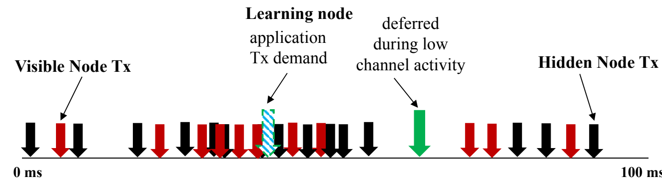

Fig. 1. Transmission deferred to period of low channel activity

Lack of a notion of Orchestration: The goal of CSMA/CA is to attribute channel access in a stochastic way to avoid concurrent transmissions by several nodes. Additionally during high channel load, transmit rate control limits the transmit rate of each node to prevent channel saturation. However, neither CSMA/CA nor transmit rate control aim to schedule or uniformly distribute the nodes transmissions along the time axis in a coordinated manner.

Channel Load calculation Granularity: Along the time axis, there can be periods of higher channel footprint during transmission bursts, when more nodes will contend for channel access. Although most transmissions are periodic or quasi-periodic during initial vehicular network deployment, some vehicles will have more advanced capabilities in the future. These vehicles will transmit multiple packets with different transmit patterns, which will result in variations of the channel footprint. This is impossible to observe by the present channel load measurement mechanisms. In the standards, the average channel load is calculated and smoothed using a FIR filter [2] over a 100ms window, while the vehicle is unaware of the granular channel activity during this window. This will degrade communication performance for future deployment scenario, involving heterogeneous and multiple safety applications per vehicle.

III. Intelligent Orchestration via Machine Learning

In this section, we present a learning node, which learns the channel activity during an observation window of 100ms and predicts neighbors' packet transmissions, packet size, type and the channel footprint for the next few windows of 100ms. The goal is to use the learned patterns of neighbors' packets to schedule one's own packets, depending on the application deadline, during periods of low or no channel activity, as shown schematically in Fig. 1.

The figure shows a typical prediction pattern of a learning node, predicting the time instances when neighbors will transmit during the next 100ms. The dotted arrow indicates that an application of the learning node needs to generate a packet at a certain point. However, according to the prediction pattern, a period of low channel footprint will be available in the current

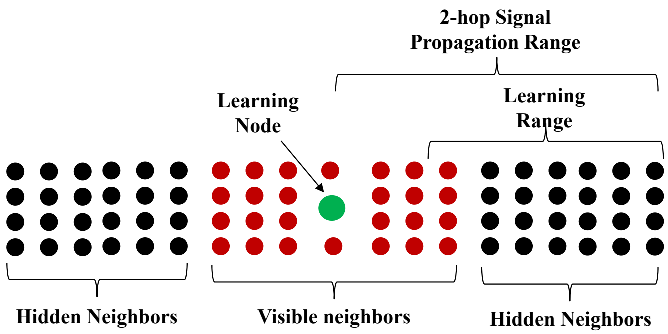

Fig. 2. Learning Distance of Intelligent Node

prediction window. Consequently, the application defers the packet generation and eventually generates and transmits the packet during a period of lower channel activity.

The tolerated delay of deferring a packet depends on the application requirement. The goal is to decrease the probability of concurrent transmissions, and avoid interfering with visible and hidden neighbors, while remaining within the packet transmission deadline requirement of the application.

The learning node monitors all received packets from visible neighbors and uses the packet reception history to predict its neighbors' future transmissions. Furthermore, each node piggybacks the packet reception pattern of its own neighbors, i.e. Neighbor ID, type of packet and reception time, inside the packets it transmits. Thanks to this piggybacking, the awareness of the learning node is extended and it becomes aware of the transmit patterns of hidden nodes as well. Although piggybacking adds extra transmission overhead in each packet, it is out of the scope of this paper. In future work we intend to analyze this overhead and increase the efficiency and scalability of such piggybacking.

Nevertheless, the number of neighbors a learning node can keep track of and predict their transmissions is limited. If a leaning node has to keep track of a large number of neighbors, such as in a scenario of high vehicle density, it becomes difficult to find vacant slots to schedule is own transmissions.

The set of 1-hop visible and 2-hop hidden neighbors that a learning node can keep track of has to be chosen optimally. Figure 2 shows a schematic scenario of learning during a high node density. In the figure, the green point indicates the learning node, the red points indicate the nodes visible to the learning node and the black points are the hidden nodes. In such scenario, the learning node prioritizes learning and predicting the transmit patterns of hidden nodes 2-hops away. As detailed in the next section, collisions due to hidden nodes play a more significant role in degrading communication performance, while potential collisions due to visible nodes are largely prevented by CSMA/CA.

A. Machine Learning for Predicting Neighbors' Transmissions

For predicting vehicular message transmissions, we use time-series prediction using RNN with LSTM. There are many algorithms for predicting sequential data, the earliest algorithm being AutoRegressive Integrated Moving Average (ARIMA). For most use cases, ARIMA or Hidden Markov Models (HMM) have become deprecated and have been replaced by RNN, for reasons outlined in [3].

The algorithms used to train HMM and vanilla RNN struggle to deal with many different inputs and to capture long term dependencies. For predicting messages from neighboring vehicles, the consequence would be that the influence of older messages on the current prediction would be ignored. LSTMs were designed to overcome this issue as discussed in [4]. For these reasons, we decided to use RNN with LSTM.

In terms of performance, deep learning is not an overkill in this use case, as the neural network is not that big and does not generate a large overhead. In this paper, we look at a simplified approach of using a time-series prediction for packet transmit patterns, for which other simpler machine learning technique could be enough. However, for future work, we will consider more advanced features, such as the impact of the CSMA/CA back-off window or cellular V2X slot allocation pattern, realistic node mobility model, signal propagation and channel model, or even the impact of wireless congestion control. Deep learning will be required to learn the complex interactions between these features.

B. Design of the Predictor

In order to predict messages from neighboring vehicles, the learning vehicle uses a *divide and conquer* approach. It maintains a sub-predictor instance for each neighbor, and predicts the neighbor's future packets based on the previous ones. The predictor is trained off-line, using the typical communication pattern of a vehicle. The sub-predictor uses one RNN for each type of packet.

The organization of the prediction program can be seen in Fig. 3. The main predictor keeps an active instance of the sub-predictor for each of the current neighbors. The sub-predictor handles all the packets received from a particular neighbor. It uses them to predict the next packet of each type from that neighbor. When a new packet is received by the sub-predictor, it pre-processes the packet to obtain the information used by the neural network and then feeds it to the corresponding neural network.

Periodically, every 100 milliseconds, the learning node inquires the predictor for the predicted packets for the next 100ms. The main predictor iterates through all the active instances of the sub-predictors to fetch packet predictions, and returns a complete list of future packet transmissions and the packet air time. After a time-to-live, if no more packets are received from a neighbor, the corresponding sub-predictor instance is deleted. This means that the neighbor has moved out of the learning node's communication range and is no longer relevant.

Although the learning node feeds the predictor and inquires future packet pattern every 100ms, the sub-predictors also consider older messages during prediction. The sub-predictors do not explicitly save the older messages, but the LSTMs have

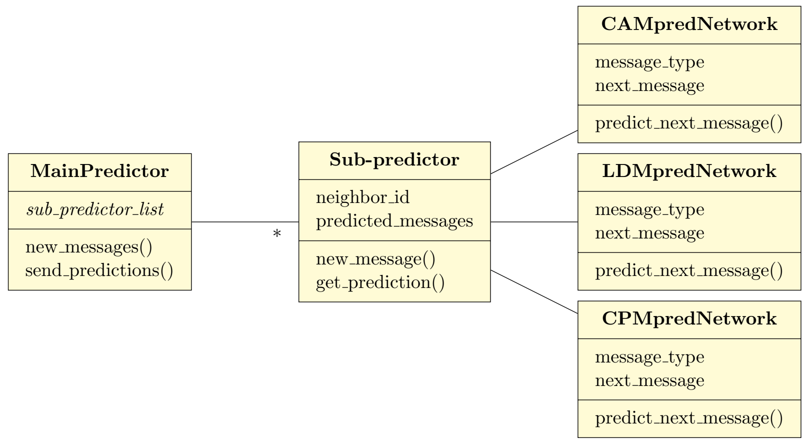

Fig. 3. Predictor Architecture

an internal state that acts as a memory, and the information needed for future predictions are saved in this state.

C. Features selection and preparation

The learning node predicts three types of packets transmitted by each neighbor, i.e. motion-event triggered and periodic Cooperative Awareness Messages (CAM), event triggered bursts of Cooperative Perception Message (CPM) and periodic exchange of High Definition Maps between vehicles, using a message called Local Dynamic Map (LDM). These packets are further explained in the next section.

For each type of packet, a separate neural network is used. Each neural network receives as input the time interval between the currently received packet and the previous packet of the same type from a particular neighbor. Conceptually, this means that the interval to the next packet is predicted using the interval between the two previous packets.

CAMs are triggered by a change in a vehicle's speed, direction or position, and the values of speed, direction and position of the CAM sender are contained inside the CAM. Values of vehicle dynamics and their gradients are also fed into the neural network. All these input features are normalized before being fed to the RNN. We use feature scaling to map the values between -1 and 1.

IV. Evaluation

We perform a simulation based evaluation to demonstrate the communication performance improvements achieved by learning and predicting neighbors' transmissions, and orchestrating transmissions during periods of low channel usage.

We analyze the effectiveness of our machine learning method in reducing collisions through the transmissions of visible nodes within 1-hop distance, and hidden nodes beyond the range of carrier sense (i.e. within 2-hop range). The Packet Reception Ratio (PRR) by all neighbors of the learning node as function of the distance is the primary metric of our performance evaluation.

A 10km long dense highway scenario is used, consisting of 50 vehicles/lane/km and 3 lanes in each direction. Vehicles move at speeds between 20 to 45 m/s, following a Gauss-Markov mobility model. The simulator used is called iTETRIS [5], which has a full ITS-G5 protocol stack implemented on top of NS-3.

We consider 3 types of packets (i) CAM (periodic 10Hz and motion triggered), (ii) CPM (bursts) and (iii) LDM (periodic). The European standard ETSI EN 302 637-2 [6], specifies that CAMs are generated as a function of changes in vehicle dynamics, either a 4m variation in position or a 4 degree change in heading or a 0.5m/s difference in speed. We also consider CAM transmitted at 10Hz, as a comparison point to Basic Safety Messages (SAE J2735 [7]) transmitted in the US at 10Hz.The CAM size is fixed to 300 Bytes.

CPMs are being standardized in ETSI TS 103 324 [8], and are triggered upon detection of new sensor data or road objects. In our simulation, CPMs are triggered following an uniform

TABLE I
SIMULATION PARAMETERS

Parameter	Value
Transmit Rate	CAM: 10 [Hz] & Triggered CPM: 5 [Hz], LDM: 1 [Hz]
Transmit Power	20 dBm
Packet Size	CAM: 300 Bytes, CPM 500 Bytes LDM: 750 Bytes
EDCA Packet Priority	CAM: Best Effort, CPM & LDM: Background
DataRate	6 Mbps
Mobility	3 by 3 lane 10 km highway Speed 20 to 45 [m/s] Gauss Markov, Memory level 0.95 Sampling period 0.1 [s]
Node Density	50 vehicles/lane/km
PHY and MAC	ITS-G5 802.11p in 5.9 GHz (10 MHz Control Channel)
Attenuation	Log Distance Path Loss
Preamble Detection Threshold	- 95 dBm
Neural Network	4 layers: 40, 50, 60 neurons & LSTM unit layer
Training	Off-line, ADAM algorithm Stochastic gradient descent
Performance Indicators	Packet Reception Ratio 50 runs, 95% Confidence Interval

TABLE II
AVERAGE CHANNEL LOAD FOR DIFFERENT TRANSMIT PATTERNS

Transmit Pattern	Average Channel Load
10 Hz CAM	65.35 %
Triggered CAM Higher Speed	50.74 %
Triggered Lower Speed	35.47 %
CAM + CPM	52.10 %
CAM + CPM + LDM	66.90 %

random distribution, where 5 messages are emitted in burts within 500ms. Unlike CAMs, CPMs are not mandatory and only vehicles with appropriate object detection capability will generate them. Thus, in our simulation, we only consider 50% of the nodes to emit CPMs with a fixed size 500 Bytes.

Lastly LDM as described in ETSI TR 102 863 [9], are messages intended to exchange HD maps data between cars. In our simulations, we considered LDMs to be emitted at 1 Hz with a fixed size of 750 Bytes. Each node starts transmission following an uniform random distribution, including a small jitter of 500μs during transmission of each packet. The results are averaged over 50 simulation runs with 95% Confidence Interval.

For machine learning and prediction, the LSTM with RNN have been implemented in tensorflow. The neural network consists of 4 hidden layers, with 40, 50 and 60 neurons and a LSTM unit layer. Without loss of generality, the configuration of the the neural network has been chosen empirically for this use case, to keep it large enough to capture the complexity of the data, and small enough to be trained efficiently.

The training is done using the ADAM Optimizer, with stochastic gradient descent. The batch size is 1 in order to capture the time dependencies between the packets. The training is done off-line using packets logged during simulation runs on highway scenarios. The prediction is done on-line during the run time as the learning node receives transmissions from its neighbors. Table I summarizes the main simulation parameters.

Figure 4 shows the Packet Reception Ratio (PRR) on the y-axis by the neighbors of the learning node when vehicles emit 10Hz CAMs, producing an average channel load of 65.35% as shown in Table II. The x-axis corresponds to the distance between the learning node and the receiving nodes.

As it can be seen, the case with no learning performs worse compared to when a node transmits according to predicted transmissions of its visible and hidden neighbors. The reception performance is improved a bit by predicting and avoiding concurrent transmissions with 1-hop visible neighbors. However, the performance improvement is the highest, when the learning node predicts the transmissions of hidden nodes. This indicates that collisions with hidden nodes play a more significant role than visible nodes in performance degradation .

Nevertheless, when the learning node predicts the transmissions of both 1-hop visible and 2-hop hidden nodes, the performance reduces a bit compared to the case with learning only hidden nodes. In the simulations, within a distance of a 2-hop signal propagation range, approximately 280 nodes in total are spread across 500m in both directions. In an attempt to avoid concurrent transmissions with such a high number of nodes, the learning node cannot find enough vacant periods to schedule its own transmissions before the packet TTL, and thus transmits immediately. Nevertheless, transmitting to avoid concurrent transmissions with only hidden nodes, produces an improvement of respectively 10% and 25% PRR at distances of 100m and 200m.

Figure 5 shows the PRR when CAMs are triggered according to vehicle dynamics. Compared to 10Hz transmission, the PRR is higher, as a velocity between 35 to 45 m/s triggers CAMs between 5 and 10Hz creating a lower channel load of 50.74% compared to a 65.35% channel load produced by the earlier 10Hz periodic CAMs scenario. A lower channel load results in lesser collisions, giving a better PRR. The

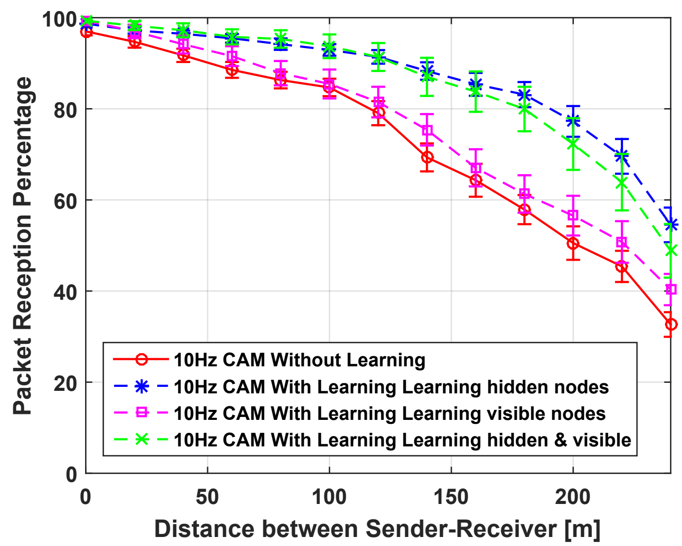

Fig. 4. Packet Reception Ratio of 10 Hz Periodic CAMs

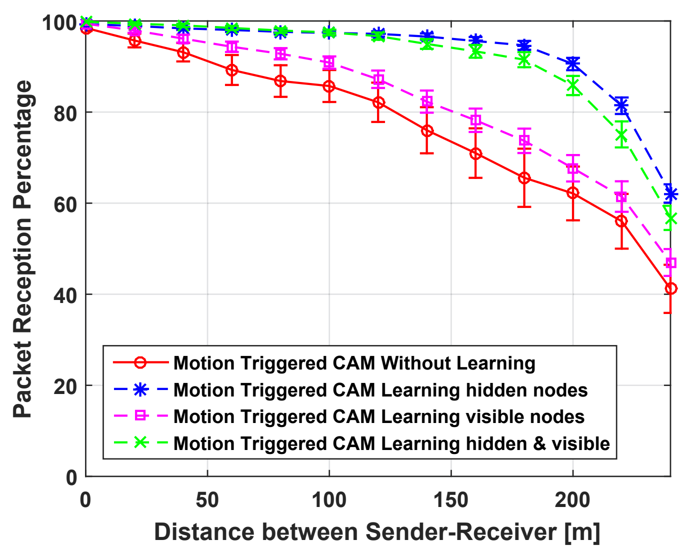

Fig. 5. Packet Reception Ratio of Triggered CAMs for vehicle speed of 35-45 m/s

trend is similar, i.e. learning only hidden nodes' transmissions performs the best, followed by learning both hidden and visible nodes, then learning only visible nodes. As expected, the no learning case performs the worst.

This trend continues when the channel load gets even lower at 35.47% for a velocity of 20-30m/s as shown in Fig. 6. However, at a low channel load of 35.47%, collisions with visible nodes are almost negligible, therefore learning transmissions of visible nodes only, provides no improvement. At a distance of 200m, learning induced PRR improvements is around 30% and 35% for channel loads of 50.74% and 35.47% respectively (i.e. for CAMs triggered at high and low speeds).

In addition to a single CAM application, we analyze the packet reception performance when 50% of the nodes emit Cooperative Perception Messages (CPM) to broadcast their sensor information. The PRR is shown in Fig. 7, when the learning node predicts the pattern of its hidden neighbors only and transmits accordingly. CPM being larger than CAMs, the combined CAM and CPM transmissions generate an average channel load of 52.1%.

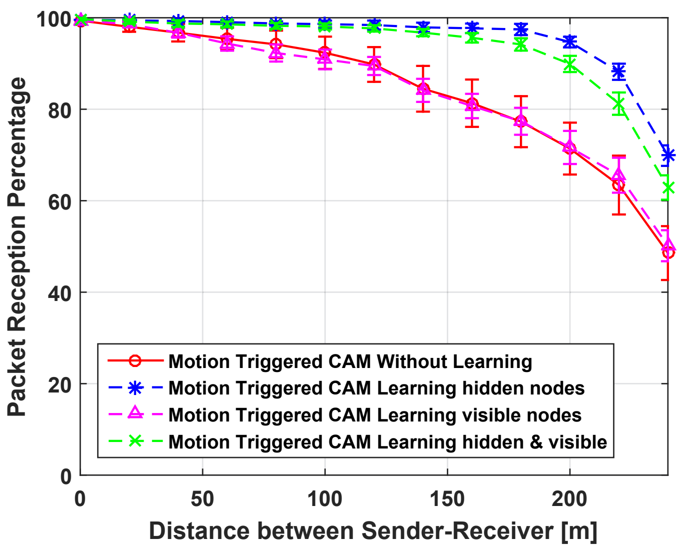

Fig. 6. Packet Reception Ratio of Triggered CAMs for vehicle speed of 20-30 m/s

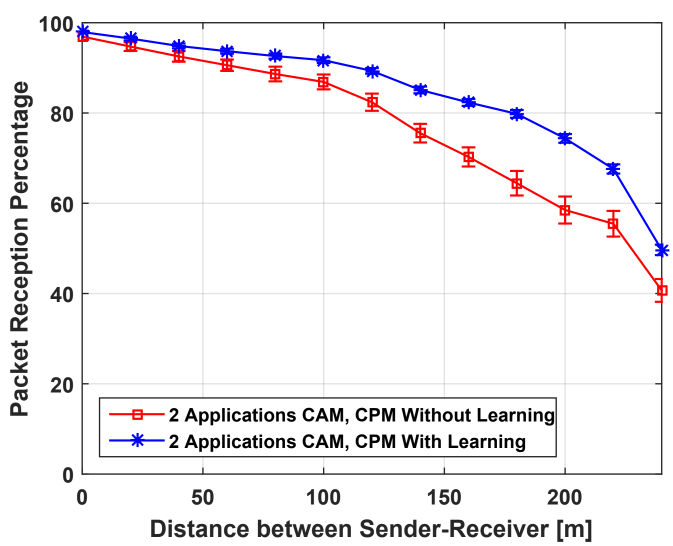

Fig. 7. Packet Reception Ratio of Two Applications CAM and CPM

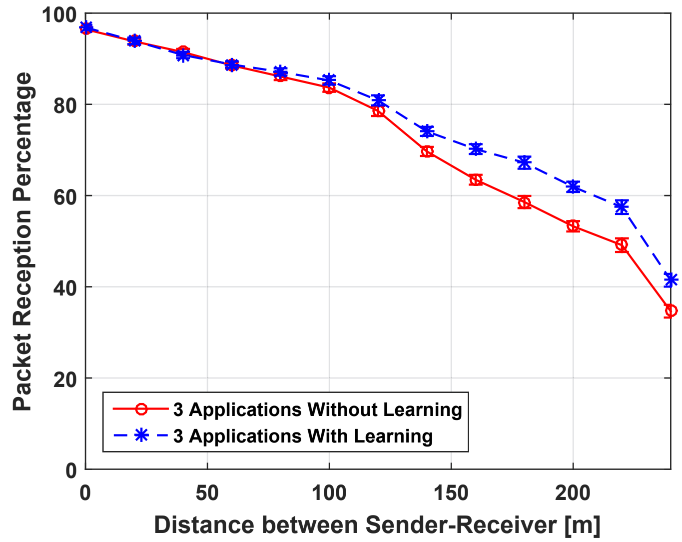

Fig. 8. Packet Reception Ratio of Three Applications CAM, CPM, LDM

However the reception performance improvement due to learning and predicting is less than the case with only CAMs. Unlike CAMs, CPMs are triggered randomly and 5 packets are emitted in a burst, making it difficult to predict the first packet of the burst. The prediction error degrades the orchestration performance, thus affecting the packet reception ratio. Nonetheless, the learning induced PRR improvements is 5% at 100m, and 18% at 200m respectively.

Lastly, Fig. 8 shows the PRR, when the nodes transmit 750 Bytes LDM packets along with CAMs and CPMs, producing a higher average channel load of around 66.9%. However, as the channel load increases, the performance improvement due to learning is less compared to the previous scenarios at lower channel loads. As mentioned before, at high channel loads, the learning node cannot find sufficient vacant windows of low channel activities to orchestrate its own packets before the application TTL, and thus transmits immediately. Nevertheless, at high channel load, the transmit rate control mechanism of the ETSI DCC is supposed to be activated to prevent such channel saturation, which has not been considered in this work. As part of our future work, we will investigate the behavior of the learning node along with transmit rate control at high channel loads.

V. Related work

A. *Medium Access Control for V2X Communication*

Over the years a plethora of medium access control protocols for vehicular communication have been proposed in literature. It can be broadly categorized as contention based and contention free [10]. Contention based algorithms involve

Carrier Sense Multiple Access (CSMA), random back-off and retransmission. The PHY and MAC layers of ITS-G5 and DSRC are based on IEEE 802.11p, involving contention-based medium access.

A promising alternative to DSRC/ITS-G5 is 3GPP LTE-V2X, which involves contention free medium access. It has been officially standardized in 2016 for safety-critical V2X communications, as described by Gallo & Härri [11]. It supports infrastructure-based (mode 3) and ad-hoc (mode 4) resource allocations.

For mode 3 LTE-V2X, no open specification exists for resource management, whereas a Listen-before-Talk (LBT) and Semi-Persistent scheduling mechanism has been standardized by the 3GPP for mode 4 (ad-hoc). Several works investigated its performance [12]–[15], compared it against ITS-G5/DSRC [16], or evaluated wireless congestion control mechanisms [17]. All these studies showed that the LTE-V2X mode 4 (ad-hoc) is subject to similar challenges as ITS-G5/DSRC, due to its distributed channel access control and near-far effects.

Similarly, other variations of medium access have been proposed in the literature, such as via Space Division Multiple Access (SDMA) or clustering nodes in geographic proximity, to handle mobility, limit channel contention, and implement spatial reuse of channel resource. The goal is to reduce interference among hidden nodes by allocating same slots to nodes sufficiently far apart [18].

Most of these aforementioned works have intended to optimize the MAC layer scheduling for a single type of packet, mainly single hop periodic broadcast of CAM/BSM, using a fixed packet frequency, packet size and traffic pattern. However, is future there will be heterogeneity of network traffic pattern. For example a highly autonomous vehicle will communicate more compared to a human driven vehicle. Some works have analyzed multiple packet types considering strict IEEE 802.11 EDCA priority [19]. However other works have found the limitations of MAC layer EDCA prioritization, in the ETSI ITS stack during scarce channel resource [20], [21].

In this work, our goal is not to introduce a new MAC protocol. Based on the standardized ITS-G5 MAC, we rather propose a multi-service/application resource orchestration at a higher layer in order to optimize packet generation and transmission effectively increasing the reception probability at the receivers.We propose a novel approach to reduce collisions and improve packet reception performance, by increasing a node's awareness of the channel usage via machine learning. We do not focus on the LTE-V2X technology in this work, but will evaluate the benefit of the proposed mechanism on it in future work.

B. Machine Learning for V2X Communication

Recently machine learning is being implemented for predicting various aspects of vehicular networking, such as node mobility, network connectivity, network congestion control, wireless resource management etc. Ide *et al.* [22] use Poisson regression trees to predict LTE network connectivity and vehicular traffic. Authors in [23] use deep reinforced learning to jointly optimize network resource allocation, caching and edge computing. In the domain of network congestion control, authors in [24] present a centralized controller to manage channel congestion at urban intersections using k-means clustering.

A survey of machine learning for vehicular network is presented in [25]. The survey highlights the challenges of adapting the existing ML methods to these new type of networks that are highly dynamic. Besides, the survey indicates the use of RNN with LSTM as an open issue to be solved, which we precisely address in this paper with a machine learning approach using RNN with LSTM.

Moreover, existing machine learning approaches for vehicular networking do not consider a fully decentralized ad-hoc network, which we analyze in this paper. Lastly, most road safety related communications in vehicular networks involve broadcast transmissions, which has not been sufficiently addressed in existing studies on machine learning for vehicular communication.

VI. Conclusion

In this paper, we have shown that using recurrent neural network, a *intelligent* vehicle can learn and predict the transmit patterns of its neighbors. This knowledge can then be used to orchestrate its own transmissions during periods of low channel activity, leading to improved packet reception. In particular, our deep learning aided resource orchestration showed to be able to perform best on detecting and avoiding collisions with hidden nodes. We further showed that recurrent neural networks can also learn the transmit patterns of multiple V2X messages, such as CAM, CPM and LDM altogether, and are able to provide a more efficient resource orchestration than a plain CSMA/CA scheduler.

Quite a few open challenges yet remain ahead. Firstly, piggybacking creates redundancy and extra transmission overhead, which has not been analyzed in this paper. Moreover, in a scenario with multiple learning nodes, the intelligence of each learning node has to be coordinated with other learning neighbors, also in a decentralized manner. Similarly, the global performance in a hybrid scenario consisting of a varying percentage of learning nodes, i.e. some nodes having learning capability, while other nodes do not, has to be investigated. Last but not the least, transmit rate control has to be incorporated with learning, which with no doubt will impact the learning efficiency. These are left to future work.

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