Ensemble Learning for LSTM-based Vehicle Channel Estimation Generalization

Ana Flávia dos Reis, Glauber Brante, Bruno Sens Chang, Yahia Medjahdi, Faouzi Bader and Jérémie Sublime

***Abstract*— This work proposes a generalized learning architecture for vehicular channel estimation using the Ensemble Learning (EL) technique applied to a method based on the long-term memory network (LSTM). The challenge of estimating wireless vehicular channels is addressed, where few methods explore generalizing models for variations in wireless channel models. The proposed approach is robust to changes in Doppler-delay characteristics across different environments and channel models, resulting in an estimator that can work under varying conditions without added online complexity. The results show the possibility of achieving a generalized model with improved performance compared to specific channel condition models.**

***Keywords*— Channel estimation, Ensemble Learning, LSTM, Vehicular communication.**

I. Introduction

Accurate channel estimation is essential for efficient and reliable communication in vehicular networks, a topic that has received great attention as one of the main areas of 6G research. However, the vehicular channel is highly dynamic and varies rapidly due to the vehicle's mobility, which makes channel estimation challenging [1]. Various channel estimation techniques have been proposed in the literature, including pilot-based methods [2], [3], channel modeling [4] and machine learning (ML)-based approaches [5].

Moreover, because it is based on multi-carrier communication schemes such as the classical Orthogonal Frequency Division Multiplexing (OFDM), Peak-to-Average Power Ratio (PAPR) is a critical problem that arises in vehicular communication systems. The amplitude of the OFDM signal can vary widely due to the constructive and destructive interference of the subcarriers, which can result in high PAPR, leading to signal distortion and reduced system performance, especially in power-limited systems. Various techniques have been proposed to mitigate PAPR, such as clipping, filtering [6], and digital pre-distortion (DPD) [7]. These techniques are applied to the transmitted signal and aim to reduce the amplitude fluctuations of the OFDM signal. Alternatively, these nonlinearities can be compensated at the receiver along with the channel estimation, which results in lower power consumption and minimizes the impact on the system performance.

Several schemes have been proposed to estimate the vehicular channel, where deep neural network (DNN)-based techniques have shown to improve vehicular channel estimation compared with classical methods. The work in [5] summarizes some channel estimation techniques based on deep learning (DL), presenting that it is possible to achieve robust estimation over doubly-dispersive environments. The literature also shows that receivers based on long-term memory network (LSTM), a structure capable of handling sequential information where there is a correlation over time, present gains when estimating the vehicular channel, efficiently learning and tracking channel information [8], [9]. For instance, our previous work in [10] considers a classical estimation such as data pilot-aided (DPA) as input to LSTM to improve error compensation and channel estimation. This proposal also exploits the smooth variation of vehicular channels to perform a sampling of the channel information, reducing the complexity compared to previous proposals such as in [8], [9].

One of the challenges of LSTM-based vehicular channel estimation is to provide robust solutions against model parameters variations. Concerning the channel model, the works in [5] and [10] commonly base the training on specific channel conditions, such as power delay profile (PDP), speed, and modulation order. However, these characteristics can vary depending on the location of the vehicles and the environment in which they operate. Since different conditions can impact the accuracy of wireless channel estimates, it is important to have a model that can perform well across various scenarios. Extending the discussion proposed in [10], the present study is built on practical aspects regarding the training of the LSTM-NN-based model for vehicular channel estimation, proposing a solution robust against changes in the channel model of the same scenario and generalizing the learning architectures to estimate channels under different conditions.

Various techniques, such as regularization, cross-validation, and data augmentation, have been proposed to enhance the generalization capability of ML models. However, when applied to a model trained for a specific pattern, these techniques may not be enough for complex tasks [11]. In tasks such as wireless channel estimation, the data may exhibit diverse patterns, and the relationship between input and output variables may be highly non-linear, making it challenging for a single model to capture all the relevant information and provide an accurate estimation.

Ensemble Learning (EL) [12], [13] has shown to be promis-

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ing for improving generalization by combining multiple base models to capture diverse patterns in the data. This ML technique can combine models trained on different feature sets or multiple learning algorithms to improve robustness. By doing so, the EL method can leverage the strengths of each individual model and provide a more accurate estimate across a wider range of scenarios. Among the EL techniques, bagging and boosting algorithms have been widely recognized for improving predictive performance by aggregating diverse model predictions [14]. As a contribution to vehicular channel estimation, this work aims to present that EL is an effective tool to combine the predictions of multiple models, *e.g.* each for a different power delay profile and speeds, demonstrating the effectiveness of this approach for providing model generalization in vehicular channel estimation.

II. System Model

The IEEE 802.11p standard [15] is considered for the deployed vehicular communication scenario, with OFDM modulation being used in the transmission scheme. Each transmitted packet consists in a preamble used to conduct the synchronization of the channel, a signal field, which carries the physical layer information, and a data field. The data field contains $K = 64$ subcarriers employed within each OFDM symbol, in which only $K_{\mathrm{on}} = 52$ are active and 12 inactive subcarriers are used as guard band. Moreover, $K_{\mathrm{p}} = 4$ out of the K_{on} subcarriers are allocated as pilots, while the remaining 48 subcarriers carry the data. For each active subcarrier $k \in \mathcal{K}_{\mathrm{on}}$, with $\mathcal{K}_{\mathrm{on}}$ being the set containing the K_{on} active subcarriers, the received OFDM symbols are written as

$$\mathbf{y}_i[k] = \mathbf{h}_i[k]\mathbf{u}_i[k] + \mathbf{n}_i[k], \tag{1}$$

where for all k subcarriers within the i-th OFDM symbol, $\mathbf{h}_i[k]$ represents the time variant frequency response of the subcarriers, $\mathbf{u}_i[k]$ denotes the k-th subcarrier in the i-th transmitted OFDM data symbol affected by the HPA-induced distortions and $\mathbf{n}_i[k]$ is the Gaussian noise.

The frequency response of the channel coefficients $\mathbf{h}_i[k]$ is modeled by a Rayleigh fading channel model, which incorporates Jakes' Doppler spectrum. The Doppler frequency is given by

$$f_{\mathrm{D}} = \frac{v}{c} f_{\mathrm{c}}, \tag{2}$$

where v is the speed of the vehicle in m/s, c is the speed of light in m/s and f_{c} is the carrier frequency.

A. High Power Amplifier

The HPA-induced distortions are modeled in the time-domain, where we denote the signal at the input of the HPA as $\mathbf{x}(t)$ being obtained by means of the inverse fast fourier transform (iFFT) of the transmitted QAM data symbols for all k subcarriers within each i-th symbol, expressed as $\mathbf{X}_{i,k}$. In order to reduce the effects of the nonlinearities, we consider that the HPA operates at a given input back-off (IBO) from the 1 dB compression point, which refers to the input power level where the characteristics of the amplifier have dropped by 1 dB from the ideal linear characteristics [16]. Therefore,

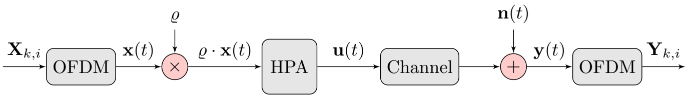


Fig. 1: Transmission system model.

the input signal $\mathbf{x}(t)$ is scaled by the gain ϱ before being amplified by the HPA to ensure the desired IBO, given by

$$\varrho = \sqrt{\frac{\tau_{1\mathrm{dB}}}{10^{\frac{\mathrm{IBO}}{10}} \tau_{\mathbf{x}}}}, \tag{3}$$

where $\tau_{1\mathrm{dB}}$ is the input power at 1 dB compression point, $\tau_{\mathbf{x}_i[k]}$ is the mean power of the input signal, and the IBO is given in dB.

Then, we have the output of the HPA given by [17]

$$\tilde{\mathbf{u}}(t) = \gamma_0 \mathbf{x}(t) + \tilde{\delta}(t), \tag{4}$$

where $\tilde{\delta}(t)$ is a NLD with zero mean and variance $\sigma_{\tilde{\delta}}{}^2$, that is uncorrelated with the input $\mathbf{x}(t)$, while γ_0 describes a complex gain. The relationship between $\tilde{\mathbf{u}}(t)$ and $\mathbf{x}(t)$ is expressed as

$$\begin{aligned} \tilde{\mathbf{u}}(t) &= \phi_a\left(\rho(t)\right) \exp\left[j(\phi_p\left(\rho(t)\right) + \varphi(t))\right] \\ &= \varsigma\left(\rho(t)\right) \exp\left(j\varphi(t)\right), \end{aligned} \tag{5}$$

where $\rho(t)$ is the input signal modulus, $\varphi(t)$ is the input signal phase, $\phi_a\left(\rho(t)\right)$ and $\phi_p\left(\rho(t)\right)$ represent the AM/AM and AM/PM characteristics of the HPA respectively, while $\varsigma\left(\rho(t)\right) = \phi_a\left(\rho(t)\right) \exp\left[j\phi_p\left(\rho(t)\right)\right]$ is the complex soft envelope of the amplified output signal. Then, following the polynomial model approximation in [17], we can write

$$\varsigma\left(\rho(t)\right) \approx \sum_{l=1}^{P} a_l \rho(t)^l, \tag{6}$$

in which a_l denotes the coefficients of the polynomial with order $P = 9$, obtained by the least square (LS) method.

Finally, following the Bussgang theorem [18] we assume perfect estimation and compensation of γ_0 and we can write the output of the HPA as

$$\mathbf{u}(t) = \mathbf{x}(t) + \delta(t), \tag{7}$$

where $\delta(t) = \tilde{\delta}(t)/\gamma_0$ is the remaining NLD. Figure 1 illustrates the transmission system modeled in the presence of the nonlinear HPA, where $\mathbf{Y}_{i,k}$ represents the received QAM data symbols for all k subcarriers within each i-th symbol.

B. Vehicular Channel Model

The present work considers different PDPs to model roadside-to-vehicle (R2V) and vehicle-to-vehicle (V2V) communication scenarios. These models are based on the Doppler-delay characteristics described by [19], which are obtained from real measurements of the communication between a transmitting antenna and a vehicle or two vehicles moving at a certain speed v. The channel models are represented as tapped-delay lines, where each tap is characterized by a Rayleigh fading distribution with a statistically defined Doppler power spectral density. Table I provides the PDP for the different channel models we selected for our analysis.

Specifically, we consider the R2V-UC case, where the vehicle in communication with a fixed antenna moves at an urban intersection, and the V2V-EX case, where two vehicles move along an expressway.

III. Vehicular Channel Estimation

A. DPA-LSTM-NN

We take advantage of the characteristics of symbol-by-symbol estimation, *i.e.*, where the channel estimation is performed for each received symbol separately using only the previous and current received pilots and, thus, without increasing the latency of the application [5]. In this context, the recently proposed DPA-LSTM-NN [10] considers the DPA estimation prior to an LSTM layer followed by a shallow neural network (NN). This is designed in order to consider a coarse estimation performed by the DPA as the initial point, which is used by the LSTM to learn the time and frequency characteristics of the channel, thus tracking its variations and reconstructing it as close as possible to the ideal channel response, finally employing the NN as an additional noise compensation step. Moreover, this estimator also samples the subcarrier information provided as the input of the LSTM layer in order to reduce complexity. As a result, DPA-LSTM-NN presents the lowest complexity among the schemes compared in [10], at the same time improving performance when compared to [8], [9].

B. Ensemble Learning

The DPA-LSTM-NN [10] scheme considers the training on a specific channel model, as well as other receivers present in the literature, even though the channel characteristics are subject to variation and are dependent on the environment in which the vehicles are operating. The most important factors to dictate the performance of the DNN-based schemes are the channel PDP, the vehicle speed, and the modulation order used in communication. Consequently, fixing the training for a given channel will significantly degrade performance when the vehicle communicates under a different channel scenario, limiting its practical deployment.

Our proposal uses the EL technique to improve the overall performance by combining the predictions from multiple models trained with datasets considering different velocities, maximum Doppler shifts, and path delays. Figure 2 presents the block diagram of the DPA-LSTM-NN channel estimator [10] with EL, where the principle of this proposal for generalization is described by the Algorithm 1. Here, we highlight the use of the Bagging method, in which the base models are trained independently and on different subsets of data using the same algorithm configuration, and the predictions of the base models are combined using averaging with equal weight in the final prediction [14]. This choice was given the potential of the Bagging algorithm to decrease the variance of the estimate by combining multiple predictions, thus avoiding overfitting [20]. In the EL algorithm, the function "Bagging" takes M LSTM-NN models $\{m_1, m_2, \cdots, m_M\}$ as input, that have been trained on different subsets with the same architecture and hyperparameters. Then, the function returns

Algorithm 1 Ensemble Learning

Require: M LSTM-NN models $\{m_1, m_2, \cdots, m_M\}$ trained on different subsets, with the same architecture and hyperparameters
Require: Input data, X
Ensure: An ensemble prediction, EL
function BAGGING$(m_1, m_2, \cdots, m_M)$
  Initialize empty list of predictions, $\mathcal{P} \leftarrow []$
  for $i = 1$ to M **do**
    Make prediction using m_i: $p_i \leftarrow m_i.predict(X)$
    Append p_i to $\mathcal{P}$: $\mathcal{P} \leftarrow \mathcal{P} + p_i$
  end for
  Average the predictions in $\mathcal{P}$: $\mathsf{EL} \leftarrow \frac{1}{M}\sum_{i=1}^{M} p_i$
  return EL
end function

an ensemble prediction (EL) that averages predictions of the M LSTM-NN models obtained.

The function initializes $\mathcal{P}$ to be an empty list of predictions. It then loops through the prediction of each input model m_i, from $i = 1$ to M, obtained using $m_i.predict(X)$. Each prediction p_i is appended to $\mathcal{P}$ and then averaged to obtain the ensemble prediction EL, which is the final output of the algorithm. By using this method, the final EL prediction is able to integrate the different offline trained models, combining the strengths of multiple LSTM-NN models trained on different datasets to achieve generalized prediction performance, increasing the flexibility and robustness of the receiver against changes in the wireless channel conditions.

IV. Simulation results

In this section, we analyze the performance impact of employing the EL technique on the DPA-LSTM-NN estimator [10]. We consider single-antenna nodes, with a transmitted OFDM frame size of $L = 50$ symbols in the scenario based on the IEEE 802.11p standard.

In Figure 3, a fixed SNR = 30 dB is considered to analyze the Normalized Mean Squared Error (NMSE) performance of DPA-LSTM-NN models trained with different speeds for the same considered PDP, deployed as the R2V-UC scenario. The results show that models trained at higher speeds than those considered in the tested scenario exhibit certain robustness, with minimized estimation error. However, it is important to note that this robustness does not hold when different PDPs are considered during testing, requiring a model that can handle this variation. Therefore, in the subsequent analysis, we focus on the bit error rate (BER) performance of the EL model, where $M = 4$ models are trained and combined using Algorithm 1. Specifically, our EL approach considers $m_1 = \{\text{R2V-UC}, v = 50 \text{ km/h}\}$, $m_2 = \{\text{R2V-UC}, v = 200 \text{ km/h}\}$, $m_3 = \{\text{V2V-EX}, v = 50 \text{ km/h}\}$, and $m_4 = \{\text{V2V-EX}, v = 200 \text{ km/h}\}$, given the PDP in Table I. Then, we compare the performance of the EL model with other models trained specifically for a given PDP/speed, in different scenarios.

Figure 4(a) presents the BER performance of the different models tested with a dataset deployed as the R2V-UC channel

TABLE I: Channel models power delay profiles.

R2V-UC	**Path delays [ns]**	0, 1, 2, 100, 101, 102, 200, 201, 300, 301, 500, 501
	Average path gains [dB]	0, 0, 0, -11.5, -11.5, -11.5, -19.0, -19.0, -25.6, -25.6, -28.1,-28.1
V2V-EX	**Path delays [ns]**	0, 1, 2, 100, 101, 200, 201, 202, 300, 301, 302
	Average path gains [dB]	0, 0, 0, -6.3, -6.3, -25.1, -25.1, -25.1, -22.7, -22.7, -22.7

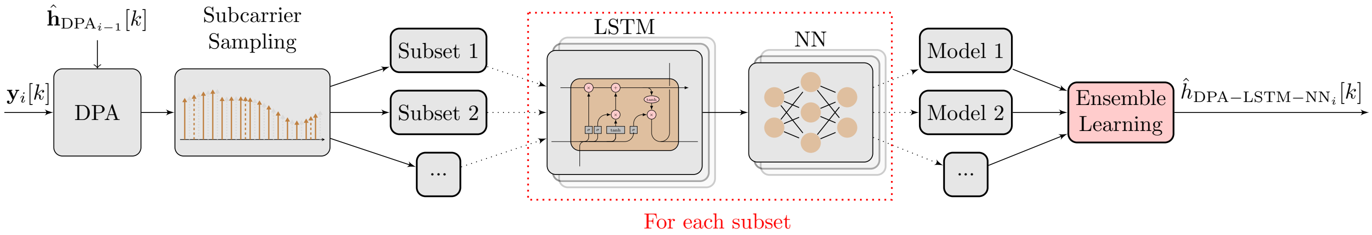


Fig. 2: Block diagram of the DPA-LSTM-NN channel estimator [10] with EL.

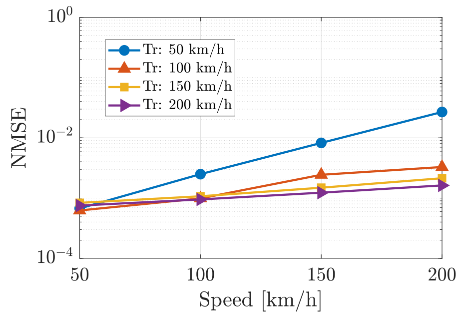


Fig. 3: NMSE for models trained with different speeds $v = \{50, 100, 150, 200\}$ km/h on the R2V-UC.

with $v = 50$ km/h. Notice that the legend of each curve indicates the scenario for which each model was trained. First, we note that the model trained with the same PDP/speed as the scenario under test is the one to achieve the best performance, while the model trained with the same PDP, but with a higher speed ($v = 200$ km/h) has almost negligible loss compared to this most effective model. Furthermore, the EL model exhibits very good performance, with almost negligible loss compared to the best-performing case. However, the same cannot be said when testing the models trained with a different PDP, *i.e.*, the V2V-EX channel in this case. In these cases, from 2 dB to 4 dB of performance loss is observed at the BER of 10^{-4}.

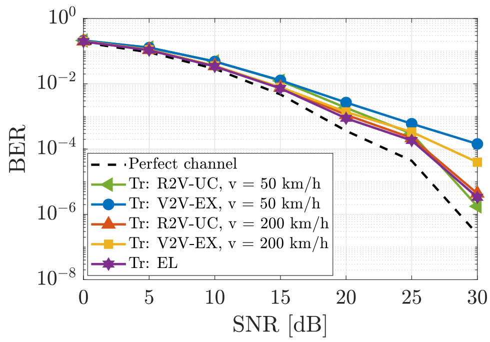
The R2V-UC channel with $v = 200$ km/h is considered in Figure 4(b). As illustrated, there is a significant loss when moving to the high-speed scenario during the test of the models trained for a specific channel condition. In this case, it is observed that apart from the PDP considered when training the model, the choice of a dataset with speed lower than the one considered in the test phase is a crucial factor for performance loss. We observe that the EL model presents a slight performance gain in this scenario, while the models trained with the same PDP and lower speed $v = 50$ km/h or different PDP show a considerable performance loss.

Figure 5(a) shows the performance of the ensemble method for the case where the V2V-EX scenario is considered during the test phase of the models. Again, it can be noticed that for the models trained with $v = 50$ km/h, the one trained with a different PDP has a higher performance loss, which justifies the need for a combined model that generalizes the solution. Moreover, the performance loss of the EL model compared to the models trained with same PDP can be understood by analyzing the path gains of the R2V-UC and V2V-EX channel models in Table I. The fact that the V2V-EX channel model has lower average path gains compared to the R2V-UC entailed in a small performance loss for the low-speed scenario. Still, we emphasize that this loss is smaller than that presented by the models trained with different PDP, evidencing the ability of the EL model to adapt to harsh conditions.

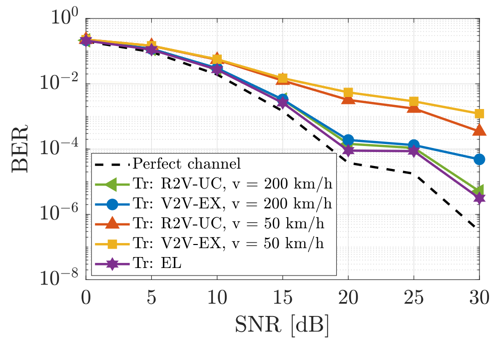
Finally, Figure 5(b) shows that the models trained with $v = 50$ km/h are not adapted to estimate the channel with $v = 200$ km/h during the testing phase in the V2V-EX channel, presenting a loss higher than 10 dB in comparison to the EL model. This substantial loss is crucial to support that models trained for specific scenarios are insufficient to generalize the DNN-based solution for vehicular channel estimation, presenting several constraints for practical deployment. On the other hand, the EL model presents an interesting alternative by offering an estimation with considerably lower losses for different channels. Additionally, it is important to emphasize that these gains are achieved without adding computational complexity to the channel estimation, as the process of obtaining the combined EL model is done offline. Another relevant factor is related to the advantage of storage of a single model capable of estimating the channel in different scenarios, resulting in a gain compared to the storage and management of multiple models, which can be computationally expensive and can result in high storage costs, particularly when dealing with large datasets.

V. Conclusions

In this study, we show that using a model trained for a specific dataset in a new scenario can lead to poor performance and reduced reliability in vehicular communication. However, our proposed method of using the EL technique to combine models overcomes these limitations and provides several benefits, including robustness to variations in PDP and speed, leading to improved performance compared to a model trained for a specific channel condition. Additionally, this technique

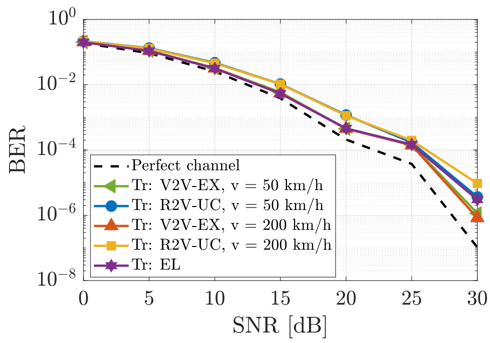


(a) $v = 50$ km/h.

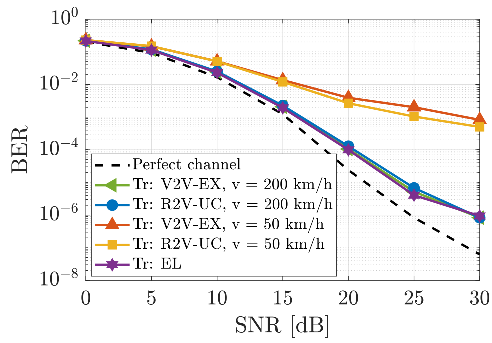


(b) $v = 200$ km/h.

Fig. 4: BER for models trained with different datasets and tested on the R2V-UC dataset



(a) $v = 50$ km/h.



(b) $v = 200$ km/h.

Fig. 5: BER for models trained with different datasets and tested on the V2V-EX dataset

is cost-effective, with the combined model acquired offline, reducing storage expenses. Therefore, the EL method offers a practical solution for accurate vehicular channel estimation in future real-world vehicular communication systems.

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