Deep learning channel estimation for 5G wireless communications

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Abstract:

Introduction/purpose: In recent years, deep learning techniques, particularly Convolutional Neural Networks (CNNs), have demonstrated remarkable performance in 5G communication systems by significantly improving the accuracy of channel estimation compared to conventional methods. This article aims to provide a comprehensive review of the existing literature on CNN-based channel estimation techniques, as well as to enhance the state-of-the-art CNN-based channel estimation methods by proposing a novel method called VDSR (Very Deep Super Resolution), inspired by Image Super-Resolution techniques.

Methods: To evaluate the effectiveness of various approaches, we conduct a comprehensive comparison considering different scenarios, including low Signal-to-Noise Ratio (SNR) and high SNR, as well as Line-of-Sight (LOS) and Non-Line-of-Sight (NLOS) scenarios. Through this comparative analysis, we assess the performance of the existing methods and highlight the advantages offered by the proposed VDSR-based technique.

Results: Our findings reveal a significant potential of CNN-based channel estimation in 5G communication systems, with the VDSR method demonstrating a consistent performance across all scenarios. This re-

search contributes to the advancement of channel estimation techniques in 5G networks, paving the way for enhanced wireless communication systems with improved reliability.

Conclusion: The VDSR architecture demonstrates remarkable adaptability to different types of channels, which results in achieving requested performances for all analyzed SNR values.

Key words: deep learning, CNN, 5G communication systems, very deep super resolution.

Introduction

With the advent of 5G communication technology, the demand for high-speed, low-latency, and reliable wireless communication is increasing exponentially (Albreem, 2015). The key enabler for 5G communication is accurate channel estimation, which refers to the process of estimating the wireless channel parameters between the transmitter and the receiver (Morocho-Cayamcela et al., 2019). Accurate channel estimation is critical for improving the performance of 5G communication systems, including data rates, spectral efficiency, and reliability (Ma et al., 2015). In recent years, convolutional neural networks (CNNs) have emerged as a promising technique for channel estimation in 5G communication systems (James et al., 2011). CNNs are powerful deep learning algorithms that can learn and extract complex features from large amounts of data. By leveraging the power of CNNs, channel estimation in 5G communication systems can achieve high accuracy, robustness, and efficiency (Ye et al., 2017; Kaur et al., 2021).

This work aims to investigate the effectiveness of CNN-aided channel estimation in 5G communication systems. Specifically, through exploring the existing literature on CNN-aided channel estimation, a novel architecture for CNN-based channel estimation is being proposed, and the performance of the suggested approach will be assessed through simulations.

The rest of this paper is structured as follows. Section 2 describes the 5G new radio SISO-OFDM system. Section 3 provides a literature review on CNN-aided channel estimation and describes the architecture used for our method. Section 4 presents the results and analysis of the simulation. Section 5 discusses the implications of our findings and provides recommendations for future research. Finally, Section 6 presents the conclusions of this work.

5G new radio SISO-OFDM system

The focus of this paper is on analyzing a SISO-OFDM system that employs a single antenna at both the transmitter and receiver. This system is depicted in the diagrams shown in Figure 1 and Figure 2 , and the channel model is constructed accordingly.

Transmitter

Figure 1 shows the architecture of the transmitter, which involves converting serial binary input bits (a sequences of zeros and ones) into a parallel form. Based on the chosen modulation scheme, the binary bits are then mapped onto symbols, with each symbol being $K - dimensional$ and the binary bits selecting one of M constellation points. Typically, K is 2, and M is determined by the modulation scheme chosen at the higher layer. Additionally, intermittent pilot symbols are inserted among the modulated symbols, which serve as a reference for channel estimation and are also recognizable to the receiver.

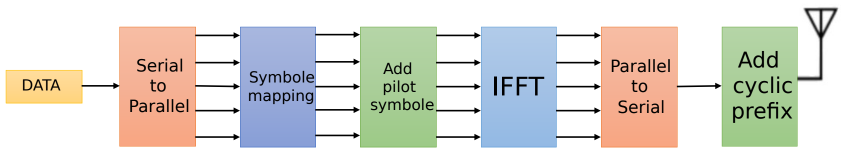

Figure 1 – Block diagram for the OFDM transmitter model
Рис. 1 – Блок-схема модели передатчика OFDM
Слика 1 – Блок-дијаграм за модел OFDM предајника

Let $X_S \in \{X_m, X_p\}$ where $X_m \in \{s_0, s_1, s_2, , s_{M-1}\}$ is the modulated symbol selected by log_2 M binary input bits and $X_p \in \{p_0, p_1, p_2, ..., p_{K-1}\}$ are pilot symbols respectively. Equation 1 in the digital domain is Inverse Discrete Fourier Transform operation which can be efficiently realized by the Inverse Fast Fourier transform (IFFT) before adding the cyclic prefix (Banerjee et al., 2022).

$$x_s(n) = \frac{1}{N_s} \sum_{k=1}^{N_S-1} X_s(k) \exp{(j2\pi \frac{k}{N_s} n)}. \tag{1}$$

where N_S is the IFFT length. A parallel to serial converter is present after the IFFT operation to serialize the output.

Receiver

Figure 2 shows the architecture of the receiver, which includes a process for estimating the timing of the received signal.

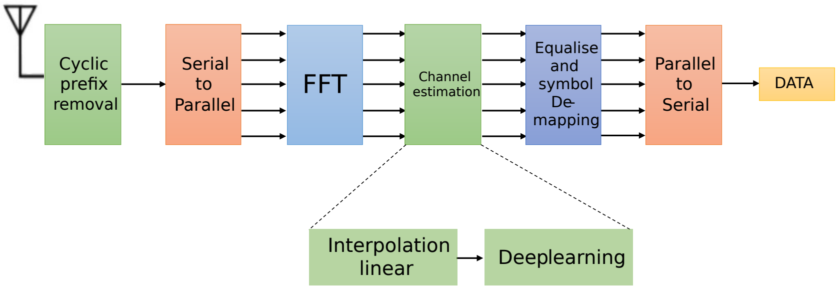

Figure 2 – Block diagram for the OFDM receiver model
Рис. 2 – Блок-схема модели приемника OFDM
Слика 2 – Блок-дијаграм за модел OFDM пријемника

This process involves cross-correlating the input waveform with a reference waveform and compensating for any timing offset. Once the timing offset has been accounted for, the cyclic prefix is removed from the received waveform. If Y_S is the received OFDM symbol and y_S is the output of the FFT operation, then y_S can be expressed in the following manner (Banerjee et al., 2022):

$$y_s(n) = \frac{1}{N_s} \sum_{l=1}^{N_S-1} Y_s(l) \exp\left(-j2\pi \frac{l}{N_s} n\right) \quad (2)$$

The pilot samples, which are located at predetermined positions, are extracted from the signal and utilized to estimate the channel characteristics. This channel estimation information is then used to equalize the output $y_S(n)$. After equalization, the signal is demodulated based on the modulation scheme that was employed at the transmitter.

Signal model

In an OFDM system (Soltani et al., 2019), for the k_{th} time slot and the ith subcarrier, the input-output relationship is represented as:

$$Y_{i,k} = H_{i,k} X_{i,k} + Z_{i,k} \quad (3)$$

Considering an OFDM subframe of size $N_S N_D$, the time slot index k is between $[0, N_D - 1]$, and the range of the subcarrier index i is $[0, N_S - 1]$.
$Y_{i,k}$: The received signal
$X_{i,k}$: Transmitted OFDM symbol
$Z_{i,k}$: white Gaussian noise
$H_{i,k}$: the (i, k) element of $H \in C^{N_S N_D}$. H represents time-frequency response of the channel for all subcarriers and time slots.

5G data architecture

The physical layer of the 5G NR is based on resource blocks allowing the NR physical layer to adapt to various spectrum allocations. A resource block spans 12 subcarriers with a given sub-carrier spacing. A radio frame has a duration of 10 ms and consists of 10 sub-frames with a sub-frame duration of $1ms$ as shown in figure 3 . A sub-frame is formed by 1 or multiple slots each having 14 adjacent symbols (a variable number of OFDM symbols per subframes, different from LTE) (3GPP. 2018).

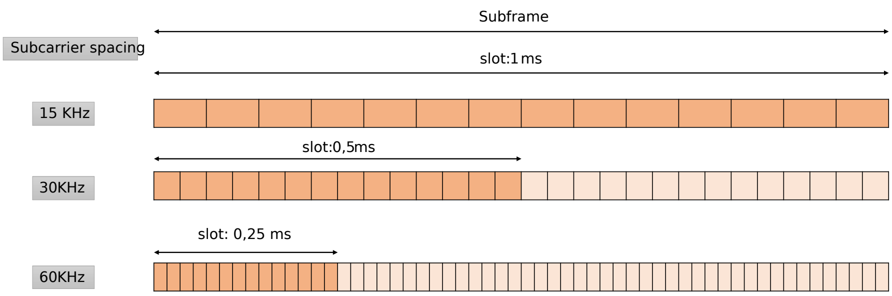

Figure 3 – Sub-frame architecture in 5G
Рис. 3 – Подкадровая архитектура в 5G
Слика 3 – Архитектура подоквира у 5G

In 5G NR, the pilot symbols are referred to as demodulation reference symbols (DMRS) and this is used by the receiver for radio channel estimation. The DMRS symbols are uniformly placed within sub-carriers as shown in figure 4. We assume the DMRS symbols used in the 3GPP specification (3GPP. 2020a).

Figure 4 shows the DM-RS pattern and frequency for type 1 and type 2. Type 1 on the left corresponds to every other resource element in the frequency being occupied by a DM-RS symbol. Type 2 on the right shows two consecutive resource elements occupied by the DM-RS symbols out of

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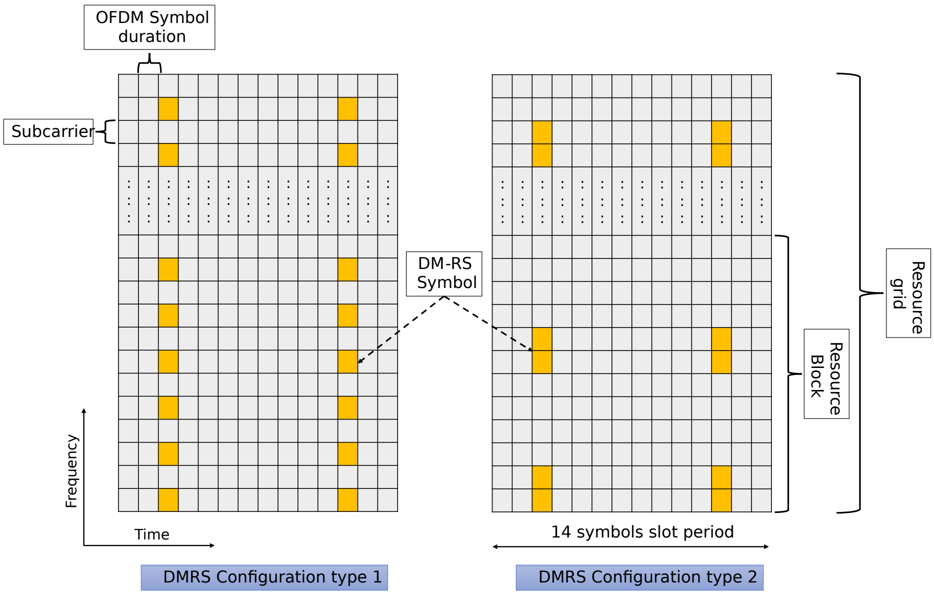


Figure 4 – Representational figure of the distribution of DM-RS
Рис. 4 – Репрезентативное изображение распределения DM-RS
Слика 4 – Репрезентативни приказ дистрибуције DM-RS

each group of six resource elements. Therefore, type 1 has a denser occupancy at 50% of the resource estimates, versus one-third of the resource elements for type 2. On the other hand, you can only have two such columns of type 1 DM-RS, whereas there can be three different sets of type 2 DM-RS as there are two more possible positions for a set of two DM-RS in each group of six resource elements. This means that type 2 supports a larger number of orthogonal signals, which is more suitable for multi-user MIMO. These two types correspond to a trade-off between density and frequency and the number of orthogonal DM-RS sequences supported.

Channel model

In wireless communication channels, the signal transmitted from a base station to user equipment not only includes a direct line-of-sight (LOS) component, but also other components that are reflected off scatterers, leading to a multipath propagation environment. Each path of the signal experiences different amounts of attenuation and delay (Wang et al., 2018). The channel's impulse response can be expressed as:

$$h(t) = \sum_{i=0}^{L-1} \alpha_i \delta(\tau - t_i), \tag{4}$$

where a_i is the attenuation and t_i is the delay in the i_{th} path.

Tap Delay Line models

In TDL models, the channel impulse response (CIR) is represented by a linear finite impulse response (FIR) filter. Each tap of the TDL model is composed of several multipath component (MPCs) with non-resolvable delays. Tap weights are modeled by a random process with amplitudes following Rayleigh, Rician, or Weibull distributions (Wang et al., 2018).

A TDL (Tap Delay Line) profile in 5G communication represents a specific channel model that simulates the characteristics of radio wave propagation in a wireless communication system. Three TDL models, namely TDL-A, TDL-B and TDL-C, are constructed to represent three different channel profiles for NLOS while TDL-D and TDL-E are constructed for LOS (3GPP. 2020b).

CNN-aided channel estimation

In recent times, there has been a significant surge in interest in channel estimation techniques based on deep learning. This is due to their ability to adapt and learn from data, as opposed to conventional estimation techniques that rely on a model-based approach.

A convolutional neural network (CNN) approach is chosen because the channel estimation problem can be modelled as an image-processing problem (Banerjee et al., 2022; Soltani et al., 2019; Gizzini et al., 2021). The CNN-based deep learning approach has proven to be efficient for handling image processing problems as it keeps the number of parameters in weight matrix less in comparison to a fully connected neural network model by making use of parameter sharing and sparsity of connections.

Recently, the channel estimation in OFDM systems has been approached using a deep learning-based framework, where the time-frequency grid of the channel response is represented as a 2D-image that is only available at the pilot positions. (Soltani et al., 2019) presented a deep learning-based framework for channel estimation in OFDM systems, which proposed an image super-resolution (SRCNN) and image denoising (DnCNN) algorithms to estimate the channel. In (Banerjee et al., 2022) a CNN model for Over-the-Air channel estimation has been applied, and the model is proposed by Matlab.

In this paper, we present a novel method for channel estimation that utilizes a very deep convolutional network inspired by VGG-net used for ImageNet classification; the method was proposed by (Kim et al., 2016) and presents a highly accurate single-image super-resolution (SR) technique. The next sections will provide detailed explanations of the three methods.

Method 1: channel estimation using super-resolution (SR-CNN) and denoising techniques

The method treats the channel grid with several pilots as a low-resolution (LR) image and aims to estimate the high-resolution (HR) channel. To achieve this, the framework models the channel response as a super-resolution image problem (Soltani et al., 2019).

The channel grid estimation is performed using two phases. In the first phase, the image super-resolution (SR) CNN-based (Convolutional Neural Network) algorithms (Dong et al., 2015), SRCNN, are implemented to increase the resolution of the low-resolution (LR) input. The schema for the CNN-based (Convolutional Neural Network) algorithms is shown in Figure 5.

In the second phase, an image restoration (IR) method based on CNN (Figure 6) is utilized to eliminate the noise effects and improve the quality of the estimated channel grid (Zhang et al., 2017).

Network architecture for SRCNN and DnCNN

The SRCNN technique involves utilizing an interpolation technique to estimate the high-resolution image (channel) values initially, and then refining the resolution by employing a three-layer convolutional network as shown in Figure 7:

- The first convolutional layer uses 64 filters of size 9×9 followed by ReLu activation,
- The second layer uses 32 filters of size 1×1 followed by ReLu activation.

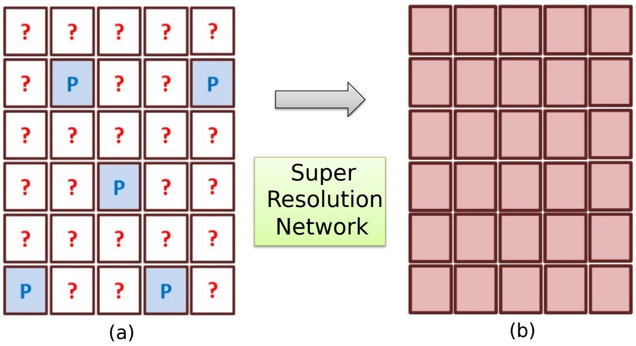


Figure 5 – Super-resolution based CNN, (a) 2D-image which is known only at the pilot positions, (b) estimated channel as a high-resolution
Рис. 5 – CNN на основе сверхразрешения, (a) 2D-изображение, известное только на позициях пилота, (b) оцениваемый канал высокого разрешения
Слика 5 – CNN заснован на супер резолуцији, (a) 2D-слика која је позната само на пилот позицијама, (b) процењени канал високе резолуције

- The final layer uses only one filter of size 5×5 to reconstruct the grid channel.

The DnCNN technique in Figure 8 is a residual-learning based network composed of 20 convolutional layers:

- The first layer uses 64 filters of size $3 \times 3 \times 1$ followed by a ReLU,
- Each of the succeeding 18 convolutional layers uses 64 filters of size $3 \times 3 \times 64$ followed by batch-normalization and ReLU, and
- The last layer uses one $3 \times 3 \times 64$ filter to reconstruct the output.

Method 2: channel estimation using a regression method

The approach used for channel estimation is the same as the first method; the channel estimation problem was considered as an image processing problem by viewing the resource grid as a 2D image. A regression method based on deep learning is used in (Banerjee et al., 2022) to estimate a perfect channel. The input to the deep learning model is the LS channel estimated data and the CNN model can be trained against a perfect channel estimate as a reference, based on the statistical information available. CNN operates by applying convolution operations between images and kernels of different sizes to extract feature information. This process occurs in a multilayered system where the output of the convolution opera-

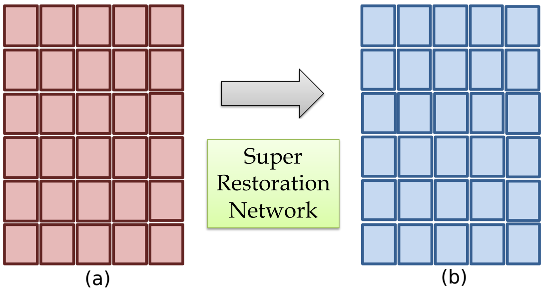


Figure 6 – Denoising based CNN, (a) estimated channel which is considered as a noised image, (b) estimated channel
Рис. 6 – CNN на основе шумоподавления, (a) оценочный канал, который рассматривается как зашумленное изображение, (b) оценочный канал
Слика 6 – CNN заснован на смањењу шума, (a) процењени канал који се сматра сликом са шумом, (b) процењени канал

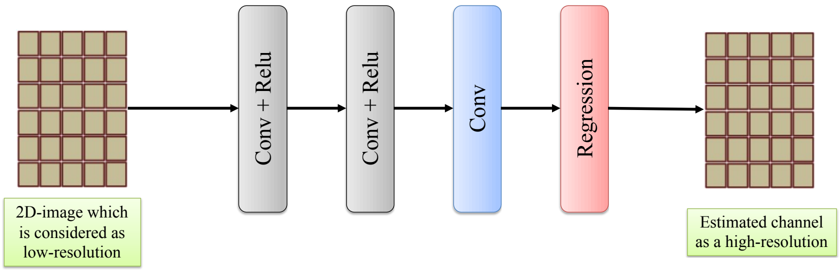


Figure 7 – SRCNN architecture
Рис. 7 – Архитектура SRCNN
Слика 7 – Архитектура SRCNN

tion is passed through an activation function, which is a non-linear function that transforms data. In regression problems, the final output layer is a regression layer that calculates the half-mean-squared-error loss. Finally, an optimization function is used to optimize the multilayered system, and the choice of optimization function is determined by the user.

Network architecture for the regression technique

The CNN model consists of 5 hidden layers as shown in Figure 9, where the first four hidden layers are associated with a ReLU activation function.

The fifth layer is associated only with the regression layer, as in regression problems the CNN output does not require an activation function.

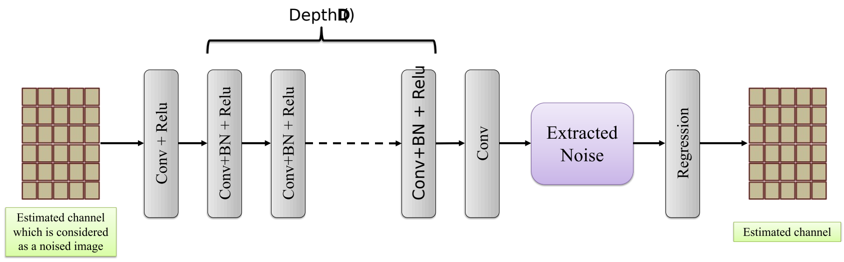


Figure 8 – DnCNN architecture
Рис. 8 – Архитектура DnCNN
Слика 8 – Архитектура DnCNN

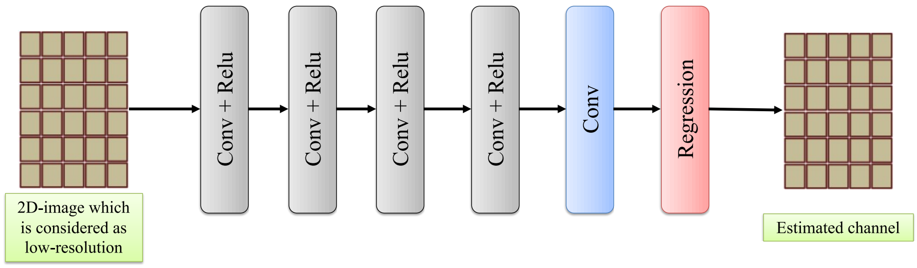


Figure 9 – Regression technique architecture
Рис. 9 – Архитектура метода регрессии
Слика 9 – Архитектура технике регресије

The layers are ordered as follows:
- The first convolutional layer uses 64 filters of size 9×9 followed by ReLu activation,
- Each of the succeeding 2 convolutional layers uses 64 filters of size 5×5 followed by ReLu activation,
- The fourth layer uses 32 filters of size 5×5 followed by ReLu activation, and
- The final layer uses only one filter of size 5×5 followed by the regression layer to reconstruct the grid channel.

Method 3: channel estimation using Very Deep Convolutional Networks

The channel estimation problem in this method was also modelled as an image-processing problem, the main difference being that this technique is using a very deep convolutional network to improve the performance. The SRCNN technique failed to create deeper models for super resolution with superior performance. However, (Kim et al., 2016) presented a method (VDSR: Very Deep Super-Resolution) that utilizes a very deep convolutional network inspired by VGG-net used for ImageNet classification, and it is found that increasing the depth significantly boosts the estimation performances. Given that VDSR shows a highly accurate single-image super-resolution, we want to apply this technique in the channel estimation problem.

Network architecture for VDSR

The VDSR (Kim et al., 2016) technique uses a very deep convolutional network inspired by Simonyan and Zisserman (Simonyan & Zisserman, 2014). The network structure cascades a pair of layers (convolutional and nonlinear) repeatedly. An interpolated low-resolution (CLR) channel goes through the layers and transforms into a high-resolution (HR) channel. The network predicts a residual image and the addition of CLR and the residual gives the desired output.

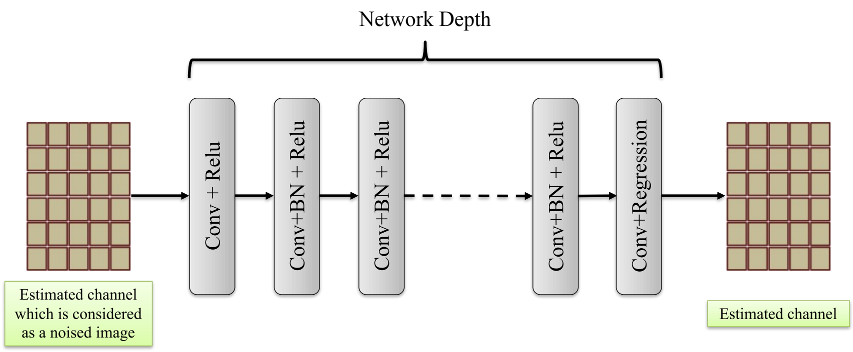


Figure 10 – VDSR architecture
Рис. 10 – Архитектура VDSR
Слика 10 – Архитектура VDSR

The VDSR architecture, depicted in Figure 10, consist of 20 layers where layers except the first and the last, are of the same type:

- The first layer operates on the input grid channel,
- Each of the 18 convolutional layers uses 64 filters of size $3 \times 3 \times 64$ followed by ReLU, and

- The last layer, used for grid channel reconstruction, consists of a single filter of size $3 \times 3 \times 64$ followed by the regression layer.

Results and discussion

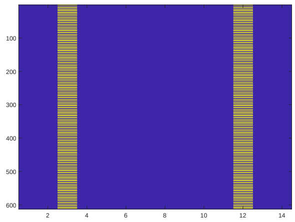
In this section, all the networks introduced in Section 3 were trained. Following that, the Mean Squared Error (MSE) was evaluated across a range of Signal-to-Noise Ratios (SNRs). The setup involves a single antenna as both the transmitter and the receiver. The 5G Toolbox in Matlab was used for the channel modeling and pilot transmission. The training, testing, and validation sets comprised 40000, 5000, and 5000 channels respectively.

For the purpose of creating test scenarios, a slot period of resource grid consisting of 51 resource blocks was selected to form PDSCH data, forming a matrix of resource elements with dimensions 612 by 14. In order to map the pilots, a slot-wise type A mapping solution was adopted with the DM-RS symbol position set to 2. Furthermore, a single DR-MS symbol was introduced, featuring an additional position of 1.It is worth noting that these parameters and decisions were made in accordance with the rigorous guidelines set forth by the 3GPP standard (3GPP. 2020b).

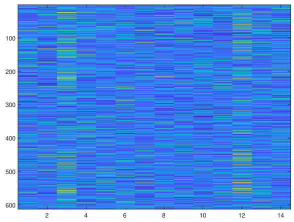
The parameters used for data generation are presented in Table 1. During this process, a sub-carrier spacing of 30 kHz was maintained, and the actual data symbols were set to zero. Instead, only the DM-RS symbols were embedded in the data as displayed in Figure 11. For the data transmission, a repeated transmission approach was employed. This involved looping through the data of a single slot period, which lasts 0.5 ms. By repeating the transmission within this time frame, the integrity and continuity of the data were effectively maintained. Finally, the collected data was partitioned into the training, validation, and test sets in order to train the CNN models.

Training CNN based channel models

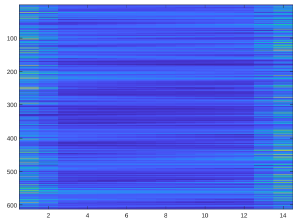
The performance of the neural network-based channel estimation methods relies on the SNR value. Ideally, the weights of the neural network should be optimized for each SNR value to achieve the best performance. However, in practice, this approach is not feasible since the SNR value is continuous, and retraining the network for every possible SNR value is computationally intensive.



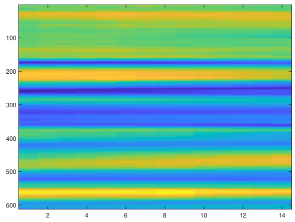
(a) DM-RS in transmitter



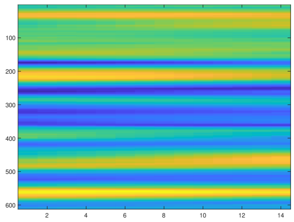
(b) DR-MS in receiver



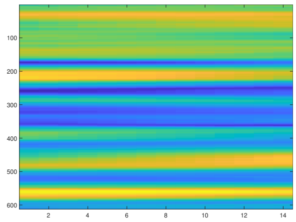
(c) interpolation



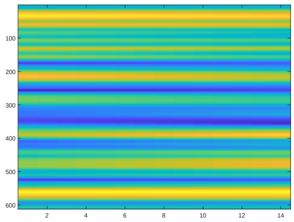
(d) estimated channel with SRCNN + DnCNN



(e) estimated channel with regression CNN



(f) estimated channel with VDSR



(g) perfect channel

Figure 11 – Resource grid images
Рис. 11 – Изображения сети ресурсов
Слика 11 – Слике мреже ресурса

Fortunately, training the neural network for a few representative SNR values can still yield satisfactory performance. In such cases, the neural network can estimate the channel for SNR values that are close to the ones it was trained on, and can interpolate to SNR values that are not covered in the training. Therefore, in our work, we have selected two ranges of representative SNR values for training the neural network, a range of discrete values $[0, 5]$ for low SNR and $[20, 25]$ for high SNR.

It is worth noting that for each of three methods, two models have been trained, one for low SNR and the other for high SNR values Also, the models were trained using the parameters specified in Tables 2,3,4,5, for each range of the Signal-to-Noise Ratio (SNR)

Table 1 – Parameters for PDSCH DM-RS data generation
Таблица 1 – Параметры генерации данных PDSCH DM-RS
Табела 1 – Параметри за генерисање PDSCH DMRS података

Parameters	value
PDSCH Mapping Type	Type A
DR-MS TypeA Position	2
DM-RS Additional Position	1
DM-RS Configuration Type	1
Subcarrier Spacing	30 kHz
Cyclic Prefix	Normal
Bandwidth in number of resource blocks	51
Model Channel	TDL
Power Delay Profile	All profiles

Table 2 – Training parameters for the SRCNN method
Таблица 2 – Параметры обучения по методу SRCNN
Табела 2 – Параметри обуке за SRCNN метод

Training Parameters	Value
Solver for training network	Adam (Adaptive Moment Estimation)
Batch Size	128
Initial Learn Rate	0.001
Max Epochs	5

Training progress for low SNR values

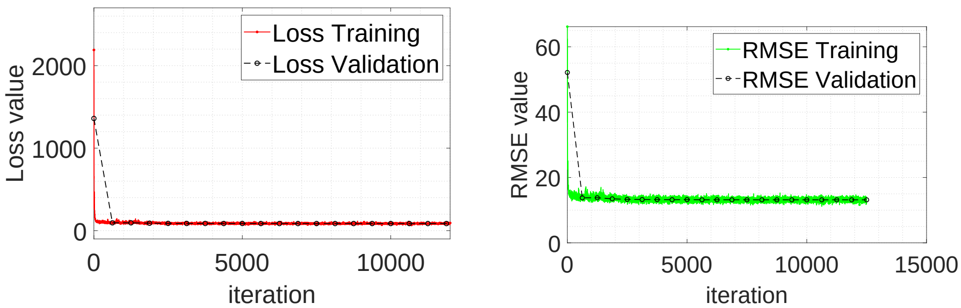
From the Loss graph in figures below (12,13 and 14), we can see that both the training and validation losses decrease steadily over iterations, indicating that the model is learning effectively without over-fitting. The validation loss is consistently similar to the training loss, which suggests that the model is generalizing well to new data.

Table 3 – Training parameters for the DnCNN method
Таблица 3 – Параметры обучения по методу DnCNN
Табела 3 – Параметри обуке за DnCNN метод

Parameters	Value
Solver for training network	Sgdm (Stochastic Gradient Descent with Momentum)
Momentum	0.9
Initial Learn Rate	0.001
Learn Rate Schedule	piecewise
Gradient Threshold Method	absolute-value
Gradient Threshold	0.005
L2Regularization	0.0001
Batch Size	128
Max Epochs	30

Table 4 – Training parameters for the regression CNN method
Таблица 4 – Параметры обучения по регрессионному методу CNN
Табела 4 – Параметри обуке за регресиону CNN методу

Training Parameters	Value
Solver for training network	Adam (Adaptive Moment Estimation)
Batch Size	32
Initial Learn Rate	0.0003
Max Epochs	5



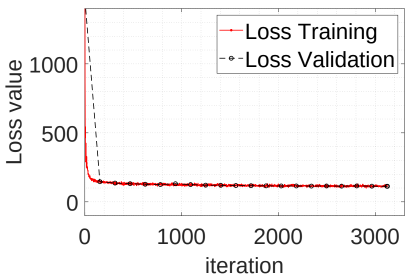
(a) Loss *(b) RMSE*

Figure 12 – Training progress for regression model
Рис. 12 − Прогресс обучения по регрессионной модели
Слика 12 – Напредак у фази обучавања за регресиони модел

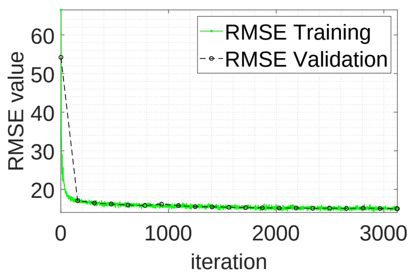
Similarly, from the RMSE graph, we can see that both the training and validation RMSEs displayed a consistent downward trend, indicating good learning and that the models were gradually fitting the training data.

Table 5 – Training parameters for the VDSR method
Таблица 5 – Параметры обучения по методу VDSR
Табела 5 – Параметри обуке за VDSR метод

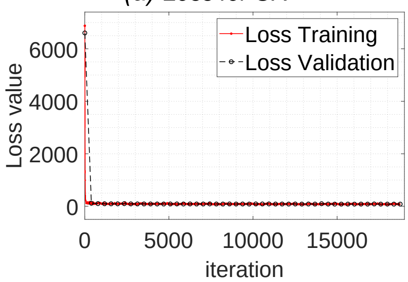
Parameters	value
Solver for training network	Sgdm (Stochastic Gradient Descent with Momentum)
Momentum	0.9
Initial Learn Rate	0.1
Learn Rate Schedule	piecewise
Learn Rate Drop Period	10
Learn Rate Drop Factor	0.1
L2Regularization	0.0001
Batch Size	32
Max Epochs	100
Gradient Threshold Method	l2norm
Gradient Threshold	0.01



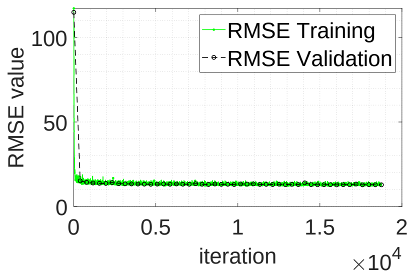
(a) Loss for SR



(b) RMSE for SR



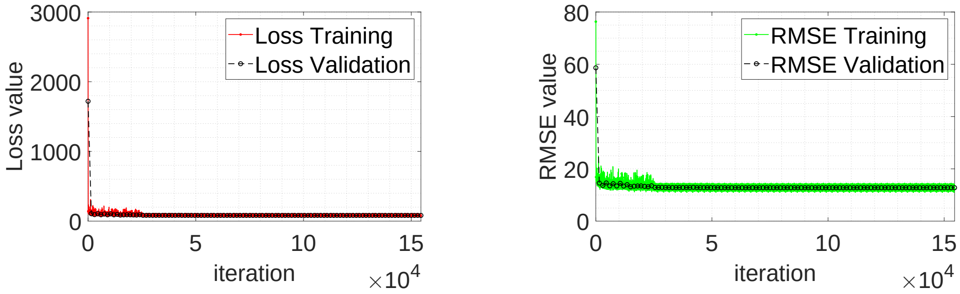
(c) Loss for Dn



(d) RMSE for Dn

Figure 13 – Training progress for the SRDn model
Рис. 13 – Прогресс в обучении по модели SRDn
Слика 13 – Напредак у фази обучавања за SRDn модел

In the initial epochs, the loss and RMSE for Regression, SRDn and VDSR show a rapid drop, suggesting that the models quickly learned from the training samples. However, after that, the rate of improvement slowed down, and the training was stopped after the loss and RMSE curve flattened, indicating that the model had reached the limit of learning from data.



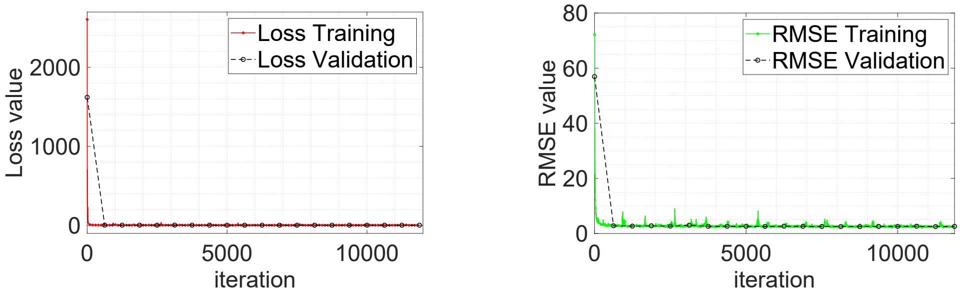
(a) Loss *(b) RMSE*

Figure 14 – Training progress for the VDSR model
Рис. 14 − Прогресс в обучении по VDSR
Слика 14 – Напредак у фази обучавања за VDSR модел

It is worth noting that for VDSR, the RMSE curve experienced some fluctuations, which could be attributed to the complexity of the dataset. However, the Regression and SRDn models could not capture this complexity.

Training progress for high SNR values

The figures below (15,16 and 17) present the Loss and RMSE progress

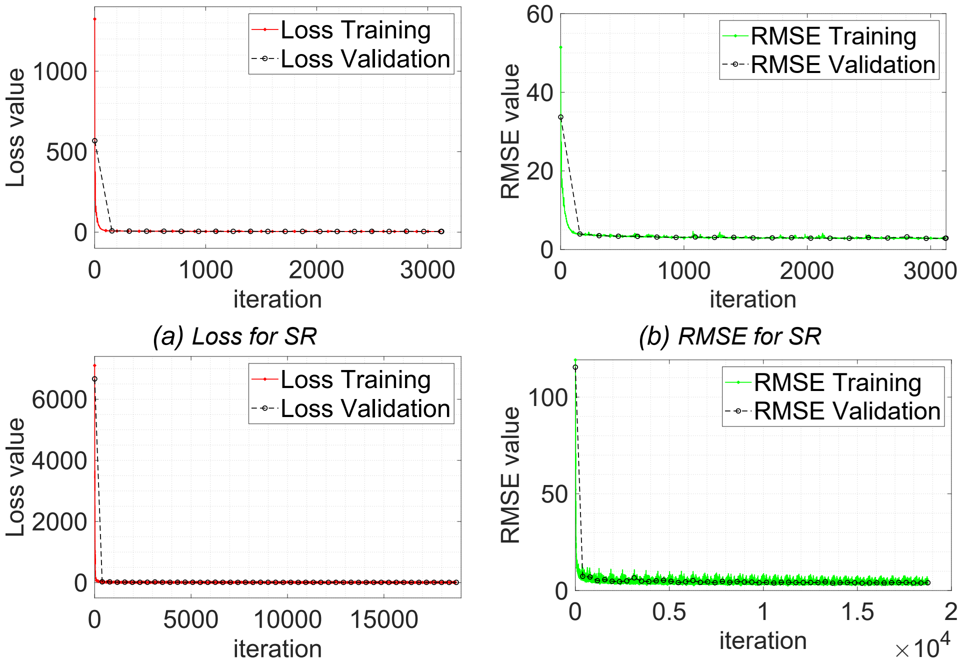


(a) Loss *(b) RMSE*

Figure 15 – Training progress for the regression model
Рис. 15 − Прогресс в обучении по регрессионной модели
Слика 15 – Напредак у фази обучавања за регресиони модел

Comparing the Loss and RMSE graphs in the preceding figures (15,16 and 17), it is clear that the trends follow a similar pattern. The models show promising results, with no evidence of over-fitting or under-fitting.

As in the case of the low SNR, the training process presents a downward trend of the loss and RMSE functions, showing that the models were gradually fitting the training data in the same way as in the low SNR.

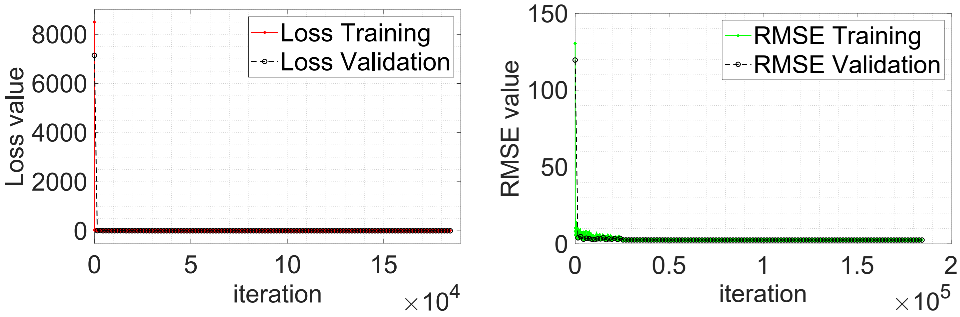


(a) Loss for SR *(b) RMSE for SR*

(c) Loss for Dn *(d) RMSE for Dn*

Figure 16 – Training progress for the SRDn model
Рис. 16 – Прогресс в обучении по модели SRDn
Слика 16 – Напредак у фази обучавања за SRDn модел

The RMSE curve presents some fluctuations in the cases of Regression, SRDn and VDSR model training, which indicates the ability of models to capture the complexity of the channel in the high SNR.



(a) Loss *(b) RMSE*

Figure 17 – Training progress for the VDSR model
Рис. 17 − Прогресс в обучении по модели VDSR
Слика 17 – Напредак у фази обучавања за VDSR модел

In summary, it could be seen in both low and high SNR values that the VDSR presented fluctuation in RMSE during the training, which indicates a high adaptability to the complexity of the channel.

Performance evaluation of CNN models using test data

The three methods (SRCNN + DnCNN, Regression CNN and VDSR) are evaluated on 5000 random channels in both low and high SNR conditions. Based on the provided RMSE (Root Mean Squared Error) values, their performance can be compared with the traditional method of LS (Least Squares). The results are presented in Table 6.

Table 6 – Performance evaluation of the CNN models
Таблица 6 – Оценка производительности моделей CNN
Табела 6 – Процена перформанси CNN модела

Model	RMSE (Low SNR)	RMSE (Hight SNR)
Least Square	2.0850	0.2425
Method1: SRCNN + DnCNN	0.4776	0.1299
Method2: Regression CNN	0.4942	0.1006
Method3: VDSR	0.4797	0.0968

For the low SNR, the SRCNN + DnCNN method and the VDSR method have similar performances, with the RMSE values of 0.4776 and 0.4797, respectively. The Regression CNN method has a slightly higher RMSE. However, all three methods significantly outperform the Least Square method.

For the high SNR, the VDSR method has the best performance followed by the Regression CNN method and the SRCNN + DnCNN method. Again, all three methods significantly outperform the Least Square method.

In summary, the deep learning-based methods (SRCNN + DnCNN, Regression CNN, and VDSR) are more effective than the traditional Least Square method for channel estimation in both low and high SNR conditions. Among the deep learning-based methods, VDSR appears to be the most effective for high SNR conditions, while SRCNN + DnCNN and VDSR have similar performance for low SNR conditions. The Regression CNN method has slightly lower performance than the other two deep learning-based methods, but is still significantly better than the Least Square method. These results demonstrate the effectiveness of deep learning-based methods for channel estimation in wireless communication systems.

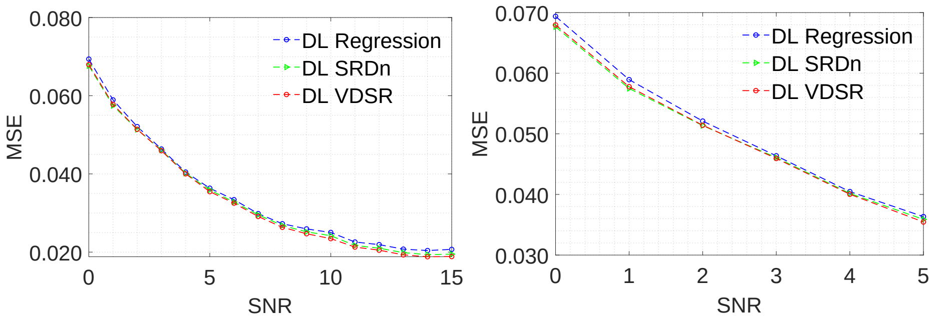
Channel Estimation MSE in terms of SNR for different channel profiles

The accuracy of channel estimation can be evaluated using the mean square error (MSE) metric. The MSE is a measure of the average difference between the estimated channel and the actual channel, and it is commonly used to compare different channel estimation methods. The MSE of channel estimation is affected by several factors, including the channel profile and the signal-to-noise ratio (SNR)

To illustrate the impact of channel profile and SNR on channel estimation for each of the three methods mentioned before, we have calculated the MSE for each of the scenarios, Non-Line-of-Sight NLOS (TDL-A, TDL-B and TDL-C) and Line-of-Sight LOS (TDL-D and TDL-E), in both low and high SNR conditions.

Channel Estimation MSE for NLOS communication

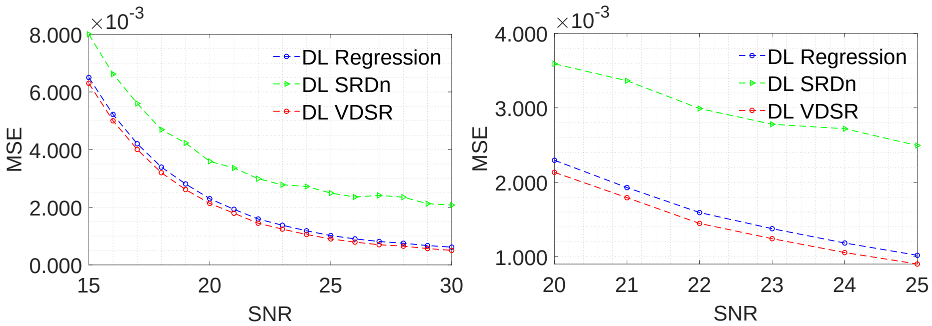
In the context of NLOS communication, where there is no direct line-of-sight between transmitting and receiving antennas, the signal travels along multiple paths to reach the receiver, causing severe signal attenuation, delay spread, and inter-symbol interference. The performance of the three aforementioned channel estimation methods is impacted by the SNR values.



(a) SNR from 0 to 15 *(b) SNR from 0 to 5*

Figure 18 – Channel Estimation MSE in terms of a low SNR for NLOS
Рис. 18 – Оценка канала MSE с точки зрения низкого SNR для NLOS
Слика 18 – Процена канала MSE у код ниског SNR за NLOS

In very low SNR conditions (Figure 18), with a high number of multipaths, the SRCNN + DnCNN and VDSR methods outperform the CNN regression method, with VDSR exhibiting slightly better performance. The superior performance of these deep architectures can be attributed to their ability to better capture the complexity of the channel model.



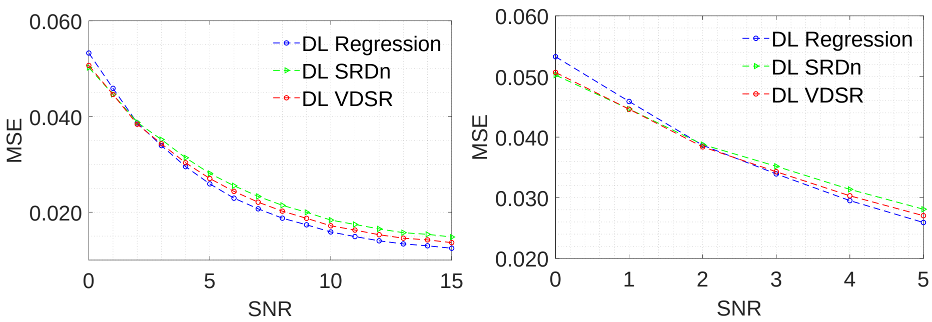
(a) SNR from 15 to 30 *(b) SNR from 20 to 25*

Figure 19 – Channel Estimation MSE in terms of a high SNR for NLOS
Рис. 19 – Оценка канала MSE с точки зрения высокого SNR для NLOS
Слика 19 – Процена канала MSE у код високог односа SNR за NLOS

However, as SNR values increase (Figure 19), the performance of the SRCNN + DnCNN method decreases drastically in comparison to the remaining methods. In contrast, the VDSR method continues to outperform all other methods.

Channel Estimation MSE for LOS communication

Line-of-Sight (LOS) scenarios are often preferred due to a clear, unobstructed path between transmitting and receiving antennas. In such scenarios, the signal travels directly between the antennas without being scattered or reflected by obstacles, resulting in minimal attenuation and distortion. As a result, channel estimation in the LOS scenarios is less challenging than in the NLOS scenarios.



(a) SNR from 0 to 15 *(b) SNR from 0 to 5*

Figure 20 – Channel Estimation MSE in terms of a low SNR for LOS
Рис. 20 − Оценка канала MSE с точки зрения низкого SNR для LOS
Слика 20 – Процена канала MSE у смислу ниског SNR за LOS

However, even in the LOS scenarios (Figure 20), the accuracy of channel estimation is still impacted by SNR values. In a very low SNR values (SNR < 2), the deep CNN architectures (SRCNN + DnCNN and VDSR) outperform the simplistic architecture of CNN regression, due to their ability to capture the complexity of the channel model. The SRCNN + DnCNN and VDSR methods are better suited for achieving accurate channel estimation in such scenarios.

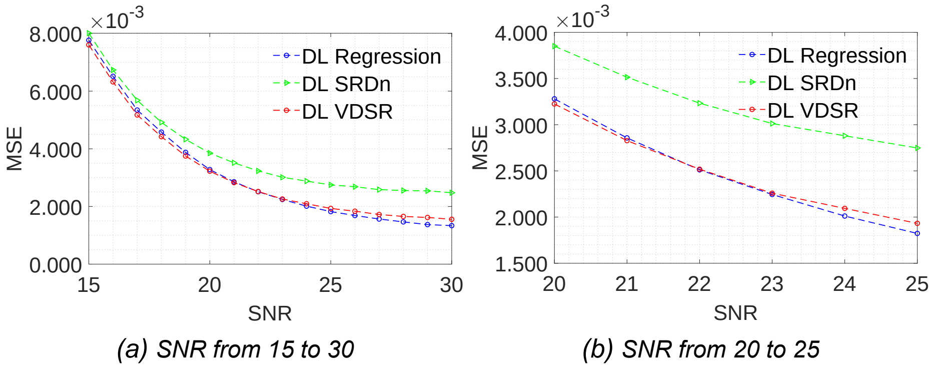


Figure 21 – Channel Estimation MSE in terms of a high SNR for LOS
Рис. 21 – Оценка канала MSE с точки зрения высокого SNR для LOS
Слика 21 – Процена канала MSE код високог односа SNR за NLOS

As SNR values increase (Figure 21), the performance of the CNN regression method becomes more favorable, due to its simplistic architecture being well adapted to the low complexity of the channel. On the other hand, the performance of SRCNN + DnCNN decreases significantly due to the negative impact of its deep denoising architecture (DnCNN). The VDSR architecture, however, demonstrates remarkable adaptability to the channel complexity, resulting in stable performance across a range of SNR values.

Conclusion

By leveraging the power of deep learning algorithms such as CNNs, channel estimation in 5G communication systems can be improved significantly. This work has showcased the potential that CNN offers compared to the traditional method of the Least square for an accurate channel estimation.

First, by conducting a comprehensive review of the existing literature on CNN-based channel estimation, two of widely used methods were chosen, namely the super-resolution and denoising method (SRCNN+DnCNN) and the CNN regression method. Besides that, a novel method (VDSR, Very Deep Super Resolution) was proposed in order to improve the accuracy of the state-of-the-art CNN based channel estimation methods. The three CNN models were trained on a large dataset in both low and high SNR conditions.

The trained models were evaluated and the results were compared to the traditional method of Least Square. The compared results have demonstrated the superiority of deep learning-based methods under varying SNR conditions. Moreover, the novel method exhibits the best overall performance in comparison to the two other deep learning-based methods.

Further, the impact of channel complexity on estimation accuracy was investigated in the case of the CNN based methods. The results highlighted the importance of selecting an appropriate channel estimation model based on the specific communication scenario's complexity and SNR values.

In NLOS scenarios with very low SNR values and a high number of multipaths, deep architectures such as SRCNN + DnCNN and VDSR outperform the CNN regression method due to their ability to capture the complexity of the channel model.

In contrast, in LOS scenarios, signal attenuation and distortion are minimal, making channel estimation less challenging. Nonetheless, the accuracy of channel estimation is still heavily impacted by SNR values, and deep CNN architectures such as SRCNN + DnCNN and VDSR remain better suited for achieving accurate channel estimation in very low SNR values.

As the SNR values increase, the CNN regression method exhibits improved performance due to its simplistic architecture that is well-suited to the low complexity of the channel. Conversely, the performance of SRCNN + DnCNN deteriorates significantly due to the adverse impact of its deep denoising architecture (DnCNN).

Notably, the VDSR architecture demonstrates remarkable adaptability to the channel complexity, resulting in consistent performance across all range of SNR values. This makes it a promising method for channel estimation in diverse 5G communication scenarios (NLOS and LOS).

In future work, we propose to extend the evaluation of the proposed method, VDSR (Very Deep Super Resolution), to Single-Input Multiple-Output (SIMO) and Multiple-Input Multiple-Output (MIMO) channel models for 5G wireless communication. The performance of VDSR has shown promising results in our current research, particularly in terms of its adaptability to varying channel complexities and SNR values. The extended evaluation will provide valuable insights into the performance and robustness of VDSR across different wireless communication setups, further enhancing its applicability and potential for real-world 5G deployments. Additionally, investigating the impact of various system parameters, such as the number of Additional DM-RS and DM-RS configuration types, on the performance of VDSR in SIMO and MIMO models will enable to optimize and tailor the method for specific wireless communication scenarios, paving the way for improved channel estimation techniques in future 5G networks.

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Оценка канала глубокого обучения в 5G беспроводной связи

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РУБРИКА ГРНТИ: 49.33.29 Сети связи,
20.23.25 Информационные системы с базами знаний
ВИД СТАТЬИ: оригинальная научная статья

Резюме:

Введение/цель: За последние годы методы глубокого обуче- ния, в частности сверточные нейронные сети (CNN), показали высокую производительность в системах связи 5G, значительно повысив точность оценки канала по сравнению с обычными методами. Целью данной статьи является всесторонний обзор существующей литературы по методам оценки канала на основе CNN. Помимио того, статья нацелена на усовершенствование современных методов оценки канала на основе CNN путем предложения нового метода под названием VDSR (Very Deep Super Resolution), вдохновленного методами изображения Super-Resolution.

Методы: Для того чтобы оценить эффективность различных подходов было проведено всестороннее сравнение с учетом различных сценариев, в том числе с низким соотношением сигнал-шум (SNR) и высоким SNR, а также в условиях прямой видимости (LOS) и вне прямой видимости. Учитывались также сценарии вне пределов видимости (NLOS). С помощью сравнительного анализа была произведена оценка эффективности существующих методов и выявлены преимущества предлагаемого метода, основанного на VDSR.

Результаты: Результаты данного исследования показывают значительный потенциал оценки канала, основанного на CNN в системах связи 5G, при этом метод VDSR демонстрирует стабильную производительность во всех сценариях. Данное исследование способствует совершенствованию методов оценки каналов в сетях 5G, прокладывая путь усовершенствованным системам беспроводной связи с повышенной надежностью.

Выводы: ААрхитектура VDSR прекрасно приспособлена к сложности канала, что обеспечивает стабильную производительность во всем диапазоне значений SNR.

Ключевые слова: глубокое обучение, CNN, системы связи 5G, сверхглубокое сверхвысокое разрешение.

Процена канала дубоког учења за 5G бежичне комуникације

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КАТЕГОРИЈА (ТИП) ЧЛАНКА: оригинални научни рад

Сажетак:

Увод/циљ: Технике дубоког учења, посебно конволуционе неуронске мреже (CNN), последњих година показале су изузетне перформансе у 5G комуникационим системима тако што су значајно побољшале тачност процене канала у поређењу са конвенционалним методама. У овом раду представљен је свеобухватан преглед постојеће литературе о тех- никама процене канала заснованих на CNN-у. Поред тога, основни циљ рада јесте унапређивање најсавременијих метода за процену канала заснованих на CNN-у, што је резултирало предлагањем нове методе под називом VDSR (Very Deep Super Resolution), инспирисане техникама Super Resolution слике.

Методе: Да би се извршила процена ефикасности различитих приступа, спроведено је свеобухватно поређење различитих сценарија, укључујући низак однос сигнал-шум (SNR) и висок SNR, као и линију оптичке видљивости (LOS) и сценарио без видљивости (NLOS). Кроз ову компаративну анализу процењене су перформансе постојећих метода и истакнуте предности које нуди предложена техника заснована на VDSR.

Резултати: На основу добијених резултата откривен је значајан потенцијал процене канала заснованог на CNN-у у 5G комуникационим системима, при чему VDSR метод показује константну предност у свим сценаријима. Основни циљ истраживања јесте унапређење техника процене канала у 5G мрежама, чиме се дају основе побољшаним бежичним комуникационим системима са већом поузданошћу.

Закључак: VDSR архитектура показује изузетну прилагодљивост различитим врстама канала, што резултира обезбеђењем захтеваних перформанси за све анализиране вредности SNR.

Кључне речи: дубоко учење, CNN, 5G комуникациони системи, веома дубока супер резолуција.

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