

# An Efficient Machine Learning-based Channel Prediction Technique for OFDM Sub-Bands

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**Abstract**—The acquisition of accurate channel state information (CSI) is of utmost importance since it provides performance improvement of wireless communication systems. However, acquiring accurate CSI, which can be done through channel estimation or channel prediction, is an intricate task due to the complexity of the time-varying and frequency selectivity of the wireless environment. To this end, we propose an efficient machine learning (ML)-based technique for channel prediction in orthogonal frequency-division multiplexing (OFDM) sub-bands. The novelty of the proposed approach lies in the training of channel fading samples used to estimate future channel behaviour in selective fading.

**Index Terms**—Channel prediction, deep learning, frequency division multiplexing, selective fading.

## I. INTRODUCTION

The increase in user density and the improvement of spectral efficiency requirements for various wireless communication systems have driven the development of multi-carrier modulation techniques. For example, orthogonal frequency-division multiplexing (OFDM) has been implemented in the current fifth generation (5G) networks and have emerged as a promising candidate for future sixth generation (6G) communication systems thanks to its robustness against multipath fading and its great performance in terms of spectral efficiency [1]. One important aspect to ensure reliable transmission in OFDM systems is the acquisition of accurate channel state information (CSI). However, estimating channel information in a precise manner is challenging and in some cases impractical due to the complexity of the time-varying wireless environment. Consequently, the channel coefficients may be outdated during the estimation process as the channels may have already changed due to its rapid fluctuations within two consecutive packets [2], and thus lead to the performance degradation of the system. To overcome this issue, channel prediction can be exploited. Unlike channel estimation, channel prediction allows to forecast the estimated channel information for future channel responses [3]. Furthermore, channel prediction reduces the transmitted overhead information and therefore, does not negatively impact the date rate.

A large number of sub-carriers are employed in OFDM systems to combat the deleterious effects of frequency selective

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fading. Moreover, the use of OFDM over frequency-selective fading channels can be advantageous due to the breakdown of the available frequency band into sub-bands. Since the coherence bandwidth is narrow compared to the available bandwidth, it is possible to slice the spectrum into sub-bands of uncorrelated fading. Consequently, the effects of frequency selective fading may only degrade one sub-band of a multi-carrier system. However, such degradation could be severe on the system performance and could be avoided through efficient sub-band allocation or channel prediction. Some studies have proposed techniques to address: (a) the sub-band allocation problem in fourth generation (4G) mobile networks, such as space division multiple access orthogonal frequency-division multiplexing (SDMA-OFDM) [4]; (b) the channel prediction issue in adaptive OFDM systems [5]. However, traditional approaches used for channel prediction (e.g., in reference [5]) consist of a tedious estimation process of propagation parameters and often rely on impractical assumptions yielding inaccurate CSI.

Deep learning and neural networks (NNs) are excellent tools that can be used for event prediction and pattern Recognition [6]. Recently, ML has been applied in OFDM-based systems to improve the accuracy of channel prediction techniques [7]–[9]. In [7], a prediction-enabled multiple-input-multiple-output (MIMO)-OFDM with transmit antenna selection (TAS) is investigated, while the work of [8] proposes a deep NN-based approach for channel prediction in an underwater acoustic orthogonal frequency-division multiple access (OFDMA) system. In [9], a deep learning (DL)-based channel prediction is proposed in an effort to reduce the demand of pilot symbols in OFDM systems. Different from [7]–[9], our proposed channel prediction approach based on convolutional neural network (CNN) assumes that the fading behaviour of a particular channel exhibits some peculiar characteristic, i.e., a signature that represents how physical objects are acting within the propagation environment. However, a mathematical model capable of accurately predicting all possible multipaths that the transmitted signal can travel through to the receiver is not trivial and is generally intractable. Motivated by the preceding discussion, we aim to address this challenge by adopting a ML approach that efficiently predicts the fading behaviour of a channel based on past-trained samples. Hence, we focus on the forecast of unsuitable sub-bands used for signal transmission. Furthermore, we obtain some promising results with the aid of a CNN method operating in the time-frequency domain.

The proposed technique can find some benefits in 6G use-case scenarios; for instance, low-latency applications would be able to mitigate the delay due to retransmissions by properly predicting the state of the channel at a future point and thus selecting the most appropriate time and sub-band for the transmission. Furthermore, this work can be beneficial to several proposed use cases for 5G, especially environments where there is an equipment powered by batteries that may benefit from a prediction of the fading behaviour by (i) saving energy with unmodulated carrier transmission for channel

estimation and (ii) transmitting in bands with less severe fading. These environments may require a high density of equipment and extremely efficient use of the battery.

The remainder of the paper is organised as follows. In Section II, the method adopted for the simulation of the channel is described and a brief discussion about other mobile radio channel sample generation techniques is carried out. We introduce and discuss the adopted CNN for channel prediction in Section III. We assess the performance and some remarks of the proposed predictor through numerical results in Section IV. The work ends with brief conclusions in Section V.

## II. CHANNEL MODEL SIMULATOR

Although the effects of an antenna (mainly its radiation pattern) are relevant in the description of the received signal, we can omit them—at least for now and consider their analysis in future works—from our channel simulations. Namely, modern mobile radio channel simulators deal separately with relevant aspects of wave propagation and antenna characteristics, such as Wireless World Initiative for New Radio (WINNER) II [10] and quasi deterministic radio channel generator (QuaDRiGa) [11]. Generally speaking, the radiation pattern of the receiving antenna only weighs in the received signal envelope, but not the behaviour of the multipath clusters over time [12]. Hence, we omit the impact of antenna parameters on the channel response<sup>1</sup>. Another simplification adopted is the evaluation of the channel on a two-dimensional (2-D) plane through which the mobile radio channel simulator consists of reflection points of the signal transmitted in the 2-D plane. Keeping that in mind, the simplified model which allows some reflecting points to move randomly during the channel simulation can be used to address the birth and death problem of multipath clusters.

Here, our goal is to confirm that the frequency response of the mobile radio channel may exhibit predictable behaviour patterns over the following conditions: (i) a base station (BS) covers a wide area; (ii) BS uses an omnidirectional antenna; (iii) a single set of large-scale parameters can effectively describe the simulated environment; (iv) the simulated environment is such that there are multipaths.

In what follows, we focus our discussion on this random movement of the reflection points. Suppose that the underlying environment is a densely populated area (i.e., city centre) with cars, pedestrians, buildings, etc, that could reflect or spread the signal. We aim to predict the channel behaviour over ten frames of the 5G new radio (NR). Consequently, our proposed approach predicts the channel behaviour up to 100 ms in the future since each 5G NR frame has a period of 10 ms [13]. Given the conditions of the movement and acceleration inherent to these reflective objects, the 100 ms is undoubtedly a despicable time to expect any dramatic change. In other words, given a relatively short time, we can expect that the reflection points will either provide short linear routes with constant speed or remain static. Thus, it can be assumed that the reflection points move at a constant speed and direction over time.

We now present a step-by-step guide for generating the channel samples. To begin with, an environment layout to be created should contain the following pieces of information: the relative position of the transmitter  $\mathbf{P}_{tx}$  in Cartesian coordinates, the relative position of the receiver  $\mathbf{P}_{rx}$  in Cartesian coordinates, the speed vector of the receiver  $\mathbf{S}_{rx}$ , the total number of reflection points  $N_r$ , the number of mobile reflection points  $N_m$ , the initial position of the reflection points  $\mathbf{P}_r$  (randomly generated), the speed vector of the reflection points  $\mathbf{S}$ , the

carrier frequency  $f_c$ , the sampling frequency  $f_s$ , the bandwidth of the transmitted signal  $B$ , and the sampling time window  $p$ . Notice that  $\mathbf{P}_r$ ,  $\mathbf{S}_{rx}$ , and  $\mathbf{S}$  have their coordinates generated according to a Gaussian distribution  $\mathcal{N}(\mu_p, \sigma_p^2)$ ,  $\mathcal{N}(\mu_{rx}, \sigma_{rx}^2)$  and  $\mathcal{N}(\mu_s, \sigma_s^2)$ , respectively, and only  $N_m$  positions of the vector  $\mathbf{S}$  are not null.

Moreover, we calculate the channel impulse response by first obtaining the expression of the length of a multipath  $l_i$ , for  $i = \{1, 2, \dots, N\}$ , through the Euclidean norm  $l_i = |\mathbf{P}_i - \mathbf{P}_{rx}| + |\mathbf{P}_i - \mathbf{P}_{tx}|$ , where  $\mathbf{P}_r = [\mathbf{P}_1, \mathbf{P}_2, \dots, \mathbf{P}_N]$ . The delay and phase of the multipath  $i$  can be calculated using  $\tau_i = l_i/c$  and  $\phi_i = -l_i f_c / c \bmod 2\pi$ , respectively, in which  $c$  represents the speed of light. Considering the effect of the free space attenuation for each multipath, the channel impulse response at time  $t$  in the baseband is given by

$$I = \sum_{i=1}^N \frac{c}{4\pi f_c l_i} \exp(\phi_i + 2\pi D_i l_i) \delta(\tau_i - t), \quad (1)$$

where  $\delta(\cdot)$  is the Dirac delta function and  $D_i$  is the Doppler shift. For simplicity, we adjust the delays  $\tau_i$  in such a way that the shortest route has a delay equal to zero.

It is known that the receiver only has a short  $p$ -second window to estimate the channel, assuming that the transmitted signal is given by  $s_{tx}(t) = \text{sinc}(Bt)$ , and sampling the received signal  $s_{rx}(t)$  at a rate of  $f_s$ , we have  $s_{rx}(k) = \text{sinc}(Bk) * I + n$ ,  $0 \leq k \leq p$ , in which  $n$  denotes the additive white Gaussian noise (AWGN) and  $*$  stands for the convolution operation.

The frequency response of the channel is given by the discrete Fourier transform  $\mathcal{F}(\cdot)$  of the samples collected from the received signal, and its modulus can be evaluated by  $C(f) = |\mathcal{F}(s(k))|$ . After obtaining the frequency response of the channel, the positions of the receiver and other mobile points are updated as

$$\mathbf{P}_{rx} \leftarrow \mathbf{P}_{rx} + \mathbf{S}_{rx} \Delta t \quad (2)$$

$$\mathbf{P}_r \leftarrow \mathbf{P}_r + \mathbf{S} \Delta t, \quad (3)$$

where  $\Delta t$  stands for the time between two consecutive channel simulations. Once the updates of these positions are complete, the steps previously taken to obtain the channel frequency response are repeated.

*Definition 1 (Covariance):* Let  $x_k$  and  $y_k$  be the  $k$ -th sample of stochastic processes  $X(t)$  and  $Y(t)$ , respectively. We then define the normalised covariance function by

$$R_{X,Y}(\tau) = \frac{1}{\sqrt{\text{VAR}(x)\text{VAR}(y)}} \sum_j x_j y_{j-\tau}, \quad (4)$$

where  $\text{VAR}(\cdot)$  represents the variance of the samples. Figure 1 depicts the frequency response over time for one simulation of the mobile radio channel in the frequency bands as the metric of interest. Moreover, Fig. 2 (a) shows cross-covariance  $R_{|C_0|, |C_1|}(\tau)$  between the magnitude (power) of the frequency response  $C_0(f)$  and  $C_1(f)$  of two distinct channels (i.e., two completely different initial conditions of channel simulation). The following simulation parameters are used:  $f_c = 900$  MHz,  $f_s = 51.2$  MHz,  $B = 12.8$  MHz,  $p = 10$   $\mu$ s,  $\mu_p = 0$ ,  $\sigma_p^2 = 4900$ ,  $\mu_{rx} = 1$ ,  $\sigma_{rx}^2 = 4$ ,  $\mu_s = 0$ ,  $\sigma_s^2 = 30.25$  and 12 dB of signal-to-noise ratio (SNR). In addition to these parameters, we have  $N_r = 100$  and  $N_m = 63$  for Fig. 1,  $N_r = 300$  and  $N_m = 200$  for  $C_0(f)$  in Fig. 2, and  $N_r = 2$  and  $N_m = 2$  for  $C_1(f)$  in Fig. 2 (a). The presence of deep fading at specific frequencies—in some cases, corrupting an entire sub-band—is evident in Fig. 1. It is also clear that our simulation of the channel behaves dynamically over time. One can notice in Fig. 2 that (i) the proposed channel simulation is capable of generating two uncorrelated channels and (ii) guaranteeing

<sup>1</sup>However, it will be unquestionably of great value to include the effect of the radiation pattern of the antennas in future studies.

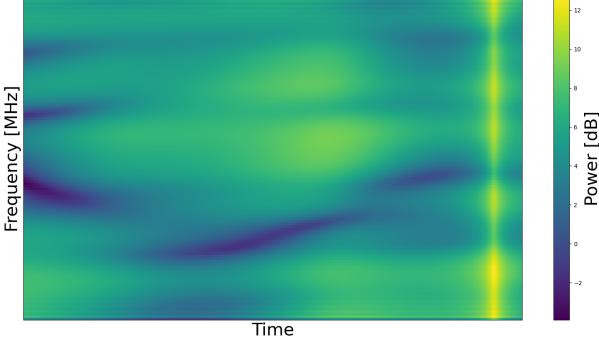


Fig. 1. Frequency response of the channel over time.

a temporal covariance that decreases rapidly with increasing  $\tau$ . Therefore, at least for the purpose of this work, we can say that the simulation of the channel was effective.

### III. CHANNEL PREDICTION

To obtain an accurate measure of the channel transfer function is a challenging task and this appears to be intractable from a practical viewpoint. To circumvent this issue, a widespread technique with relatively good accuracy that consists of transmitting a reference signal embedded in the transmitted signal can be adopted. Consequently, the estimate of the channel transfer function from the received signal becomes feasible. Up to this point, the time dependence of the channel frequency response (CFR) has been conveniently omitted; nevertheless, it can be directly associated as follows. Let  $F$  be the total number of sub-carriers for which channel state information is available,  $D$  be the total number of steps ahead desired for simultaneous forecasting (whole prediction span), and  $T$  be the time length of the input layer of the proposed NN (number of consecutive observations of the CFR over time). In addition, we denote  $\mathbf{H}_j \in \mathbb{C}^F$  as the sequence of complex samples of the CFR in the  $j$ th estimation. Therefore, we have a sampling of the response channel at time  $t = j\Delta t$  seconds. Due to the AWGN and the temporal truncation of the received signal,  $\mathbf{H}_j$  is a noisy and slightly distorted version of the CFR.

Since our interest remains in feeding the NN with the channel samples, it is crucial to adjust the vector  $\mathbf{H}_j$ . Thus, one needs to first convert the observation series  $\mathbf{H}_j$  into three-dimensional (3-D) tensors  $X \in \mathbb{C}^{(J \times F \times T)}$ , in which the index  $j$  represents the time length of the tensor, i.e., the sample number of the CFR. Then, as the proposed NN requires a real sample set for its entry, another dimension to the tensor  $X$  needs to be added. This transformation can mathematically be expressed

$$X_{j,f,i,0} = \text{Re}(H_{j-T+i}(f)), \quad (5a)$$

$$X_{j,f,i,1} = \text{Im}(H_{j-T+i}(f)), \quad (5b)$$

$\forall j, f$  and  $i$ . Now, the tensor  $X$  with dimensions  $(j \times H \times T \times 2)$  can be used as an input of the underlying NN.

The prediction problem consists of optimising the mathematical model parameters,  $\Gamma$ , called predictor, such that the proposed prediction is as close as possible to the training labels. For any discrete-time  $j$ , the training labels are  $\mathbf{H}_{\{j+1,j+2,\dots,j+D\}}$ , and the tensor of input variables for the NN is given by  $X_{j,f,i,c}$ ,  $\forall f, i$  and  $c$ . The Gamma predictor  $\Gamma(\cdot, \zeta)$  is parameterised by a real-valued vector of parameters  $\zeta \in \mathbb{R}^Z$ . The output of the underlying NN is also a

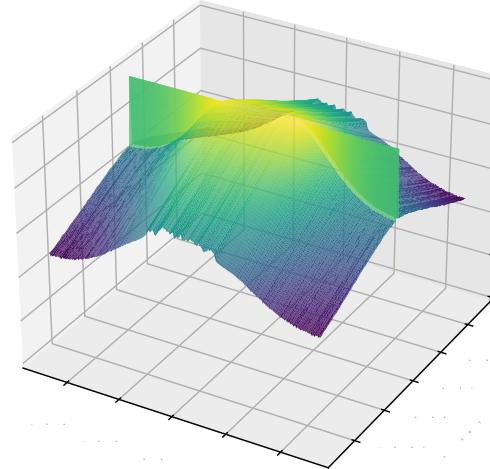
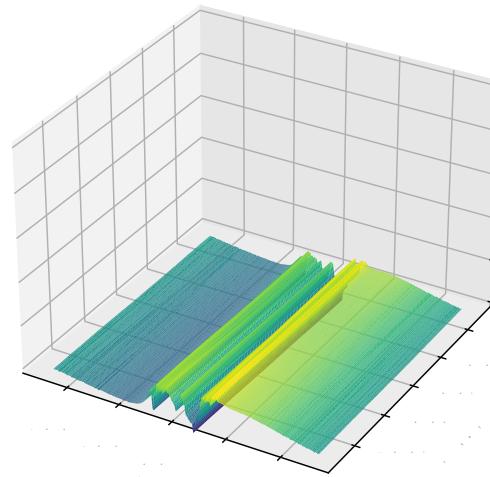


Fig. 2. (a) Cross-covariance and (b) autocovariance over  $\tau$  for the frequency band of interest.

four-dimensional (4-D) tensor  $y \in \mathbb{R}^{(j \times F \times T \times 2)}$ . Given an input tensor  $X$ , one can evaluate  $y$  with the predictor  $\Gamma$  as  $y = \Gamma(X, \zeta)$ . In the sequel, we deal with some aspects pertinent to the prediction model  $\Gamma$ , and we also describe the transformation process that occurs internally in the proposed NN.

#### A. Causality

Causality is a condition inherent in any physical model of temporal prediction. Since the model must estimate future outcomes given past events, no mathematical operation internal to the model can be non-causal. In other words, assuming that the predictor—more precisely, one or more layers of the predictor model—has access to future events is implausible. In order to guarantee the causality of the convolution operation, temporal indices of convolution kernels consist purely of non-negative integers, and the frequency axis is symmetrical.

TABLE I  
SUMMARY OF THE CHARACTERISTICS OF THE PREDICTOR LAYERS.

#	Channels	Kernel size	Dilation rate	Activation function
1	2	(3 × 10)	(1 × 1)	tanh(·)
2	3	(10 × 10)	(1 × 16)	tanh(·)
3	3	(10 × 10)	(10 × 1)	tanh(·)
4	2	(10 × 3)	(1 × 64)	tanh(·)
5	$D$	(1 × 64)	(1 × 1)	exponential

### B. CNN Predictor

The predictor proposed in this work is composed primarily of layers of spatial convolution, which operate in a  $d$ -dimensional space. To simplify the notation, we denote  $x \in \mathbb{R}^{(v_0 \times v_1 \times \dots \times v_{d-1})}$  to be a  $d$ -dimensional tensor, in which a specific position can be accessed by  $x_{u_1, \dots, u_{d-1}}$ . Its indices  $u_1, \dots, u_{d-1}$  will be denoted as a vector  $\mathbf{u}$ , and hereafter,  $x_{u_1, \dots, u_{d-1}}$  will be referred to as  $x_{\mathbf{u}}$ . Let  $x$  and  $k$  be a pair of  $d$ -dimensional tensors, with  $d \in \mathbb{N}^*$ . The  $d$ -dimensional convolution of  $x$  with  $k$ , indicated by  $x * k$ , is established as

$$(x * k)_{\mathbf{u}} := \sum_{\mathbf{v}} x_{\mathbf{u}-\mathbf{v}} k_{\mathbf{v}}, \quad (6)$$

$\forall \mathbf{u}$  and  $\mathbf{v}$  cover all terms in which  $x$  and  $k$  are defined. Regarding convolutional layers of NNs, the tensor  $k$  refers to the tunable parameters, and it is commonly called convolution kernel.

A kernel dilation may be used to impose a fixed integer number of consecutive null values along a dimension on the kernel tensor. Equivalently, given the convolution defined in (6), the vector  $\mathbf{v}$  is replaced with the index sets of the form  $\{0, \Delta, 2\Delta, \dots\}$ , where  $\Delta \in \mathbb{N}^*$  is an additional hyper-parameter called the dilation factor. Notice that, it is not mandatory to adopt identical dilation factor values for all the dimensions. In addition, the number of tunable parameters does not change when employing a dilation factor. In an effort to classify the signal quality of a reduced set of subband for the CFR multi-steps, we propose a structure composed of partially dilated CNNs in series. More precisely, the proposed predictor has four partially dilated 2-D convolutional layers with activation function given by  $\beta(\cdot) = \tanh(\cdot)$  and one 2-D convolutional as the output layer. Table I summarises the characteristics of each of the five chosen convolutional layers, and the sequence of the layers presented follows the order in which the input data are processed.

### C. CNN Classifier

Our classification process consists of predicting whether the channel intensity will be below a threshold. Thus, the proposed classifier aims to previously identify which subbands will be subject to severe fading. The proposed classifier has four partially dilated 2-D convolutional layers identical to the predictor and one 2-D convolutional as the output layer. The output layer of the classifier has  $D$  channels, kernel size of  $(1 \times 64)$ , no dilation rate, and a *sigmoid* as an activation function. Note that the output is a 4-D tensor  $o \in \mathbb{R}^{(j \times F \times 1 \times D)}$  with  $0 \leq o \leq 1$ .

## IV. NUMERICAL RESULTS AND REMARKS

### A. Channel

We perform simulation runs using Python in order to obtain the samples of the CFR. These simulations follow the methods described throughout this paper. As already discussed, the

TABLE II  
SUMMARY OF CHANNEL SIMULATION SETTINGS.

Symbol	Value	Description
$P_{tx}$	(−200, 0)	Transmitter's relative starting position
$P_{rx}$	(200, 0)	Receiver's relative starting position
$N_r$	256	Number of reflection points
$N_m$	63	Number of mobile reflection points
$f_c$	900 MHz	Carrier frequency
$f_s$	51.2 MHz	Sampling frequency
$B$	12.8 MHz	Bandwidth of the transmitted signal
$p$	10 $\mu$ s	Sampling time window
$\mu_p$	0	Mean of the Gaussian distribution used for the initial position of the reflection points
$\sigma_p^2$	$70^2$	Variance of the Gaussian distribution used for the initial position of the reflection points
$\mu_{rx}$	1	Mean of the Gaussian distribution used for the receiver's speed
$\sigma_{rx}^2$	4	Variance of the Gaussian distribution used for the receiver's speed
$\mu_s$	0	Mean of the Gaussian distribution used for the reflection points' speed.
$\sigma_s^2$	100	Variance of the Gaussian distribution used for the reflection points' speed
SNR	12 dB	Signal-to-Noise ratio at receiver
$\Delta t$	500 $\mu$ s	Time between two consecutive simulations of the channel

transformation given by (5) to all samples in the channel is applied. The set of simulation parameters for the underlying channel is shown in Table II. We randomly start two simulation runs (a training set is composed of two distinct channels) with the parameters described in Table II. We accumulate the first 4096 tensors of the complex frequency response from each simulation run to build a training set. The test set consists of the subsequent 512 tensor samples of the complex frequency response from each simulation run. Consequently, there are 8192 samples for the training of the predictor and 1024 samples for the test.

### B. Training

We used the mean squared error and binary cross entropy as the loss function for predictor and classifier, respectively, which evaluate the multi-step ahead of predictions with the total prediction span  $D$  set to 10. More precisely, we present to the predictor and to classifier a small (one mini-batch) set of tensors—this process is widely known as batch training or batch learning—during the training phase. The mini-batch has a size of 64 tensors. At the end of this process, the vector parameters  $\zeta$  are adjusted by employing refined versions of the adaptive moment estimation (ADAM) algorithm with a learning rate of 0.003. Another important concept of the training phase is Epoch which is said to be completed when the whole set of input samples is evaluated. Here, the proposed model is trained for 30 epochs.

Figure 3 shows the mean squared error (MSE) over 30 training epochs. The results obtained by evaluating the training sets are plotted in dotted lines, while the ones for the MSE of the test set are shown in solid lines. From both sets of samples, it is clear from Fig. 3 that Predictor has smoother training and converges. Also, it can be noticed that with just 8 training epochs, Predictor achieves a satisfactory MSE.

Figure 4 presents the receiver operating characteristic (ROC) curves of the classifier for the different steps ahead predictions considering only a single sub-band. The classifier performed satisfactorily. Furthermore, it is clear from the Fig. 4 that

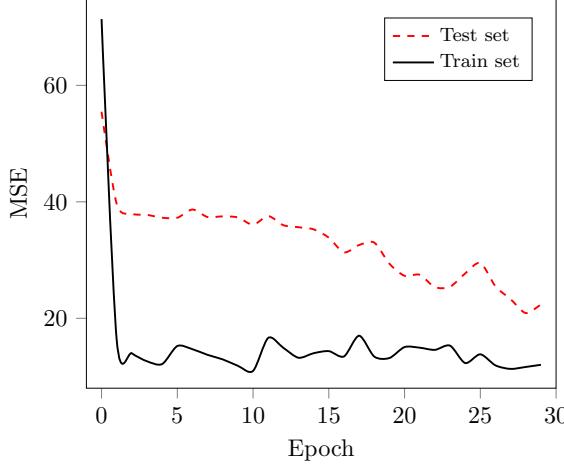


Fig. 3. Mean Squared Error during training. The solid line refers to the training set and the dashed one to the test set.

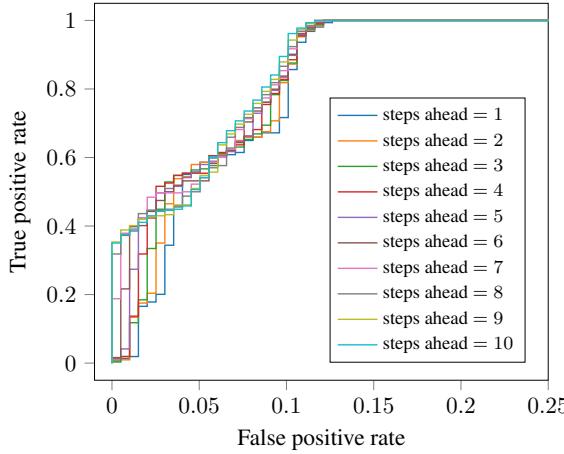


Fig. 4. ROC curves for a single sub-band and for the different steps ahead. This figure is better viewed in color.

the performance is similar among the presented curves. In other words, sorting copes equally well in predicting channel behaviour within a short term (1 step ahead) or long term (10 steps ahead).

Another run of channel simulation—which is distinct and independent from the first two simulation runs—is provided in an effort to ascertain possible overfitting on the proposed model. The new channel simulation has 4096 samples, and given the way the model is trained—notice that we purposely do not randomly split the total samples set into two sets, training and testing—an overfitting margin may exist. This issue can be evaluated by testing the predictor with new and independent samples. The obtained results for the the predictor are shown in Table III that presents the mean square error for a specific number of steps ahead. In other words, for each of the possible future steps that the proposed model performs a prediction on, the mean square error for the new set of inputs is calculated. It can be noticed that the predictor does not show an overfitting behaviour, and has a mean square error that is very close to that obtained for the first set of inputs. This characteristic is a strong indication that we can train the proposed model in a given environment and use it in an environment that is uncorrelated to the former one. This characteristic needs to be investigated comprehensively.

TABLE III  
MEAN SQUARED ERROR OVER THE 4096 SAMPLES FROM NEW CHANNEL.

Step ahead	MSE
1	24.455336
2	22.610251
3	26.049115
4	24.488873
5	23.515360
6	23.826602
7	25.350836
8	25.708386
9	25.830940
10	26.221350

However, this falls outside the scope of the present work.

## V. CONCLUSION

In this work, we have proposed a simplified way to simulate a mobile radio channel with fading. Moreover, the channel simulation results have revealed typical behaviour of broadband signals under selective fading. Additionally, a predictor and a classifier constituted by layer of CNN in sequences have be employed to predict the multi-step fading channel in wireless broadband systems.

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