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Enhanced C-V2X Uplink Resource Allocation using Vehicle Maneuver Prediction

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***Abstract*—Cooperative driving is a promising technology in the future Connected Autonomous Vehicles (CAV) because of its benefits to safety and fuel efficiency. However, since CAV will be relying heavily on wireless communication to cooperatively coordinate road maneuvering, latency and reliability of communication still pose a challenge. In this paper, we propose a novel scheme based on deep learning prediction to enhance the uplink resource allocation process in 5G C-V2X. The proposed scheme enables the base station to predict vehicle maneuvers, subsequently, assign it the required resource in advance without the need for scheduling request and granting process. This scheme improved the ability of 5G NR to support cooperative driving requirements. Moreover, we compare both traditional and proposed schemes discussing issues that arise from the introduction of prediction models and possible approaches for further enhancements in the future.**

I. Introduction

Deploying autonomous vehicles (AV) in complex traffic is challenging and has many trade-offs. A major challenge is achieving more traffic without threatening the safety of human drivers. The AV must have the ability to make decisions such as when and how to change the lane, cross an intersection, or overtake another vehicle. To apply these decisions safely, the AV needs to communicate and coordinate with surrounding vehicles. Traditionally, vehicle-to-everything (V2X) communication has been utilized for information exchange required in cooperative driving. Two main technologies have been popularized to allow V2X, the cellular-based C-V2X and dedicated short-range communication (DRSC). DRSC technology is based on IEEE 802.11p standard which faces many challenges such as limited mobility support and limited bandwidth, which result in shortcomings in terms of reliability and latency [1], [2]. On the other hand, C-V2X is gaining a foothold with the 5G new radio (NR). NR is promising capabilities that can finally allow C-V2X based cooperative driving [3] because of the better support it can provide especially for safety-related applications [4]. Release 16 of 5G-NR [5] defines the service requirements for several enhanced C-V2X scenarios, e.g. cooperative lane change, trajectory alignment, and platooning. According to Release 16 specifications, to allow cooperative driving at the lowest degree of automation, the network must be able to support a success rate over 90% in packet delivery with a maximum allowed latency of 25 ms for 300-400 bytes of payload. This level of automation, typically includes transmitting only the intention of maneuvering, however, to reach a higher level of automation a vehicle is expected to transmit further information, e.g. estimated future trajectory and sensory data. To fully support cooperative driving at the maximum level of automation, service requirements increase up to 10 ms latency, 12KB payload, and 99% packet delivery rate. These strict constraints call for innovative techniques to enhance the efficiency of how resources are allocated in the next 5G releases. These techniques must aim at reducing as much overhead as possible while satisfying the latency and reliability requirements for cooperative driving tasks. Improving network resource allocation in cellular-based V2X communications has been extensively studied in the literature. A comprehensive survey on sharing resource blocks (RB) based on user clustering was presented in [6]. Hybrid schemes in which DRSC is used to assist C-V2X were proposed in [7] [8]. Authors in [9] used machine learning (ML) techniques in predicting vehicle trajectory. This prediction is then leveraged to optimize a handcrafted reward function designed for resource allocation. Although innovative, their work lacks in terms of relying on older 4G LTE C-V2X in their analysis. Moreover, it did not account for classifying the mobility traces into their corresponding maneuvers. Coordinating different maneuvers typically depends on the levels of automation adopted, hence different service requirements and payloads for the resource allocation task. Maneuver recognition models are typically classifiers that use past motion states of the vehicles as features. Random forest classifiers, bayesian methods, hidden Markov models, and recurrent neural networks(RNNs) have been used for maneuver recognition [10]–[13]. Many approaches take into consideration visual cues, such as but not limited to braking lights, to predict the future motion of the surrounding vehicles [14]–[17]. Other works, such as [10] and [18] implicitly learn vehicle interaction from trajectory data of real traffic, while combined schemes were proposed in [10], [19], [20]. In this paper, we adopt the latter approach by relying on vehicle trajectory data solely. A comprehensive survey of maneuver-based models can be found in [21], [14].

that relies on maneuver prediction or recognition to make appropriate decisions.

An important research direction in resource management is anticipatory scheduling. To the best of the authors' knowledge, no previous proposals were made to utilize maneuver predictions in network resource allocation. Therefore, in this paper, we propose an anticipatory resource allocation for connected vehicles that relies on maneuver prediction, based on which the required resources can be decided and assigned to the subject vehicle ahead of time. which is expected to improve the future C-V2X to support the safety requirements. More specifically, we propose a novel uplink resource allocation scheme relying on a deep learning-based maneuver prediction. In addition, we perform a sensitivity analysis to investigate the impacts of varying network loads as well as the classifier prediction horizon on packet latency and delivery rate under 5G network settings. Our contribution is outlined as follows:

1) Introducing a novel scheme that leverages deep learning prediction models to allow faster uplink resource allocation in 5G NR aiming at further support for AV applications under strict network conditions.
2) Creating a simulation environment to study the performance of 5G NR in terms of latency and reliability for exchanging maneuver information between onboard UEs installed on vehicular nodes. For this purpose, we use the requirements specified in Rel. 16 of 5G-NR.
3) Performing a sensitivity analysis to compare the performance of both traditional and proposed schemes and their ability to support AV safety constraints specified by the 3GPP standard.

The rest of the paper is organized as follows. We start with a brief discussion of previous research on resource allocation schemes and the prediction of maneuver intention in a vehicular environment. In section II the system architecture of the uplink granting is presented and a high-level description of our proposed scheme for resource allocation with comparison to traditional solutions. Then, we go into further details in the simulation environment and the proposed method for predicting the maneuver intention. Finally, we discuss the performance of both traditional and proposed schemes in terms of packet latency and transmission reliability and the ability to support the strict requirements of AVs under various network conditions.

II. System Architecture

Uplink resource granting in C-V2X could be performed using either semi-static or dynamic methods. In semi-static methods, the base station allocates periodic resources to a UE in advance, e.g., a UE may be asked to transmit in a given radio resource every X msec. The semi-static scheme is prone to waste of resources, hence, the use of dynamic grant schemes is more common in C-V2X. Dynamic schemes rely on a handshake protocol to allocate resources (see Fig. 1). First, the UE transmits a scheduling request (SR) to signal

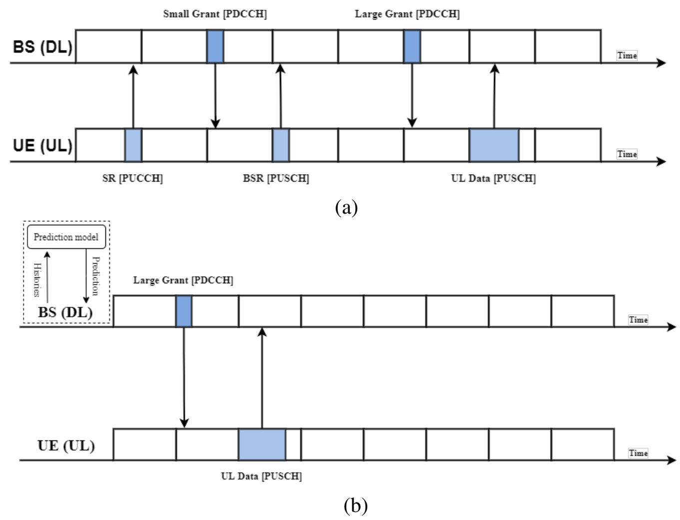


Fig. 1: Sequence Diagram For Dynamic Resource Allocation in a) Traditional Scheme and b) Proposed Scheme

its need for additional resources. After the gNB successfully decodes the SR, it schedules the UE with an uplink grant. Using SR alone, the base station cannot know exactly the amount of data the UE has in the buffer. Thus, typically the gNB sends a small UL grant which the UE can use to send buffer-status-report (BSR) that indicates the range of the amount of data that the UE has in its buffer. Finally, the base station uses BSR information to grant UE the number of needed resources. The latency resulting from this process alone can easily exceed the maximum acceptable delay to support cooperative driving in AVs [22]. In this paper, we propose a new scheme for UL scheduling. Our system, shown in Fig 2, is composed of an AV with an installed onboard UE. On the other side, a gNB with an installed prediction model is responsible for providing cellular service to vehicles. In addition to the coverage, the gNB also preserves state histories of vehicle, i.e. its location and speed, for a window of time. Using observed histories of AV states, the gNB can predict the intention of future maneuvering using the pre-installed prediction model. Consequently, it can estimate a future need for UL resources that will be needed by the vehicle's onboard UE to share its intention with the surrounding vehicles during future cooperative path planning. Based on this estimation, the gNB can proactively schedule UL resources to this UE without the need for a scheduling request/response process, which saves the round trip delay consumed in such a traditional scheduling scheme (see Fig. 1).

III. Vehicle Maneuver Prediction Model

This section describes the prediction model used for vehicle maneuver prediction and the dataset used for training and testing the model.

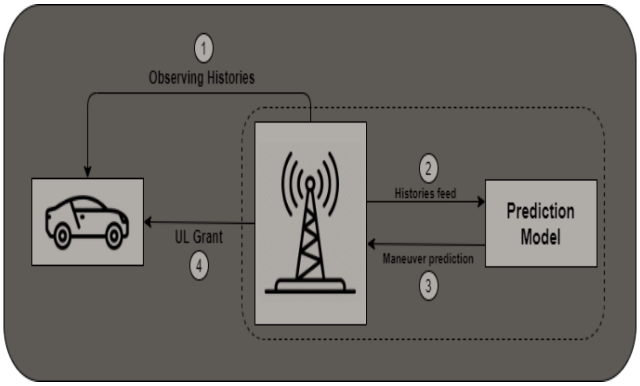


Fig. 2: Proposed scheme for uplink grants in C-V2X

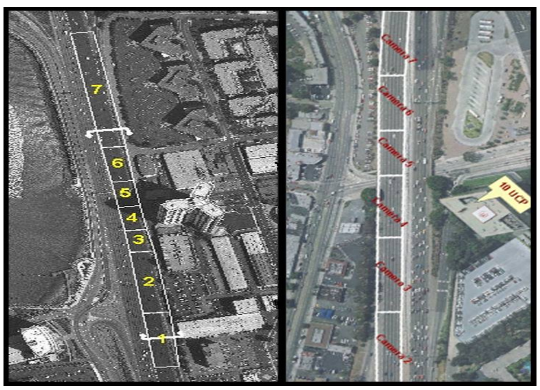


Fig. 3: Dataset: Layouts of the road sites used for collecting the NGSIM US-101 [2] and NGSIM I-80 [3] datasets. Both roads are multi-lane free ways with entry and exit ramps. The data is collected through 7 top-down cameras capturing the positions of each vehicles every 100 ms.

A. Dataset

We use the publicly available Next Generation Simulation (NGSIM) US-101 [23] and NGSIM US-I80 [24] datasets for our experiments. Each dataset consists of trajectories of real freeway traffic captured at 10 Hz over a period of 45 minutes. Each dataset consists of 15 minutes segments of mild, moderate and congested traffic conditions. The dataset provides the coordinates of vehicles projected to a local coordinate system. The total number of trajectories after processing the data is 3121 trajectories including 1184 trajectories involving a lane change. We prepossess the trajectories in the dataset to extract the features to be fed to the model. The main features that are extracted from each vehicle trajectory are the vehicle location, the vehicle speed in each time step, and lane changing events. Moreover, hand-crafted features were added to the data, i.e. a feature indicating the angle between the vehicle and the lane direction. Five features indicate if a lane change is happening within five different prediction horizons were also added.

To train and test the different models, we split the datasets into train and test sets with the test set being one-fourth of the data. We exclude vehicles with less than 6 s of saved trajectories. We also down-sample each trajectory by a factor of 10 to reduce the prediction model complexity.

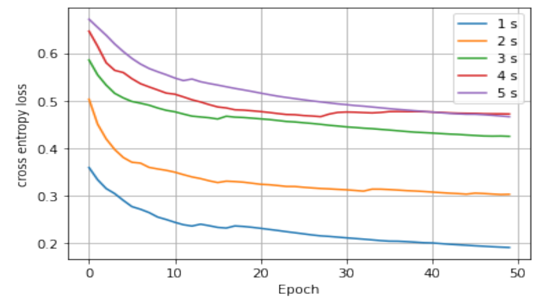


Fig. 4: LSTM model: cross entropy losses under 1-5 s prediction horizons

B. Performance Of Different Classifiers

As mentioned earlier, maneuver prediction can be considered as a classification problem based on the mobility trajectory of the vehicle. We performed an extensive analysis for different predictors to achieve the highest possible accuracy in predicting the maneuver intention. The performance of different classifiers, i.e. support vector machine (SVM), Multilayer perceptron (MLP), random forest, and Long Short term memory (LSTM) is summarized in table I. for all these models, the maneuver information is encoded within the sequence of events, i.e. relative change in speed and angle compared to previous states. As shown in table I, the Long Short Term Memory (LSTM) came on top with the highest accuracy. Fig. 4 shows LSTM cross-entropy losses under prediction horizons varying from 1-5 seconds. The poor performance of other predictors is attributed to their inability to capture the temporal correlation between parameters in the vehicle. On the other hand, Recurrent Neural Networks (RNNs), implemented in LSTM, can discover relationships between consequent states resulting in an outstanding performance.

	1s	2s	3s	4s	5s
SVM	82.1%	79.8%	77.4%	74.1%	70.7%
MLP	74.3%	70.9%	66.5%	62.2%	58%
Random Forest	84.3%	81%	78.3%	75.0%	71.6%
LSTM	89.7%	88.3%	87.1%	84.6%	82.0%

TABLE I: Performance of different classifiers for different prediction horizons

C. LSTM Implementation

Since the LSTM produces the best prediction performance, in this subsection, we will explain the LSTM implementation.

The input to our model is the tensor of track histories

$$x^t = [s_0^t, s_1^t, ..., s_n^t]$$

Where τ_h is the length of track histories, n is the number of considered surrounding vehicles, s is the state of the

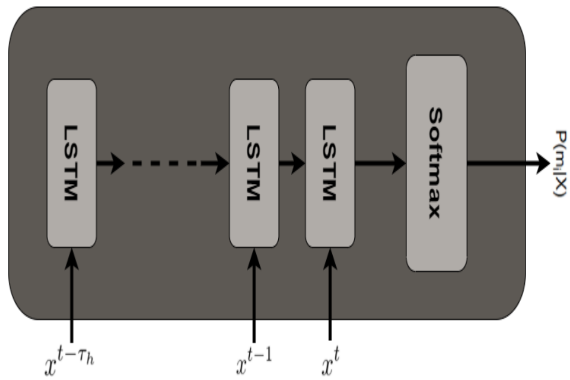


Fig. 5: LSTM model: state histories are fed to the model at each time step. The output of the model is the probability of performing maneuver within prediction horizon

surrounding vehicles, i.e. x,y coordinates, speed and the angle between the vehicle direction and a vector perpendicular on the road, at time t.

The output is formulated as a single variable Y expressing the probability of the vehicle performing lane change within the prediction horizon. Provided with sufficient data to train on, this could be easily extended to a one-dimensional vector representing the probabilities of different maneuvers. Finally, The model is trained to minimize the sum of cross-entropy losses of the predicted and ground truth of maneuver classes. Cross-entropy loss is defined as:

$$loss = -\sum p(X) log p(X)$$

We use 64 units with leaky relu activation function at every time step t of the LSTM. The training was performed using Adam optimizer [25] with a learning parameter of 0.05 and the model was implemented using Keras [26].

IV. Simulation Environment

We used 5G-LENA implementation for the 5G-NR [27] to build an environment in which we test the performance of packet exchange between vehicular nodes. 5G-LENA is an open-source 5G-NR simulation designed as a pluggable module to the NS-3 network simulator [28]. In the developed environment, vehicles are modelled in NS-3 as mobile nodes, they communicate through a base station. Each vehicle has a UDP server, and a UDP client installed. The UDP clients and servers are used to exchange cooperative driving packets which contain information intention of maneuver. Each vehicle communicates through an antenna that is installed at 1.5 meters height, with sending power of 40 dBm. The data rate for each vehicle is 53Mb/s. This rate includes data sharing for both cooperative maneuvers and cooperative perception as specified by the 3GPP standard for cooperative driving in V2X communication in 5G [22].

In our experiment, we use only one gNB to forward the maneuver messages between moving vehicles. This gNB is centred between the moving vehicles and it has 64 an isotropic antenna installed at a height of 35 meters. Moreover, in our environment, we use a single band of 20 MHz at a central frequency of 3.5 GHz. Moreover, we use NS-3 Rural Macrocell (RMa) as a propagation loss model to simulate signal propagation in highway environment [29]. To simulate background load, we create additional nodes, fixed in place and attached to the gNB, that constantly exchange packets on both uplink and downlink. The packet inter-arrival interval for this background traffic is also drawn from a uniform distribution with a maximum delay of 10 microseconds, and the packet size is 500 bytes. The number of fixed nodes is a variable to control the background traffic load on the gNB during the experiment.

Finally, to compare the performance of the two schemes, we build a scenario in which the locations of mobile nodes are updated each 100 ms bases on positions extracted from the NGSIM dataset. We schedule NS-3 events that perform maneuver data exchange between a mobile node and its surrounding. These events are scheduled at the maneuver times also extracted from the aforementioned dataset. Based on this setting the mean maneuver packets delay is collected and used as a metric to evaluate the ability of the traditional uplink dynamic scheduling scheme to 5G-NR the cooperative driving application.

To assess the performance of the proposed scheme, we collect statistics on the latency resulting from uplink grant scheduling then shift the scheduling times of maneuver packet exchange back in time based on the collected statistics and maneuver prediction. The goal is to compensate for the latency resulting from the scheduling process whenever the maneuver is predicted correctly in advance. The required statistics could be collected in NS-3 by logging transmission times of control messages (SR, PUCCH, and PDCCH) on the mac layer of the netDevice installed on mobile nodes. Specifically, the following steps are executed to assess the performance of the proposed scheme:

1) Conduct the aforementioned experiment using a dynamic UL scheduling scheme.
2) For each vehicle: log the times of receiving large UL grants over PDCCH.
3) Outside NS-3: run the predictor on vehicle trajectories
   a) For false negative predictions, i.e. Vehicle predicted as not intending to perform maneuver while it intends to perform a maneuver: schedule the transmission time as t where t is the transmission time as in step 1 left intact.
   b) For false positive predictions, i.e. Vehicles predicted as intending to perform a maneuver while it does not intend to perform a maneuver: add new transmissions to the NS-3 scheduled maneuver files at time t = t_v where t_v is the time of the last saved coordinate for the vehicle extracted from the mobility dataset.

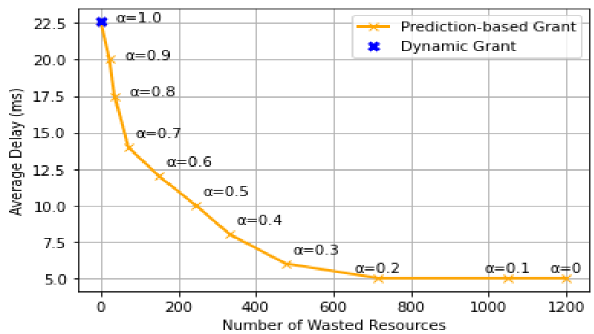


Fig. 6: Average delay and the corresponding wasted resources

4) Repeat the experiment with the modified scheduling times.

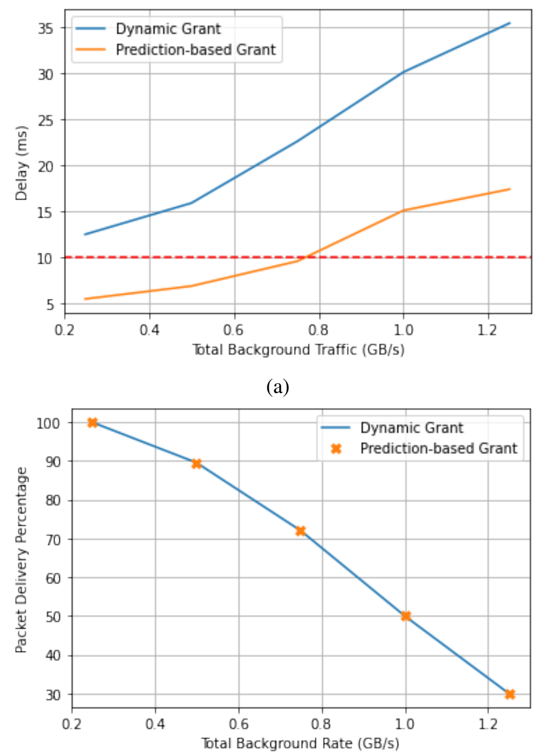
V. Sensitivity Analysis

A. Sensitivity to Prediction Threshold

Both average delay and waste of resources in the proposed scheme could be controlled by manipulating prediction thresholds α where α is defined as the minimum probability required by the model to predict maneuver intention. Increasing the prediction threshold α results in being more conservative in predicting maneuvers, hence, less waste of resources at the expense of average delay. Fig 6 shows the trade-off between the wasted resources, defined as the number of times unneeded resources are granted, and average delay under different periodicities for different values of α in the proposed method. Dynamic scheme performs best in terms of waste of resources, as it doesn't suffer from waste, however, it exhibits higher delay when compared to our scheme. Increasing the prediction threshold results in the LSTM being more conservative in predicting maneuvers, hence, the number of vehicles benefiting from the proposed scheme decrease leading to less waste of resources at the expense of average delay.

B. Sensitivity to Network Load

Fig 7 show the end-to-end latency for both traditional and proposed schemes. Even Under relaxed network conditions, the traditional scheme for resource allocation is not able to support the minimum delay required by the standard. In contrast, our proposed scheme is able to safely support the standard requirements, however, increased background traffic on the gNB side results in a gradual degradation of performance reaching failure at 0.8 GB of data. Moreover, increased background traffic also results in increased loss of packets and degradation of reliability. The number of dropped packets in both schemes is relatively close resulting in almost identical reliability scores. It is important to note that both schemes fail to satisfy the standard reliability requirements under increased network conditions.



(a)

(b)

Fig. 7: Latency and Reliability of 12KB payload for traditional and proposed schemes under varying total network background traffic

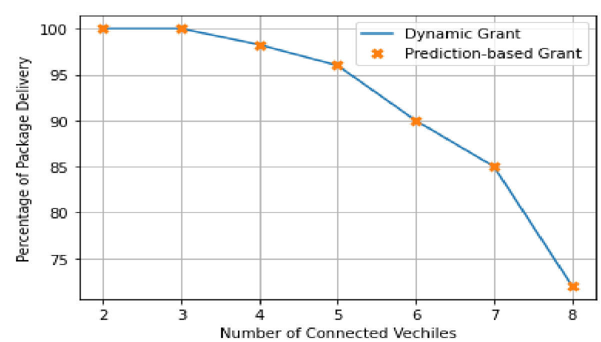


Fig. 8: Density vs reliability for 12KB and zero network load

C. Sensitivity to Vehicle's Density

Our empirical study has shown that the density of connected vehicles, defined as the number of neighbouring vehicles that acknowledge receiving maneuver intent, has minimal effect on average delay. However, the reliability of packet delivery decreases considerably with increasing the vehicle's density. Fig 8 shows the density vs reliability for 12KB and zero network load.

VI. Conclusion

In this paper, we introduced a simulation environment built on the 5G-Lena module in the simulator NS3. We studied the feasibility of relying on the current 5G C-V2X technology to support cooperative driving for AVs. We proceeded by introducing a novel scheme to enhance uplink resource allocation in C-V2X using maneuver prediction. The proposed scheme leverage the LSTM network installed on the gNB to predict vehicle maneuver intention allowing the gNB to proactively schedule uplink grants. Moreover, we performed a sensitivity analysis on the LSTM network. Finally, we empirically show that using our scheme, C-V2X can support cooperative driving applications under moderate network conditions.

Further extension of this work may include predicting network conditions to further enhance the resource allocation scheme, combining prediction-based schemes with semi-static methods, and the inclusion of visual cues in the maneuver classification model.

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