Deep Learning Based OFDM Physical-Layer Receiver for Extreme Mobility

Jaakko Pihlajasalo[1], Dani Korpi[2], Mikko Honkala[2], Janne M. J. Huttunen[2], Taneli Riihonen[1], Jukka Talvitie[1], Mikko A. Uusitalo[2], and Mikko Valkama[1]

[1]Electrical Engineering, Tampere University, Finland

[2]Nokia Bell Labs, Espoo, Finland

***Abstract*—In this paper, we propose a machine learning (ML) aided physical layer receiver technique for demodulating OFDM signals that are subject to very high Doppler effects and the corresponding distortion in the received signal. Specifically, we develop a deep learning based convolutional neural network receiver system that absorbs proper two-dimensional received signal entities in time and frequency, while containing convolutional neural network layers to efficiently and reliably demodulate the bits — when properly trained — despite the substantial Doppler distortion. Representative set of numerical results is provided, in the context of 5G NR mobile communication network and corresponding base-station demodulation performance for uplink. The obtained results show that the proposed receiver system is able to clearly outperform classical LMMSE receivers that operate on subcarrier level and neglect the Doppler-induced intercarrier interference (ICI). Additionally, the proposed ML receiver has the advantage over ICI cancellation based receivers in terms of the reference signal overhead. This paper provides the description of the method and vast set of numerical results in 5G NR network context.**

***Index Terms*—5G NR, deep learning, Doppler, intercarrier interference, machine learning, mobility, OFDM, reference signals**

I. Introduction

The first many deployments of the fifth-generation (5G) mobile networks have already taken place, providing major performance enhancements compared to fourth-generation (4G) Long Term Evolution (LTE) technology, in terms of the network capacity, peak data rates, reliability and latency [1], for example. Additionally, stemming already from the International Telecommunication Union (ITU) 5G requirements [2], enhanced mobility support up to 500 km/h, or even beyond, is one essential requirement. A good example of such high-mobility use cases is the high-speed train (HST) scenario studied, e.g., in [3]. Following the 3GPP guidelines for the 5G New Radio (NR) high-speed scenario specified in [4], it was illustrated that signal impairments due to extreme mobility conditions must be handled properly in order to support high data rates and the possible underlying mission-critical railway management functionalities.

One technical challenge related to high user equipment (UE) mobility in orthogonal frequency division multiplexing (OFDM) based networks, such as 5G NR, is the Doppler phenomenon stemming from the time-varying mobile radio channel [5], [6]. Specifically, the Doppler spread is known to induce intercarrier interference (ICI) to the received signal, challenging the data demodulation. One system engineering approach to reduce or control the impact of the ICI is to design the radio interface numerology, specifically the subcarrier spacing (SCS), such that OFDM symbols are sufficiently short compared to mobile channel coherence time. However, assuming that a fixed cyclic prefix (CP) overhead is pursued, this then directly means that the CP duration is also shorter compared to the case of smaller SCS and longer symbols. Short CP duration, in turn, reduces the feasible cell size and time-dispersion tolerance in the system. An alternative technical approach is to develop and deploy more advanced receivers that can estimate and cancel the ICI along the demodulation process, see, e.g., [3], [6], [7] and the references therein. However, such approaches call for additional system overhead in terms of properly designed reference signals while also imposing increased receiver complexity.

In this article, we propose a trained machine learning (ML) aided physical-layer receiver system as an alternative to existing ICI cancellation based receivers, for efficiently demodulating OFDM signals under the presence of severe Doppler distortion. The ML receiver system contains customized convolutional layers such that, when complemented with proper training procedures, the receiver can efficiently and reliably demodulate the received signal without any additional ICI-related reference signals. This allows for reducing the system reference signal overhead, while at the same time facilitating support for extreme Doppler spreads in the order of 10% of the SCS, or even beyond. Therefore, the proposed receiver scheme allows for supporting large UE velocities in the network with smaller SCS values, compared to normal system design trade-offs, which in turn helps in increasing the cell size in the network.

The proposed scheme is evaluated with numerical results in the context of 5G NR mobile networks, which specifically explore the performance under varying Doppler distortion. The results show that the ML-based receiver compensates the effects of the ICI even under high Doppler distortion.

Notation: Matrices are represented with boldface uppercase letters and they can consist of either real- or complex-valued elements, i.e., $\mathbf{X} \in \mathbb{F}^{N \times M}$, where $\mathbb{F}$ stands for either $\mathbb{R}$ or $\mathbb{C}$.

II. ML Receivers – State-of-the-Art

ML-aided radio reception has already been considered in several works, which have investigated implementing certain parts of the receiver chain with learned layers. For instance, channel estimation with neural networks has been studied in [8], [9], while [10] utilizes convolutional neural networks (CNNs) [11] for equalization. ML-based demapping has been considered in [12], where it was shown to achieve nearly the same accuracy as the optimal demapping rule, albeit with greatly reduced computational cost. Some works also propose augmenting the receiver processing flow with deep learning components [13]–[15] and show improved performance in comparison to conventional benchmark receivers.

A fully convolutional neural network based receiver, referred to as DeepRx, was proposed in [16], [17], and it was shown to achieve high performance especially under sparse pilot configurations. In addition to that, there are also other ML-based solutions for learning larger portions of the receiver, such as the work in [18], where channel estimation and signal detection are carried out jointly using a fully-connected neural network. There it is shown that the proposed ML-based receiver outperforms the conventional receiver when there are few channel estimation pilots or when the cyclic prefix is omitted. In addition, it is shown to be capable of dealing rather well with clipping noise, a type of hard nonlinearity. The work in [19], on the other hand, applies CNNs to implement a receiver that extracts the bit estimates directly from a time-domain RX signal by learning the discrete Fourier transform (DFT).

The prospect of learning the transmitter and receiver jointly has also been investigated by various works [20]–[23]. Such schemes do not assume any pre-specified modulation scheme or waveform, but instead learn everything from scratch. Such end-to-end learning has been shown to have potential to outperform traditional heuristic radio links, e.g., by learning a better constellation shape [22] or by learning to communicate under a nonlinear power amplifier [23].

Despite the wide body of literature regarding ML-based radio receivers and the various demonstrations of their promising performance, the effects of severe Doppler and corresponding ICI have been largely omitted in the analysis thus far — to the best of the authors' knowledge. In this paper, we specifically address this issue and describe a CNN-based receiver architecture, inspired by [16], that is capable of accurate and reliable OFDM signal demodulation under heavy Doppler-induced ICI distortion.

III. System Model

Figure 1 depicts the general framework of the considered receiver architecture. The upper part of Fig. 1 illustrates a conventional OFDM receiver, highlighting the parts replaced by the learned CNN receiver in this work. Let us first define the received signal model under time-varing multipath channel. Using baseband equivalents, it can be expressed as

$$y(n) = \sum_{m=0}^{M-1} h_{m,n} x(n-m) + w(n), \tag{1}$$

where $h_{m,n}$ denotes the time-varying M-path channel impulse response, $x(n)$ is the transmit waveform, and $w(n)$ is the noise-plus-interference signal. The ICI stems from the fact that $h_{m,n}$ varies also within each OFDM symbol (i.e., with respect to the time index n), and is commonly expressed in frequency domain, i.e., at subcarrier level.

To this end, after CP removal, the received time-domain signal is converted to frequency domain using a fast Fourier transform (FFT). Then, the ith received OFDM symbol can be expressed as

$$\mathbf{Y}_i = \mathbf{H}_i \mathbf{X}_i + \mathbf{N}_i, \tag{2}$$

where $\mathbf{Y}_i \in \mathbb{C}^{N_D \times 1}$ and $\mathbf{X}_i \in \mathbb{C}^{N_D \times 1}$ are the received and transmitted OFDM symbols in frequency domain, respectively, $\mathbf{H}_i \in \mathbb{C}^{N_D \times N_D}$ is the frequency-domain channel matrix containing also the effects of the ICI, $\mathbf{N}_i \in \mathbb{C}^{N_D \times 1}$ is the noise-plus-interference signal, and N_D denotes the number of allocated subcarriers. Specifically, $\mathbf{H}_i$ is a banded matrix, where the non-zero off-diagonal elements stem from ICI.

In a conventional receiver, the demodulation reference signals (DMRSs) are extracted from the pilot-carrying OFDM symbols in $\mathbf{Y}_i$ for channel estimation, as illustrated in Fig. 1, after which the signal is equalized and the soft bits are extracted. In this work, we consider the widely-used linear minimum mean square error (LMMSE) receiver as the baseline or reference, which performs single-tap equalization for each resource element (RE). For a description of such a receiver, see, e.g., [16]. As a final outcome, the receiver will provide the so-called log-likelihood ratios (LLRs) for each data-carrying RE.

More complex ICI estimation and cancellation based receivers, such as those in [3], [6], [7], involve also the estimation of the non-diagonal entries of the channel matrix $\mathbf{H}_i$ which can be facilitated by specifically designed additional reference signals that allow for ICI estimation [6], [24].

IV. Proposed Method and Data Generation

The goal of the proposed ML-based receiver is to detect the bits from the Doppler distorted RX signals collected during a TTI. A high-level depiction of the receiver architecture is shown in the lower part of Fig. 1. As the Doppler distortion affects the nearby subcarriers, we utilize 2D convolutional layers with residual connections that follows residual network (ResNet) structure [16]. Such 2D CNNs are generally tasked to learn features on small regions of the input. The receptive field of the complete 2D CNN structure is chosen such that it can observe the neighboring subcarriers in both frequency and time. Furthermore, as the Doppler distortion affects nearby subcarriers, we assume that trained convolutional filters with suitable receptive fields can mitigate the ICI. Our assumption is that the CNN, in addition to estimating the channel, can mitigate the distortion caused by the Doppler spread even in high mobility cases.

The inputs of the ML-based receiver are the Doppler-distorted RX signals and the raw least squares DMRS channel estimates, whose real and imaginary values are concatenated along the third input dimension. The raw channel estimate array contains zeros for the data-carrying REs. Thus, the input

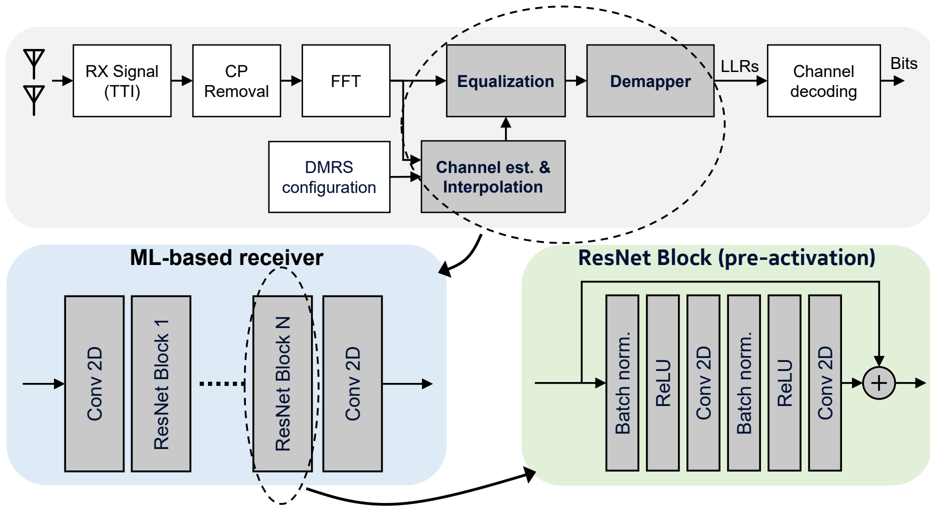


Fig. 1. General depiction of a conventional OFDM receiver (top), with the learned parts of the receiver being highlighted. The structures of the learned receiver and of an individual pre-activation ResNet block are also illustrated.

TABLE I
SIMULATION PARAMETERS FOR TRAINING AND VALIDATION

Parameter	Value	Randomization
Channel model	TDL-A to TDL-E	Uniform distribution
Center frequency	2.6 GHz	None
SNR	0 dB – 35 dB	Uniform distribution
Doppler shift	0 Hz – 1500 Hz	Uniform distribution
Channel bandwidth	5 MHz	None
Number of subcarriers (N_D)	312 subcarriers	None
FFT size (N)	512	None
Subcarrier spacing	15 kHz	None
OFDM symbol duration	71.4 μs	None
TTI length (N_{symb})	14 OFDM symbols	None
DMRS configuration	2 symbols per TTI	None
Modulation scheme	64-QAM	None

to the network is a real valued array $\mathbf{Z} \in \mathbb{R}^{N_D \times N_{\text{symb}} \times 4}$. The overall ML receiver architecture is illustrated in Fig. 1, being composed of 2D convolutional pre-activation ResNet blocks. The output of the learned receiver is a real-valued array $\mathbf{L} \in \mathbb{R}^{N_D \times N_{\text{symb}} \times N_B}$ consisting of the estimated LLRs, where N_{symb} is the number of OFDM symbols per TTI (typically 14 in 5G NR networks), and N_B is the number of bits per RE. The bit estimates are obtained by feeding the LLRs through the sigmoid-function.

A. Training and Data Generation

In order to generate training and validation data, we simulated a 5G physical uplink shared channel (PUSCH) link with Matlab's 5G Toolbox [25], using the parameters specified in Table I. Since the focus of this work is on the ML receiver's performance under severe Doppler shifts, we generated one large dataset for training with random Doppler shifts in the range of 0 to 1500 Hz. This training with a large Doppler variability is done especially in order to learn a general solution for the ICI. The dataset utilizes randomly chosen channel models among TDL-B, TDL-C and TDL-D [26] as well as randomly chosen SNR in the range of 0 to 35 dB, the total size thereof being 150 000 TTIs. The training is performed based on the binary cross entropy (CE) loss between the estimated bits and the transmitted bits, similar to [16]. The CE loss is defined as

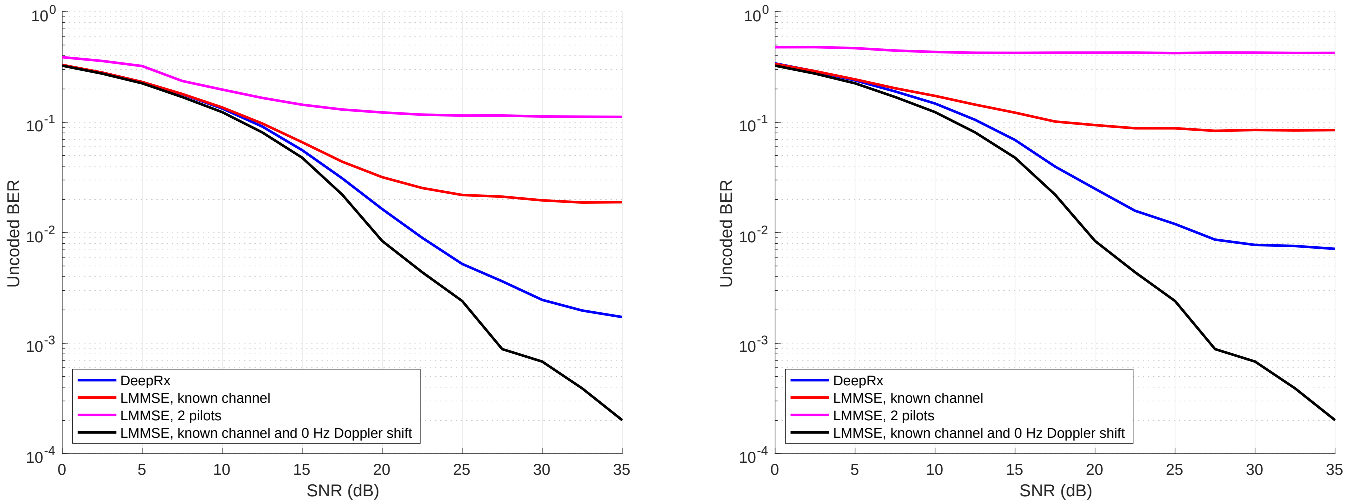
$$\mathrm{CE}(\boldsymbol{\theta}) \triangleq -\frac{1}{\#\mathcal{D}B} \sum_{(i,j)\in\mathcal{D}} \sum_{l=0}^{B-1} \Big(b_{ijl} \log\Big(\hat{b}_{ijl}\Big) + (1-b_{ijl}) \log\Big(1-\hat{b}_{ijl}\Big)\Big) \tag{3}$$

where $\boldsymbol{\theta}$ represents the set of trainable of parameters, $\mathcal{D}$ denotes the time and frequency indices of data-carrying REs, $\#\mathcal{D}$ is the total number of data-carrying REs, B is the number of bits per resource element, and $\hat{b}_{ijl}$ is the receiver's estimate for the probability that the bit b_{ijl} is one. The chosen stochastic gradient descent (SGD) algorithm in this work is the widely used Adam optimizer, which updates the weights of the network based on the binary CE loss in (3).

For validation, we generated separate datasets for each 250 Hz interval in the same range as in training. The separate datasets with varying the maximum Doppler shift allow us to observe the performance for varying levels of Doppler distortion up to 1500 Hz, which corresponds to 10% of the SCS, while representing each Doppler shift interval with equal number of samples. These datasets utilize the channel models TDL-A and TDL-E, while the SNRs are in uniform grid over the specified range with 2.5dB steps, each dataset consisting of 32 000 TTIs.

V. PERFORMANCE EVALUATION

The performance of the proposed ML-based receiver (DeepRx) is evaluated with varying levels of maximum Doppler shift, representing varying degrees of UE mobility. We consider uncoded bit error rate (BER) as the main performance criterion. The results of the ML-based receiver are



(a) 750 Hz

(b) 1500 Hz

Fig. 2. Uncoded BER performance of the ML-based receiver in comparison with benchmarks, with Doppler shift interval of (a) 500 to 750 Hz and (b) 1250 to 1500 Hz.

compared with two baseline receivers: (*i*) LMMSE equalization with least squares (LS) channel estimation based on two DMRS symbols per TTI and (*ii*) LMMSE equalization with a known channel. Note that the ML-based receiver always estimates the channel based on the two DMRS pilots. The figures show also the BER of LMMSE with a known channel and 0 Hz Doppler shift for reference, representing essentially the lower bound for the achievable BER.

Figure 2 shows the BER performance with Doppler shift intervals of 500 to 750 Hz and 1250 to 1500 Hz, corresponding to the rather extreme velocities up to 310 and 620 km/h, respectively. It is evident that with both cases, the proposed ML-based receiver achieves considerably higher performance than the benchmark LMMSE receivers. This clearly highlights that the ML-based receiver learns to mitigate the ICI very efficiently. Especially the latter case represents already very extreme mobility, demonstrating that the ML-based receiver can ensure reliable detection even with very high UE speeds.

Next, let us investigate the performance of the receiver with varying Doppler shift while considering a specific BER value. To this end, Fig. 3 shows the SNR required to achieve uncoded BER values of 10% and 5% with varying Doppler shift intervals. At low Doppler shift values of 0 to 250 Hz, all of the considered receivers have almost equal performance, due to low Doppler distortion in the signals. However, a difference in performance between the proposed receiver and LMMSE with known channel can already be observed with a Doppler shift in the order of 350 Hz, when the BER target is 5%. This difference increases considerably when the Doppler shift is increased. It is also noteworthy that the LMMSE with two pilots is not able to achieve the BER target in most of the considered cases, even though the DeepRx is also based on the two pilots. Altogether, the results show that DeepRx learns high resilience against the ICI even under the most severe nonlinear distortion that we considered, despite the fact that only ordinary sparse reference signals are considered.

VI. Conclusions

In this paper, we presented a ML-based receiver architecture, which is capable of learning a highly accurate detection scheme for extreme mobility scenarios where the received signal is subject to severe intercarrier interference. In particular, we equip the ML-based receiver with 2D convolutional layers, which allow it to observe and compensate for the effects of intercarrier interference in frequency domain even under high Doppler shifts. This is demonstrated by the provided numerical results, where the proposed ML-based receiver is shown to outperform the conventional baseline receivers with a clear margin when considering a typical 5G NR uplink scenario with Doppler shifts as high as 10% of the subcarrier spacing. This indicates that the proposed ML-based receiver architecture learns high resilience against the detrimental effects of extreme mobility and the involved interference — despite it utilizing only ordinary sparse reference signals with low system overhead.

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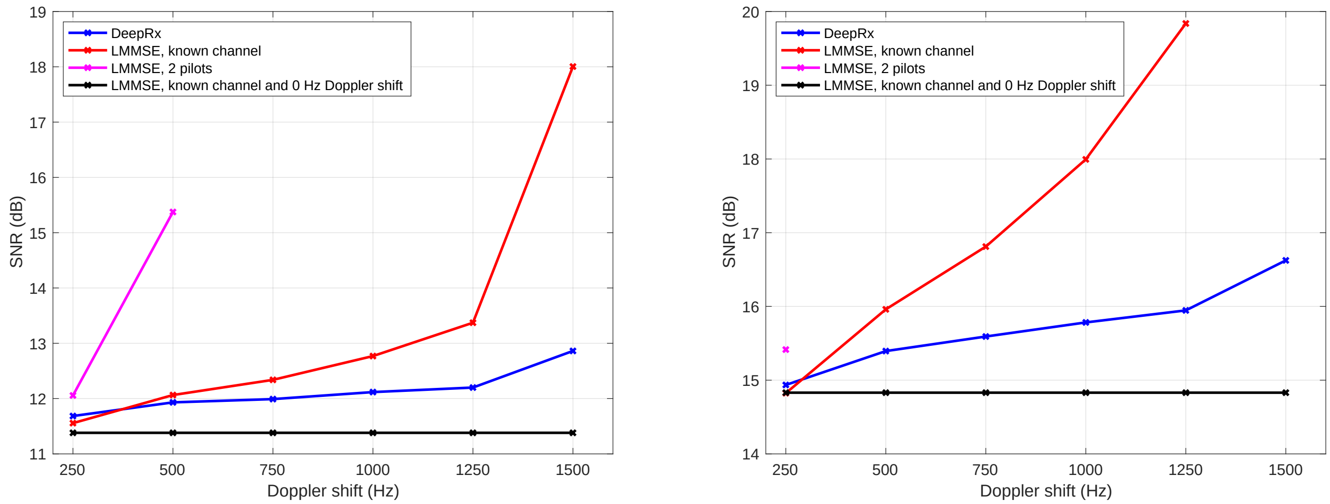
References

[1] H. Holma, A. Toskala, and T. Nakamura, Eds., *5G Technology: 3GPP New Radio*, 1st ed. Wiley, 2019.

[2] ITU-R, "Minimum requirements related to technical performance for IMT-2020 radio interface(s)," Report ITU-R M.2410-0, Nov. 2017.

[3] J. Talvitie, T. Levanen, M. Koivisto, T. Ihalainen, K. Pajukoski, and M. Valkama, "Positioning and location-aware communications for modern railways with 5G New Radio," *IEEE Communications Magazine*, vol. 57, no. 9, pp. 24–30, 2019.

[4] "3GPP TR 38.913 v16.0.0, Study on Scenarios and Requirements for Next Generation Access Technologies (Rel. 16)," July 2020.



(a) 10% BER

(b) 5% BER

Fig. 3. Performance of the considered receivers under varying maximum Doppler shift in the corresponding interval at specific BER value. The values at the horizontal axis correspond to the maximum Doppler shift in each interval. The missing cross markers indicate that the receiver is not able to achieve the considered BER target.

[5] Y. Li and L. Cimini, "Bounds on the interchannel interference of OFDM in time-varying impairments," *IEEE Transactions on Communications*, vol. 49, no. 3, pp. 401–404, 2001.

[6] X. Cai and G. Giannakis, "Bounding performance and suppressing intercarrier interference in wireless mobile OFDM," *IEEE Transactions on Communications*, vol. 51, no. 12, pp. 2047–2056, 2003.

[7] M. Faulkner, L. R. Wilhelmsson, and J. Svensson, "Low-complex ICI cancellation for improving doppler performance in OFDM systems," in *IEEE Vehicular Technology Conference*, 2006.

[8] D. Neumann, T. Wiese, and W. Utschick, "Learning the MMSE channel estimator," *IEEE Transactions on Signal Processing*, vol. 66, no. 11, pp. 2905–2917, Jun. 2018.

[9] H. He, C. Wen, S. Jin, and G. Li, "Deep learning-based channel estimation for beamspace mmWave massive MIMO systems," *IEEE Wireless Communications Letters*, vol. 7, no. 5, 2018.

[10] Z. Chang, Y. Wang, H. Li, and Z. Wang, "Complex CNN-based equalization for communication signal," in *Proc. IEEE 4th International Conference on Signal and Image Processing*, Jul. 2019.

[11] Y. LeCun, Y. Bengio, and G. E. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, pp. 436–444, 2015.

[12] O. Shental and J. Hoydis, ""Machine LLRning": Learning to softly demodulate," in *Proc. IEEE Globecom Workshops*, 2019.

[13] X. Gao, S. Jin, C. Wen, and G. Y. Li, "ComNet: Combination of deep learning and expert knowledge in OFDM receivers," *IEEE Communications Letters*, vol. 22, no. 12, pp. 2627–2630, Dec. 2018.

[14] H. He, S. Jin, C. Wen, F. Gao, G. Y. Li, and Z. Xu, "Model-driven deep learning for physical layer communications," *IEEE Wireless Communications*, vol. 26, no. 5, pp. 77–83, 2019.

[15] N. Samuel, T. Diskin, and A. Wiesel, "Learning to detect," *IEEE Transactions on Signal Processing*, vol. 67, no. 10, pp. 2554–2564, May 2019.

[16] M. Honkala, D. Korpi, and J. M. J. Huttunen, "DeepRx: Fully convolutional deep learning receiver," *IEEE Transactions on Wireless Communications*, 2021.

[17] D. Korpi, M. Honkala, J. M. J. Huttunen, and V. Starck, "DeepRx MIMO: Convolutional MIMO Detection with Learned Multiplicative Transformations," in *Proc. IEEE International Conference on Communications*, 2021.

[18] H. Ye, G. Y. Li, and B.-H. Juang, "Power of deep learning for channel estimation and signal detection in OFDM systems," *IEEE Communications Letters*, vol. 7, no. 1, pp. 114–117, 2018.

[19] Z. Zhao, M. C. Vuran, F. Guo, and S. Scott, "Deep-waveform: A learned OFDM receiver based on deep complex convolutional networks," 2018. [Online]. Available: https://arxiv.org/abs/1810.07181

[20] T. O'Shea and J. Hoydis, "An introduction to deep learning for the physical layer," *IEEE Transactions on Cognitive Communications and Networking*, vol. 3, no. 4, pp. 563–575, Dec. 2017.

[21] S. Dörner, S. Cammerer, J. Hoydis, and S. ten Brink, "Deep Learning Based Communication Over the Air," *IEEE Journal of Selected Topics in Signal Processing*, vol. 12, no. 1, pp. 132–143, Feb. 2018.

[22] F. A. Aoudia and J. Hoydis, "End-to-end Learning for OFDM: From Neural Receivers to Pilotless Communication," Aug. 2021. [Online]. Available: https://arxiv.org/abs/2009.05261

[23] A. Felix, S. Cammerer, S. Dörner, J. Hoydis, and S. ten Brink, "OFDM-Autoencoder for End-to-End Learning of Communications Systems," in *Proc. IEEE 19th International Workshop on Signal Processing Advances in Wireless Communications*, Jun. 2018.

[24] V. Syrjälä, T. Levanen, T. Ihalainen, and M. Valkama, "Pilot Allocation and Computationally Efficient Non-Iterative Estimation of Phase Noise in OFDM," *IEEE Wireless Communications Letters*, vol. 8, no. 2, pp. 640–643, Jan. 2019.

[25] Mathworks, Inc., "Matlab 5G Toolbox," https://www.mathworks.com/products/5g.html, 2020.

[26] 3GPP TR 38.901, "Study on channel model for frequencies from 0.5 to 100 GHz (Release 16)," v16.0.0, Dec. 2019.