Exploring the Feasibility of Configured Grant for Vehicular Scenario

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***Abstract*—Vehicular applications such as Augmented Reality (AR), Virtual Reality (VR), and High Definition Map (HD Map) are known for their latency-sensitive traits. But, dynamic scheduling at the MAC layer incurs significant signalling overhead (in terms of Scheduling Requests (SRs) in Uplink (UL)), leading to non-negligible latency in 5G NR. To address this issue, 5G NR introduces Configuration Grant (CG) for UL transmission, which pre-allocates radio resources to UEs (vehicles), thereby reducing signalling overhead between a vehicle and the Base Station (gNB). However, the high-speed mobility of vehicles results in rapid changes in channel conditions. Employing CG in a vehicular scenario can lead to incorrect assignment of transmission parameters (e.g., Modulation and Coding Scheme (MCS)), thereby adversely impacting the vehicles' Packet Delivery Ratio (PDR). To address this issue, this paper proposes a CG allocation algorithm that utilizes a Machine Learning (ML)-driven approach to predict the future MCS of vehicles. A data-driven ML model, derived from a real-world dataset, assists the radio resource scheduler and is evaluated using the NS-3 5G-LENA CG module. The ML-assisted CG allocation algorithm demonstrates significant improvements in terms of PDR and spectrum usage efficiency in vehicular scenarios.**

***Index Terms*—Configured Grant, Vehicular Applications, Machine Learning, Radio Resource Scheduling.**

I. Introduction

VEHICULAR applications, such as High-Definition Map (HD-map), Augmented Reality (AR), Virtual Reality (VR), and services assisted by the Vehicle-to-Everything (V2X) network, have the potential to significantly enhance traffic efficiency, road safety, and alleviate congestion. These applications are computationally intensive and generate Uplink (UL) traffic, necessitating the successful delivery at least 99.99% of packets with a packet delivery time below 1 msec [1]. To reduce packet delivery time, 3GPP has introduced several new technologies as part of 5G New Radio (NR) such as Configured Grant (CG), multiple numerologies, Bandwidth Parts (BWPs), service multiplexing, and mini-slotting.

To minimize packet latency at the MAC layer, 5G NR specifications [2], [3] introduce two types of UL channel access methods. In dynamic scheduling, a UE[1] sends a Scheduling Request (SR) to a gNB, seeking radio resource allocation for data transmission. The gNB performs scheduling and provides a Scheduling Grant (SG) to the UE (vehicle), containing a time-frequency grid and transmission parameters (e.g., Modulation and Coding Scheme (MCS)). Once the SG is received, the vehicle can transmit data in its assigned slot. However, the additional signaling overhead between the vehicle and gNB can introduce delays that may violate latency requirements for vehicular applications. To eliminate latency-inducing scheduling operations, CG channel access method is put forward, which pre-allocates radio resources in advance based on the periodicity (i.e., Inter Packet Arrival Time (IPAT)) and packet size of the data generated by the vehicular application. In [4], the authors explored the CG mechanism for shared channel resources, addressing both periodic and sporadic (random) traffic of UEs in an Industry 4.0 factory environment. Another study by the authors of [5] demonstrated that employing CG with different scheduling policies reduces Radio Link Control (RLC) delay in Industry 4.0 scenarios compared to dynamic scheduling. However, to the best of the authors' knowledge, the influence of UE mobility on Packet Delivery Ratio (PDR) and radio resource efficiency has not been thoroughly investigated. Therefore, there is a need to examine CG allocation in vehicular networks and the associated trade-offs that impact the overall performance of vehicular applications.

In vehicular environment, CG allocation approach becomes challenging due to high-speed of vehicles that experience rapid channel variations, causing frequent fluctuations in MCS values. Due to this reason, implementing CG in a V2X network can adversely affect vehicles' PDR, leading to significant performance degradation in vehicular applications. Therefore, predicting future MCS plays an important role in assigning radio resources to a vehicle for CG allocation to ensure successful packet delivery. Thereafter, careful adjustment of CG allocation at appropriate intervals (i.e., CG configuration window (CG_w)) is necessary for the conservation of radio resources. The main contributions of this paper are as follows:

- We study the effect of changing CG configuration window (i.e., CG_w) on PDR and radio resources usages. Here, the CG_w should be carefully chosen to ensure effective smoothing out channel variations caused by the fast fading of a vehicle while also considering the time-dependent changes in path loss.
- We propose a Long Short-Term Memory (LSTM) CG allocation algorithm for V2X networks. Here, LSTM model is trained using a real-world dataset called Berlin V2X [6] to

[1]Throughout this paper we use vehicles and UEs interchangeably.

predict MCS of vehicles for assisting the MAC scheduler in allocating CGs.
- Simulation results show that the proposed LSTM-assisted radio scheduling algorithm and changing CG allocation according to chosen CG_w increases PDR by 14%, 44% and saves radio resources by 6%, 2% for numerologies 1 and 2, respectively, over baseline schedulers.

The rest of the paper is organised as follows: Section II presents the related work. Section III explains system model in detail. Section IV presents CG scheduling in vehicular scenario. Section V illustrates simulation setup, Berlin V2X Dataset and discusses performance evaluation, depicted through graphs. Finally, we conclude our paper in Section VI

II. Related Work

Although there has been research efforts [4], [5] focusing on the use of CG for sensor data in the context of Industry 4.0 factory use case, the primary emphasis has been on selecting optimal CG and meeting latency requirements for UEs in sporadic or random traffic scenarios. Further, utilization of machine learning approaches to assist in CG method has been explored in research. For instance, in [7], multiple active CGs are employed for URLLC UEs to support bursty traffic. The authors propose a Double Deep Q-Network-based algorithm to allocate resources while adhering to latency. In another study [8], an energy model based on real-world setups is introduced to predict smart grid traffic, followed by radio resource allocation for CG aimed at improving latency and spectrum usage efficiency. Additionally, in [9], an Auto-Regressive Integrated Moving Average (ARIMA) model is proposed for predicting future traffic demands using real-world data. This prediction model facilitates radio resource management between URLLC and Enhanced Mobile Broadband (eMBB) slices for CG allocation.

Differing from prior studies, this paper presents a novel contribution by predicting the MCS value to do CG allocation and setting the CG_w based on the average vehicle speed. The aim is to investigate their combined impact on PDR and radio resource utilization efficiency, while considering the associated trade-offs. To the best of our knowledge, this is the first work to propose a machine learning approach that predicts MCS and adjusts the CG allocation based on the average vehicle speed, with the objective of enhancing PDR in V2X networks.

III. System Model

To study the impact of CG transmission on the PDR of vehicles in a 5G NR V2X network, we examine a scenario where V vehicles operate within the coverage of a single gNB. The vehicles generate data packets with a certain periodicity (i.e., IPAT) and fixed data sizes. The gNB plays a key role in efficiently allocating CGs to these vehicles, utilizing traffic information received from the vehicles and channel state information. This process involves vehicles sharing their traffic details, including periodicity and size of data packets, with the gNB using Radio Resource Control (RRC) messages, thereby facilitating the effective allocation of CG.

To facilitate radio resource allocation, the gNB employs a scheduling algorithm and sends associated transmission parameters, including the UL MCS and Resource Blocks (RBs), to the vehicles. To do that, gNB utilizes RRC message to convey the allocation of RBs along with the starting, ending slots and UL MCS to the vehicles for Type 1 CG allocation which adheres to the 3GPP's 5G specs [10]. The gNB can adjust the assigned RBs and UL MCS to vehicles using RRC reconfiguration message at specified intervals i.e., CG_w. This flexibility enables the gNB to reassign RBs based on the UL transmission requirements of the vehicles, which in turn depend on the vehicles' speeds, as illustrated in Fig. 1. The dynamic nature of RBs assignment contributes to efficient radio resource utilization in vehicular networks. The UL transmission in this scenario employs Orthogonal Frequency-Division Multiplexing (OFDM) with a Time Division Duplex (TDD) system, ensuring efficient utilization of the available spectrum.

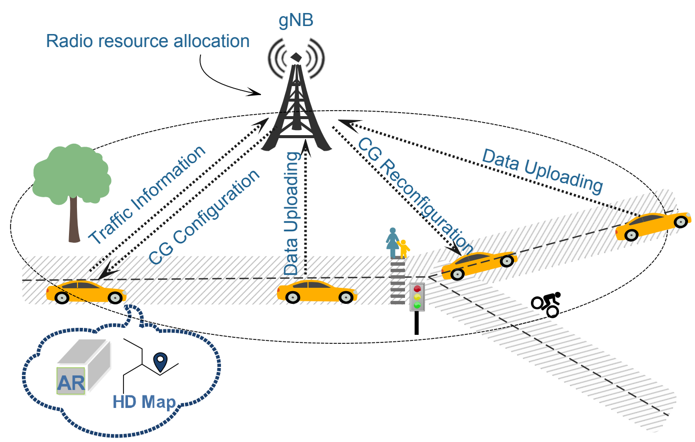


Figure 1: System model illustrating CG configuration, UL data transfer, and CG reconfiguration as a vehicle moves inside the coverage region of a gNodeB.

IV. CG Scheduling In Vehicular Scenario

In this section, we present a radio resource scheduling mechanism for the CG allocation to minimize packet drops in a vehicular scenario. Packet drops can occur because the gNB pre-assigns transmission parameters {UL MCS, RBs} for future UL data transmissions which may not be robust/sufficient due to vehicle maneuver. In case more RBs are assigned than required, then wastage of resources happens, thereby reducing spectral efficiency. Conversely, fewer RBs are assigned than required; packet drop occurs during transmission, decreasing PDR and counteracting this key goal. Here, CG_w plays a significant role in increasing PDR and conserving radio resources. A larger CG_w can increase the PDR of a vehicle, but resulting in overuse of radio resources. On the contrary, a smaller CG_w increases the number of control messages required but resulting in reduced resource consumption. Hence, challenge is to efficiently allocate RBs for a vehicle and configure an accurate CG_w for CG allocation.

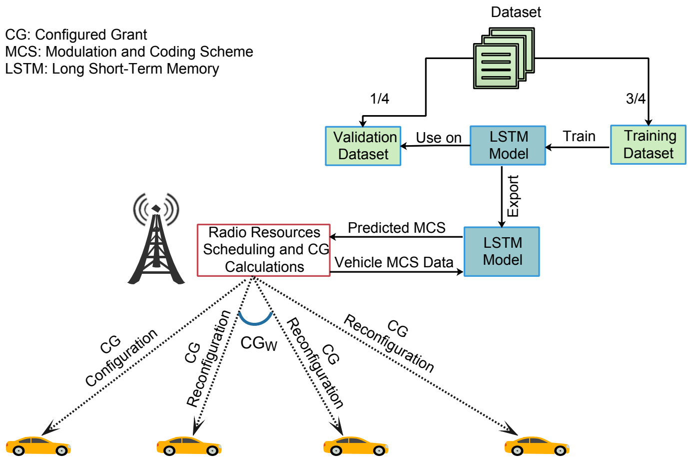


Figure 2: Training and operation flow of LSTM prediction module using a dataset for predicting MCS values to assist the MAC scheduler. CG configuration message is shown for initial CG allocation while CG reconfiguration message is used to modify transmission parameters (e.g., UL MCS and RBs allotted) of a vehicle at specified CG_w intervals.

Algorithm 1 LSTM-Assisted CG allocation

inputs: $V_{allMCS} = \{v_1, v_2, \ldots, v_i\}$ $(i \in \mathcal{V})$,
$v_i = \{mcs_1, mcs_2, \ldots, mcs_{|CG_w|}\}$,
$R_v = \{\emptyset\}$, $MCS_v = \{\emptyset\}$, $\mathcal{V}$
output: Number of RBs per UE R_v $(v \in \mathcal{V})$
forall $v_i \in V_{allMCS}$ **do**
// Initialize a list to store predicted MCS values
$MCS_{pred} \leftarrow \phi$
// Predict MCS values using LSTM model
$MCS_{pred} \leftarrow$ `LSTMpredict`(v_i)
// Find the minimum MCS from MCS_{pred} list
$MCS_v \leftarrow$ `MinimumValue`(MCS_{pred})
end
/* Calculate CG allocation for each UE based on the corresponding minimum MCS value */
$R_v \leftarrow$ `CalculateCGallocation`(MCS_v)

To achieve efficient CG allocation, we leverage a machine learning mechanism, specifically LSTM, to predict the MCS of vehicles, as depicted in Fig. 2. LSTM is a variant of Recurrent Neural Network (RNN) specifically designed to capture and learn long-term dependencies by leveraging the information retained from previous iterations of the learning process [11]. At every CG allocation, historical MCS data of the vehicle, serves as input for the LSTM model to predict future MCS of the vehicle as given in Algorithm 1. The algorithm begins with an empty set of RBs allocated to each UE v, $v \in \mathcal{V}$ is empty, i.e., $R_v = \emptyset$. The algorithm then iterates over all the UEs in V_{allMCS}, where each UE $v_i = \{mcs_1, mcs_2, \ldots, mcs_{|CG_w|}\}$ contains previous CG_w MCS values. Next, for each UE v in V_{allMCS}, the algorithm predicts the MCS values for v using the LSTM model (`LSTMpredict` ()) and stores in MCS_{pred}. After that, the algorithm finds the minimum MCS (`MinimumValue` ()) value MCS_v among the predicted values MCS_{pred} for each vehicle v. Finally, the algorithm calculates the number of RBs for CG allocation (`CalculateCGallocation` ()) for the vehicle v, using minimum MCS values in MCS_v and updates it in R_v, $v \in \mathcal{V}$.

In this process, the LSTM model assists the radio resource scheduler in allocating UL RBs to vehicles using Type-1 CG. Subsequently, the gNB conveys new transmission parameters (UL MCS and RBs) to a vehicle using the RRC reconfiguration message at every CG_w. Upon receiving the new transmission parameters from the gNB, the vehicle starts using these parameters to send pending packets. Further, the UL grant recurs using the approach mentioned in [2] for each symbol in a duration of CG_w. Here, a larger CG_w offers the possibility of more accurately predicting MCS value for a vehicle. The reason behind this is the wider range of MCS data a larger CG_w encompasses, which contributes to better training of the LSTM model. Consequently, such accurate predictions could lead to improvements in CG allocation for a vehicle. At every CG_w, the input values to the LSTM model are adjusted based on the vehicle's MCS value history from the last CG_w. Thus, an efficient LSTM model assigns RBs to a vehicle by assigning probable MCS values for a vehicle. Essentially, the LSTM model is used to balance the trade-off between RBs usage efficiency and PDR of a vehicle.

V. Simulation And Performance Evaluation

In this section, we discuss the simulation setup, the dataset used to train the LSTM model, simulation results, and analysis. Additionally, we explore different CG allocation schemes employed in the study.

A. Simulation Setup

As a case study, we used HD-Map application to evaluate the performance of the proposed scheme on the NS-3-based open-source CG implementation in 5G-LENA [5], which is used to realize 5G links for vehicles in the 5G NR-based. We consider the highway scenario where road segments taken from a city in Canada (i.e., Winnipeg) consist of a two-way Pembina Canada Highway of 250 meters stretch in length. Further, Rapid Cellular Network Simulation Framework (RACE) [12] is used to generate customised vehicular traffic. RACE framework uses the Simulation of Urban Mobility (SUMO)[2] and OpenstreetMap[3] to generate the vehicle traffic and real cellular infrastructure dataset provided by the Canadian organization of Innovation, Science and Economic Development (ISED)[4] is used. Vehicles generate CBR traffic for UL transmission with fixed periodicity and packet size. Here, simulation parameters are summarized in Table I and set according to [5]. Herein, simulation is repeated with 10 different random seeds and results are presented with 95% confidence interval.

[2]http://www.sumo.dlr.de/userdoc/SUMO.html
[3]http://www.openstreetmap.org/
[4]https://sms-sgs.ic.gc.ca/eic/site/sms-sgs-prod.nsf/eng/h_00010.html

Table I: Simulation Parameters

Parameter	Value
Number of vehicles $\|\mathcal{V}\|$	15
Mobility model	Krauss
Average vehicle speed ($\mathcal{V}_{speed}$)	20 - 80 $kmph$
5G NR gNB/Vehicle TX power	46/23 dBm
5G NR gNB antenna tilt	15°
5G NR gNG/Vehicle antenna height	25/1.5 meter
Carrier frequency	5.9 GHz
Channel model	UMa_LoS
5G NR gNB antenna model	OmniDirectional
Vehicle antenna model	Isotropic
Channel bandwidth	30 MHz
5G NR numerology (μ)	1, 2
Radio scheduler	5GL-OFDMA LSTM-5GL-OFDMA RB-OFDMA LSTM-RB-OFDMA SR-Based-RR
Packet Size (L)	60 bytes
Packet Periodicity (IPAT)	10 msec
Slot Configurations	1D13U
CG Configuration Window (CG_w)	5-15 seconds

B. Berlin V2X Dataset

We use the publicly available Berlin V2X dataset [6] to train LSTM model. Berlin V2X is a measurement campaign to capture vehicle and wireless network data collected over highways, avenues, tunnels, residential and West Berlin Park to do machine learning studies. In the dataset, the two vehicles are 1.2 to 3 km apart, and the route stretches to 17.2 km. Vehicle data is collected for 45 minutes driving on weekdays for three days for a granularity of 10 $msec$. Here, vehicles are connected to a server over the LTE network of Vodafone, and Deutsche Telekom. UL/DL data is generated using MobileInsight, *Tcp-dump* and *Iperf* using dedicated measurement equipment placed on the vehicle.

The parameters of LSTM: The parameters of LSTM model encompass its feature, timestamp, lead-time, and learning rate η. The feature of the LSTM is determined by the dimensionality of the input data. Since the prediction model takes only the previous MCS value, which is one-dimensional data, the feature is set to 1. The timestamp parameter dictates the number of historical values used to predict subsequent values. After conducting numerous experiments, it has been observed that setting the timestamp to 15 yields optimal accuracy for the LSTM model. Therefore, the timestamp is fixed at 15. Lead-time denotes the future time span for which data prediction is required, and it is set as the duration of CG_w. Regarding the learning rate η, a default value of 0.01, as documented in Keras [13], is chosen. Finally, the ideal number of training epochs for the LSTM model has been found to be 100, following extensive experimentation. We have split the dataset into two parts for training and validation, where the validation part is one-fourth of the data.

C. Comparison Schemes

We consider the following state-of-the-art, proposed, and baseline CG radio resource scheduling schemes:

- *5GL-OFDMA [5]:* 5GL-OFDMA, a constrained version of OFDMA in 5G NR, allocates one RB in the frequency domain and all the OFDMA symbols within a slot to a UE. Additionally, 5GL-OFDMA allows the division of the OFDMA symbols within a slot into two or more segments, each with a different or equal number of OFDMA symbols. The radio resources within each segment can be accessed by the UEs assigned to the same antenna beam.
- *RB-OFDMA [5]:* The RB-OFDMA scheduling policy optimizes resource allocation by minimizing the number of RBs assigned to UEs. UEs are divided into sets, where the last set of UEs may have fewer RBs assigned compared to other sets. The scheduling policy follows a first-come, first-served order, and radio resources are allocated from the first to the last symbol within a slot. RB-OFDMA efficiently distributes RBs among the maximum number of UEs, considering the minimum RBs required for each UE. RB-OFDMA calculates the minimum number of OFDMA symbols in the frequency domain and RBs in the time domain for resource assignment, aiming to minimize the number of RBs unallocated to UEs. Additionally, each UE is guaranteed to receive at least some arbitrary RBs.
- *LSTM-5GL-OFDMA:* LSTM-5GL-OFDMA is a LSTM-assisted 5GL-OFDMA algorithm that takes predicted MCS inputs from the LSTM model.
- *LSTM-RB-OFDMA:* LSTM-RB-OFDMA is an LSTM-assisted RB-OFDMA algorithm that utilizes predicted MCS inputs from the LSTM model.
- *SR-Based-Round Robin (SR-Based-RR):* SR-Based-RR scheduler allocates a fixed amount of RBs to each user in a sequential order. SR-Based-RR ensures that each UE gets an equal opportunity to access the shared resources.

The state-of-the-art CG resource allocation schemes are 5GL-OFDMA and RB-OFDMA, while LSTM-5GL-OFDMA, LSTM-RB-OFDMA are proposed LSTM-assisted schemes, and SR-Based-RR serves as the baseline. The following performance metrics are used to evaluate the performance of proposed schemes:

- *Packet Delivery Ratio (PDR):* PDR signifies the proportion of successfully delivered packets in comparison to the total number of packets sent in a network.
- *RLC delay:* The RLC delay refers to the time elapsed from the generation of a packet at the RLC layer of a UE to its reception at the RLC layer of the gNB.
- *Average RBs allocation:* The Average RBs allocation metric is a measure used to evaluate the efficiency and effectiveness of RB utilization. It indicates the percentage of allocated RBs by different CG allocation schemes, calculated with respect to the total number of RBs used for SR-Based-RR scheduling.

D. Simulation Results and Analysis

1) Effect of CG_w on PDR: To assess the impact of CG_w on PDR, we varied the CG_w size from 5 to 20 seconds with a step size of 5 seconds for LSTM-5GL-OFDMA and LSTM-RB-OFDMA. In Fig. 3, we plotted the PDR for $\mathcal{V}_{speed} = 60\ kmph$

of vehicles, while fixing the numerology $\mu = 1$ and the packet size $L = 60$, and varying CG_w. The results demonstrate that with an increase in CG_w from 5 to 20 seconds, the PDR improves until reaching the value of 15 seconds for both LSTM-RB-OFDMA and LSTM-5GL-OFDMA. The prediction of MCS values by the LSTM model depends on the size of CG_w. Properly tuning the CG_w can lead to improved PDR, particularly when the CG_w is aligned with the environmental conditions (i.e., vehicle mobility patterns). For the remainder of the simulation, we fixed the CG_w value to 15 seconds for $\mathcal{V}_{speed} = 60\ kmph$.

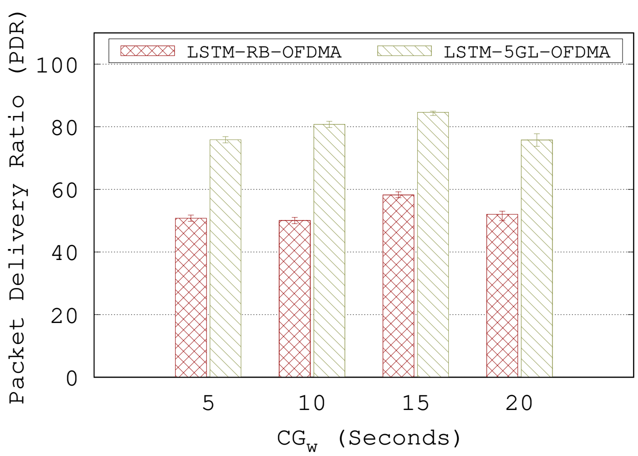
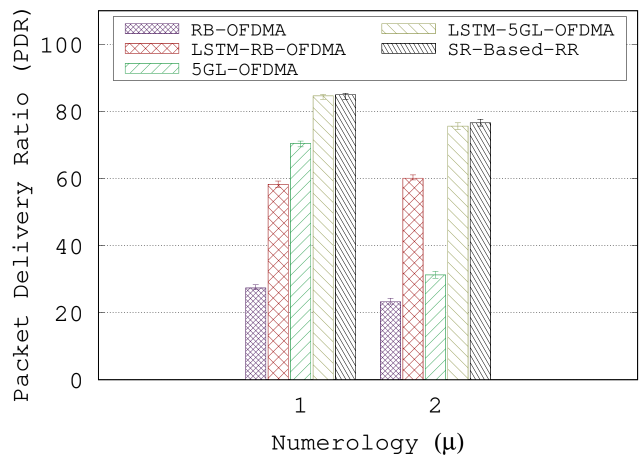
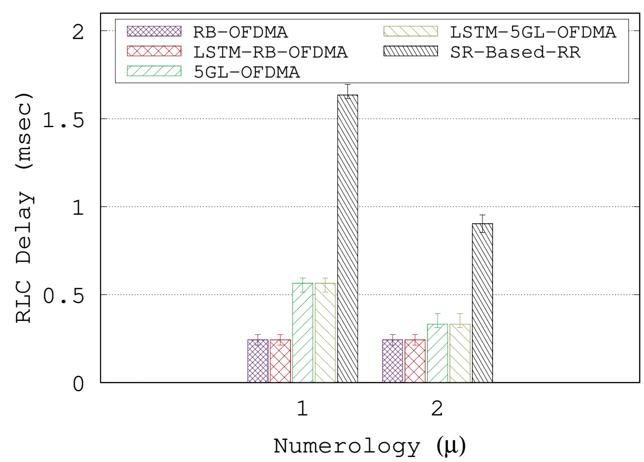


Figure 3: PDR for HD Map application with $\mu = 1$ by varying CG_w for $V = 15$ with $\mathcal{V}_{speed} = 60\ kmph$ where $L = 60$.

2) PDR and RLC delay: Figs. 4(a) and 4(b) show the PDR and RLC delay for LSTM-5GL-OFDMA, LSTM-RB-OFDMA, 5GL-OFDMA, RB-OFDMA and SR-based-RR (aka dynamic scheduling) approach for $\mu = 1$ and $\mu = 2$ for $\mathcal{V}_{speed} = 60\ kmph$. As we can see from the figure, LSTM-5GL-OFDMA and LSTM-RB-OFDMA algorithms perform better in terms of PDR and are close to SR-based-RR. This demonstrates the efficacy of the predicted MCS values using the LSTM model. In contrast, 5GL-OFDMA and RB-OFDMA achieve lower PDR because they do not use robust transmission parameters {UL MCS, RBs}. Further, RB-OFDMA incurs less RLC delay compared to 5GL-OFDMA due to the efficient allocation of RBs resulting in latency/PDR trade-offs. However, 5GL-OFDMA is more robust for vehicle mobility because allocation happens in the frequency domain rather than in time/frequency, thereby achieving better PDR as compared with RB-OFDMA. On the other hand, SR based approach performs best in terms of PDR but is always accompanied by an extensive RLC delay caused by control messages exchanged between gNB and vehicles. However, PDR is low for $\mu = 2$ compared to $\mu = 1$ for all radio resource algorithms due to the fragmentation of packets happening more in $\mu = 2$ because of the reduced slot time. The LSTM-5GL-OFDMA algorithm shows a consistent upward trend in comparison LSTM-RB-OFDMA, 5GL-OFDMA, RB-OFDMA and results in an increase in PDR of 14% and 44%



((a)) PDR.



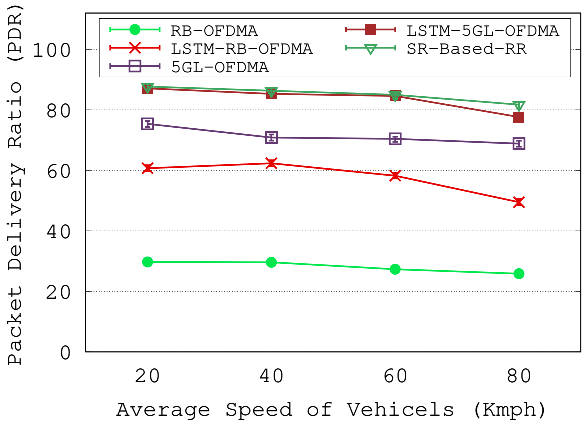
((b)) RLC delay.

Figure 4: Result observed for HD Map application by varying numerology for $V = 15$ with $\mathcal{V}_{speed} = 60\ kmph$ where $L = 60$ and $CG_w = 15$.

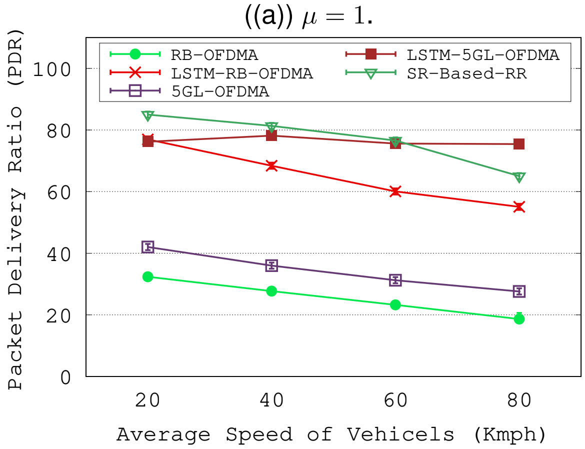
for $\mu = 1$ and $\mu = 2$, respectively, when compared to 5GL-OFDMA.

3) Speed of vehicles: To study the impact of the speed of vehicles on PDR for different radio resource algorithms, the average speed of vehicles is changed using acceleration and speed parameters of vehicles in SUMO. Thereafter, results for different numerology are taken by exporting SUMO traces in NS-3. As shown in Figs. 5(a) and 5(b), PDR drops with an increase in the average speed of vehicles from $\mathcal{V}_{speed} = 20\ kmph$ to $\mathcal{V}_{speed} = 80\ kmph$ for $\mu = 1$ and $\mu = 2$ for all algorithms under study. Impressively, LSTM-5GL-OFDMA performs close to the SR-based-RR approach for both numerologies.

4) Average RBs allocation: Fig. 6 depicts the average radio resource allocation of LSTM-5GL-OFDMA, LSTM-RB-OFDMA 5GL-OFDMA and RB-OFDMA for $\mu = 1$ and $\mu = 2$ for $\mathcal{V}_{speed} = 60\ kmph$ and $L = 60$. We can observe that RB-OFDMA uses 20% and 19% more radio resources than 5GL-OFDMA to serve vehicle demand for $\mu = 1$ and $\mu = 2$,



((a)) $\mu = 1$.



((b)) $\mu = 2$.

Figure 5: Result observed for HD Map application by varying speed of vehicles for $V = 15$ where $L = 60$ and $CG_w = 15$.

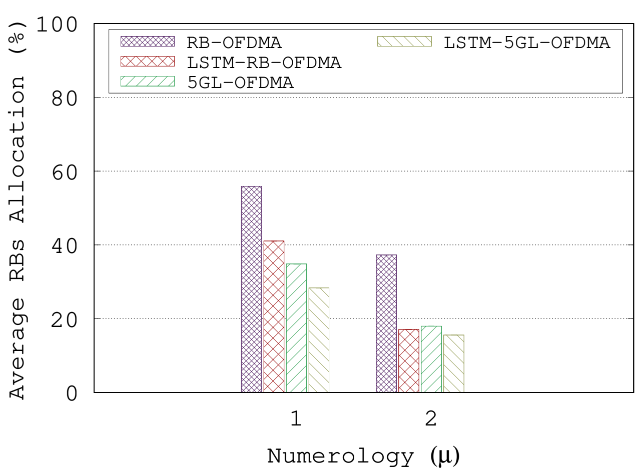


Figure 6: RBs allocation with respect to SR-based-RR observed by varying numerology for $V = 15$ with $\mathcal{V}_{speed} = 60$ $kmph$ where $L = 60$ and $CG_w = 15$.

respectively, but RB-OFDMA incurs less RLC delay. Moreover, LSTM-RB-OFDMA and LSTM-5GL-OFDMA use 14%, 6% and 20%, 2% less RBs than RB-OFDMA, and 5GL-OFDMA for $\mu = 1$ and $\mu = 2$, respectively. The reason is, ML-driven LSTM predictive model forecasts vehicle's transmission parameters $\{$UL MCS, RBs$\}$ for vehicles. Thereafter, gNB re-configures transmission parameters using RRC reconfiguration message at a specified window of $CG_w = 15$, enabling radio resource savings.

VI. Conclusions

This paper presented the first insight into using Configured Grant (CG) in Vehicle-to-Everything (V2X) networks. Here, we considered a case study where vehicles run HD-Map applications which generate packets at a fixed periodicity and packet size. To efficiently allocate CG in a vehicular scenario, we proposed an LSTM-assisted CG algorithm. The LSTM model was trained using a real dataset from Berlin V2X, enabling accurate predictions of a vehicle's future MCS and assisting in efficient radio resource scheduling. Specifically, the efficacy of the LSTM model demonstrated PDR enhancement and radio resource saving for vehicles by changing the transmission parameters of a CG using RRC reconfiguration messages at a fixed window size. Moreover, we showed that the allocation of radio resources in the frequency domain is more robust as compared to time-frequency domain allocation for moving vehicles. This paper lays the groundwork for future research for CG usages in V2X networks.

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