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Joint TRFI and Deep Learning for Vehicular Channel Estimation

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Abstract—IEEE 802.11p standard enables the wireless technology that defines vehicular communications. However, IEEE 802.11p frame structure employing low pilot density is not enough to track the channel variations in high mobility scenarios, leading to significant performance degradation. Therefore, ensuring communication reliability in vehicular environments is considered as a major challenge. In this work, this challenge is tackled by employing deep learning into conventional channel estimation through utilizing deep neural networks (DNN) as an additional non-linear processing unit to correct the interpolation error of the time domain reliable test frequency domain interpolation (TRFI) channel estimates, besides learning higher order statistics of the estimated channel, resulting in a better channel tracking over time. Simulation results demonstrate the performance superiority of the proposed TRFI-DNN scheme over conventional schemes and the recently proposed DNN estimators with a significant computational complexity decrease, especially in high mobility vehicular scenarios.

Index Terms—Channel estimation; deep learning; DNN; IEEE 802.11p standard; vehicular communications.

I. INTRODUCTION

In vehicular environments, wireless channel is defined as a double selective channel [1]. It shows frequency and time selective fading characteristics due to the multi-path propagation effects, and the vehicles motion. Therefore, vehicular channel suffers from significant variations between the start and end of the transmitted frame. IEEE 802.11p standard [2] was proposed as an international standard that manages the communications between different vehicular network units: vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications. IEEE 802.11p allocates four pilots within each transmitted symbol, which are insufficient for tracking the channel variations in vehicular environments. Moreover, the channel is estimated once at the beginning of the frame, and used to equalize all the received symbols within the frame. However, due to rapid channel variations in vehicular environments, the estimated channel at the beginning of the frame becomes quickly outdated leading to poor system performance in realistic vehicular environments. Therefore, robust and accurate channel estimation is necessary to ensure communication reliability.

Several conventional channel estimation techniques have been proposed to track a rapidly varying channel [3], [4]. In this paper, those that adapt to the IEEE 802.11p standard structure are discussed. The spectral temporal averaging (STA) [5] scheme employs time and frequency averaging in estimating

the channel. It can provide better channel estimates in low signal-to-noise ratio (SNR) region but significant flooring of the performance occurs in a high SNR region, due to the fixed time and frequency averaging window size. The constructed data pilots (CDP) scheme [6] assumes high correlation between the received symbols, it effectively estimates the channel, especially, in high SNR regions, but it still cannot provide acceptable error performance in high mobility scenarios. The authors in [7] have proposed a time domain reliable test frequency domain interpolation (TRFI) scheme in order to improve the CDP performance, where frequency domain interpolation is employed to estimate the channel at unreliable subcarriers that do not pass the reliability test.

Conventional IEEE 802.11p channel estimation schemes are based on the data-pilot aided (DPA) estimation, where the demapped data subcarriers from the previously received symbol is used to estimate the channel for the current symbol. Due to the rapid vehicular channel variations and the noise imperfections, DPA suffers from the demapping error that depends on the accuracy of previous estimation. Moreover, this error propagates and enlarged among the received frame, thus leading to a significant performance degradation especially in high mobility vehicular scenarios.

Recently, deep learning (DL) has been employed to overcome wireless communication problems, especially in channel estimation. In this context, auto-encoder deep neural network (AE-DNN) has been proposed in [8] for channel estimation in vehicular communications. AE-DNN performs DPA channel estimation, then the DPA estimated channels are fed as an input to deep neural networks (DNN) that is employed for correcting DPA estimation errors. AE-DNN requires high computation complexity due to the employed DNN architecture, and it does not sufficiently learn the time-frequency correlation of the channel at successive symbols.

In our previous research work [9], we have proposed a novel optimized STA-DNN channel estimation scheme, where DNN is used as a post non-linear processing module to improve the conventional STA scheme performance by capturing more features of the time-frequency correlations of the channel samples and therefore, overcoming the problem of fixing the time and frequency averaging coefficients as performed in conventional STA scheme. STA-DNN schemes outperform conventional estimators and the AE-DNN especially in low SNR regions. However, for high mobility scenarios where

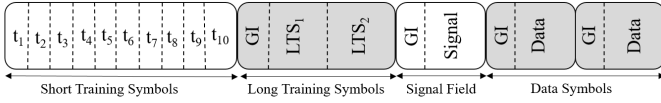


Fig. 1: IEEE 802.11p transmitted frame structure.

vehicle's velocity is greater than 120 Km/h, the performance of STA-DNN starts to degrade in high SNR regions. Therefore, a more accurate and robust channel estimation is required in such scenarios.

Motivated by the fact that the conventional TRFI scheme outperforms conventional STA schemes especially in high SNR regions, in this work, DNN processing is applied on top of conventional TRFI in order to improve the learning of the channel statistics and thus implicitly correct the conventional TRFI interpolation errors, resulting in better channel estimation in high SNR regions. The proposed TRFI-DNN architecture is optimized to reduce the computational complexity. Numerical results reveal that our TRFI-DNN scheme outperforms the conventional channel estimators. It also outperforms AE-DNN and STA-DNN especially in high mobility scenarios and high SNR regions.

The rest of this paper is organized as follows. The IEEE 802.11p standard definition and the system model are presented in Section II. Section III illustrates conventional IEEE 802.11p channel estimations schemes. Proposed TRFI-DNN schemes are defined and explained in Section IV. Experimental results and detailed computational complexity analysis are given in Section V. Finally, Section VI concludes the paper.

II. SYSTEM DESCRIPTION

The IEEE 802.11p physical layer [10] is based on orthogonal frequency-division multiplexing (OFDM) and employs $K = 64$ subcarriers within each transmitted OFDM symbol, only $K_{on} = 52$ of them are active, where K_{on} denotes the active subcarriers indices within each OFDM symbol. These active subcarriers are divided into $K_p = 4$ pilot subcarriers employed for channel tracking, and $K_d = 48$ subcarriers to carry the actual transmitted data. IEEE 802.11p transmitted frame shown in Fig. 1, starts with *short training symbols* which are used by the receiver for signal detection and time synchronization. Then *two long training symbols* are transmitted for channel estimation. The *signal field* provides information about the transmission such as the used code rate and the modulation order employed. Finally, the *data field* contains a sequence of OFDM symbols corresponding to the data payload.

In our work we assume perfect synchronization and ignore the signal field. Therefore, we consider only the two long training symbols followed by I OFDM data symbols within each transmitted frame. The received OFDM symbol can be expressed in terms of K_{on} active sub-carriers as:

$$\mathbf{y}_i[k] = \tilde{\mathbf{h}}_i[k]\mathbf{x}_i[k] + \mathbf{n}_i[k], \quad k \in \mathcal{K}_{on}, \quad (1)$$

where $\mathbf{x}_i[k]$ and $\mathbf{y}_i[k]$ denote the i -th transmitted and received OFDM symbol. $\mathbf{n}_i[k]$ and $\tilde{\mathbf{h}}_i[k]$ express the noise and the time

variant frequency-domain channel gain of the k -th subcarrier at the i -th OFDM symbol, respectively.

III. CONVENTIONAL CHANNEL ESTIMATION SCHEMES

This section introduces the conventional channel estimation schemes that adhere to the IEEE 802.11p standard structure and the recently proposed AE-DNN and STA-DNN schemes.

A. LS Estimation Scheme

The least square (LS) channel estimation is the basic scheme used in IEEE 802.11p, where the received preambles denoted as $\mathbf{y}_1^{(p)}[k]$, and $\mathbf{y}_2^{(p)}[k]$, and the predefined preamble sequence $\mathbf{p}[k]$ are employed to estimate the channel such that:

$$\hat{\mathbf{h}}_{LS}[k] = \frac{\mathbf{y}_1^{(p)}[k] + \mathbf{y}_2^{(p)}[k]}{2\mathbf{p}[k]}. \quad (2)$$

Employing $\hat{\mathbf{h}}_{LS}$ for equalizing all the symbols in the frame will significantly degrade the performance under mobility conditions, since it becomes invalid within the duration of a frame. Therefore, the LS scheme cannot provide an acceptable error performance in a realistic system.

B. DPA Estimation Scheme

The DPA scheme is based on employing the previous received OFDM symbol as a preamble to estimate the channel for the current OFDM symbol. Therefore the first step in the DPA estimation can be expressed as follows:

$$\mathbf{y}_{eq_i}[k] = \frac{\mathbf{y}_i[k]}{\hat{\mathbf{h}}_{DPA_{i-1}}[k]}, \quad \hat{\mathbf{h}}_{DPA_0}[k] = \hat{\mathbf{h}}_{LS}[k]. \quad (3)$$

After that, $\mathbf{y}_{eq_i}[k]$ is demapped to the nearest constellation point to obtain $\mathbf{d}_i[k]$. Finally, the DPA scheme updates the final channel estimate as:

$$\hat{\mathbf{h}}_{DPA_i}[k] = \frac{\mathbf{y}_i[k]}{\mathbf{d}_i[k]}. \quad (4)$$

DPA scheme is considered as the basic estimation process applied by all IEEE 802.11p conventional channel estimation schemes, which are illustrated in Fig. 2 and presented in the next subsections.

C. STA Estimation Scheme

The STA scheme [5] has been proposed to tackle the problem of vehicular channel variations. STA employs frequency and time correlation between successive received OFDM symbols. First of all, STA performs the DPA estimation according to (3) and (4). After that, frequency domain averaging is applied to (4) as follows:

$$\hat{\mathbf{h}}_{FD_i}[k'] = \sum_{\lambda=-\beta}^{\lambda=\beta} \omega_{\lambda} \hat{\mathbf{h}}_{DPA_i}[k + \lambda], \quad \omega_{\lambda} = \frac{1}{2\beta + 1}, \quad (5)$$

where each subcarrier in $\hat{\mathbf{h}}_{FD_i}[k']$ is calculated as a weighted summation of its neighboring subcarriers. Here $k' \in [\mathcal{K}_{on} \setminus \{1, 2, 51, 52\}]$ as the first and last two subcarriers in $\hat{\mathbf{h}}_{DPA_i}[k]$ are excluded from the frequency averaging operation.

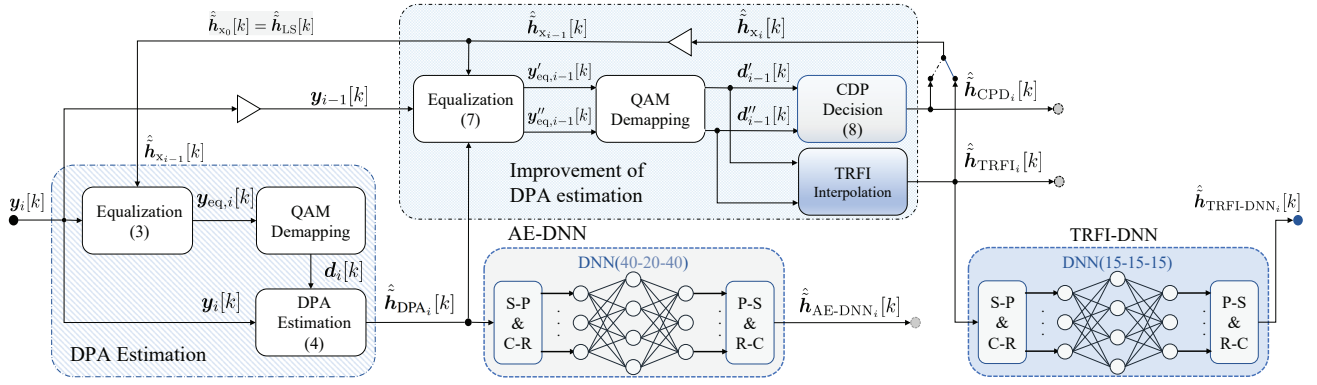


Fig. 2: Time-variant channel estimation schemes block diagram.

According to [5], the STA frequency averaging coefficient β is fixed to 2, therefore all the averaged subcarriers are multiplied by the same weight ω_λ . Finally, the STA channel estimate is updated using time averaging between the previously estimated channel and the frequency averaged channel in (5), such that:

$$\hat{h}_{\text{STA}_i}[k] = (1 - \frac{1}{\alpha})\hat{h}_{\text{STA}_{i-1}}[k] + \frac{1}{\alpha}\hat{h}_{\text{FD}_i}[k], \quad (6)$$

where $\hat{h}_{\text{STA}_0}[k] = \hat{h}_{\text{LS}}[k]$, and α represents the time averaging coefficient used in the STA scheme. The STA performance highly depends on accurately estimating α and β parameters. However, the detailed analysis performed in [5], reveals that α and β estimation requires vehicular channel statistics knowledge in real time. Due to the fact that this required knowledge is hard to obtain in real case scenarios, α and β are used as fixed values. These values are chosen experimentally to achieve an acceptable performance degradation.

D. CDP and TRFI Estimation Schemes

The CDP estimation scheme [6] assumes that the time correlation of the channel response between two adjacent OFDM symbols is high. Based on the assumption of CDP scheme, the TRFI scheme [7] has been proposed. TRFI applies the same estimation steps as CDP, except the last one, where TRFI updates the final channel estimates using frequency domain cubic interpolation. CDP and TRFI schemes apply first the DPA estimation steps, and then proceed according to the following steps where $x \in \{\text{CDP}, \text{TRFI}\}$ refers to the used channel estimation scheme:

- The previously received OFDM symbol is equalized by $\hat{h}_{\text{DPA}_i}[k]$ and $\hat{h}_{x_{i-1}}[k]$, where
$$\mathbf{y}'_{\text{eq}_{i-1}}[k] = \frac{\mathbf{y}_{i-1}[k]}{\hat{h}_{\text{DPA}_i}[k]}, \quad \mathbf{y}''_{\text{eq}_{i-1}}[k] = \frac{\mathbf{y}_{i-1}[k]}{\hat{h}_{x_{i-1}}[k]}. \quad (7)$$
- The obtained $\mathbf{y}'_{\text{eq}_{i-1}}[k]$ and $\mathbf{y}''_{\text{eq}_{i-1}}[k]$ are demapped into $\mathbf{d}'_{i-1}[k]$ and $\mathbf{d}''_{i-1}[k]$, respectively.

The final $\hat{h}_{\text{CDP}_i}[k]$ is updated based on $\mathbf{d}'_{i-1}[k]$ and $\mathbf{d}''_{i-1}[k]$ according to:

$$\hat{h}_{\text{CDP}_i}[k] = \begin{cases} \hat{h}_{\text{CDP}_{i-1}}[k], & \mathbf{d}'_{i-1}[k] \neq \mathbf{d}''_{i-1}[k]. \\ \hat{h}_{\text{DPA}_i}[k], & \mathbf{d}'_{i-1}[k] = \mathbf{d}''_{i-1}[k]. \end{cases} \quad (8)$$

The TRFI scheme updates the estimated channel using interpolation. First, the subcarriers are split into two sets; (i) reliable subcarriers (RS) set contains the four pilot subcarriers, in addition to the data subcarriers that fulfills $\mathbf{d}'_{i-1}[k] = \mathbf{d}''_{i-1}[k]$, and (ii) unreliable subcarriers (URS) set includes the data subcarriers where $\mathbf{d}'_{i-1}[k] \neq \mathbf{d}''_{i-1}[k]$. Frequency-domain cubic interpolation [7] is applied by using the channel estimates in RS to determine the channel estimates for the URS.

E. AE-DNN Estimation Scheme

AE-DNN channel estimation [8] has been proposed to compensate the DPA scheme estimation error that is caused by demapping errors resulting from (4), due to the noise imperfections and vehicular channel variations. As shown in Fig. 2, $\hat{h}_{\text{DPA}_i}[k]$ is fed to a three-hidden-layers DNN. Using the DNN on top of DPA scheme gives good performance but it is not sufficient, since it ignores the time and frequency correlation between successive received OFDM symbols. Moreover, the employed DNN architecture can be optimized to decrease the channel estimation computational complexity.

F. STA-DNN Estimation Scheme

In our recent research [9], DNN is used as a post non-linear processing unit after the conventional STA scheme. Conventional STA scheme updates the final estimate according to a linear combination between the previously estimated channel (6) and the frequency averaged channel estimates (5). However, in real case scenarios this linear combination leads to a significant performance degradation because the vehicular channel suffers from non-linear imperfections. Therefore, STA-DNN captures more features of the time-frequency correlations of the channel samples, besides correcting the conventional STA estimation error. Moreover, the optimized STA-DNN architecture achieves better performance than AE-DNN with 55.74% computational complexity decrease.

IV. PROPOSED TRFI-DNN ESTIMATION SCHEME

Neural networks [11] can be defined as a function that maps several inputs to the relative desired outputs. It consists of a group of neurons that are stacked together to form a layer. The neural network consists of at least one layer. Each

TABLE I: Proposed DNN parameters.

(Hidden layers; Neurons per layer)	(3;15-15-15)
Activation function	ReLU ($y = \max(0, x)$)
Number of epochs	500
Training samples	800000
Testing samples	200000
Batch size	128
Optimizer	ADAM
Loss function	MSE
Learning rate	0.001
Training SNR	30 dB

neuron performs a mathematical function that applies a non-linear processing to its inputs. DNN has mainly two phases: (i) *Training phase*: where the DNN updates its parameters by minimizing the input-output difference. (ii) *Testing phase*: where the DNN performance is evaluated.

Conventional TRFI assumes high correlation between two successive received OFDM symbols to estimate the channel of the RS and improve the estimation of the URS by applying frequency domain cubic interpolation. In realistic scenarios, vehicular channel suffers from non-linear imperfections, and thus, this assumption will be invalid and interpolation errors will occur. Therefore, as shown in Fig. 2, adding DNN as a post processing unit to the conventional TRFI scheme, higher order channel statistics can be learned by the DNN. In addition to capturing the non-linear dependencies between the previous and the current channel samples. Thereby, the DNN processing implicitly corrects the estimation and interpolation errors caused by the relatively low resolution cubic interpolation employed by the conventional TRFI. Moreover, it is worth mentioning that adding a DNN based block on top of an existing classical estimation scheme is compatible with the standard as it does not require a major physical layer changes of the IEEE 802.11p standard.

The proposed TRFI-DNN scheme aims to minimize the mean squared error (MSE) between the ideal channel $\tilde{\mathbf{h}}_i$ and TRFI estimated channel $\hat{\mathbf{h}}_{\text{TRFI}_i}$ such that:

$$\text{MSE}_{\text{TRFI-DNN}} = \frac{1}{N_{\text{Train}}} \sum_{i=1}^{N_{\text{Train}}} \left\| \tilde{\mathbf{h}}_i - \hat{\mathbf{h}}_{\text{TRFI}_i} \right\|^2. \quad (9)$$

N_{Train} denotes the number of DNN training samples. The proposed TRFI-DNN scheme parameters are summarized in Table. I, and it proceeds as follows:

- 1) The conventional TRFI channel estimate is converted from complex to real valued domain by stacking the real and imaginary values in one vector such that $\hat{\mathbf{h}}_{\text{TRFI}_i}^{(R)} \in \mathbb{R}^{2K_{\text{on}} \times 1}$.
- 2) $\hat{\mathbf{h}}_{\text{TRFI}_i}^{(R)}$ is fed as an input to the TRFI-DNN.
- 3) Finally, the corrected TRFI complex-valued channel estimate $\hat{\mathbf{h}}_{\text{TRFI-DNN}_i}$ is obtained by converting the real-valued output vector of TRFI-DNN to the complex-valued vector.

The DNN training is performed using SNR = 30 dB to achieve the best performance as observed in [12], due to the fact that when the training is performed for a high SNR value, the DNN is able to better learn the channel statistics, and due to its good generalization DNN ability, it can still perform well in low SNR regions, where the noise is dominant. It is worth mentioning that the training is performed offline which does not increase the online computational complexity. Moreover, intensive experiments are performed using the grid search algorithm [11] in order to select the best suitable DNN hyper parameters in terms of both performance and complexity.

V. SIMULATION RESULTS

The performance of the proposed TRFI-DNN channel estimation schemes versus conventional estimators, AE-DNN, and STA-DNN is evaluated using normalized mean-squared error (NMSE) and bit error rate (BER). After that, a detailed computational complexity analysis is presented.

There are several realistic vehicular channel models that are considered by IEEE 802.11p standard [13]. In our simulation, VTV Expressway (VTV-EX) vehicular channel model that represents the communication channel between two vehicles moving on a highway with high velocities is considered with two simulation scenarios: (i) $V = 120$ Km/h, and (ii) $V = 180$ Km/h. VTV-EX vehicular channel model is characterized by 11 multi-path propagation with high Doppler shifts (1000-1200 Hz), thus frequency and time selectivity are well represented. Moreover, the simulation is performed using 16QAM modulation order, and the transmitted OFDM frame size is 100 symbols.

A. BER and NMSE Performance

It can be seen from Fig. 3a, and 3b that conventional TRFI scheme achieves better performance than conventional STA and CDP schemes, where $V = 120$ Km/h. This is due to the performance degradation of conventional STA resulting from fixing the time and frequency averaging coefficients in (5) and (6). On the other hand, applying frequency domain cubic interpolation on top of conventional CDP is able to improve its performance, especially in high SNR region, where the assumption that the estimated channels of successive received OFDM symbols are highly correlated is valid, since the impact of noise is very low. Moreover, it is clearly shown that integrating DNN as a post non-linear processing unit after conventional estimation schemes reveals a significant performance superiority over conventional schemes. Therefore, as an intuitive interpretation, we can say that the DNNs was able to learn more about the statistics of the channel. Our simulations show that using AE-DNN after the DPA estimation is not sufficient, even though AE-DNN is able to outperform conventional estimation schemes. Due to the fact that DPA estimation ignores the time and frequency correlation between successive OFDM symbols, and suffers from high enlarged de-mapping error. Thus, AE-DNN is used to improve the DPA estimation by implicitly correcting the demapping error resulting from (4). STA-DNN outperforms both AE-DNN and

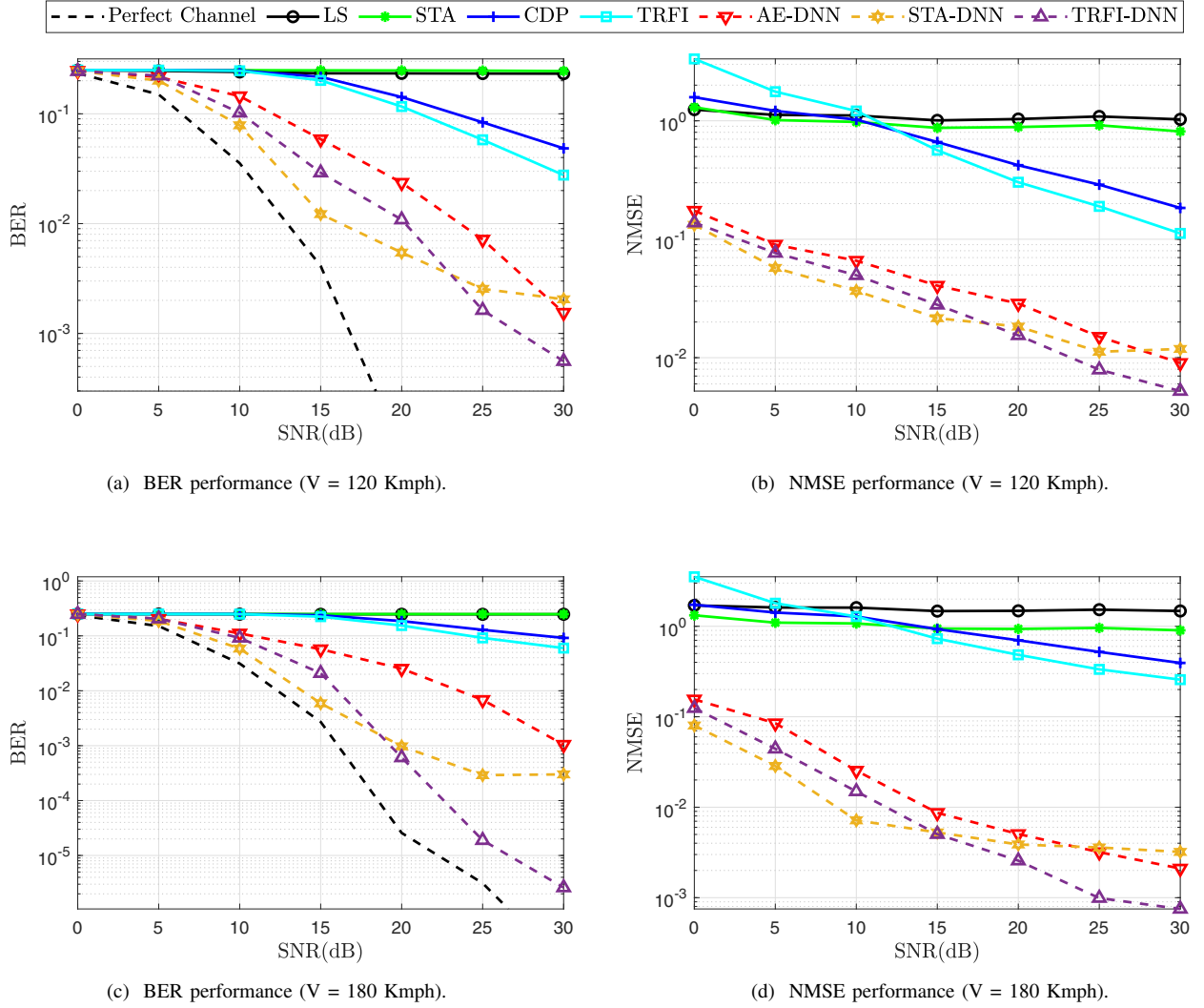


Fig. 3: BER and NMSE simulation results for VTV-EX vehicular channel model.

TRFI-DNN in low SNR regions, but an error floor appears starting from SNR = 20 dB. Starting from SNR = 25, TRFI-DNN outperforms the STA-DNN. On the other hand, TRFI-DNN outperforms AE-DNN by around 3 dB in terms of SNRs for a BER = 10^{-3} . Moreover, when higher mobility vehicular scenarios are employed as shown in Fig. 3c and 3d, it can be seen that the STA-DNN error floor starts to appear from SNR = 17 dB, while TRFI-DNN shows its significant performance superiority over STA-DNN in the high SNR region. It is worth mentioning that the optimized TRFI-DNN architecture achieves around 50% computational complexity decrease compared with AE-DNN, while it has almost similar computational complexity as STA-DNN as discussed in Section V-B.

B. Computational complexity analysis

The computational complexity is computed in terms of the number of total real-valued operations required to estimate the channel for a received OFDM symbol. When working with complex-valued operations, each complex-valued division

requires 8 real-valued multiplications/division and 3 real-valued summations/subtraction. The CDP scheme proceeds in (2), (3), (4), (7), and (8). Therefore, the overall computational complexity of CDP scheme is $34K_d$ multiplication/division, and $14K_d$ summation/subtraction, where LS scheme (2) requires $2K_{on}$ multiplication/division and $2K_{on}$ summation/subtraction.

The TRFI scheme performs the same operations as CDP scheme except (8). Instead of updating the final channel estimates as shown in (8), TRFI schemes perform cubic interpolation to improve the estimation of the unreliable subcarriers. $K_{int} = 10$ is the average number of unreliable subcarriers to be interpolated in each OFDM symbol. Cubic interpolation is performed by manipulating the third degree polynomial coefficients that defines the function curve that passes through the interpolated points within a specific interval [14]. The total TRFI computational complexity can be expressed by $34K_{on} + 26K_{int}$ multiplication/division, and $14K_d + 30K_{int}$ summation/subtraction, where 13 multiplica-

TABLE II: Computation complexity.

	Mul./Div.	Sum./Sub.
LS	$2K_{\text{on}}$	$2K_{\text{on}}$
STA	$22K_{\text{on}} + 2K_{\text{d}}$	$10K_{\text{on}} + 10K_{\text{d}}$
CDP	$34K_{\text{d}}$	$14K_{\text{d}}$
TRFI	$34K_{\text{on}} + 26K_{\text{int}}$	$14K_{\text{on}} + 30K_{\text{int}}$
AE-DNN	$178K_{\text{on}} + 1600$	$168K_{\text{on}} + 1600$
STA-DNN	$82K_{\text{on}} + 2K_{\text{d}} + 450$	$70K_{\text{on}} + 10K_{\text{d}} + 450$
TRFI-DNN	$94K_{\text{on}} + 26K_{\text{int}} + 450$	$74K_{\text{on}} + 30K_{\text{int}} + 450$

tions/divisions and 15 summations/subtractions are required to interpolate a single subcarrier. Similarly for the DNN online computational complexity, it can be expressed by the total number of multiplications and summations performed by all neurons in all DNN layers, such that:

$$C_{\text{DNN}} = 2 \sum_{l=0}^{L+1} N_{l-1}N_l, \text{ where } N_0 = N_{L+1} = 2K_{\text{on}}, \quad (10)$$

where L denotes the number of DNN hidden layers where $1 \leq l \leq L$. N_l denotes the number of neurons in the l -th hidden layer. The AE-DNN consists of three hidden layers with 40, 20, and 40 neurons respectively. Its overall computational complexity can be expressed as $178K_{\text{on}} + 1600$ multiplications and $168K_{\text{on}} + 1600$ summations/subtractions, where DPA estimation requires $18K_{\text{on}}$ multiplications, and $8K_{\text{on}}$ summations/subtractions, and AE-DNN operations require $160K_{\text{on}} + 1600$ multiplications and $160K_{\text{on}} + 1600$ summations/subtractions. As presented in [9], the computational complexity of STA-DNN is expressed by $82K_{\text{on}} + 2K_{\text{d}} + 450$ multiplications, and $70K_{\text{on}} + 10K_{\text{d}} + 450$ summations/subtractions, where STA scheme requires $22K_{\text{on}} + 2K_{\text{d}}$ multiplications/divisions and $10K_{\text{on}} + 10K_{\text{d}}$ summations/subtractions. The proposed TRFI-DNN architecture is less complex than the AE-DNN architecture, where TRFI-DNN consists of three hidden layers with equal neurons $N_1 = N_2 = N_3 = 15$. Hence, the total computational complexity of TRFI-DNN is $94K_{\text{on}} + 26K_{\text{int}} + 450$ multiplications, and $74K_{\text{on}} + 30K_{\text{int}} + 450$ summations/subtractions. Table II shows the cumulative computational complexity of the studied schemes. The proposed TRFI-DNN scheme decreases the number of multiplications and summations by 48% and 56%, respectively, in comparison with AE-DNN, while it has almost similar computational complexity as STA-DNN. It is worth mentioning that STA-DNN and TRFI-DNN can be employed to work in an adaptive manner, especially in high mobility scenarios, where STA-DNN can be used in low SNR regions while TRFI-DNN is utilized in high SNR regions. Therefore, significant BER and NMSE performance improvement can be achieved with reduced computational complexity.

VI. CONCLUSION

In this work, IEEE 802.11p conventional channel estimation schemes, besides the recently proposed AE-DNN and STA-DNN have been investigated. We have proposed a deep

learning based scheme that combines the use of the conventional TRFI channel estimation and DNN so that DNN can learn more channel statistics, besides the time and frequency correlations between the channel samples, thus correcting the interpolation errors, resulting in more improved channel variations tracking. Simulation results performed using high mobility vehicular channel model have shown that the proposed TRFI-DNN outperforms conventional estimators, AE-DNN, and STA-DNN in high SNR regions, and reduces the computational complexity by around 50% compared with the recently proposed AE-DNN, while it has almost the same computational complexity as STA-DNN.

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