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State-of-the-Art in PHY Layer Deep Learning for Future Wireless Communication Systems and Networks

Konstantinos Koufos[1], Karim El Haloui[1], Cong Zhou[1], Valerio Frascolla[2] and Mehrdad Dianati[1]

Abstract Ongoing activities by several standardisation bodies, experimental demonstrations in research projects, and recent trends and investments by the telecommunication sector reveal that the next generation of wireless communication systems will offer a multitude of unprecedented use cases, such as enhanced mobile broadband for ultra-high-speed railways, augmented reality, and 3d connectivity involving unmanned aerial vehicles and intelligent reflecting surfaces. Furthermore, well-established and verified mathematical models, such as those utilised for channel equalisation, link adaptation, and symbol detection, will likely fall short once applied in wireless systems operating in higher frequencies and deployed in challenging environments. Fortunately, recent advancements in data collection and storage, together with breakthroughs in artificial intelligence (AI) and machine learning (ML), will allow communication engineers to construct data-driven solutions for optimising the performance of envisioned future networks. Motivated by these potentials, in this chapter, we provide the interested readers with a comprehensive analysis and review of the most recent progress in using data-driven and ML-based approaches at the PHY layer of modern communications. We review the performance of purely data-driven auto-encoders and put an emphasis on model-aided transfer learning schemes for PHY layer operation. Key studies reveal that embedding ML into traditional model-based schemes can significantly enhance the performance of various PHY layer functions. Nevertheless, the explainability of neural networks remains an open issue and is expected to be an active area of research in the coming years, lying at the intersection of computer science and PHY layer communications.

1 Introduction

The recent advances on programmable wireless networks using software-defined networking principles and network function virtualisation (SDN/NFV) together with the ongoing breakthroughs in machine learning, artificial intelligence (AI/ML) and computational capabilities set a stage where future communication networks can thrive. The next generation of wireless communication systems is expected to penetrate across various vertical industries, offering highly heterogeneous services with stringent requirements over the same unified physical infrastructure, while keeping both OpEx and CapEx low, see Figure 1. Not surprisingly, extensive data collection, big data analytics and AI/ML are indispensable enablers in realising the goal of automation, orchestration, and performance optimisation of such a complex ecosystem, see the vision papers in [1-6]. During the past few years, the ongoing activities by several organisations and standardisation bodies in the telecommunication sector, led by 3GPP, ETSI ENI (ETSI experiential networking intelligence), ETSI ZSM (ETSI zero-touch network and service management), and O-RAN Alliance, confirm the pivotal role that AI/ML will play in next generation communication networks.

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The standard development organisations and the telecommunication industry have so far joined forces to resolve vendor inter-operability issues by leveraging open interfaces and develop AI/ML-based solutions that operate at long timescales. For instance, 3GPP has introduced in Rel-15 the network data analytics function (NWDAF) for the instantiation, orchestration, and management of network slices [7]. Also, the ETSI ENI committee has designed a system, which provides intelligent recommendations for network management to another system, e.g., a mobile network operator (MNO) [8]. Furthermore, the ETSI ZSM committee has developed a generalised functional reference architecture of future communication networks that supports high levels of autonomy, self-healing, and self-optimisation [9]. And finally, the O-RAN Alliance has introduced closed control loops at the RAN, i.e., the near-real-time and the non-real-time RAN intelligent controllers (RICs), operating respectively at timescales between 10ms and 1000ms and more than 1000ms [10]. More contextually, the non-real-time RIC is mostly about instantiation of network slices and optimisation of RAN policies, while the real-time RIC handles spectrum management, traffic steering and admission control, to name a few.

While embedding AI/ML in network functions that operate at long timescales is of paramount importance, several organisations and major research projects are actively working on the real-time RIC by providing ML-assisted operation at the PHY layer, i.e., at timescales less than 10ms (the frame duration in the 5G NR). To give some representative examples, the ITU-T study group launched in 2017 the focus group on ML for future networks including 5G (FG-ML5G), which has listed ML-based channel modelling, channel prediction and link adaptation optimisation as important use cases for future networks [11]. We provide an updated review of research activities in these important areas in Section 5 and Section 7. Furthermore, the ongoing project ARIADNE, funded by the European H2020 research framework, investigates the potential of using reflecting intelligent surfaces (RIS) for implementing the high data-rate backhaul of millimetre-wave (mm-wave) small cell networks in the D-band (130-174.8GHz) [12]. As explained in Section 8.3, the ML-based optimisation of phase shifters in RIS is a research topic that is worth pursuing. The expected operations of future wireless networks in higher frequency spectrum such as mm-wave frequencies and THz bands make the well-validated understanding of sub-6GHz wireless communications inadequate and superfluous. New techniques should be developed for channel equalisation and symbol detection in higher frequencies and high doppler channels[13, 14], and as it is explored in Section 3 and Section 4, AI/ML can assist in this direction.

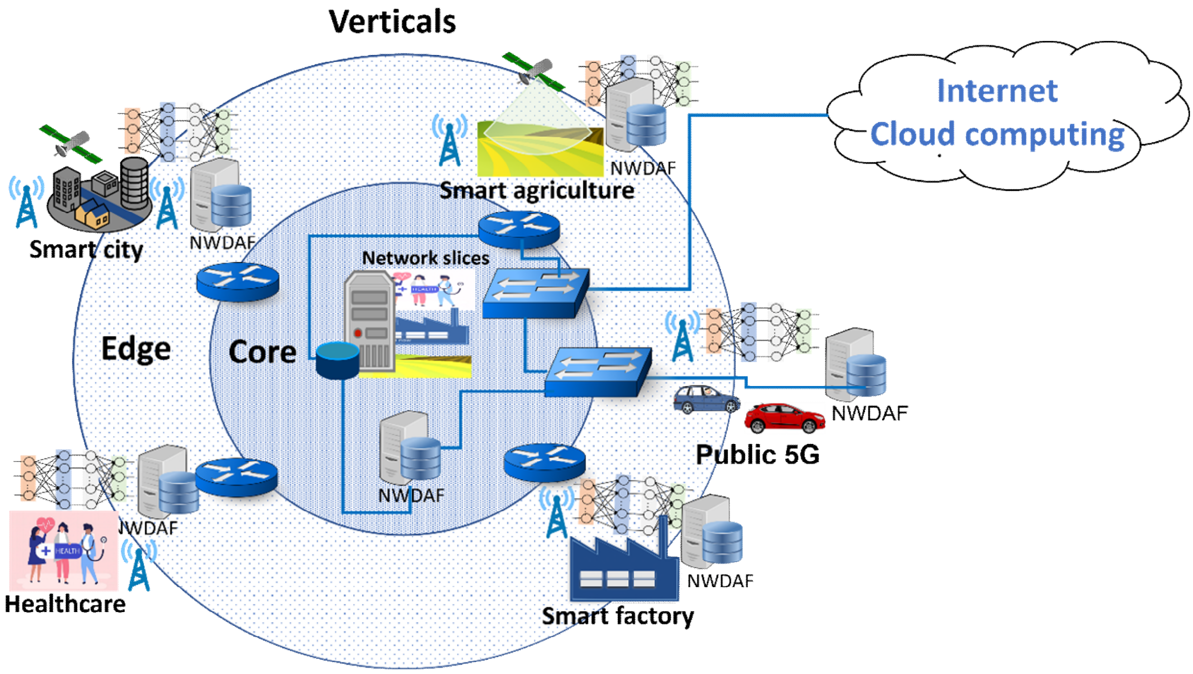


Figure 1: The deployment of a unified physical infrastructure (core network) reduces the total CapEx and OpEx compared to the deployment of dedicated networks for each vertical and allows identifying profitable use cases. Edge computing is employed for satisfying the requirements of time-critical services. Big data analytics with AI/ML through the NWDAF is used at the core network for dynamic assignment of network slices to verticals and at the edge for analysing various KPIs and optimising the operation at the RAN. For presentation clarity, the figure illustrates the connections to the cloud and the core network only for one of the verticals (smart agriculture).

Motivated by the aforementioned potentials, in this book chapter, we aim to provide the interested readers with a comprehensive analysis and review of the most recent progress in the use of data-driven and ML-based approaches at the PHY layer in the study of modern communication systems and networks. Before that, an overview of related survey articles is provided.

1.1 Related survey papers

The overview studies in [15-18] focus on ML techniques for cognitive radio-based vehicular ad-hoc networks (CR-VANETs) [15], wireless sensor networks (WSNs) [16], internet-of-things (IoT) for smart cities [17] and industrial IoT [18]. These surveys are certainly important as the transportation and IoT sectors would significantly benefit from the 5G and 6G ecosystems. In the same vein, the authors in [19, 20] present an overview of ML techniques encountered in self-organised cellular networks, including self-configuration of operational and radio parameters, self-optimisation, and self-healing. Likewise, the study in [21] reviews artificial neural networks (ANNs) for optimising various aspects of wireless networks capitalising on unmanned aerial vehicles (UAVs). Resource allocation and content caching for wireless virtual reality, failure detection, target surveillance, and user activity classification for IoT are also summarised in [21].

Taxonomy of survey articles				
Application-oriented		**Layering-oriented**		**ML-oriented**
WSN	[16]	PHY	[22] [23] [24] [25, 26] [27]	[28], [29]
IoT	[17] [18]	MAC	[23] [30] [31] [24] [25] [26] [27]	
VANET	[15]	NET	[32] [24, 32] [25] [26] [27]	

Cellular	[19] [20]	Edge	[23]	
UAV	[21]			

Table 1: Taxonomy of survey articles on intelligent communications & networking.

The surveys in [26] and [27] adopt a different approach without explicitly considering use cases, but instead, separate research contributions based on the protocol layer where the ML component operates, see Table 1. The authors in [22] have compiled a critical review of ML algorithms at the PHY layer with an emphasis on MIMO systems and hardware imperfections due to RF and power amplifier non-linearities. At the MAC layer, intelligent power control and resource allocation in OFDMA downlink are explored in [23] and [30], respectively. Besides, the review paper in [31] presents an in-depth analysis of ML-based approaches at the MAC layer, including spectrum, backhaul, and cache management. In the network layer, intelligent base station clustering, switching control, mobility management, user association, and routing are treated, while in the application layer, intelligent localisation is considered [31]. An overview of distributed ML techniques at the edge, such as the recently recommended federated learning by 3GPP, is also included in [23]. The authors in [32] mainly discuss the use of ML techniques for fundamental network layer issues, which are related to network slicing, such as traffic prediction and classification, congestion control, fault/QoS management and network security.

The survey paper [24] is another extensive review of ML-empowered wireless communications covering all protocol layers and stressing the importance of collecting data analytics at the edge for time-critical services. The mainstream open-source libraries and platforms for NN deployment and training are presented, which is of interest to communications engineers starting to explore ML platforms. The study in [25] is a short review of ML-enabled RAN that highlights essential points, including channel estimation, symbol detection, channel coding, and dynamic spectrum access at RAN layer 1 and 2, while fault recovery, energy optimisation, and the formation of cell sectors are reviewed at RAN layer 3. The activities of O-RAN Alliance and the recommendations in 3GPP Release 16 towards an intelligent RAN and 5G core are acknowledged. In [33], one may find a detailed overview of new features introduced by 3GPP Releases 16 and 17, but the treatment of data analytics is limited.

Another way to organise AI/ML techniques applied to wireless communication networks is to consider the employed learning method such as supervised, unsupervised, reinforcement, and deep learning. This taxonomy is followed in [28] and can be beneficial for those with a keen interest in the learning methods and advancements brought along in this area. In our view, deep reinforcement learning is of particular interest in wireless networks as it can be used for distributed intelligent decision making in the face of uncertainty, as detailed in [29]. Finally, the authors in [34] present an overview of ongoing standardisation activities, trends in the industry and major research projects on intelligent communications and networking.

1.2 Summary of this chapter

The remainder of this chapter is organised as follows. In Section 2, we divide the state-of-art into purely data-driven and model-aided ML techniques as suggested by Renzo et. al. [35]. In Section 3, we review deep learning methods for symbol detection, including model-aided auto-encoders and sequential detectors. Intelligent channel equalisation and prediction are presented in Section 4 and Section 5, respectively. ML-assisted channel coding and link adaptation are the topics of Section 6 and Section 7, respectively. In Section 8, we discuss AI/ML methods for enhancing the signal detection performance using spectrum sensing, convolutional neural networks (CNNs) for automatic modulation classification and intelligent radio environment using reflecting surfaces. Note that while the standardisation efforts on intelligent communications are mostly focused on cellular systems, the implementation of signal processing functions using machine learning techniques is pervasive to other wireless technologies such as WLAN and Zigbee. In Section 9, we have included a review of performance evaluation techniques of wireless networks combining machine learning and stochastic geometry based on performance metrics pertinent to the PHY layer. We conclude this chapter in Section 10.

2 Data-driven ML methods for transceiver optimisation

The long-established systematic approach in the study and design of general communications systems, and more specifically wireless transceivers, is to decompose them into functional blocks. Each block is studied independently and optimised in a disarticulated manner leading to suboptimal transceiver designs. With the advent of ML/AI, new revolutionary paradigms and techniques, that lead to spectacular advances across many fields, can be leveraged to bring forward new architectures and potentially allow to design optimal transceivers.

The overarching principle of a communication system is to receive a faithful copy of what is transmitted. In this end, using ML, the complete system can be seen as a single unit and be optimised to learn the optimal system mapping between source and received symbols. In the literature, this approach is also known as pure data-driven technique [35]. It replaces all signal processing blocks, e.g., modulation, channel coding, phase correction, error correction, matched filtering, etc. into a purely data-driven autoencoder which learns how to map source symbols to adapted signal waveforms robust to channel corruption together with an optimal decoding scheme at the receiver.

The decomposition into several blocks of the communication chain can be leveraged by incorporating domain expert knowledge into the design of a block. At times, a trade-off, between optimality and mathematical tractability, is necessary. Accurate mathematical models can be devised but these may lead to high order computational complexity problems and restrict their usage if real-time operation is required [22]. Furthermore, accurate models are not always achievable and might not capture the whole complexity coming for example from hardware imperfections or other non-linearities [35]. Nevertheless, we will shortly see below that imperfect models can still provide good-enough solutions, which can serve as initialisation vectors in ML algorithms, and thus, reduce their training time.

In Section 2.1, we review key studies on ML-based design at the PHY layer using pure data-driven techniques. Then, in Section 2.2 we discuss another approach for optimising the transceiver design where ML and mathematical modelling work together and mutually benefit from each other.

2.1 Data-driven approach for end-to-end transceiver optimisation

A natural ML architecture that fits the structure of a transceiver is the autoencoder which is composed of an encoder, the transmitter, and a decoder, the receiver. The difference of a communications system autoencoder architecture is the insertion of extra-layers in-between the encoder and decoder to model the channel [36]. Different channel profiles from the additive white Gaussian noise (AWGN) to more complex channels can be modelled this way [37].

The channel, and in particular, its gradient must be known to carry out backpropagation and train the NN at the transmitter. This condition poses the following challenges:

- The channel used for training must be similar to the actual channel where communication takes place.
- The channel transfer function must be differentiable.

Provided that these constraints are met, the autoencoder can be trained over all possible source messages using gradient descent. Unlike other ML applications, due to the random nature of the wireless channel, overfitting is likely not an issue here [38]. With sufficient training, the transmitter can learn a robust and accurate mapping of the source output to transmitted symbols, whilst the receiver trains its NN to implement, for instance, maximum likelihood decoding of the received symbols. Usually, a softmax activation function is the last layer of a NN performing classification tasks. Its output can then be interpreted as a probability mass function over the set of transmitted symbols [39] and thus, the softmax activation function is tailored to receivers implementing soft decoding.

Transceivers designed as autoencoders perform equally as traditional designs [36, 37] demonstrating that ML techniques can provide alternative solutions. Yet, many challenges can preclude the adoption of autoencoders as practical solutions. These are related to aspects of training and explainability of NNs in general. On the one hand, a requirement for training is the full differentiability of the weights of the NN as a function of the neurons which is not guaranteed and is rarely the case for channels because of the following reasons.

- Firstly, the channel displays non-deterministic characteristics due to noise or its fading profiles.
- Secondly, there might be signal processing blocks, such as quantisation, that are by essence non-differentiable.
- And lastly, some blocks may be poorly understood or inaccurate, e.g., the frequency response of power amplifiers.

The above-mentioned issues make the learning challenging as traditional learning techniques become inoperative. On the other hand, explainability of NN is crucial to understand the relationship between the network architecture and the required end-to-end performance. Unlike conventional methods, explainability and insight is lost completely when employing purely data-driven autoencoders.

To mitigate the impact of small discrepancies between the actual channel and the model used for training, the study in [38] has enhanced the performance of a wireless system designed as an autoencoder by dividing the training phase into two stages. Firstly, the autoencoder is trained offline on a stochastic channel model which should closely approximate the actual channel. Secondly, on-line collected pilots are used to fine-tune the NN at the receiver using supervised learning. The technique of using an already trained NN and tune it is known in the literature as transfer learning. In this case, the knowledge of the transfer function is required in the first stage of the training and only a partial transfer learning is performed to fine-tune the receiver to the actual channel but not the transmitter.

To enhance the transmitter's performance, one may separate the NNs of the transmitter and receiver and iteratively optimise them during training [40]. Firstly, given the parameters of the transmitter's NN, the receiver's weights are fine-tuned using supervised learning. Next, given the receiver's weights, the transmitter can explore various symbol mappings and receive the quality of each mapping (the value of the loss function) over a feedback channel. Essentially, the autoencoder has been replaced by a supervised learning method at the receiver and a reinforcement learning method at the transmitter. In this way, a channel model is not required anymore at the cost of implementing a feedback link. Practical implementations using software-defined radios have indicated that the training is robust to noisy feedback channels with SNRs higher than 6 dB [41].

Other solutions to overcome the unknown channel impairments involve the use of generative adversarial networks (GANs) [42] and channel gradient estimation using perturbation techniques [43]. Firstly, it is noted that the lack of a channel model does not affect at all the training of the receiver provided that the loss function is differentiable, and that the receiver is aware of the data sent for training. Next, a model of the actual channel can be generated through training using a GAN, or the gradient of the channel can be numerically approximated using stochastic optimisation. Finally, given the channel generator or the approximated channel gradients, a backpropagation algorithm can be applied to propagate and calculate gradients from the receiver to the transmitter through the channel, and thus, allowing us to train the NN at the transmitter. After all, the system designer should evaluate the cost of implementing a feedback channel [40, 41], the required time and cost of training a GAN over the communication channel [42], and the required complexity to estimate the gradients using stochastic optimisation [43]. All these techniques achieve similar performance in AWGN and Rayleigh block fading channels with supervised learning assuming perfect channel knowledge. Unfortunately, scalability to long block lengths and time variations of the channel remain open issues in all the above studies.

Even though the training of NNs is mostly executed offline, the required amount of labelled data and the training time should not be overlooked. All sources of randomness need to be represented within the training set, which inevitably increases its size. Also, note that measurement campaigns and data labelling are costly. These, in turn, could seriously impede the deployment of such methods. One way to reduce the training time is to incorporate expert knowledge into ML. The study in [36] is perhaps the first to employ this technique in the PHY layer and suggest splitting the NN at the receiver into two NNs: The first equalizes the channel and the second soft decodes the received symbols. The study in [36] has inspired numerous follow-up studies suggesting the integration of mathematical models into ML for PHY layer processing.

2.2 Model-aided data-driven methods for modular transceiver optimisation

The main idea behind model-aided ML transceiver design is to keep the modular structure of the transceiver and use ML to optimise only some of the signal processing blocks, especially those involving complicated computations or for which, some simplifications are assumed to make them mathematically tractable. As compared to the traditional model-based framework, there are two noticeable improvements: (i) the computational time could be reduced once the NN is trained, and (ii) the performance could be enhanced if the employed models are just approximations. As compared to end-to-end data-driven techniques, the training time and the need for available labelled datasets decreases in the model-aided approach [44]. Also, according to transfer learning, imperfect or inaccurate models can be used advantageously in the ML process flow to initialise ML weights and reduce further the training time. Then, ML training can fine-tune the weights obtained by the selected models. For an overview of the model-aided ML at the PHY layer, readers can refer to [44].

A detailed per-block review of model-based data-driven techniques for intelligent transceiver design follows in the next sections.

3 Deep learning for symbol detection

In this section, the body of literature demonstrates that incorporating simple expert knowledge, e.g., the properties of Orthogonal Frequency Division Multiplexing (OFDM) transmitted waveforms, into the design of autoencoders and NN-based receivers can simplify their operation and enhance the symbol detection performance compared to the baseline model-based schemes.

3.1 Incorporating expert knowledge into autoencoders

It is well-known that in OFDM with cyclic prefix, frame synchronisation is achieved with an auto-correlation-based peak detector given the size of the Fast Fourier Transform (FFT) and the length of the cyclic prefix. Therefore, OFDM communication systems, designed as autoencoders, do not need a separate NN at the receiver to track sampling errors [45]. OFDM can also transform the signal model from wideband to narrowband simplifying the equalisation process. Therefore, at the transmitter's side, it becomes easier to learn a constellation mapping (or precoding) which counteracts the impact of channel effects. For instance, the autoencoder designed in [41] shapes a non-symmetrical and non-centred constellation, which is robust to channel distortions, thereby bypassing the need of inserting pilots in the transmitted signals. As a result, a separate NN at the receiver for single-tap channel equalisation is not needed either. Autoencoders can therefore eliminate the need of pilots, thus, increasing the useful data rate and reducing the overall implementation complexity for OFDM-based systems. Furthermore, the study in [45] does not apply a separate NN for correcting the carrier frequency offset either with negligible impact on the bit error ratio (BER). On the contrary, in traditional model-based systems, single-tap equalisation using dedicated pilots, carrier frequency offset compensation and OFDM symbol detection are separately done.

Unfortunately, the robustness of OFDM to frequency selectivity does not come without cost. The combined effect of the Inverse Fast Fourier Transform (IFFT) block and the non-linearity of the power amplifier may result in detrimental signal distortion. In [46], the encoder learns to map source symbols onto constellation points for each subcarrier so that a loss function, which equals the weighted sum of the BER and the peak-to-average-power-ratio (PAPR) is kept low. The proposed scheme outperforms conventional PAPR reduction schemes and achieves a lower bit error ratio (BER) than the classical OFDM in Rayleigh fading channels with AWGN. However, the study in [46] does not assess the performance with a realistic model for the power amplifier, and therefore one cannot draw solid conclusions about the autoencoder's performance.

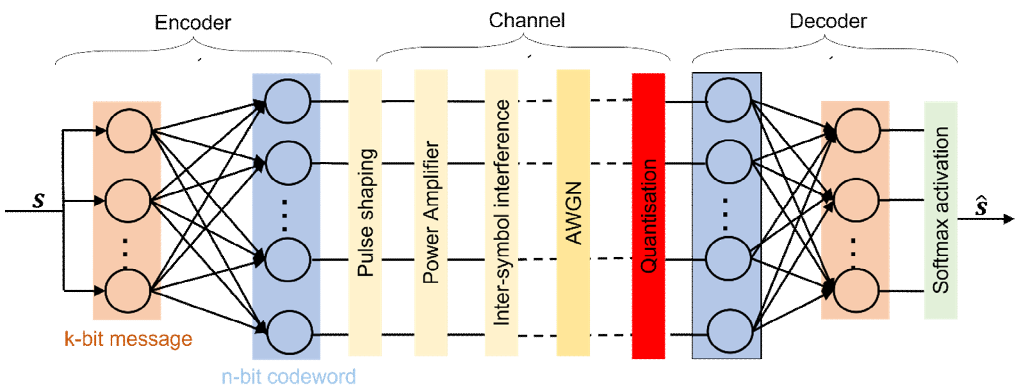


Figure 2: Block diagram of an auto-encoder with the channel incorporating linear effects (inter-symbol interference, AWGN), non-linear distortions (pulse shaping, power amplifier) and a non-differentiable layer modelling quantisation preventing end-to-end training of the encoder.

Another source of signal distortion (inter-carrier interference) in OFDM is the quantisation at the receiver. Quantisation prevents end-to-end training of the autoencoder because it essentially inserts a non-differentiable layer before signal detection, as illustrated in Figure 2. One way to overcome this limitation is presented in [41, 47], where the encoder and decoder are alternatively trained without knowing the channel at the transmitter. In this architecture, the decoder can be normally trained using supervised learning and some algorithm for back-propagation without explicitly considering the channel. In [41], the encoder is trained using reinforcement learning based on rewards calculated at the receiver and fed back to the transmitter. Therefore, unlike the decoder, the training of the encoder is essentially done on-line, which is the penalty paid for an agent (the transmitter) operating in unknown environments.

3.2 Implementing NNs at the receiver

An auto-encoder optimises both ends of a communication link, but its training overhead can be significant. When the required resources for training become prohibitively high, an alternative approach suggests implementing symbol detection using a NN only at the receiver. The transmitter generates a standard OFDM waveform, and at the receiver the (offline) learning phase is done over a class of channel models with known statistical properties, which should have a similar distribution to the actual channels, see Figure 3. The minimum mean squared error (MMSE) equaliser, see [48], with one pilot every eight subcarriers experiences much higher BER than the deep neural network (DNN)-based receiver designed in [49]. This is because the MMSE-based receiver with this proportion of pilots is not able to estimate the channel perfectly, while the DNN extracts more accurate information about the channel during training. Similarly, the DNN-based receiver outperforms MMSE over non-linear distorted channels due to waveform clipping in [49]. With many pilots, the BER performances of DNN and MMSE are comparable. Nevertheless, the DNN does not need to estimate the channel state information (CSI), and it learns to decode the transmitted symbols only based on the received data, resulting in a much simpler implementation at the cost of offline training.

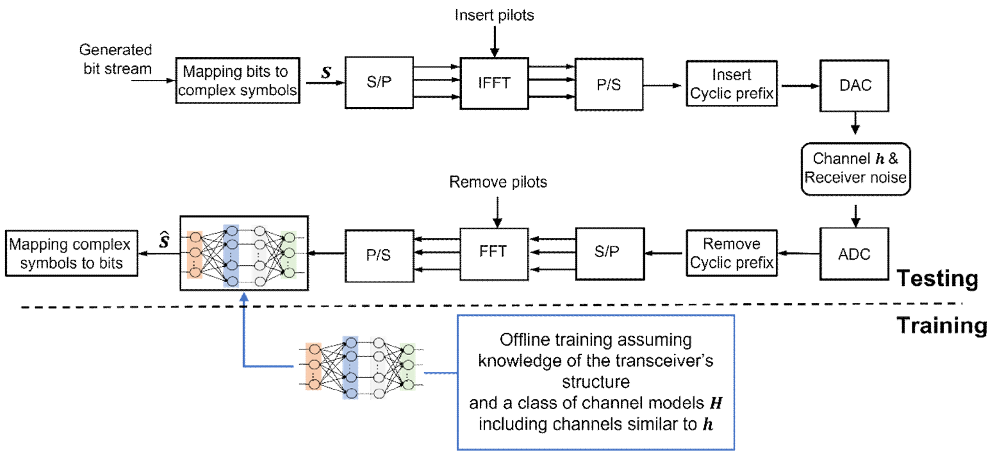


Figure 3: Block diagram of an OFDM communication system with symbol detection implemented using a FC-DNN which is trained offline using a class of channel models. S/P stands for serial-to-parallel.

To accelerate training, the study in [50] cascades two NNs at the receiver, instead of one fully-connected deep neural network (FC-DNN) and incorporates expert knowledge to initialise the NN weights. The first NN has a single layer and performs channel equalisation, while the second NN is a bidirectional long short-term memory (LSTM) for symbol detection. To initialise their weights, the NNs use linear-MMSE for channel estimation and zero-forcing for symbol detection. Then, the DNNs are trained to refine the coarse initial inputs. The proposed method achieves the same BER performance as reported in [49] but is ten times faster with a weights reduction of eight. This example demonstrates that carefully embedding expert knowledge into data-driven techniques, e.g., by transfer learning, could be rewarding.

MIMO detection is another area where incorporating expert knowledge into ML can offer clear benefits using the idea of deep unfolding [51]. Particularly, iterative algorithms for MIMO detection like the projected gradient descent in [52] can be unfolded such that each iteration is associated with a hidden layer. Deep unfolding can simplify the detector's implementation if the iterations involve simple operations. In [52], the NN-based detector achieves competitive performance, in terms of symbol error rate, over independent and identically distributed (iid) Gaussian channels to state-of-art algorithms like approximate message passing (AMP) and semidefinite relaxation, but with 30 times less running time. Despite this promising result, the associated NN involves a few million weights and is not flexible to changes in constellation size, requiring either training anew or will suffer from significant performance degradation with link adaptation. Under highly correlated channels, it also performs clearly worse than semidefinite relaxation. In the same vein, the study in [53] unfolds the AMP algorithm and employs linear MMSE for channel equalisation. As a result, it reduces the number of trainable parameters and leads to stronger robustness to modulation order, imperfect CSI, and channel correlation than [52]. However, the authors in [54] claim that the performance of the NN designed in [53] is poor compared to (optimal) maximum likelihood decoding (MLD) when tested with 3GPP spatially correlated channels. To solve this issue, the authors devise an architecture that does not amplify the noise under correlated channels, and report symbol error rates within 1.5 dB from MLD.

All studies [52-54] have adopted the idea of deep unfolding to incorporate expert knowledge into ML. In Section 6, we will see that belief propagation decoding of polar and low-density parity check (LDPC) codes is another area where iterative algorithms are unfolded and represented as NNs, simplifying the operation of the decoder.

3.3 Sequential detectors using ML

One of the main sources of received signal quality degradation for wideband transmissions is inter-symbol interference (ISI). Naturally, a CNN-based equaliser can capture the effects of ISI on the received signal samples better than a FC-DNN, because each neuron gets input only from a limited set of nearby nodes from the previously hidden layer. In [55], a seven-layer CNN-based equaliser yields smaller BER than a five-layer DNN-based equaliser, especially at high SNRs. Apart from achieving lower BER, the subject CNN, despite having more hidden layers, has in fact fewer weights than the DNN, resulting also in less training time. Therefore, including basic domain features into the selection of the NN's architecture can reduce the complexity of channel equalisation.

In wireless channels with ISI, the Viterbi algorithm is a popular technique for sequential symbol detection [56]. It is optimal, in terms of BER, for stationary and causal channels with finite memory and a known statistical relationship between the input and the output of the channel. In practice, this relation - distribution might be poorly estimated especially in time-varying channels or might not be available at all. In this case, the performance of the Viterbi decoding algorithm significantly degrades. To cope with imperfect CSI in multi-tap channels, the authors in [57] have suggested recurrent neural networks (RNNs), where the multiple delayed copies of a symbol are encoded into the states of an RNN. Furthermore, Viterbinet, a FC-NN which learns the log-likelihood ratios (LLRs) of the received signal sample for all possible transmitted sequences of symbols has been implemented in [58]. The receiver needs to know the channel memory length and the constellation size, which are much easier to obtain or estimate than the CSI. Apart from the ML-based computation of the LLRs, the rest of the detector employs the classical Viterbi algorithm, see Figure 4.

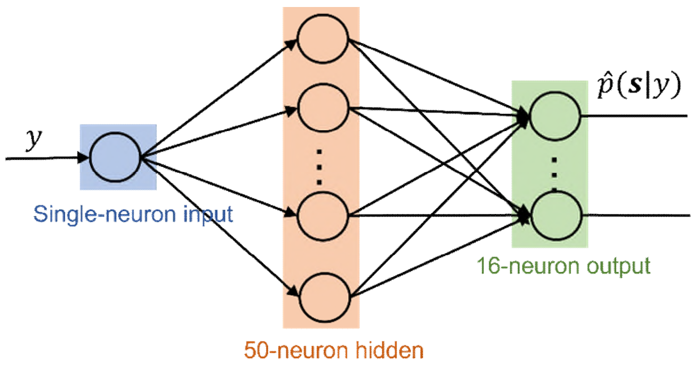
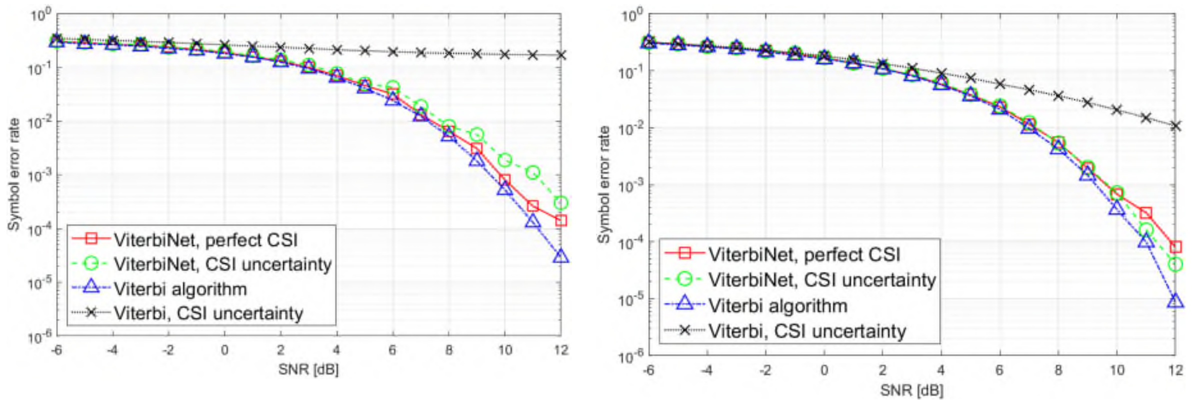


Figure 4: Viterbinet learns to estimate only the LLR of the received signal sample y for all possible transmitted sequences of symbols $\boldsymbol{s}$. For channel memory length $l = 4$ and BPSK modulated symbols, we have $\boldsymbol{s} = (s_1\ s_2\ s_3\ s_4)$ with $s_i \in \{-1,1\}\ \forall i$. In our implementation of Viterbinet, we use a NN with just a single hidden layer and we do not estimate the marginal probability of the channel output $\widehat{p}(y)$. The 16-neuron output layer applies a softmax activation to estimate the conditional probabilities while other layers apply ReLU. The total number of trainable parameters is less than 1 000.

In Figure 5 it is illustrated that the symbol error performance of Viterbinet in ISI channels with AWGN approaches that of Viterbi decoding when the channels used for training and testing are identical, compare the blue and red curve over there. Moreover, when the Viterbinet is trained over a class of channels, emulating imperfect knowledge of the CSI at the receiver, it clearly outperforms Viterbi decoding operating at the same level of channel uncertainty, compare the green and black curves in Figure 5. Moreover, Viterbinet shows good resilience to the SNR used for training as illustrated in Figure 6 and Figure 7. Nevertheless, Figure 6 and Figure 7 indicate that the SNR hyperparameter used for training can clearly impact the performance of Viterbinet.



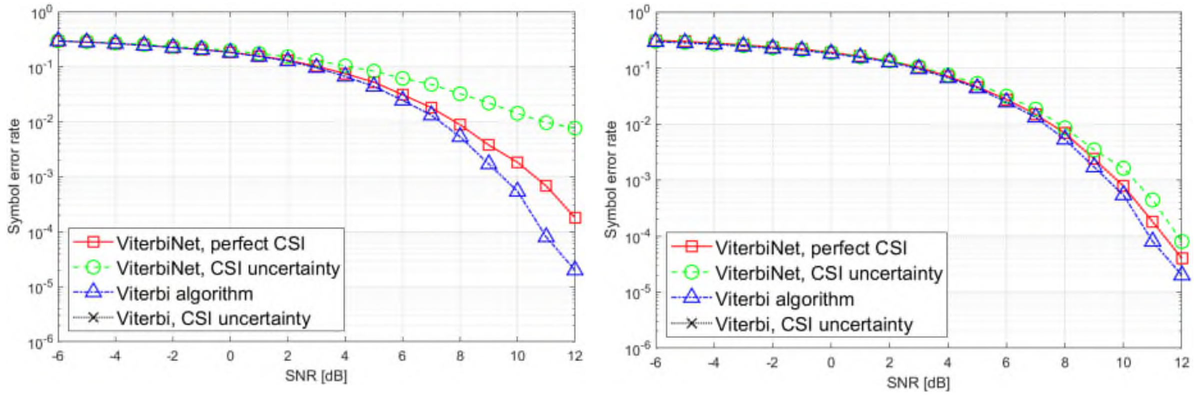
(a) Strong ISI (b) Weak ISI

Figure 5: Symbol error probability comparison of Viterbi decoding and Viterbinet in channels with strong and weak ISI at various SNRs. The power delay profile is $\sum_{\tau=1}^{l} e^{-\gamma(\tau-1)}$ with $\gamma = 0.1$ modelling strong ISI (a), and $\gamma = 1$ modelling weak ISI (b). To simulate Viterbi decoding with CSI uncertainty, we corrupt the power delay profile with additive white Gaussian noise that has variance equal to 0.2. Training Viterbinet with CSI uncertainty is carried out over 100 realisations of corrupted power delay profiles with a block of 50 generated symbols in each realisation. For testing Viterbinet, 50 000 transmitted symbols are simulated in a single simulation run using the power delay profile. We have used cross-entropy loss provided by the Adam optimiser. The learning rate is 0.01, the number of epochs is 100 and the mini batch size is 27. See also the caption of Figure 4 for the structure of the NN and more details on parameter settings[3].

In block fading time-varying channels, the performance of Viterbinet can be enhanced by integrating an on-line learning module, which can track the changes in the channel and update the weights accordingly [58]. For this purpose, error detection and forward error correction must be implemented at the receiver to ensure that the received codeword is decoded correctly. In that case, the corrected

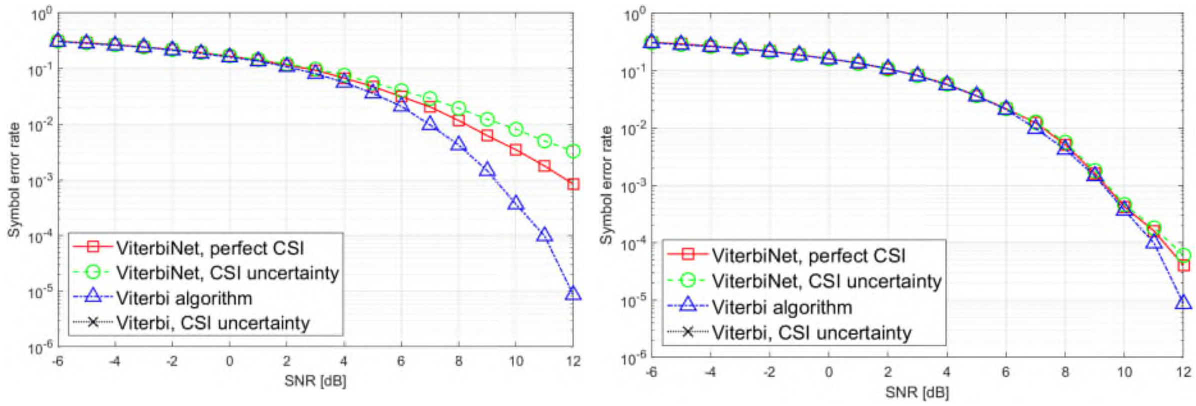
[3] Our simulation results for Viterbinet are generated by modifying the code based on Yoav Cohen's work shared on GitHub https://github.com/yoavchoen/ViterbiNet-in-Python

symbols and the associated decoder input can be used to re-train the NN. This method is known as meta-learning and reduces the BER by successfully correcting discrepancies between the actual fading channel and the fading model used for training [58].



(a) Strong ISI & Training at SNR = -3 dB (b) Strong ISI & Training at SNR = 6 dB

Figure 6: Finding a good value for the SNR hyperparameter to train Viterbinet. A single SNR is used for training under strong ISI $\gamma = 1$. *The SNR used for training is -3 dB (a), and 6 dB (b). See the caption of Figure 5 for the rest of parameter settings. The blue curve is included for comparison purposes as it represents a bound on the performance.*



(a) Weak ISI & Training at SNR = -3 dB(a) (b) Weak ISI & Training at SNR = 6 dB

Figure 7: Finding a good value for the SNR hyperparameter to train Viterbinet. A single SNR is used for training under weak ISI $\gamma = 0.1$. *The SNR used for training is -3 dB (a), and 6 dB (b). See the caption of Figure 5 for the rest of parameter settings.*

4 Channel estimation using ML

While in the previous section we discussed NN architectures that jointly perform channel equalisation and symbol detection, in this section, we review ML techniques tailored to channel estimation. The authors in [59] investigate channel estimation in a challenging environment combining time- and frequency selective fading. They initialise the DNN using (truncated) normally distributed random weights and a model-based method, e.g., pilot transmission along with traditional least-squares (LS) estimation at the receiver. Then, they iteratively fine-tune the weights with supervised learning, see Figure 8. This method tracks the amplitude and phase of channels unseen during training better than linear MMSE yielding lower BERs. One reason for the improved performance is that the DNN can learn the time correlations in the channel from the previously estimated CSIs.

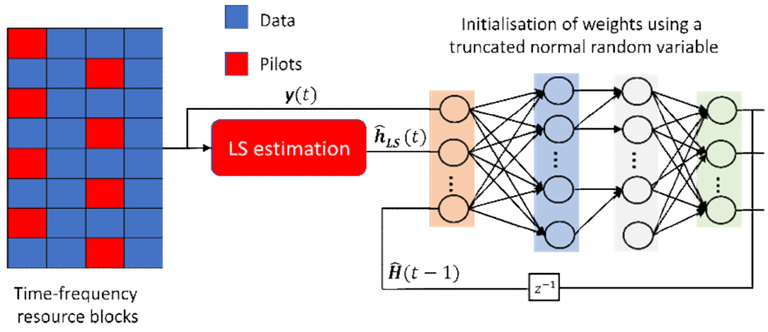


Figure 8: A block diagram for the training process for DNN-based channel estimation used in [Yang2019]. At time t, the inputs to the NN are the vector of the received symbols $\boldsymbol{y}(t)$, the least-square channel estimate $\widehat{\boldsymbol{h}_{LS}}(t)$ based on the transmitted pilot sequence, and the output of the NN in the previous timestep $\widehat{\boldsymbol{H}}(t-1)$. The latter allows to track the channel variations. For illustration simplicity, the vector inputs to the NN are shown as inputs to a single neuron. The z-transform z^{-1} is used to indicate delay by one time step.

The study in [60] treats the time-frequency response of a fast-fading channel as a 2d image. The unknown pixels are estimated from the constellation of pilots in the image, which are assumed to be perfectly known at the receiver. The CNN-based algorithm achieves a lower mean squared error (MSE) than MMSE, if the latter estimates the channel correlation matrix from the received signal samples. For a detailed review of channel equalisation methods using DNNs and CNNs see the review papers [22, 61] and the references therein. Recurrent neural networks (RNNs), that can sequentially process the received signal samples, have also been proposed for adaptive channel equalisation since the early 1990s [62]. RNN-based equalisers perform well under both linear and nonlinear channels and outperform traditional linear equalisers provided that the channel has deep spectral nulls or suffers from nonlinear distortions [63].

The study in [64] utilises meta-learning that can rapidly adapt to channels which were not experienced in the training phase. Different categories of channels constitute different classes, where a class can be for example the Rayleigh fading channel trained at few Doppler frequencies. The main idea is that the meta-learner can identify, only from few pilots, the class that resembles the most to the actual channel and construct a good enough initialisation vector for training. It is shown in [64] that the meta-learner can outperform in terms of BER the DNN-based equaliser in [49], when the two schemes are compared in unseen nonlinear channels, e.g., slow fading Rayleigh, where traditional approaches like the least-squares and MMSE do not perform well either. Meta-learning is also used in [65] but in a different context. This study considers sporadic transmissions of IoT, where due to the limited number of pilots per device, the base station cannot reliably estimate the E2E channel, including the effects of fading and power amplifier, for each device. Therefore, it uses previously received pilots from other devices as meta-data, for fast training of the new device.

Linear MMSE is typically used for downlink channel estimation in MIMO systems, but its performance degrades when the pilot length becomes smaller than the number of transmit antennas [66], or the number of RF chains at the receiver is limited [67]. Another issue in Frequency Division Duplex (FDD) MIMO is the feedback of estimated CSIs to the base station, which can create an excessive signalling overhead when the number of transmit antennas gets large. The 5G NR Rel-15 supports two codebook-based CSI feedback schemes, which essentially quantise the acquired CSIs, striking a balance between the accuracy of received CSIs at the base station and the signalling overhead. For massive MIMO systems, type-II CSI feedback including both the amplitude of CSI and the beam direction may still incur a high overhead [68].

A typical model-based method to deal with excessive CSI feedback assumes channel sparsity in the feedback link and uses a compressive sensing algorithm, however, in practice, the propagation channels are often not sparse. The authors of [69] propose CsiNet, which reduces the CSI overhead using an autoencoder in the feedback link for CSI compression at the encoder (the receiver) and reconstruction at the decoder (the transmitter). Their idea mimics the operation of compressive sensing but achieves lower MSE between the original and the recovered channels than state-of-art compressive sensing methods. For a detailed review of deep learning (DL)-based methods for CSI feedback compression, see [23].

5 Channel prediction in frequency- and time-domain using ML

ML-aided channel prediction has been listed as an important use case for emerging wireless networks by ITU FG-ML5G[4]. In this direction, the studies in [70, 71] design DNNs, which learn to predict the downlink CSI from the uplink CSI, eliminating the need for receiver feedback, essentially imitating a TDD system by learning some sort of weaker channel reciprocity between the frequency bands used for uplink and downlink communication. The intuition is that in (massive) MIMO systems the uplink and downlink channels experience nearly the same scatterers and physical propagation paths and thus, there must exist a high correlation in the amplitude of their CSIs. On the other hand, the phases of the CSIs between uplink and downlink are uncorrelated [72]. In [71], ray-tracing simulations are executed for the uplink and downlink of a MISO system with 128 antennas and 200 paths. It is illustrated that the DNN-based prediction of downlink CSIs performs well, especially when the propagation paths have small angular spreads.

Another issue in adaptive communication schemes is that the received CSI might become quickly outdated, resulting in sub-optimal link adaptation, erroneous transmit antenna selection, etc. Outdated CSI can become a major problem when the channel has a relatively short coherence time, e.g., in high-speed railway and vehicular communications. The traditional model-based approach to handle this issue is to consider the wireless channel as an autoregressive process and use time-series predictions, e.g., a Kalman filter, to feedback the estimated subsequent, instead of the current, CSI to the transmitter [73]. Unfortunately, autoregressive models suffer from error propagation at long-range predictions. Additionally, they require the precise knowledge of either the autocorrelation function or the Doppler spectrum (the power spectral density) of the channel. Finally, they can only exploit temporal correlations and, thus, perform sub-optimally in MIMO channels, which can exhibit both spatial and temporal correlations.

[4] https://www.itu.int/en/ITU-T/focusgroups/ml5g/Pages/default.aspx

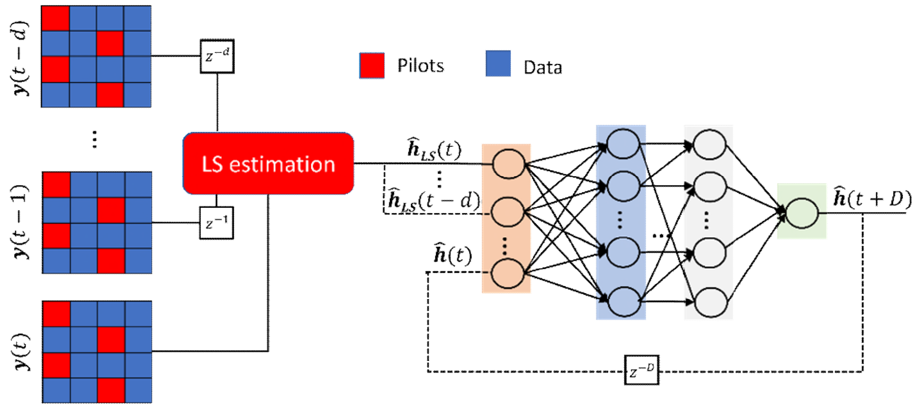


Figure 9: The trained NN takes as input the least-square channel estimation $\widehat{\boldsymbol{h}}_{LS}(t-i)$ based on the received pilot sequence at time $(t-i), i = 0,1, \dots d$ and the predicted channel $\widehat{\boldsymbol{h}}(t)$ at time t to predict the channel at time $(t+D)$. For illustration simplicity, the vector inputs/outputs to the NN are shown as inputs/outputs to a single neuron. The z-transform z^{-j} is used to indicate delay by j time steps.

The use of ML can help alleviate the problem of outdated CSI at the cost of training. Temporal correlations in the fading channel can be predicted using RNNs which are well-known good predictors for time series. By adapting the number of neurons in the input layer to the number of transmitting, receiving antennas, and the input delay, RNNs can simultaneously learn spatial and temporal correlations [74]. Furthermore, RNNs can predict long-range channel correlations by feeding the predicted channel output after the required time delay as an input to the NN, see Figure 9. Finally, in frequency selective channels, RNNs can be combined with the traditional block-type pilot arrangement in OFDM systems that uses interpolation to estimate the CSI for all subcarriers from a known constellation of pilots. In [75], the designed RNN leverages temporal and spatial channel correlations and, thus, consistently outperforms Kalman filters in terms of BER under the 3GPP extended vehicular and typical urban channel models in a 4x1 MIMO system.

6 Channel coding using AI/ML

In future heterogeneous wireless networks, different services will have very diverged latencies, connectivity and throughput requirements. These requirements shall determine the performance constraints the channel codes must meet, in terms of error correction capability, decoding latency, and implementation complexity. Therefore, the selection of coding schemes for 5G and beyond is likely to be application-specific [76]. Note that advances in channel coding can deliver significant cost enhancements for mobile network operators (MNOs)[5].

The block-based structure of LDPC codes allows for a much more efficient parallelisation than that for Turbo codes, which opens up communication systems to new applications and services by reducing latency. Therefore, LDPC codes have replaced Turbo coding in the data plane of 5G NR with codeword lengths in the order of 10 000 bits. Polar codes outperform other candidate coding schemes at short packets, 100-1000 bits, and they have been adopted for the control plane of enhanced mobile broadband (eMBB) and the physical broadcast channel, offering negligible BER at low code rates. However, the high complexity of successive cancellation for decoding polar codes at practical block lengths justifies the use of LDPC codes in 5G New-Radio (NR) [77].

[5] https://www.accelercomm.com/news/193m-savings-with-improvements-in-5g-radio-signal-processing

Naturally, decoding can be viewed as a classification task, which can be addressed by a neural network (NN). One key strength of NNs vs. many traditional decoding schemes is their linear architecture and avoidance of iterative calculations. Thus, NNs can simplify decoding without sacrificing much on the block error rate (BLER). On the downside, their main bottleneck and limitation are the high training time required once scaled to practical block lengths. This scalability issue partly explains why most attempts to integrate channel coding with DNNs have, so far, used short polar codes.

The study in [78] implements DNN-based decoding of ½ rate polar codes with block length $N = 16$ in AWGN. A three-layer (128, 64, 32) DNN with 2^{18} training epochs attains a BER almost identical to (optimal) map a posteriori (MAP) decoding. To optimise the signal-to-noise ratio (SNR) hyperparameter used for training, the following two points are observed: at high SNRs, the NN does not learn how noise corrupts data, and at low SNRs, noise corrupts data so much that the NN cannot distil the encoding structure. An SNR equal to 1 dB is finally chosen for the training phase, and during testing, the DNN maintains its performance close to MAP decoding for all considered SNRs. Another promising finding is that the DNN generalises well to unseen codewords during training, i.e., it can learn the encoding rule only from a limited set of codewords, but without approaching the performance of MAP decoder in that case. Unlike polar codes, it has been observed that the generalisation property does not hold for unstructured codes, e.g., LDPC and random coding. It is worth mentioning that even for polar codes, the generalisation property has only been confirmed for block lengths up to $N = 32$, and thus, might not hold in practice.

To extend the operation of DNN-based decoding to larger blocks, the study in [79] adopts expert knowledge, i.e., the belief propagation (BP) decoding of polar codes and partitions the encoding graph into multiple independent blocks. Each block contains only a part of the codeword and is associated with a single DNN. Similar to [78], each DNN has three hidden layers and individually decodes its part of the codeword nearly at MAP performance. Afterwards, all the decoded bits propagate through the remaining stages of the BP graph to generate the estimated codeword. Different blocks can vary in size, but they should all be small enough to be successfully replaced by NNs. Finally, the DNN with $N = 128$ bits and eight blocks attain similar BER to BP at significantly lower latency, as it completely avoids iterations. The latency-complexity trade-off can be controlled through the selection of the number and sizes of blocks.

Despite their good error-correction performance, the latency of Turbo codes is prohibitively high for some time-sensitive applications such as those supported by 5G ultra-reliable and low-latency communications (uRLLC). The study in [80] designs the Turbonet, a DL NN integrated into the max-log-MAP turbo decoder leveraging the iterative structure of Turbo codes and replacing each iteration by a DNN decoding unit. The DNN only estimates the extrinsic LLRs through supervised learning, while preserving the rest of the standard Turbo decoder architecture. This idea resembles that of Viterbinet [58], where the NN only replaces the calculation of LLRs for all possible transmitted sequences of symbols using supervised learning too. A Turbonet with three DNNs outperforms the max-log-MAP algorithm that uses three iterations in terms of BER and approaches the performance of the log-MAP decoder while reducing the computation time 10-fold [80]. Finally, the Turbonet generalises well for unseen SNRs and code rates.

The studies discussed so far implement DNNs to optimise the decoding performance. However, RNNs can naturally model sequential codes, e.g., convolutional and Turbo codes. The states of the RNN are essentially the cell states of the (convolutional) decoder determined by the previously seen bits. We have already seen in [57] that RNNs can outperform the Viterbi algorithm for (uncoded) symbol detection over multi-tap channels with imperfect CSI. In [81], a 100-bit and ½ rate recursive systematic convolutional code is trained at 0 dB in the AWGN channel and shows excellent generalisation capabilities to other SNRs and block lengths during testing. Finally, some further studies using NNs to construct efficient channel codes are summarised in [22].

7 Intelligent link adaptation

Link adaptation in Long-Term Evolution (LTE) utilises static lookup tables that map each modulation-and-coding-scheme (MCS) to a channel quality indicator (CQI). The user equipment (UE) estimates the downlink signal-to-interference and noise ratio (SINR) for each subcarrier and selects the MCS that maximises its rate for BLER not exceeding some threshold (10% is used in LTE). To calculate the BLER, the UE consults link-level SNR vs. BER curves, which are pre-calculated assuming a specific channel model. The UE feedbacks the selected MCS, in the form of CQI, to the base station, and the latter adapts the MCS using the lookup table which is also sent back to the UE. The main issue in the above process is that link adaptation does not consider the actual channel where communication takes place, potentially leading to inaccurate MCS selections. In addition, the UE only periodically feedbacks the CQI to the base station to reduce signalling overhead. As a result, in time-varying channels such as those experienced in vehicular communications, the received CQI might be outdated, compromising spectral efficiency [82, 83].

To mitigate the issue of outdated CQI, outer-loop link adaptation (OLLA) is incorporated into 5G NR. According to OLLA, the mapping of SINR to CQI in the lookup table is continuously adapted using offsets that are calculated based on the received hybrid automatic repeat request (HARQ) negative or positive acknowledgements, see Figure 10. Besides, ML techniques have been suggested for outdated CQIs mostly utilising reinforcement learning [84], because otherwise, the required amount of training time and data labelling becomes enormous. Reinforcement learning (RL) and especially Markov decision processes are excellent decision-making tools in discrete-time stochastic environments complying with the Markovian property, i.e., the next environment state solely depends on the current state-action pair.

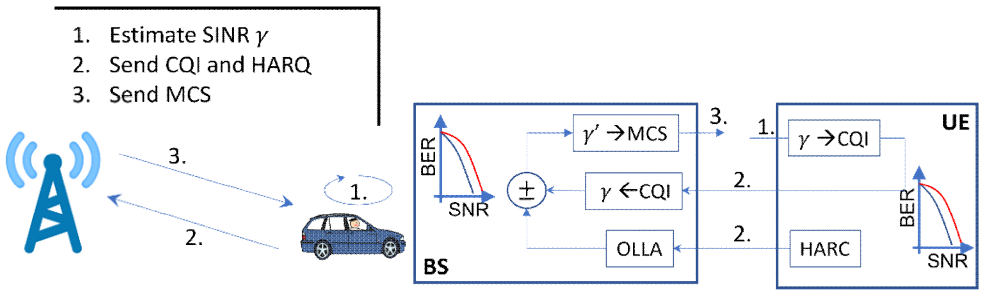


Figure 10: Schematic diagram for downlink outer-loop link adaptation (OLLA).

The system model in [85] uses OFDM, and the environmental state is described by the (discretised) average SNR across all subcarriers. The action is the selected MCS, and the reward is the throughput that the agent will experience. Under coloured interference, the agent, in the long run, can achieve higher expected spectral efficiency than the standard method based on the lookup tables. Nevertheless, calculating the average SNR as in [85] might not be optimal when the channel coherence bandwidth is larger than the bandwidth occupied by the considered block of subcarriers; Optimising the MCS over a set of correlated subcarriers is considered in [83]. In [86], a cognitive heterogeneous network is considered, where the primary system learns the interference pattern of secondary users with DRL, and based on the predicted interference, selects the MCS maximising its expected discounted rate. Finally, in [87], a multi-user MIMO mm-wave system with link adaptation using supervised learning is considered. The UE learns to select the modulation order and the spatial multiplexing or diversity order that maximises its throughput based on the estimated SNR. For an overview of supervised learning techniques for adaptive modulation and coding (AMC) including k nearest-neighbours and support vector machines see [55].

To sum up, the B5G/6G networks will need more flexible and agile AMC than the standard lookup tables because of the diversified service requirements and the highly unpredictable channel and interference conditions, which are difficult to model or even simulate. AI/ML and particularly DRL is a promising option for better adaptability of the MCS to the actual environment and service type.

8 Intelligent radios

Even though emerging wireless networks will operate at mm-wave, visible light, and THz frequencies, where a vast amount of spectrum is still unoccupied, it is necessary to utilise sub-6 GHz frequencies as efficiently as possible, owing to their favourable wireless propagation conditions. A significant volume of research and implementation have been already carried out using software-defined radios that can opportunistically exploit unoccupied spectrum using spectrum sensing and geolocation databases [88, 89]. Soon, AI/ML-empowered radios will apply sophisticated techniques, uncovering hidden spectrum usage patterns and enhancing spectrum utilisation efficiency [90]. Furthermore, with the recent invention of reconfigurable metamaterials, not only the transceiver but also the environment can be controlled, programmed, and adapted through AI/ML. Next, we review some of the key AI/ML-based methods for cooperative spectrum sensing, automatic wireless signal classification, and reconfigurable intelligent surfaces (RIS).

8.1 Intelligent spectrum sensing

Spectrum sensing aims to identify unoccupied spectrum chunks in space and/or time that can be used opportunistically by unlicensed (or secondary) systems. This mitigates spectrum scarcity under the constraint that the generated disturbances to the licensed (or primary) users can be tolerated. The main hurdle of using spectrum sensing for secondary spectrum access is its reliability under multipath fading and shadowing, yielding the well-known hidden node problem. The secondary user may not detect the primary signals due to a deep fade, and erroneously perceive the spectrum as unoccupied, generating unacceptable interference levels to the licensed users. Cooperative spectrum sensing (CSS) may alleviate the hidden node problem and reduce the spectrum sensing tasks per user [91].

Naturally, the spectrum occupancy statistics vary in space and time. The topology of the secondary network, e.g., due to mobility, is subject to change too. As a result, the traditional CSS schemes using hand-engineered fixed decision rules become quickly suboptimal. Instead of casting spectrum sensing as an m-ary hypothesis testing problem, it is equivalent to view it as a classification task and apply ML to maintain a good performance in time-varying environments. The study in [92] suggests various unsupervised (k-means, Gaussian mixture models) and supervised learning (K-nearest-neighbours and support vector machines) methods, which improve the detection performance at the cost of training. The training module should be activated only when the environment changes but maintaining an up-to-date dataset by continuously collecting and storing spectrum data measurements is costly. The study in [93] suggests using GANs to generate new labelled data for a given environment and a combination of GANs with autoencoders to generate new datasets when the environment changes.

Secondary users located close to each other naturally experience correlated propagation path loss to the primary users. A CNN can exploit such correlations by learning the appropriate convolutional kernels. If there are multiple spectrum bands available for sensing, the CNN is fed with a two-dimensional matrix, where each row contains the spectrum sensing outcomes for a secondary user across the different frequencies. It is expected that closely located rows of the matrix correspond to closely located users. Then, the CNN can leverage both spatial and spectral correlations. The receiver-operating-characteristic (ROC) curve of the CNN-based CSS scheme upper-bounds that of the traditional K-out-of-N hard decision rule at the cost of training, increased computational time and knowledge of the secondary user locations [94]. Overall, the supervised learning techniques appear to attain the best detection performance at the cost of labelled data.

The distribution of sensing measurements across multiple secondary users and spectrum bands can be used to uncover more secondary spectrum usage opportunities while keeping low the energy cost per user [95]. When a user must sense very wide bandwidths, sampling at the Nyquist rate might not be possible due to hardware limitations. Compressive sensing leverages signal sparsity over the considered frequency range and allows sub-Nyquist sampling rates without losing much signal information [96]. Traditionally, the expected value of occupancy over the entire wideband spectrum is calculated, yielding suboptimal performance when spectrum utilisation considerably varies from one spectrum band to the other. To obtain better spectrum occupancy statistics, the study in [97] proposes ML to take advantage of the inherent temporal correlations in spectrum usage that allow the user to make more accurate predictions of spectrum utilisation per block. In this way, the required number of collected samples becomes adaptive and reflects the real-time spectrum activity. Finally, the recent advances in spectrum sensing using ML may complement existing methods and standards for secondary spectrum access using geolocation databases [98].

8.2 Automatic signal recognition using CNNs

Signal recognition may refer to modulation classification, e.g., analog vs. digital, PSK vs. QAM, or wireless signal classification, e.g., WiFi vs. Zigbee, or Bluetooth waveforms. It is an important enabler for intelligent radio because it allows adapting the transmission parameters to the wireless carriers in the vicinity of the transceiver. For instance, automatic signal recognition can yield more sophisticated interference control, more efficient dynamic spectrum access and improved spectrum monitoring than simplistic signal detection.

Automatic modulation classification has been a well-researched topic over the past three decades, see [99] for an overview, which has been recently flourished by the adoption of ML techniques in wireless communications [55]. The conventional approaches utilise maximum likelihood or feature-based detection for modulation discrimination. The maximum likelihood detection computes the conditional PDF of the received data for each candidate modulation scheme and results in optimal classification provided that the channel impairments are perfectly known. In practice, expectation-maximisation algorithms are adopted to estimate the latent variables, e.g., the CSI [61]. The (sub-optimal) feature-based classifications rely on the higher-order cumulants of modulation schemes, and they are much simpler to implement [100].

CNNs are expected to be more effective than other ML techniques for modulation classification because they can successfully extract features from multi-dimensional and highly unstructured data. The study in [101] has produced a large dataset of radio signals using software-defined radios and applied CNNs to discriminate among 24 modulation schemes in various SNRs and channel conditions, including carrier frequency offsets, various symbol rates, AWGN, and multipath fading channels. It has shown that CNNs outperform complicated probabilistic and feature-based classifiers. Naturally, CNNs can implement image-based modulation identification on constellation diagrams, signal distributions and spectrograms [102]. These techniques can further enhance the classification accuracy even at low SNRs, but they require extra resources for data transformation and visualisation.

8.3 Intelligent radio environment

Intelligent radios can help deal with the problem of spectrum scarcity, however, the forthcoming services in 5G/6G wireless networks create spectrum demands which are unlikely to be satisfied in sub-6 GHz frequency bands. The mm-wave and THz frequency spectrum are largely unoccupied and conducive to high data rate applications but unfortunately subject to high attenuation. At the same time, deploying relays to enhance the signal quality at the receiver is costly because it requires extra RF chains and signal-processing, analog-to-digital (ADC) and digital-to-analog (DAC) converters, and power amplifiers. Also, it is well-known that relays suffer from high self-interference in full-duplex mode and halving the achievable data rates in half-duplex operation. On the contrary, reflectors made of a massive number of inexpensive antennas or nearly passive meta-materials do not have these limitations [103].

Metamaterial-based reflecting surfaces, hereafter referred to as reflecting intelligent surfaces (RIS), are man-made electromagnetic structures that are very thin, large in transverse size, and exhibit properties not found in nature. They consist of sub-wavelength artificial scattering particles (meta-atoms arranged in a grid-like structure with sub-wavelength grid distance), which can be fabricated to alter the electromagnetic waves impinged upon them in a desirable way, e.g., reflecting the incoming waves towards the intended direction without necessarily complying with Snell's law, see [104] for a detailed overview. Once configured, they do not require any power supply to operate, justifying their naming after nearly passive reflectors. The breakthrough of using RIS in wireless networks came when it became possible to control and customise the RIS operation through software. For instance, the RIS can be programmed to apply time-varying transformations to the incident waves (absorption, refraction, beamforming) depending on the CSIs. In principle, the use of RIS extends the concepts of software-defined networking and radio to include a programmable environment too. Note that controlling the environment might be particularly useful when there are limited options for transceiver optimisation, e.g., in single antenna low-power IoT.

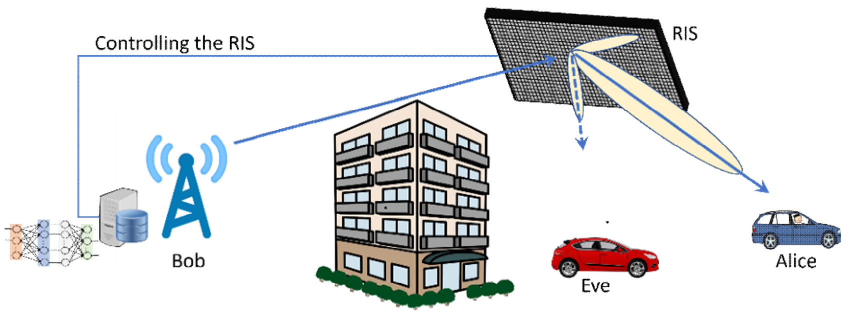


Figure 11: Illustration of the smart radio environment. A RIS is used to enhance non-line-of-sight communication in urban vehicular networks with physical layer security. The main beam is directed to Alice and artificial noise is transmitted towards Eve. The RIS is controlled from the base station which employs a DNN that learns to design the phase shifts.

Due to their conformal geometry, the RIS can coat sizeable parts of ceilings, furniture, windows, and buildings. The study in [105] suggests a planar meta-material the HyperSurface tile which also carries a lightweight IoT device capable of receiving commands from a central gateway to control its electromagnetics response, e.g., the phase shifts applied to the incoming wave so that, for instance, all multipath components add coherently at the receiver. Due to the combined effect of the large surface aperture with reflecting beamforming, the received power approximately scales proportionally to N^2 where N is the number of the tiles [106]; Recall that in massive MIMO the received power scales only linearly with the number of transmit antennas. It has been shown that the RIS can create local hotspots, help cancel interference, improve spectrum sharing and enhance physical layer security [103, 107, 108], see Figure 11. For instance, a RIS can turn a low-rank into a full-rank channel by introducing rich-scattering propagation towards the receiver [103].

Even though the analytical models for RIS have just started to gain maturity [109], and the experimental setups are so far limited [110], researchers have been already investigating the application of AI/ML in RIS-empowered wireless networks [104]. They envision that both the transceiver and the radio environment would be controlled and optimised through AI/ML in future communication networks [35]. The study in [111] estimates the direct and the cascade channels for each user with supervised learning, however, the phase shifts between each reflecting element and the user are assumed to be perfectly known. In practice, the major problem in RIS-assisted communication is the design of phase shifts. For instance, using the configuration described in [Ian2018], a RIS equipped with low-cost devices capable of sensing and reporting back to a gateway enables a centralised controller to learn the CSIs of both channels, i.e., base station to RIS and RIS to mobile users. After sufficient training, a DNN can optimally control the reflecting phases in real-time, which reduces the controller's complexity [112]. Nevertheless, due to the large number of reflecting elements, the challenge lies in the huge training overhead. To tackle this problem, a combination of compressive sensing and DL is suggested in [113].

9 ML for system-level performance evaluation of wireless networks

The traditional approach for assessing the system-level performance of wireless networks have been simulations and simplified models for the deployment and interference, e.g., the hexagonal grid for the locations of base stations and the Wyner model for modelling inter-cell interference [114]. With the advent of heterogeneous networks due to hot spots and nonuniform population densities, the traditional models become less accurate as they do not capture the irregular network structure. In this direction, during the past two decades, tools from stochastic geometry have been employed to obtain tractable solutions for random networks at low computational complexity [115]. Recent advances have also paved the way towards analytical methods that describe the statistical distribution of the network-wide performance, provided that the underlying point processes are ergodic [116-118].

While the analysis using stochastic geometry accounts for various sources of randomness, including the locations and activities of transmitters and the wireless fading channel, simplified assumptions are often adopted for the sake of tractability, leading to erroneous results, as they cannot capture the entire complexity of the wireless system. For example, the coverage probability in interference-limited Poisson networks with nearest base station association, single-antenna network entities, and Rayleigh fading is found to be independent of the transmit power level and the density of base stations. Furthermore, due to this independence, the ergodic area spectral efficiency (ASE) with link adaptation is found to increase linearly with the density of base stations, and thus, it diverges in the ultra-dense limit [115]. Both results do not reflect the reality of typical network deployments. The study in [119] argues that the divergence of ASE is due to the misuse of the power-law propagation pathloss model, which is inaccurate for small to medium distances. Using a fitted stretched-exponential pathloss function instead, the authors find that the ASE is a non-decreasing function of the base station density and reaches a plateau in the ultra-dense regime. While the adopted model results in tractable expressions for the ASE, this might not always be the case for other performance metrics. Therefore, the integration of stochastic geometry with data-driven approaches can be promising [120, 121]. Nevertheless, engaging ML tools into the system-level performance evaluation of wireless networks is still in its infancy.

The authors in [122] observe that the coverage probability of a randomly selected user in Poisson cellular networks is well-approximated by the sigmoid function. Then, they train a NN to fit the sigmoid to the input parameters which are the base station density, operation threshold, pathloss exponent, and the standard deviation and correlation distance of shadowing. The suggested method lacks scalability as it is a pure data-driven technique, but it incorporates details, e.g., the shadowing correlation distance, that are not taken care of by existing models. The study in [123] first derives a mathematical expression for the subject question, i.e., the secrecy outage probability of the ground-to-air communication link in the presence of aerial colluding eavesdroppers. Then, it generates labelled datasets using this expression and trains a NN to predict the performance given the input parameters. It turns out that the NN can compute the performance metric 1000 times faster than the mathematical expression at the cost of reduced explainability.

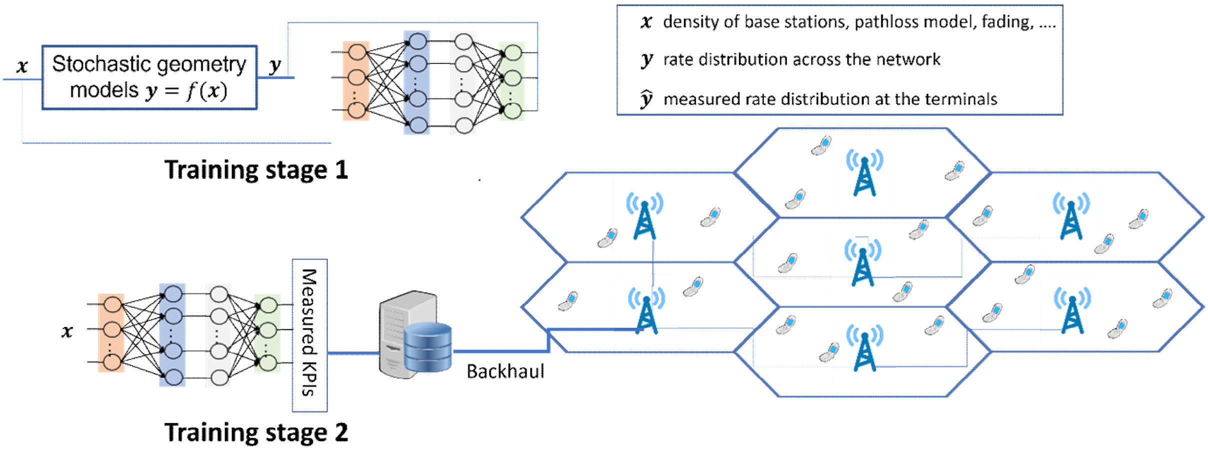


Figure 12: Transfer learning combining mathematical models based on stochastic geometry and rate measurements at the user terminals for training a DNN that estimates the distribution of user rates across the network. The trained NN at stage 1 is used to initialise the training at stage 2.

Deep transfer learning is perhaps the most promising way to integrate ML into stochastic geometry to improve the accuracy and complexity of the system-level performance evaluation of future wireless networks. In [124], a NN is trained to optimise the transmit power level of base stations given their density. The weights are initialised using the closed-form expression derived in [125] to accelerate training. Then, the weights are fine-tuned using limited measurement data to correct model imperfections. In this study, model imperfections may stem from an inaccurate power consumption model during training or an imprecise deployment model for the base stations, which is likely closer to a repulsive than a Poisson point process [126]. The need for measurement data is significantly reduced with deep transfer learning because the largest portion of the training dataset is generated using a mathematical expression. It is expected to witness more examples of deep transfer learning in this area sooner than later, e.g., refining the distribution of per-link reliability across the network, also known as the meta-distribution of the rate or SINR, with limited rate measurements at mobile terminals, see Figure 12.

10 Conclusions

It is undeniable that ML/AI have demonstrated at multiple times excellent performance levels for channel estimation, channel prediction, channel coding, etc. These novel techniques can prove essential in the design of RAN intelligent control loops at short timescales for future networks. The role of ML/AI at the PHY layer was also part of an ITU-T initiative devised to trigger the exploration of ML techniques for future networks with the aim to indisputably set the stage of future research activities within public institutions, Universities, and the private sector. In this book chapter, we have explored key discoveries and headways that will forge the future of a symbiotic relationship between AI and communication systems whilst focusing on critical and pivotal applications, e.g., channel estimation, channel prediction, and channel coding. Of particular interest is the control of reflecting intelligent surfaces using ML and how it can help in mm-wave vehicular communication in urban areas with strong attenuation. Nevertheless, ML/AI and more particularly deep learning methods often lack the crucial characteristic of explainability to shed vital light on their intrinsic mechanisms. This weakness is not only suffered by purely data-driven methods but also by NNs serving at the heart of model-aided modular transceivers. This lack of visibility of the internal mechanisms limits fundamental advances in the design of NNs to improve performances or extend their scope of applications [127]. Techniques based on transfer learning are executed in an ad-hoc fashion and still lack explainability. It was also noted that optimal NN parameters and architecture seem partially disconnected from the parameters of each use case. This seemingly disparage observation calls for innovative solutions to not only tackle the explainability but also more generally the trustworthiness of NNs to increase their adoption and acceptance by mobile network operators, and other stakeholders.

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