



Towards Explainable AI for Channel Estimation in Wireless Communications

Journal:	<i>IEEE Transactions on Vehicular Technology</i>
Manuscript ID	VT-2023-01637
Suggested Category:	Correspondence
Date Submitted by the Author:	25-Apr-2023
Complete List of Authors:	Gizzini, Abdul Karim; Institut Mines-Télécom Lille Douai, CERI-SN Medjahdi, Yahia; Institut Mines-Télécom Lille Douai, CERI-SN Ghandour, Ali ; National Council for Scientific Research, National Center for Remote Sensing Clavier, Laurent; Institut Mines-Télécom Lille Douai, CERI-SN
Keywords:	Channel Estimation, Artificial intelligence, Time-varying channels, Explainable AI (XAI)

Towards Explainable AI for Channel Estimation in Wireless Communications

Abdul Karim Gizzini, Yahia Medjahdi, Ali J. Ghandour, Laurent Clavier

Abstract—Research into 6G networks has been initiated to support a variety of critical artificial intelligence (AI) assisted applications such as autonomous driving. In such applications, AI-based decisions should be performed in a real-time manner. These decisions include resource allocation, localization, channel estimation, etc. Considering the black-box nature of existing AI-based models, it is highly challenging to understand and trust the decision-making behavior of such models. Therefore, explaining the logic behind those models through explainable AI (XAI) techniques is essential for their employment in critical applications. This manuscript proposes a novel XAI-based channel estimation (XAI-CHEST) scheme that provides detailed reasonable interpretability of the deep learning (DL) models that are employed in doubly-selective channel estimation. The aim of the proposed XAI-CHEST scheme is to identify the relevant model inputs by inducing high noise on the irrelevant ones. As a result, the behavior of the studied DL-based channel estimators can be further analyzed and evaluated based on the generated interpretations. Simulation results show that the proposed XAI-CHEST scheme provides valid interpretations of the DL-based channel estimators for different scenarios.

Index Terms—6G, AI, XAI, channel estimation, XAI-CHEST

I. INTRODUCTION

It is envisioned that 6G technology will provide a new era of mass digital connectivity and automation of several advanced smart services such as autonomous driving and remote surgery [1]. Such services are mission critical, where high data rates, low latency, and robust communications must be established and guaranteed [2]. Artificial intelligence (AI) will be a key element in future smart applications, due to its great success in providing good performance compared to conventional methods. However, the recent deep learning (DL)-based schemes proposed for wireless communications suffer mainly from the lack of transparency and trust. In this context, the development of trustworthy DL-based schemes is a crucial need in order to provide explainability for the DL model decisions in a logical and understandable manner [3]. Motivated by the fact that reliable communications can be guaranteed by accurate channel estimation, recently, DL algorithms have been integrated into channel estimation [4] to handle the limitations of conventional channel estimators represented by prior data knowledge, high complexity and statistical assumptions. These limitations lead to significant

performance degradation, especially in doubly-selective environments, where the channel varies in both time and frequency. In contrast, DL-based channel estimators have succeeded in improving the overall system performance, especially when used on top of low-complexity conventional estimators. This success is mainly due to the robustness, low complexity, and good generalization ability of DL techniques. A variety of DL techniques are employed in the doubly-selective channel estimation [5], however, this paper considers the recently proposed feed-forward neural network (FNN)-based channel estimators [6]–[8].

Even though DL-based channel estimators provide a good performance-complexity trade-off, they lack decision-making interpretability. Hence, they are classified as black-box DL models with a main trustworthiness problem. This lack of interpretability can be addressed by developing explainable AI (XAI) schemes that increase the black-box models' transparency and explain why certain decisions were made. XAI schemes are able to provide reasoning and justifications of the DL behavior, thus, transforming the black-box model into a white-box model and ensuring the adaptation, trustfulness and transparency of a given model.

It should be noted that XAI schemes are used primarily in computer vision applications [9]. Procedures and methodology for adopting and deploying such schemes in the wireless communications discipline are still unclear. In this context, this paper proposes a novel XAI based channel estimation (XAI-CHEST) scheme, where the interpretability of recently proposed FNN-based channel estimators is investigated. The key idea is to employ an FNN model, denoted as the interpretability model, to provide interpretations for the considered black-box model denoted as the utility model. The interpretability model role is to induce noise on the FNN inputs without degrading the performance of the utility model. To achieve this, the interpretability model will only induce high noise on the FNN inputs that are not substantial to the utility model proper functioning. As a result, the interpretability model generates a noise mask that includes the corresponding noise weight for each FNN input, where the FNN inputs can be classified as either relevant or irrelevant inputs. Simulation results reveal that the proposed XAI-CHEST scheme is able to accurately illustrate the behavior of the utility model, thus transforming it into a white-box model. Furthermore, we show that employing only selected relevant inputs instead of the full inputs improves the FNN-based channel estimators performance.

To the best of our knowledge, this is the first work to propose an XAI scheme for physical layer applications in

Abdul Karim Gizzini, Yahia Medjahdi, and Laurent Clavier are with the Center for Digital Systems, IMT Nord Europe, Institut Mines-Télécom, University of Lille, France (e-mail: {abdul-karim.gizzini, yahia.medjahdi, laurent.clavier}@imt-nord-europe.fr).

Ali J. Ghandour is with the National Center for Remote Sensing - CNRS, Lebanon (e-mail: aghandour@cnrs.edu.lb).

wireless communications, specifically, channel estimation. In summary, the contributions of this paper are threefolds

- Proposing an XAI-CHEST scheme that provides detailed interpretability to the recently proposed FNN-based channel estimators.
- Showing that the interpretability of the studied FNN models can be achieved by inducing noise on the model inputs while maximizing their accuracy. Therefore, the inputs of the model are classified into relevant and irrelevant sets based on the induced noise mask.
- Providing an extensive performance evaluation of the proposed XAI-CHEST scheme in different scenarios, where we show that using only relevant inputs instead of the full set improves the performance of the studied FNN-based channel estimators and vice-versa.

The remainder of this paper is organized as follows: Section II presents the system model. The DL-based channel estimators to be interpreted are presented in Section III. Section IV illustrates the proposed XAI-CHEST scheme. In Section V, the performance of the proposed XAI-CHEST scheme in terms of bit error rate (BER) is analyzed. Finally, Section VI concludes the manuscript.

II. SYSTEM MODEL

Consider a frame consisting of I orthogonal frequency division multiplexing (OFDM) symbols. The i -th transmitted frequency-domain OFDM symbol $\tilde{\mathbf{x}}_i[k]$, is denoted by

$$\tilde{\mathbf{x}}_i[k] = \begin{cases} \tilde{\mathbf{x}}_{i,d}[k], & k \in \mathcal{K}_d \\ \tilde{\mathbf{x}}_{i,p}[k], & k \in \mathcal{K}_p \\ 0, & k \in \mathcal{K}_n \end{cases} \quad (1)$$

where $0 \leq k \leq K-1$. The total number of used subcarriers is divided into $K_{on} = K_d + K_p$ subcarriers in addition to K_n null guard band subcarriers, where $\tilde{\mathbf{x}}_{i,d}[k]$ and $\tilde{\mathbf{x}}_{i,p}[k]$ represent the modulated data symbols and the predefined pilot symbols allocated at a set of subcarriers denoted \mathcal{K}_d and \mathcal{K}_p , respectively. The received frequency-domain OFDM symbol denoted as $\tilde{\mathbf{y}}_i[k]$ is expressed as follows:

$$\tilde{\mathbf{y}}_i[k] = \tilde{\mathbf{h}}_i[k]\tilde{\mathbf{x}}_i[k] + \tilde{\mathbf{e}}_i[k] + \tilde{\mathbf{v}}_i[k], \quad k \in \mathcal{K}_{on} \quad (2)$$

where $\tilde{\mathbf{h}}_i[k] \in \mathbb{C}^{K_{on} \times 1}$ refers to the frequency response of the doubly-selective channel at the i -th OFDM symbol and k -th subcarrier. $\tilde{\mathbf{v}}_i[k]$ signifies the additive white Gaussian noise (AWGN) of variance σ^2 and $\tilde{\mathbf{e}}_i[k]$ denotes the Doppler interference derived in [5].

III. DL-BASED CHANNEL ESTIMATION SCHEMES

Conventional channel estimators are based on preamble-based channel estimation, where the channel is estimated once at the beginning of the received frame. In this case, the estimated channel becomes outdated in high-mobility environments. Pilot subcarriers allocated within a transmitted OFDM symbol are limited and cannot fully capture the doubly selective channel variations. In this context, several channel estimators are proposed in the literature to allow better channel

tracking over time, where FNN is applied as a post-processing on top of conventional channel estimators. In this work, the interpretability of the recently proposed spectral temporal averaging (STA)-FNN and time-domain reliable test frequency domain interpolation (TRFI)-FNN channel estimators is investigated.

A. STA-FNN

In the STA estimator [10], frequency- and time- domain averaging are applied on top of the data-pilot aided (DPA) channel estimation. We note that DPA channel estimation utilizes the demapped data subcarriers of the previously received OFDM symbol to estimate the channel for the current OFDM symbol such that

$$\tilde{\mathbf{d}}_i[k] = \mathfrak{D}\left(\frac{\tilde{\mathbf{y}}_i[k]}{\hat{\mathbf{h}}_{\text{DPA}_{i-1}}[k]}\right), \quad \hat{\mathbf{h}}_{\text{DPA}_0}[k] = \hat{\mathbf{h}}_{\text{LS}}[k] \quad (3)$$

where $\mathfrak{D}(\cdot)$ refers to the demapping operation to the nearest constellation point in accordance with the employed modulation order. $\hat{\mathbf{h}}_{\text{LS}}$ stands for the LS estimated channel at the received preambles. Thereafter, the final DPA channel estimates are updated in the following manner

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

Finally, frequency- and time- domain averaging are implemented as follows:

$$\hat{\mathbf{h}}_{\text{FD}_i}[k] = \sum_{\lambda=-\beta}^{\lambda=\beta} \omega_\lambda \hat{\mathbf{h}}_{\text{DPA}_i}[k+\lambda], \quad \omega_\lambda = \frac{1}{2\beta+1} \quad (5)$$

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

STA estimator performs well in low signal-to-noise ratio (SNR) region. However, it suffers from a considerable error floor in high SNR regions due to: (i) large DPA demapping error and (ii) fixed frequency and time averaging coefficients $\alpha = \beta = 2$. Therefore, STA channel estimator suffers from a significant performance degradation in real-case scenarios due to the high doubly-selective channel variations. As a workaround, FNN is utilized as a nonlinear post-processing unit following STA [6]. STA-FNN is able to better capture the time-frequency correlations of the channel samples, in addition to correcting the conventional STA estimation error.

B. TRFI-FNN

TRFI estimation scheme [11] is another methodology used for improving the DPA estimation in (4). Assuming that the time correlation of the channel response between two adjacent OFDM symbols is high, TRFI defines two sets of subcarriers such that: (i) \mathcal{RS}_i set that includes the reliable subcarriers indices, and (ii) \mathcal{URS}_i set which contains the unreliable subcarriers indices. The estimated channels for \mathcal{URS}_i are then interpolated using the \mathcal{RS}_i channel estimates by means of

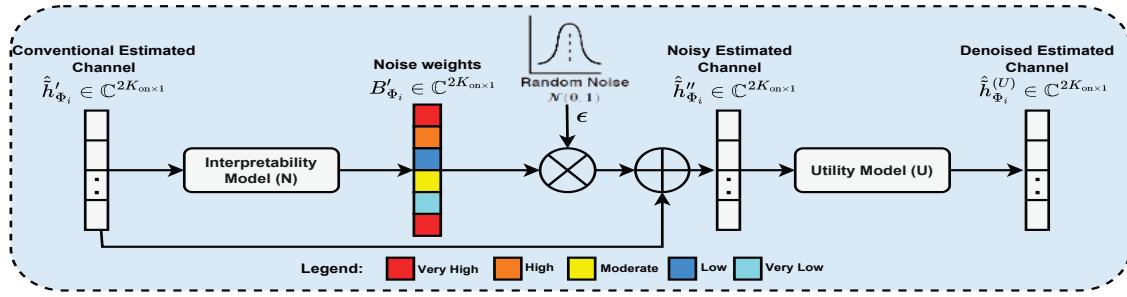


Fig. 1: Block diagram of the proposed XAI-CHEST scheme.

the frequency-domain cubic interpolation¹. TRFI outperforms STA, especially in high SNR region. However, TRFI still suffers from demapping and interpolation errors, as the number of reliable subcarriers (RS) subcarriers is inversely proportional to the channel frequency selectivity. Therefore, applying cubic interpolation with only a few RS subcarriers degrades the performance. Therefore, an optimized FNN architecture is coined in [7] with $\hat{\mathbf{h}}_{\text{TRFI}}[k]$ as an input instead of $\hat{\mathbf{h}}_{\text{STA}}[k]$. TRFI-FNN corrects the cubic interpolation error, thus leading to improved performance in high SNR regions. Since real-valued FNN model is considered, the conventional estimated channel should be converted from complex to real domain by stacking the real and imaginary parts of FNN input vector, where $\hat{\mathbf{h}}'_{\Phi_i} \in \mathbb{R}^{2K_{on} \times 1}$ denotes the converted estimated channel vector, such that

$$\hat{\mathbf{h}}'_{\Phi_i} = [\Re(\hat{\mathbf{h}}_{\Phi_i}); \Im(\hat{\mathbf{h}}_{\Phi_i})] \quad (7)$$

where $\hat{\mathbf{h}}_{\Phi_i} \in \mathbb{C}^{K_{on} \times 1}$ denotes the initially estimated channel and $\Phi \in [\text{STA}, \text{TRFI}]$ refers to the estimation scheme.

IV. PROPOSED XAI-CHEST SCHEME

The proposed XAI-CHEST scheme is based on the intuition that if a subcarrier is relevant for the decision-making of a trained model, then adding noise with high weight to this subcarrier would negatively impact the accuracy of the trained model and vice-versa. Thus, it is expected that considering only the relevant subcarriers as model inputs would improve channel estimation performance. In this context, we assume a utility model U with parameters θ_U , which accounts for the model whose decisions we want to interpret, i.e., STA-FNN or TRFI-FNN, and an interpretability model N , with parameters θ_N , whose purpose is to compute the value of the induced noise weight to each subcarrier within the FNN input vector, i.e. $\hat{\mathbf{h}}_{\text{STA}_i}$ or $\hat{\mathbf{h}}_{\text{TRFI}_i}$, while simultaneously maximizing the performance of the utility model. We note that both U and N models have the same FNN architecture as illustrated in Figure 1. Let $\hat{\mathbf{h}}'_{\Phi_i} \in \mathbb{R}^{2K_{on} \times 1}$ be the interpretability model input, where the latter produces a mask $B'_{\Phi_i} \in \mathbb{R}^{2K_{on} \times 1}$ that can be represented as follows

¹The reliable/unreliable subcarriers are classified by TRFI channel estimator, while relevant/irrelevant subcarriers are classified by the proposed XAI scheme.

$$B'_{\Phi_i} = N(\hat{\mathbf{h}}'_{\Phi_i}, \theta_N) \quad (8)$$

where $B'_{\Phi_i} \in [0, 1]$ determines the weight of noise applied to each element in $\hat{\mathbf{h}}'_{\Phi_i}$. We note that the scaling of B'_{Φ_i} is achieved by using the sigmoid activation function. Based on B'_{Φ_i} , the conventional estimated channel vector including the induced noise $\hat{\mathbf{h}}''_{\Phi_i}$ can be expressed such that

$$\hat{\mathbf{h}}''_{\Phi_i} = \hat{\mathbf{h}}'_{\Phi_i} + B'_{\Phi_i} \epsilon \quad (9)$$

Here, $\epsilon \sim \mathcal{N}(0, 1)$ denotes the random noise sampled from the standard normal distribution. After that, $\hat{\mathbf{h}}''_{\Phi_i}$ is fed as input to the frozen utility model U , i.e., STA-FNN or TRFI-FNN, such that

$$\hat{\mathbf{h}}^{(U)}_{\Phi_i} = U(\hat{\mathbf{h}}''_{\Phi_i}, \theta_U) \quad (10)$$

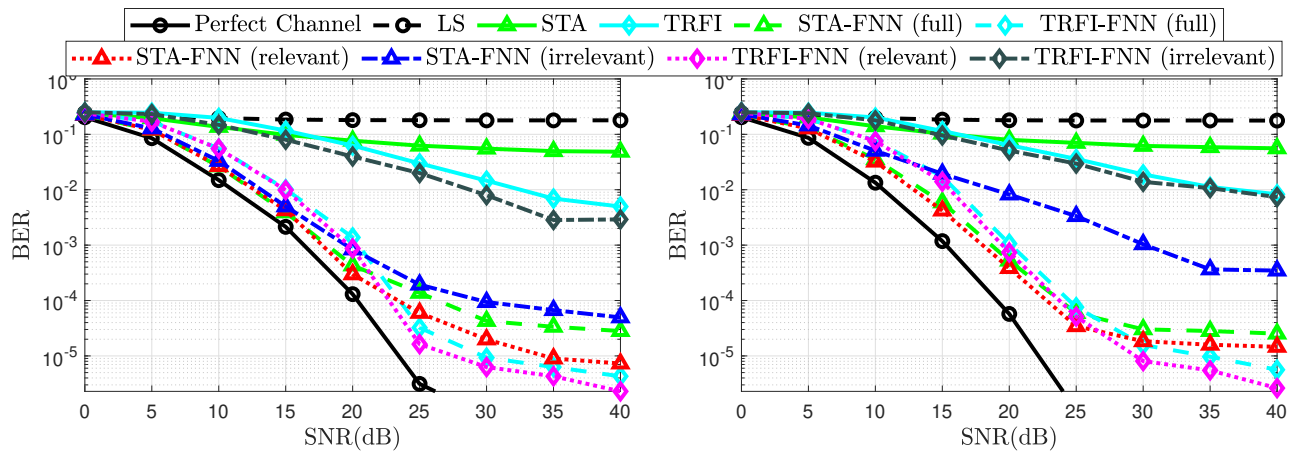
The aim of training the interpretability model is to minimize the following customized loss function:

$$\text{Loss}_N = \min_{\theta_N} [-\log(\text{Loss}_U) - \lambda \log(B'_{\Phi_i})] \quad (11)$$

The first term in Eq. (11) is the loss function of the utility model U that represents mean squared error (MSE) between the initially estimated channel $\hat{\mathbf{h}}'_{\Phi_i}$ and the true channel $\tilde{\mathbf{h}}_{\Phi_i}$, such that:

$$\text{Loss}_U = \frac{1}{N_{tr}} \cdot \sum_{i=1}^{N_{tr}} (\tilde{\mathbf{h}}_{\Phi_i} - \hat{\mathbf{h}}'_{\Phi_i})^2 \quad (12)$$

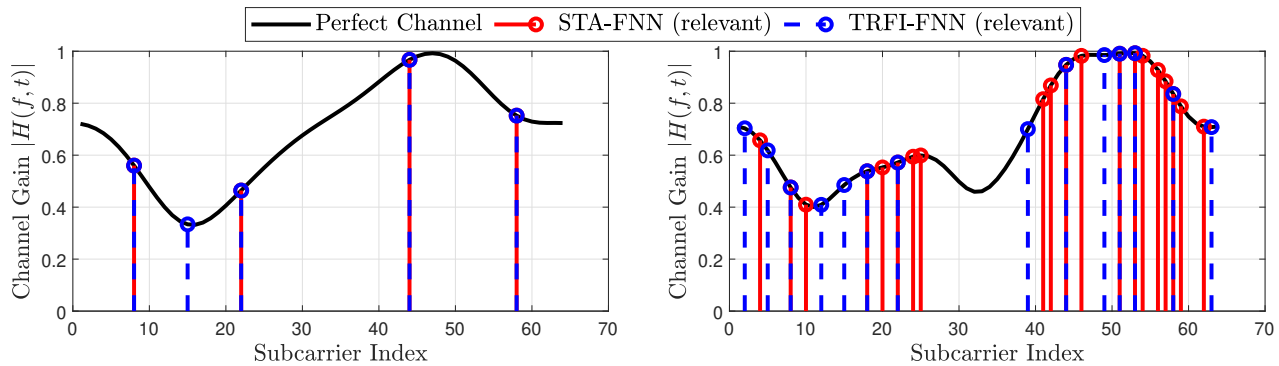
where N_{tr} is the number of training samples used. The second term in (11) boosts the growth of the noise weight for each element in $\hat{\mathbf{h}}''_{\Phi_i}$ so that relevant and irrelevant subcarriers can be identified. We would like to mention that the training of the interpretability model N is performed once according to the channel model used. In the testing phase, the obtained B'_{Φ_i} includes the noise weights for the real and imaginary parts of each input subcarrier. B'_{Φ_i} is scaled back to $B_{\Phi_i} \in \mathbb{R}^{K_{on} \times 1}$, where the noise weight of the real and imaginary parts for each subcarrier are averaged. The motivation behind this averaging lies in the fact that it is noticed during the training phase that the interpretability model produces almost the same noise weight for the real and imaging parts of each subcarrier within $\hat{\mathbf{h}}'_{\Phi_i}$. Figure 1 shows the block diagram of the proposed XAI-CHEST scheme.



(a) Low frequency-selective vehicular channel model.

(b) High frequency-selective vehicular channel model.

Fig. 2: BER Performance for high mobility vehicular channel models.



(a) Low frequency-selective vehicular channel model.

(b) High frequency-selective vehicular channel model.

Fig. 3: Selected relevant subcarriers by the proposed interpretability model.

V. SIMULATION RESULTS

This section illustrates the performance evaluation of the proposed XAI-CHEST scheme, where BER performance of STA-FNN and TRFI-FNN estimators is analyzed taking into consideration full, relevant, and irrelevant subcarriers. We note that the noise thresholds used to classify the subcarriers are empirically chosen and defined as $N_{\text{TRFI-th}} = 0.6$ and $N_{\text{STA-th}} = 0.3$, where the systematic fine-tuning of them is kept as future work. This means that all the subcarriers given a noise weight greater than the defined threshold are classified as irrelevant subcarriers and vice-versa.

BER is evaluated using two vehicular channel models [12] as shown in Table I: (i) Low-frequency selectivity, where Vehicle-to-Vehicle urban scenario (VTV-US) is employed. (ii) High-frequency selectivity, where Vehicle-to-Infrastructure urban scenario (VTI-US) is considered. In both scenarios, Doppler frequency $f_d = 1000$ Hz is considered. Both the interpretability and utility models are trained using a 100,000 OFDM symbols dataset, splitted into 80% training and 20% testing. ADAM optimizer is used with a learning rate $lr = 0.001$ with batch size equals 128 for 500 epoch. Simulation

parameters are based on the IEEE 802.11p standard [5], where the comb pilot allocation is used so that $K_p = 4$, $K_d = 48$, $K_n = 12$, and $I = 50$. QPSK modulation is considered with SNR ranges $[0, 5, \dots, 40]$ dB.

Figure 2 depicts the BER performance of the STA-FNN and TRFI-FNN channel estimation schemes studied. It is clearly shown that employing only the LS channel estimation suffers from severe performance degradation, as the channel becomes outdated among the received OFDM symbols. Moreover, limited improvement can be achieved with the conventional STA and TRFI channel estimation scheme due to the enlarged DPA demapping error. This is attributed to the fact that conventional STA estimation outperforms TRFI in low SNR regions because of frequency and time averaging operations that can alleviate the impact of noise and demapping error in low SNR regions. However, the averaging operations are not useful in high SNR regions since the impact of noise is low, and the STA averaging coefficients are fixed. Hence, the TRFI channel estimation is more accurate in high SNR regions. As observed, FNN can implicitly learn the channel correlations apart from preventing a high demapping error

Table I: Characteristics of the employed channel models following Jake's Doppler spectrum.

Channel model	Average path gains [dB]	Path delays [ns]
VTV-US	[0, 0, -10, -10, -10, -17.8, -17.8, -17.8, -21.1, -21.1, -26.3, -26.3]	[0, 1, 100, 101, 102, 200, 201,202, 300, 301,400, 401]
VTI-US	[0, 0, -9.3, -9.3, -14, -14, -18, -18, -19.4,-24.9, -27.5, -29.8]	[0, 1, 100, 101, 200, 201, 300,301, 400, 500, 600, 700]

arising from conventional estimation where STA-FNN and TRFI-FNN significantly outperform conventional STA and TRFI estimators.

In order to evaluate the performance of the proposed XAI-CHEST scheme, both STA-FNN and TRFI-FNN estimators are implemented in three different configurations: (i) Full where $\hat{\mathbf{h}}'_{\Phi_i} \in \mathbb{R}^{2K_{on} \times 1}$ includes all sub-carriers as an FNN input. (ii) Relevant where only relevant subcarriers experiencing noise below the defined $N_{\Phi-th}$ are fed to the FNN. (ii) Irrelevant where irrelevant subcarriers recording noise weights above the defined threshold are considered. It is worth mentioning that when the relevant subcarriers are used instead of the full subcarriers, STA-FNN and TRFI-FNN perform better and 2 dB and 1 dB gain are achieved in terms of SNR for $BER = 10^{-4}$, respectively. On the contrary, significant performance degradation can be noticed for both STA-FNN and TRFI-FNN estimators when irrelevant subcarriers are used, even though the number of irrelevant subcarriers is greater than the number of relevant subcarriers².

In order to further validate the recorded BER results, the position of relevant subcarriers selected by the interpretability model is analyzed, as illustrated in Figure 3. It is clearly shown that the relevant subcarriers experiencing low noise induced by the interpretability model are distributed among the sharp channel variations. This reveals that it is not necessary for the FNN model to have the full $K_{on} = 52$ subcarriers as an input. It can perform better by choosing the appropriate subcarriers to capture the main channel variation among the subcarriers. Moreover, the number of selected relevant subcarriers increases with the increase in frequency selectivity. In high-frequency selectivity, the channel variation across the subcarriers becomes more challenging, and thus more subcarriers are required by the FNN to accurately estimate the channel. Moreover, it can be noticed that as the accuracy of the initial estimation increases, the number of selected relevant subcarriers decreases, where STA-FNN requires more relevant subcarriers than TRFI-FNN. This means that the interpretability model is able to induce more noise weight to the irrelevant subcarriers within TRFI-FNN since it is more accurate, whereas less noise is induced to the STA-FNN input since it is already noisy. Finally, fine-tuning the noise threshold can be achieved by studying the characteristics of the channel model employed and the BER requirement. However, in all cases, using the proposed XAI-CHEST scheme to select the relevant subcarriers optimizes the FNN input size in addition to improving the BER performance and providing a reasonable interpretation of the behavior of the employed FNN model.

²BER is computed over all the data subcarriers within the received OFDM symbols. The difference lies in the size of the FNN input vector that includes the relevant or irrelevant subcarriers.

VI. CONCLUSION

Building trust and transparency of the AI-based solution is a critical issue in future 6G communications. The need to provide reasonable interpretability of the black box AI models is a must. In this context, an XAI-CHEST scheme is proposed where the interpretability of the recently proposed FNN-based channel estimation schemes is thoroughly investigated. The proposed XAI-CHEST scheme aims to induce higher noise weights on the irrelevant feed-forward neural network (FNN) input subcarriers, thus, enabling a trustworthy, optimized, and robust channel estimation. Simulation results reveal that employing only the relevant subcarriers within the channel estimation leads to a significant improvement in the BER performance while optimizing the FNN input. Therefore, ensuring that FNN models are able to learn the most relevant features that maximize the channel estimation accuracy.

REFERENCES

- [1] W. Guo, "Explainable artificial intelligence for 6g: Improving trust between human and machine," *IEEE Communications Magazine*, vol. 58, no. 6, pp. 39–45, 2020.
- [2] R. S. Balan, S. Deepa, and C. Balakrishnan, "Transforming towards 6g: Critical review of key performance indicators," in *2022 4th International Conference on Circuits, Control, Communication and Computing (I4C)*, 2022, pp. 341–346.
- [3] M. Zolanvari, Z. Yang, K. Khan, R. Jain, and N. Meskin, "Trust xai: Model-agnostic explanations for ai with a case study on iiot security," *IEEE Internet of Things Journal*, vol. 10, no. 4, pp. 2967–2978, 2023.
- [4] Y. Yang, F. Gao, X. Ma, and S. Zhang, "Deep Learning-Based Channel Estimation for Doubly Selective Fading Channels," *IEEE Access*, vol. 7, pp. 36 579–36 589, 2019.
- [5] A. K. Gizzini and M. Chafii, "A survey on deep learning based channel estimation in doubly dispersive environments," *IEEE Access*, vol. 10, pp. 70 595–70 619, 2022.
- [6] A. K. Gizzini, M. Chafii, A. Nimr, and G. Fettweis, "Deep Learning Based Channel Estimation Schemes for IEEE 802.11p Standard," *IEEE Access*, vol. 8, pp. 113 751–113 765, 2020.
- [7] A. K. Gizzini, M. Chafii, A. Nimr, and G. Fettweis, "Joint TRFI and Deep Learning for Vehicular Channel Estimation," in *IEEE GLOBE-COM 2020*, Taipei, Taiwan, Dec. 2020.
- [8] A. Karim Gizzini, M. Chafii, A. Nimr, R. M. Shubair, and G. Fettweis, "Cnn aided weighted interpolation for channel estimation in vehicular communications," *IEEE Transactions on Vehicular Technology*, vol. 70, no. 12, pp. 12 796–12 811, 2021.
- [9] T. Koker, F. Mireshghallah, T. Titcombe, and G. Kaissis, "U-noise: Learnable noise masks for interpretable image segmentation," in *2021 IEEE International Conference on Image Processing (ICIP)*. IEEE, 2021, pp. 394–398.
- [10] J. A. Fernandez, K. Borries, L. Cheng, B. V. K. Vijaya Kumar, D. D. Stancil, and F. Bai, "Performance of the 802.11p Physical Layer in Vehicle-to-Vehicle Environments," *IEEE Transactions on Vehicular Technology*, vol. 61, no. 1, pp. 3–14, 2012.
- [11] Yoon-Kyeong Kim, Jang-Mi Oh, Yoo-Ho Shin, and Cheol Mun, "Time and Frequency Domain Channel Estimation Scheme for IEEE 802.11p," in *17th International IEEE Conference on Intelligent Transportation Systems (ITSC)*, 2014, pp. 1085–1090.
- [12] I. Sen and D. W. Matolak, "Vehicle-vehicle channel models for the 5-ghz band," *IEEE Transactions on Intelligent Transportation Systems*, vol. 9, no. 2, pp. 235–245, 2008.