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Abstract*—In recent years, vehicular communication has attracted significant research attention for its potential as a fifth generation (5G) application. The IEEE 802.11p standard enables the wireless technology that defines vehicular communication and, due to the time-varying characteristic, one of its critical challenges is to ensure communication reliability. Moreover, this standard is based on orthogonal frequency division multiplexing (OFDM) transmission scheme, which may suffer from nonlinear distortions induced by high power amplifiers (HPA) at the transmitter, degrading the channel estimation and detection performance of the receivers. In this work, the application of deep learning (DL) based channel estimation schemes to the IEEE 802.11p standard in presence of HPA distortions is presented. Simulation results show that the deep neural network (DNN) based estimation schemes outperform conventional data-pilot aided (DPA) and spectral temporal averaging (STA) estimators in terms of bit error rate and normalized mean squared error, evidencing their superiority in providing reliable estimation in mobility scenarios in presence of HPA nonlinear distortions. Furthermore, the hybrid solution, employing a joint DNN-based post-processing and conventional estimation, achieves less computational complexity than the DL-based proposal on top of the initial DPA estimation.

***Index Terms*—IEEE 802.11p standard; OFDM; HPA distortions; Channel estimation; Deep learning.**

I. Introduction

Vehicular communication systems are important to enable some of the key 5G applications, such as autonomous driving, route planning optimization and real-time traffic safety information. The IEEE 802.11p [1] standard defines the physical layer specifications of these communication scenarios. However, by considering OFDM transmission and using only four pilot subcarriers to estimate the channel, combined to a high mobile and complex communication environment, this standard introduces several challenges to achieve accurate estimation and, therefore, ensure communication reliability.

Several methods considered to perform channel estimation in IEEE 802.11p networks are based on the DPA estimation, that employs the demapped data symbols in order to improve the limited number of data pilots, providing a low computational complexity solution. By averaging the channels estimations in both time and frequency domains, the STA introduced by [2] improves the DPA initial estimation in low SNR region, where the impact of noise and interference are high and the averaging steps are capable to alleviate the error. However, it suffers from relevant performance decrease compared to the DPA in high SNRs, where this noise impact becomes neglected, but there is a large impact from the demapping error.

Recently, DNN-based schemes have been successfully employed to several wireless communication problems. In the context of channel estimation to vehicular communication scenarios, DNN techniques improve the accuracy from conventional solutions by learning the channel frequency correlation and correcting the error from previous estimators. The AE-DNN proposed by [3] improves the DPA method by implementing an offline trained DNN to reduce the error propagation, while correcting the errors between the initial DPA estimation and the ideal channel. However, besides these improvements, this proposal presents considerable complexity. The authors in [4] show that it is possible to reduce the complexity of the DNN-based channel estimation schemes by applying the offline trained DNN on top of the classical STA estimator, in order to achieve fine channel estimation. The goal of the DNN in [4] is to reconstruct the estimation from the conventional method as close as possible to the ideal channel. This nonlinear processing allows the estimator to capture more features of the channel, providing less computational complexity and performance improvements.

Furthermore, even though OFDM improves capacity and spectral efficiency, it introduces significant power consumption due to the high peak-to-average power ratio (PAPR) [5]. This high PAPR leads to nonlinear distortions in the outputs of the high power amplifiers (HPA) required at the transmitter, affecting the channel estimation at the receivers and considerably degrading the system performance. Several works in the literature show the impact of a high PAPR in multicarrier modulation techniques. For instance, the bit error rate (BER) performance effects due to the presence of memoryless HPA in OFDM are evaluated in [6]. In addition, different multicarrier waveforms are further discussed in [7], where the authors presented a theoretical characterization of nonlinear distortions caused by HPAs in terms of symbols error rate, as well as the analytical expressions to model communications systems subjected to these distortions.

At the transmitter side, digital linearization is one of the most employed techniques to mitigate the high PAPR in mul-

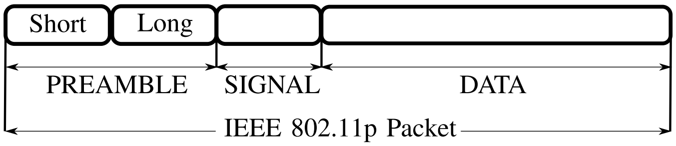


Fig. 1: IEEE 802.11p packet structure [1].

ticarrier signals. This technique integrates the nonlinear HPA with its inverse function modeled by one digital predistorter (DPD) before transmission, enabling a more linear output from the HPA, reducing PAPR effects. Many recent DPD designs also employ neural networks in order to enhance performance [8]–[11]. Nevertheless, remaining nonlinear distortions are still present even in state-of-art DPD designs.

Unlike the works cited above, our proposal focuses at the receiver side. Thus, our goal is to deal with the remaining nonlinear effects of the HPA by considering and comparing different estimators at the receiver. In this paper we aim to:

- Analyze the effects of HPA-induced nonlinearities on a vehicular communication scenario, typical of the IEEE 802.11p standard;
- Analyze the impact of HPA nonlinear distortions, combined with a IEEE 802.11p mobility scenario, for both conventional and DNN-based estimators' proposed in the literature, comparing performance in terms of BER, NMSE and complexity in number of neurons.

To the best of our knowledge, the scenario including both mobility deployed by the IEEE 802.11p standard and HPA-induced nonlinearities has not been addressed in the literature.

Notations: We use capital letters and lowercase letters in boldface to denote matrices and vectors, respectively. Notation $\exp(\cdot)$ denotes an exponential function.

The remainder of this paper is organized as follows. The IEEE 802.11p communication scenario is presented in Section II. The main features of the considered HPA model are provided in Section III. The conventional and DNN-based methods considered to provide channel estimation are detailed in Section IV, while results and discussions are presented in Section V. Finally, Section VI concludes the paper.

II. System Model

Let us consider a vehicular communication scenario following the IEEE 802.11p standard [1], which is used to provide vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication. This standard considers an OFDM transmission scheme, with Figure 1 describing the IEEE 802.11p frame structure, where each transmitted packet consists in a preamble that includes known short and long training symbols to conduct the synchronization of the channel, a signal field, which carries the physical layer information, and a data field. In the data field, $K = 64$ subcarriers are employed within each OFDM symbol, in which only $K_{\text{on}} = 52$ are active and 12 are virtual, *i.e.,* inactive subcarriers. For simplicity, perfect synchronization at the receiver is assumed and the signal field is ignored. In addition, considering the K_{on} subcarriers, only 4 of them are allocated as pilots, while the remaining 48 subcarriers carry the data. The channel estimation is constantly updated utilizing the pilots, as well as the estimation from the previous OFDM symbol. For each active subcarrier $k \in \mathcal{K}_{\text{on}}$, with $\mathcal{K}_{\text{on}}$ being the set of K_{on} active subcarriers, the OFDM frame at the receiver is written as

$$\mathbf{Y}[k,i] = \mathbf{H}[k,i]\mathbf{U}[k,i] + \mathbf{N}[k,i], \tag{1}$$

where for all k subcarriers within the i-th OFDM symbol, $\mathbf{H}[k,i]$ represents the time variant frequency response of the channel, $\mathbf{U}[k,i]$ is the transmitted OFDM symbol affected by the HPA distortion and $\mathbf{N}[k,i]$ is the Gaussian noise, with power

$$\eta_0 = \frac{\varepsilon_p}{\xi \cdot K}, \tag{2}$$

with ε_p being the preamble power per sample and ξ the average signal-to-noise ratio (SNR) at the receiver.

Due to the mobility, the Doppler shift affects the performance of the OFDM transmission. In this sense, $\mathbf{H}[k,i]$ coefficients are modeled over a Rayleigh fading with Jakes' Doppler spectrum with Doppler frequency given by

$$f_{\text{D}} = \frac{v}{c} f_{\text{c}}, \tag{3}$$

where v is the velocity of the vehicle in m/s, c is the speed of light in m/s and f_{c} is the carrier frequency. To simplify this analysis, the received OFDM symbols can be expressed as

$$\mathbf{y}_i[k] = \mathbf{h}_i[k]\mathbf{u}_i[k] + \mathbf{n}_i[k], \tag{4}$$

where $\mathbf{u}_i[k]$ denotes the k-th subcarrier in the i-th transmitted OFDM data symbol affected by the HPA distortion.

Let us denote the signal at the input of the HPA as $\mathbf{x}_i[k]$, so that following [7] we have the output given by $\tilde{\mathbf{u}}_i[k] = \gamma_0\mathbf{x}_i[k] + \tilde{\delta}_i[k]$, where $\tilde{\delta}_i[k]$ is a nonlinear distortion with zero mean and variance $\sigma_{\tilde{\delta}}{}^2$, that is uncorrelated with the input, while γ_0 describes a complex gain. Then, since γ_0 is usually compensated at the transmitter, we can write the output of the HPA as

$$\mathbf{u}_i[k] = \mathbf{x}_i[k] + \delta_i[k], \tag{5}$$

where $\delta_i[k] = \tilde{\delta}_i[k]/\gamma_0$ is the remaining nonlinear distortion of the HPA, so that we can re-write (4) as

$$\mathbf{y}_i[k] = \mathbf{h}_i[k]\mathbf{x}_i[k] + \mathbf{h}_i[k]\delta_i[k] + \mathbf{n}_i[k], \tag{6}$$

in which the effect of the term $\mathbf{h}_i[k]\delta_i[k]$ usually yields a BER floor at the receiver [6].

III. High Power Amplifier

To address the high PAPR issue and, therefore, the distortions caused by HPA in OFDM transmission, we use a memoryless HPA based in the polynomial model as in [7]. This model is based on a commercial evaluation of a HPA following the 3GPP model and the description in [12], which exhibits both amplitude to amplitude (AM/AM) and amplitude to phase (AM/PM) distortions by approximating its characterizations with a polynomial. Thus, for a given input signal $\mathbf{x}_i[k]$, the amplified output signal $\mathbf{u}_i[k]$ can be expressed as

$$\begin{aligned}\mathbf{u}_i[k] &= \phi_a\left(\rho[k]\right)\,\exp\left[j(\phi_p\left(\rho[k]\right)+\varphi[k])\right] \\ &= \varsigma\left(\rho[k]\right)\,\exp\left(j\varphi[k]\right),\end{aligned} \tag{7}$$

in which $\rho[k] = |\mathbf{x}_i[k]|$ is the input signal modulus, $\varphi[k] = \angle\mathbf{x}_i[k]$ is the input signal phase, $\phi_a\left(\rho[k]\right)$ and $\phi_p\left(\rho[k]\right)$ represent the AM/AM and AM/PM characteristics of the HPA, respectively, while $\varsigma\left(\rho[k]\right) = \phi_a\left(\rho[k]\right)\exp\left[j\phi_p\left(\rho[k]\right)\right]$ is the complex soft envelope of the amplified output signal $\mathbf{u}_i[k]$.

Moreover, the soft envelope of the amplified signal employed in our simulations is approximated by

$$\varsigma\left(\rho[k]\right) \approx \sum_{l=1}^{P} a_l \rho[k]^l, \tag{8}$$

where, following the description to the polynomial model [7], a_l denotes the complex coefficients of the polynomial with order $P = 9$, obtained with a least square (LS) method.

Finally, in order to reduce the effects of the nonlinearities, 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 [13]. In this matter, before amplifying the signal by the HPA, it is scaled by the gain ϱ to ensure the desired IBO, given by

$$\varrho = \sqrt{\frac{\tau_{1\mathrm{dB}}}{10^{\frac{\mathrm{IBO}}{10}}\tau_{\mathbf{x}_i[k]}}}, \tag{9}$$

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

IV. Channel Estimation Schemes

Several methods to provide channel estimation in time varying channels have been proposed in the literature. In this section, we present the DPA and STA conventional estimators, as well as DNN-based estimators such as the AE-DNN and the STA-DNN.

A. Conventional Channel Estimators

1) DPA initial estimation: The basic method considered to provide initial channel estimation in the IEEE 802.11p standard is the LS estimator [2]–[4]. In this case, the preamble is divided into two long training predefined symbols $\mathbf{t}_{p,1}$ and $\mathbf{t}_{p,2}$, which are demodulated to obtain the received frequency domain symbols for each k-th subcarrier, denoted by $\mathbf{y}_{p,1}[k]$ and $\mathbf{y}_{p,2}[k]$. Thus, the LS channel estimation is given by

$$\hat{\mathbf{h}}_{\mathrm{LS}}[k] = \frac{\mathbf{y}_{p,1}[k] + \mathbf{y}_{p,2}[k]}{2\mathbf{p}[k]}, \tag{10}$$

where $\mathbf{p}[k]$ is the predefined preamble sequence in frequency domain. Then, the estimate $\hat{\mathbf{h}}_{\mathrm{LS}}[k]$ is applied to equalize all received data in the frame, which causes significant degradation due to variations over its duration.

The DPA method enhances the LS estimator performance by exploring the high correlation characteristics between adjacent symbols in OFDM, so that it employs the previous received symbol as a preamble to estimate the channel for the current symbol. Considering the initial estimate as $\hat{\mathbf{h}}_{\mathrm{DPA}_0}[k] = \hat{\mathbf{h}}_{\mathrm{LS}}[k]$, the equalization of the current i-th symbol at the k-th subcarrier is given by

$$\hat{\mathbf{y}}_{\mathrm{eq}_i}[k] = \frac{\mathbf{y}_i[k]}{\hat{\mathbf{h}}_{\mathrm{DPA}_{i-1}}[k]}, \tag{11}$$

so that $\hat{\mathbf{y}}_{\mathrm{eq}_i}[k]$ is then demapped to the nearest constellation point to result in the $\mathbf{d}_i[k]$. The DPA initial channel estimate is obtained as

$$\hat{\mathbf{h}}_{\mathrm{DPA}_i}[k] = \frac{\mathbf{y}_i[k]}{\mathbf{d}_i[k]}. \tag{12}$$

2) STA estimation: Several channel estimation schemes based on DPA method have been proposed in the literature to rapidly track varying channels. For instance, the STA method has been introduced in [2], where an average of the estimated channels in time and frequency domains is performed after the DPA estimation. First, averaging (12) in the frequency domain we have that

$$\hat{\mathbf{h}}_{\mathrm{update}_i}[k] = \sum_{\lambda=-\beta}^{\lambda=\beta} \omega_\lambda \hat{\mathbf{h}}_{\mathrm{DPA}_i}[k+\lambda], \tag{13}$$

where $\omega_\lambda = \frac{1}{2\beta+1}$, with β being the frequency averaging coefficient. Next, the STA channel estimation is computed as

$$\hat{\mathbf{h}}_{\mathrm{STA}_i}[k] = \left(1 - \frac{1}{\alpha}\right)\hat{\mathbf{h}}_{\mathrm{STA}_{i-1}}[k] + \frac{1}{\alpha}\hat{\mathbf{h}}_{\mathrm{update}_i}[k], \tag{14}$$

with α being the time averaging coefficient that, as well as β, is an integer parameter inherent to the STA method. It is worth to mention that to improve the STA performance, α and β must be chosen experimentally depending on the channel variation and fixing these parameters can increase the gradually accumulated demapping error from $\mathbf{d}_i[k]$ [2].

B. DNN-Based Channel Estimation

It is worth mentioning that the estimators presented in Section IV-A suffer from considerable performance degradation when applied to high mobility scenarios, due to the increasing error propagation over the OFDM frame [4]. Therefore, DNN-based solutions appear as reasonable tools, since these algorithms are capable of capturing varying characteristics and, given the proper training and architecture, they involve low computational complexity. Figure 2 illustrates the AE-DNN and the STA-DNN deployments considered in this work. As we can notice, both designs receive as input the $\hat{\mathbf{h}}_{\mathrm{DPA}_i}[k]$ estimate obtained in (12), while different structures for the DNN are used in these methods, which are detailed as follows.

1) AE-DNN estimation: The AE-DNN solution proposed in [3] improves the DPA method by combining it with an offline trained AE with three hidden layers, consisting respectively of 40, 20 and 40 neurons, which are used to update the channel estimations while correcting the errors between the DPA estimate and the ideal channel. The authors in [3] have shown that the AE-DNN is capable of learning the frequency

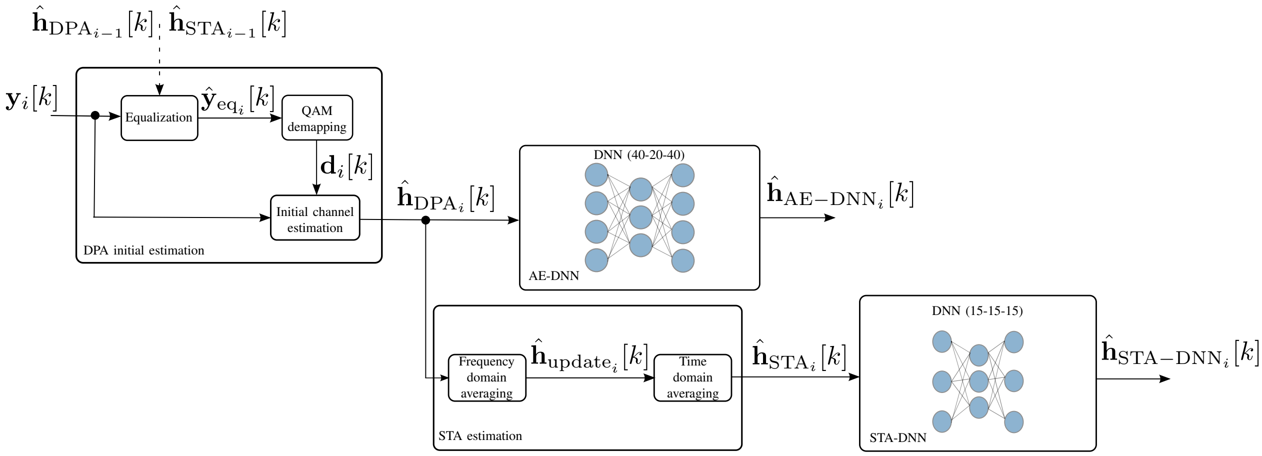


Fig. 2: Block diagram of the DNN-based estimators: AE-DNN and STA-DNN.

domain characteristics of the channel, recovering estimation errors and attenuating the error propagation issue from the previous DPA process.

However, the drawback of the AE-DNN solution is its high computational complexity, due to the high number of neurons of the hidden layers, necessary to deploy a network capable to relate the ideal estimation to the initial DPA estimation. Figure 2 illustrates such approach as a complete DNN that uses $\hat{\mathbf{h}}_{\mathrm{DPA}_i}[k]$ as input and delivers $\hat{\mathbf{h}}_{\mathrm{AE-DNN}_i}[k]$ at its output.

2) STA-DNN estimation: In order to reduce complexity when compared to the scheme proposed in [3], the authors in [4] considered a three layer DNN, with 15 neurons in each layer, which is used as a post-process to the conventional STA estimator. Figure 2 illustrates such approach, in which $\hat{\mathbf{h}}_{\mathrm{DPA}_i}[k]$ is used by the STA estimator in (14), so that $\hat{\mathbf{h}}_{\mathrm{STA}_i}[k]$ is used as the input of the DNN in order to produce $\hat{\mathbf{h}}_{\mathrm{STA-DNN}_i}[k]$.

The goal of the employed DNN is to minimize the mean squared error (MSE) between the ideal channel and the STA estimate, so that

$$\mathrm{MSE}_{\mathrm{STA-DNN}} = \frac{1}{N_{\mathrm{T}}} \cdot \sum_{i=1}^{N_{\mathrm{T}}} \left(\mathbf{h}_{\mathrm{ideal_i}} - \hat{\mathbf{h}}_{\mathrm{STA}_i} \right), \tag{15}$$

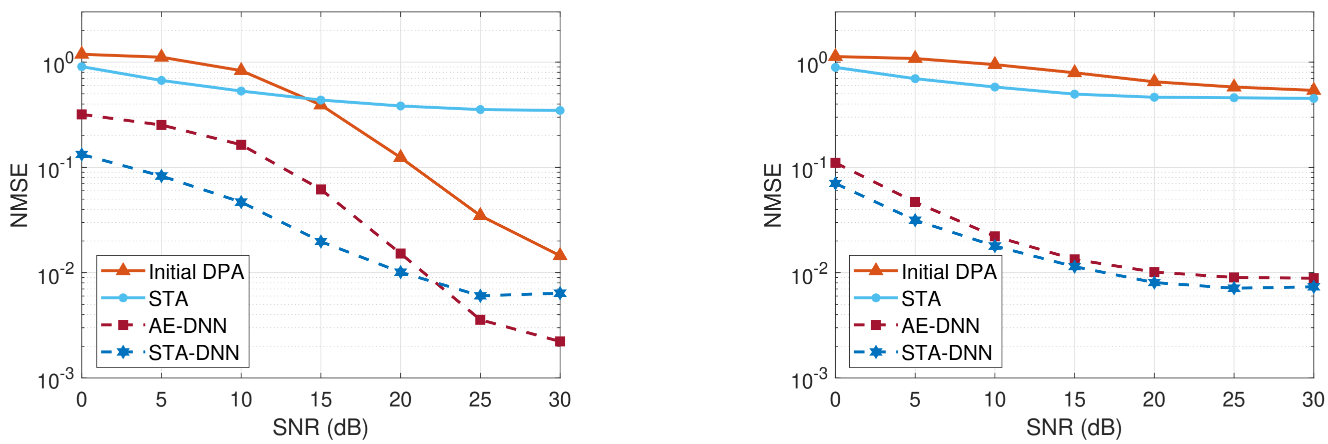
where N_{T} is the number of training samples. Unlike the proposal in [3], the nonlinear processing along with the classical STA allows the proposed estimator to capture more features of the time and frequency correlations of the channel. The results demonstrated that the proposed STA-DNN scheme provides a performance improvement while reducing the computational complexity of the solution.

In the present work, the same training objective and hyperparameters from the learning process presented in [3] and [4] are considered. However, while employing the DNNs to reduce the MSE between the ideal performance and the channel estimation from the conventional method, HPA-induced distortions are considered into the communication environment and, in order to provide proper channel estimation, the DNNs are required to deal with both mobility and HPA-induced nonlinear effects. Since the STA scheme is suited to deal with the correlation between successive OFDM symbols, we expect to reduce the complexity of the DNN, in terms of number of neurons, when comparing STA-DNN and AE-DNN schemes. In addition, the HPA-induced nonlinear distortions are usually seen at the receiver as an additional source of noise, so that we also expect that the DNN training will be able to deal with this effect, reducing the BER floor typically observed in these scenarios.

V. Simulation results

This section presents the performance analysis for the conventional and DNN-based channel estimators when applied to the IEEE 802.11p standard in presence of distortions due to HPA nonlinearities. V2V Urban Canyon (V2V-UC) [14] is considered as vehicular channel model, that deploys the communication channel between two vehicles moving at $v = 48$ km/h in a dense traffic environment. We assume a carrier frequency of $f_{\mathrm{c}} = 5.9$ GHz and 10 MHz of signal bandwidth. The estimations are performed by considering 16-QAM modulation and a transmitted OFDM frame size of 100 symbols. Finally, we compare the IEEE 802.11p wireless communication scenario without HPA nonlinearities and when including HPA nonlinearities, based on the polynomial model as described in Section III.

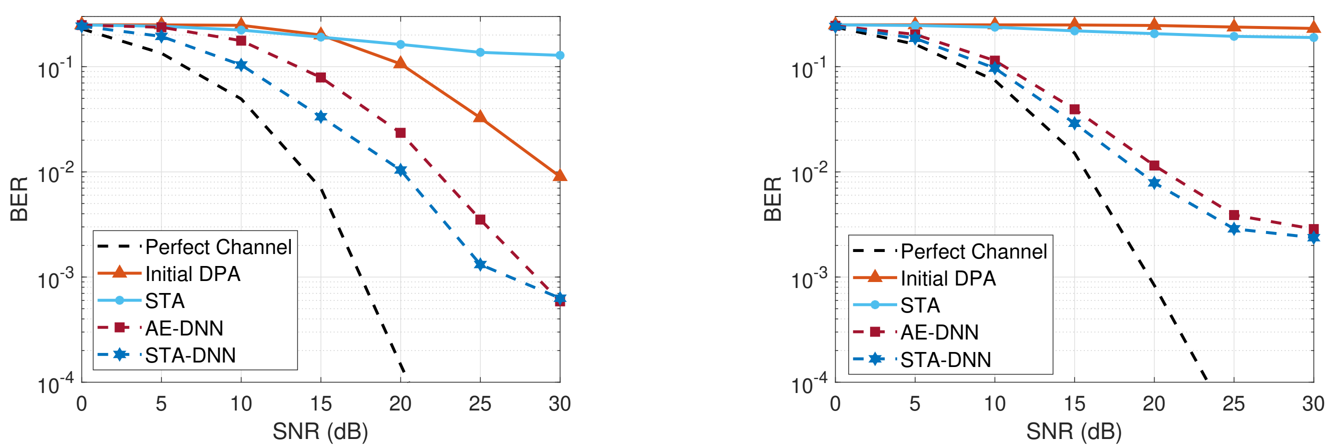
Figure 3 and Figure 4 present the normalized mean squared error (NMSE) and the BER performance, respectively, when considering a fixed IBO $= 4$ dB. Let us highlight that the objective of the DNN in both DL-based solutions is to minimize the MSE between the ideal channel and the channel estimation from the chosen conventional method. However, in our proposed scenario, this is done without any prior knowledge regarding the HPA nonlinearities. The superiority of the DNN-based methods in estimating the channel can be seen in Figure 3, presenting that using DNN as a nonlinear process considerably enhance the conventional estimators performance, adding the ability to learn features about the channel and reducing the error between its estimation



(a) Without HPA nonlinearities.

(b) With HPA nonlinearities and IBO $= 4$ dB.

Fig. 3: NMSE performance in the IEEE 802.11p wireless communication scenario with $v = 48$ km/h.



(a) Without HPA nonlinearities.

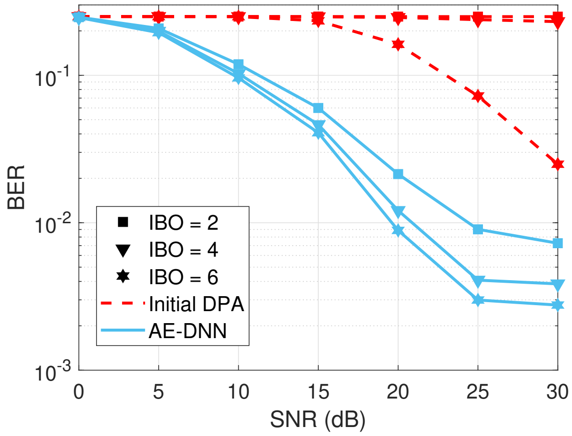
(b) With HPA nonlinearities and IBO $= 4$ dB.

Fig. 4: BER performance in the IEEE 802.11p wireless communication scenario with $v = 48$ km/h.

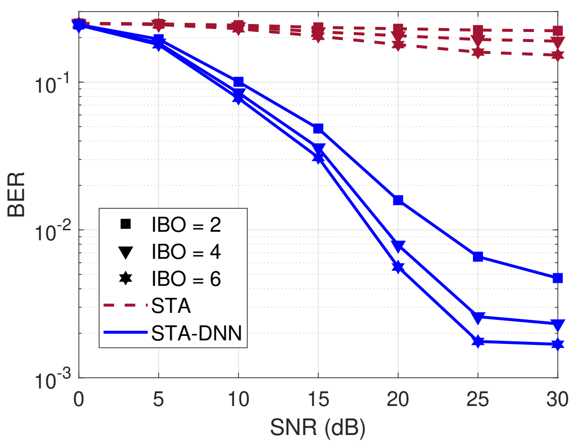
and the ideal channel, even when impacted by non-expected distortions. Figure 3a shows that, starting from the SNR of $\xi = 20$ dB, the AE-DNN presents less channel estimation error than the STA-DNN estimator, once the impact due to demapping error is small for high SNR region and the initial DPA estimation emerges over STA. Moreover, the results presented by Figure 3b show that, when the impacts from HPA distortions are considered, the STA-DNN hybrid solution slightly outperforms the AE-DNN, proving to be more likely to capture the nonlinearities of the HPA while reducing also the computational complexity due to its DNN architecture. In addition, Figure 4 shows that the DNN-based estimators outperform the BER provided by the conventional estimators in all considered scenarios. Moreover, in Figure 4b we observe that the DNN-based estimators still present a BER floor at high SNR when the HPA-induced distortions are included. Nevertheless, they are still capable to provide a BER of around 10^{-2} at $\xi = 20$ dB, while the conventional estimators suffer from severe performance degradation.

It is worth to highlight that, in performing an average of the estimated channels in time and frequency domains, the classical STA takes more about the correlation of the channel gain over successive received OFDM symbols into account than the initial DPA estimation, providing a better entry for the DNN. As a consequence, the complexity of the STA-DNN in terms of number of neurons of the DNN can be considerably reduced when compared to the AE-DNN, while still providing a slightly better BER performance in all considered scenarios.

In order to compare the estimators with different nonlinear distortion effects, Figure 5 presents the BER performance by employing different IBO values. Intuitively, since increasing the IBO represents an approximation to the characteristics of the ideal HPA and its linear properties, a lower IBO implies in a worse BER performance as an expected result. In accordance with that, it is possible to notice that both classical and DNN-based estimators show better performance with the increase of the IBO. Nevertheless, the DNN-based estimators are more robust to these nonlinear effects, since the variation



(a) Initial DPA and AE-DNN estimators



(b) STA and STA-DNN estimators.

Fig. 5: BER performance for IBO $\in \{2, 4, 6\}$ dB.

in performance is smaller than the one from the conventional estimators. The results presented in Figures 5a and 5b show that, even for the scenario with IBO $= 2$ dB, both AE-DNN and STA-DNN are capable to achieve BER lower than 10^{-2} at $\xi = 25$ dB, whereas the conventional initial DPA estimator and the STA estimator exhibit respectively high error rates of 0.25 and 0.22. This performance difference validates the hybrid approach, using classical estimation techniques together with a DNN, considered in this work. It is also possible to notice a performance improvement when we compare the results obtained with the STA-DNN estimator with the ones from the AE-DNN scheme.

VI. Conclusion

This work analyzes the impact of HPA nonlinearities on the performance of channel estimation schemes employed in a vehicular scenario, typical of the IEEE 802.11p standard. The simulations show that the use of DNNs present better performance compared to conventional estimators, in terms of both NMSE and BER. In addition, the combination of the DNNs with conventional estimators is also shown as an important design characteristic. By comparing the AE-DNN scheme, which is composed by a neural network processing after the initial DPA estimation, with the STA-DNN scheme, which employs a DNN after the conventional STA estimator, we observe that STA-DNN presents the best performance, with less complexity, *i.e.*, with a smaller number of neurons per layer. As future works, we aim to explore noise cancellation techniques in order to further reduce the effects of the HPA distortions, as well as to investigate how to improve the DNN training by inserting more information regarding the dynamic scenario, the HPA model and by considering more advanced DL algorithms such as long short-term memory (LSTM). Another work extension aims to consider more vehicules communicating in the traffic environment and, with this increase in the complexity of the channel, we expect that DL-based solutions will be even more suitable for channel estimation given their generalization properties.

VII. Acknowledgements

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