# Machine Learning-Based Non-Orthogonal Frequency Division Multiplexing for Data Overlay Transmission and Reception

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**Abstract.** The rapid evolution of mobile communication technologies like 5G and the anticipated emergence of 6G have necessitated enhanced resource utilization and reception efficiency in wireless communication systems. One of the challenges faced in existing systems is the resource competition arising from the overlapped transmission of pilot frequency and data. This paper addresses this issue by proposing a deep learning-based solution that leverages machine learning techniques to decode transmitted data efficiently. Through a combination of non-orthogonal pilot-frequency and data-overlapped transmission schemes, the proposed solution effectively mitigates interference problems, leading to improved resource utilization and reception performance. Experimental and simulation analyses validate the efficacy and feasibility of the proposed approach, showcasing a decoding accuracy of up to 93% under specific conditions.

**Keywords:** wireless communication; resource utilization; non-orthogonal guide frequency; data overlay transmission; deep learning.

## 1. Introduction

As 5G continues to advance, wireless communication technology is becoming increasingly pivotal in future communication applications. Offering higher speed, lower latency, and greater connection density, 5G creates a vast development landscape for emerging scenarios. The rapid progression of 6G further amplifies communication demands, leading to an expansion in network services and equipment. For instance, the Internet of Things (IoT) is experiencing rapid growth, resulting in a multitude of connected devices using various protocols. This surge underscores the urgent need for efficient spectrum resource utilization, especially in managing spectrum radio resources to support ultra-high densities.

In a wireless communication system, the fundamental workflow involves several stages. At the transmitting end, the source bit stream is encoded and modulated to generate modulated symbols. These symbols are then combined with frequency guide symbols for channel estimation and transmitted through the channel to the receiving end. Here, the receiver leverages the guide frequency for channel estimation, followed by symbol detection, demodulation, decoding, and bit stream recovery. The receivers estimation and recovery of the wireless channel significantly impact data recovery performance due to the complexity and dynamic nature of the wireless channel environment. To facilitate channel estimation, the transmitter assigns specific guide frequency symbols, such as DMRS signals and PT-RS signals, at different resource locations. The receiver then estimates channel information based on received guide frequency signals, contributing to subsequent data recovery processes.

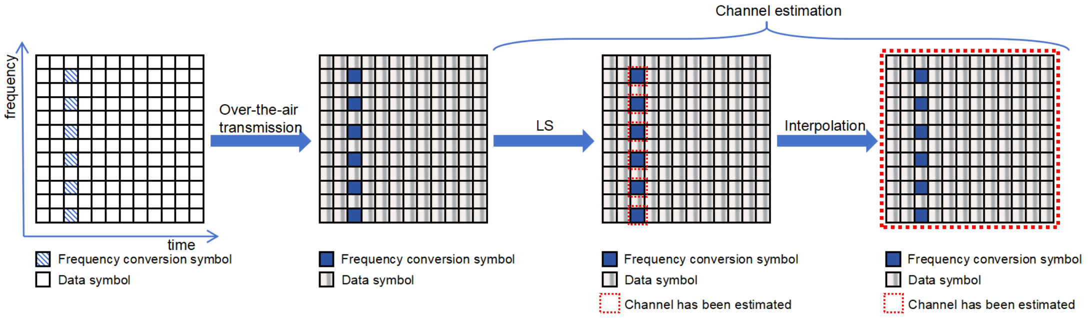


Fig. 1 Quadrature guides in existing communications $Y = H[X_D;X_P] + N$.

In 5G NR, data symbols and frequency-conducting symbols are assigned to distinct resource locations, ensuring their independence and orthogonality in both time and frequency domains. However, this allocation strategy creates a competitive dynamic between frequency-conducting symbols and data symbols within a fixed transmission resource. Increasing the resource allocation for frequency-conducting symbols diminishes the resources available for data transmission, resulting in less efficient utilization of data transmission resources. To address this challenge, we propose leveraging the robust information processing capabilities of artificial intelligence to design a receiver using non-orthogonal guided-frequency transmission. Our approach effectively mitigates the guided-frequency resource overhead problem, as demonstrated through simulations in a broadband, high-speed, and lightweight scenario, where our scheme significantly improves resource utilization and data recovery accuracy.

The subsequent sections of this paper are structured as follows: Section II provides a review of related literature on guided channel estimation and artificial intelligence. Section III outlines our approach to managing the guided frequency and data transmission relationship in wireless communication systems, including the design of the AI/ML-based receiver. Section IV presents the experimental setup and analyzes the experimental results. Finally, Section V presents our conclusions based on the findings.

## 2. Related works

Wireless communication technology has evolved significantly, transitioning from 2G to the current 5G era, driving substantial changes and conveniences in human society. The integration of Artificial Intelligence (AI) into wireless communications has enhanced spectrum utilization, signal processing, and network management, improving communication services. Notably, AI has seen success in image recognition and natural language processing, contributing to the development of advanced network structures like AMFISTANet and dl-based CSI feedback NN as discussed in literature [1] and [2]. Additionally, literature [3] explores AIs potential in optimizing 5G systems, covering network optimization, resource allocation, and other key areas

Modern wireless communication systems face challenges due to the complex channel environment, impacting communication quality stability. Channel estimation plays a critical role in ensuring reliable signal transmission between transmitters and receivers. Guided-frequency-assisted techniques, using known guide frequency sequences, are commonly employed for accurate channel estimation and system performance improvement. Literature [4] introduces a scheme with combined guide frequencies for a collaborative relay network, addressing interference issues and estimating channel characteristics effectively. In [5], an adaptive guide frequency optimization algorithm reduces overhead in massive MIMO systems through compressed sensing theory. Additionally, [6] explores efficient frequency-guided transmission schemes across various systems to enhance performance and spectral efficiency. [7] proposes a channel estimation method based on WDSR networks, showing improved performance and reduced guide frequency overhead, albeit requiring further optimization for computational efficiency and time-varying characteristics consideration.

## 3. Scheme design

This section delves into non-orthogonal guided frequency and data overlay transmission schemes, leveraging artificial intelligence and machine learning for efficient signal reception.

### 3.1 Non-orthogonal frequency conduction and data overlay transmission scheme

As shown in Fig. 2, the input of the superimposed frequency-conducting processing model is the received symbol Y after modulation, frequency-conducting non-orthogonal superposition, and over-channeling of the original information bit X. The output of the superimposed frequency-conducting processing model (AI receiver) is the recovered information X of the original information bit X. The AI receiver can be used as an overlay on the original information bit X. The AI receiver can be used as an overlay on the original information bit X.

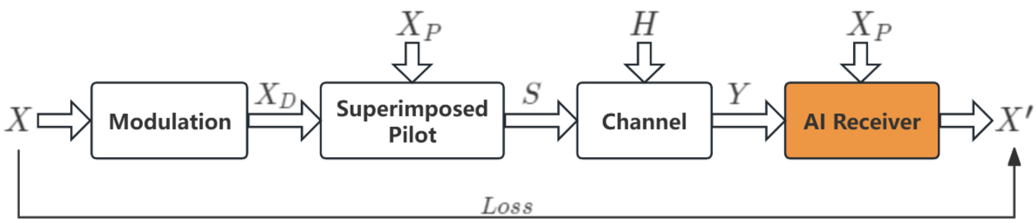


Fig. 2 Transmission process of non-orthogonal guide frequency with data superposition

Assume a downlink transmission with $N_t$ transmitter antenna, $N_r$ receiver antenna, and L layer under a transmission resource configuration of S subcarriers in the frequency domain and T symbols in the time domain. where the transmitter performs orthogonal amplitude modulation of order $2^M$ on the information bitstream tensor X $\in \{0,1\}^{L\times T\times S\times M}$ to obtain the data symbol tensor $X_D \in C^{L\times T\times S}$ (C denotes the set of complex numbers) Further, the transmitter performs non-orthogonal superposition of the guiding frequency with the data to obtain the superimposed symbols, i.e.

$$S = \mathrm{sqrt}(W) \odot X_D + \mathrm{sqrt}(V) \odot X_P \tag{1}$$

where $X_P \in C^{L\times T\times S}$ denotes the guided-frequency symbol tensor, $S \in C^{L\times T\times S}$ is the superimposed symbol tensor, $W \in R^{L\times T\times S}$ and $V \in R^{L\times T\times S}$ (R denotes the set of real numbers) denote the data and the guided-frequency weight tensor, respectively, sqrt(-) denotes the square-root computation, and $\odot$ denotes the hadronic product.

The superimposed symbols are transmitted through the channel and sent to the receiver to obtain the received signal, i.e.

$$Y_r = \sum_{l=1}^{L} H_{r,l} \odot S_l + N_r \tag{2}$$

where $Y_r \in C^{T\times S}$ denotes the received signal of the rth receive antenna, $1 \leqslant r \leqslant N_r$ and $1 \leqslant l \leqslant L$ denote the receive antenna and transport layer indexes, respectively, $H_{r,l} \in C^{T\times S}$ denotes the equivalent channel of the lth transport layer of the rth receive antenna, and $N_r \in C^{T\times S}$ denotes the additive Gaussian white noise. Finally, the received signal Yr obtained from the $N_r$th receive antenna is spliced to obtain the final received signal $Y \in C^{Nr\times T\times S}$.

Under the above non-orthogonal frequency conduction and data superposition transmission scheme, the receiver f(-) scheme is designed to realize the high accuracy reception of the information bit stream tensor, i.e.

$$X' = p(f(Y, X_P)) \in \{0,1\}^{L\times T\times S\times M} \tag{3}$$

where p(-) denotes the hard judgment process (p(b) = 0 when b < 0 and p(b) = 1 when b $\geqslant$ 0).

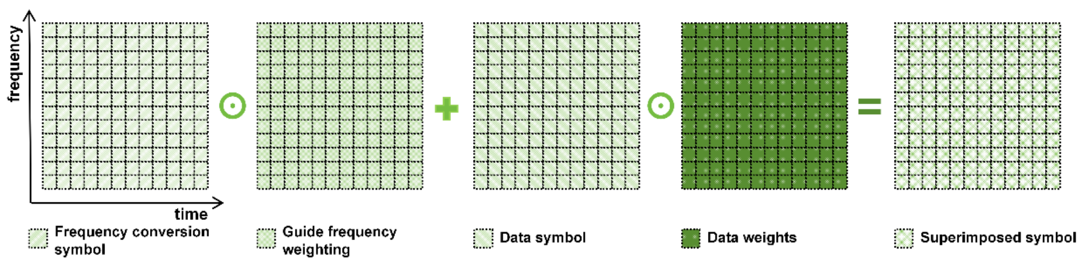


Fig. 3 Non-orthogonal frequency guides with data superposition Y = H[XD+XP] + N

### 3.2 AI-based reception scheme

The non-orthogonal guide-frequency and data overlay transmission scheme enhances channel estimation performance and maximizes resource utilization during data transmission. However, it faces a critical challenge: interference between the guide frequency and data due to their superposition. To address this issue, we propose leveraging an AI-based receiver for receiving superimposed symbols, significantly improving spectral efficiency and ensuring successful reception.

Our design includes a convolutional neural network (CNN)-based receiver model tailored for wireless communication, specifically for decoding multiple data streams in multicarrier modulation systems. The CNN in this model handles signal processing tasks such as demodulation and channel estimation, extracting crucial features from the signal to improve system performance. The model incorporates multiple residual blocks to capture key features effectively and mitigate the gradient vanishing problem through shortcut connections, enhancing its learning capabilities.

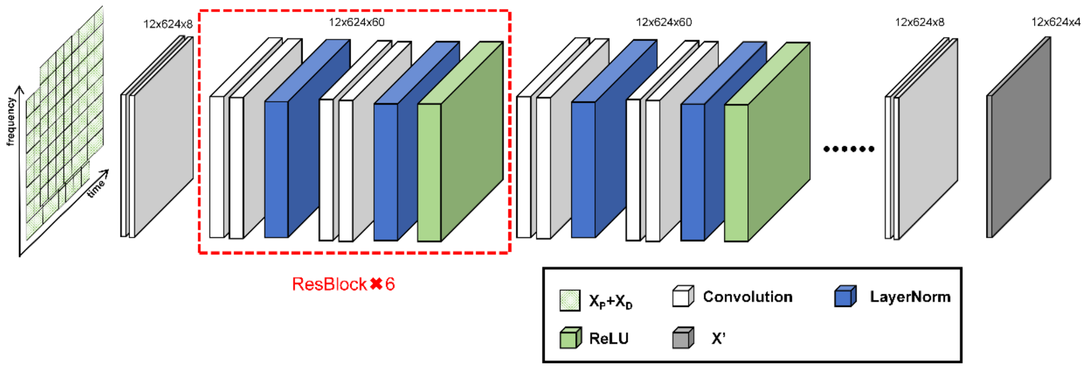


Fig. 4 Flowchart of the framework of the residual block.

The model comprises two key components: the ResBlock and the overall receiver structure. The ResBlock class serves as a residual learning module featuring two convolutional layers and a LayerNorm layer. It performs two convolution operations on the input data, preserving original features and boosting learning capacity by adding the convolved output with the input through the ADDITION operation. The convolutional layer extracts features, while the LayerNorm layer normalizes input data, aiding in faster model training convergence.

The Neural_receiver class constructs a comprehensive receiver network architecture, taking the OFDM modulated signal y and the known frequency guide signal template_pilot as inputs. The model preprocesses data to fit the convolutional layers input requirements and combines the received signal with the guide frequency signal in the channel dimension.

In the network structure, an input convolutional layer initially extracts features from the combined signal. The signal then undergoes processing through a sequence of ResBlock modules to enhance important features layer by layer. The processed features are then mapped to bit estimates on each subcarrier via an output convolutional layer. Multiple dimensional transformations ensure correct convolution operations and reshape results. The final output is a reconstructed signal matrix z representing bit estimates for data streams on each subcarrier across symbol time periods and layers. This model effectively handles wireless communication signal recovery tasks in multi-layer multi-stream transmission settings, showcasing the potential of deep learning in such systems.

## 4. Experiments and results

In this section, we will show experimental results analyzing our proposed AI/ML-based receiver model. First, we will present the dataset and parameter settings we used. Then, the performance comparison at different parameters is given through simulation.

### 4.1 Experimental setup

1. dataset:

In this experiment, we generate a dataset based on a wireless communication scenario. Specifically, we simulate a broadband, high-speed, and lightweight communication scenario with the following parameter settings:

Table 1. Setting of specific parameters

| Parameter type | parameter symbol | Parameter setting |
|---|---|---|
| Number of frequency domain subcarriers | S | 624 |
| Number of time domain symbols | T | 12 |
| Number of transmitting antennas | Nt | 2 |
| Number of receiving antennas | Nr | 2 |
| Number of transmission layers | L | 2 |
| Number of bits per symbol | M | 4 |
| User travel speed range | - | 3 ~120 km/h |

Table 2. Settings of training data

| Data Type | Number of Samples | Number of Antennas | Number of Symbols | Number of Subcarriers | Number of Bits per Symbol | Real/Imaginary Parts |
|---|---|---|---|---|---|---|
| Received signal tensor | 20000 | 2 | 12 | 624 | - | Yes |
| Transmit Bitstream | 20000 | 2 | 12 | 624 | 4 | No |
| Conductivity tensor | - | - | 12 | 624 | - | Yes |

The following is a further explanation of the superimposed configuration of guide frequency and data for the above scenario in graphical form, using 12 subcarriers * 12 symbols as an example.

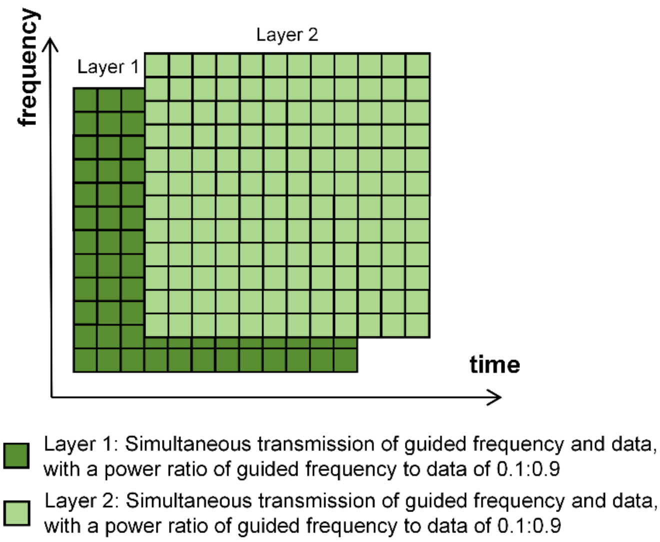


Fig. 5 Overlay configuration of guide frequency and data.

2. Parameter settings

In this experiment, we performed multiple sets of settings for the training parameters of the neural receiver model in order to systematically evaluate the effects of different parameters on the models performance and to select the best combination. We first adjusted the total training period to (2000, 5000, 8000) to determine the performance of the model under different training durations. Next, we set the learning rate for the optimizer, choosing 1e-3 to balance the speed of model parameter updates with the stability of convergence. Next, we adjusted the number of residual blocks in the neural receiver model to 6 to explore the effect of model complexity on performance. Then, we tried different channel list settings including (48, 48, 48), (60, 60, 60), and (128, 128, 128) options to investigate the effect of the number of channels on the model performance. Finally, we also adjusted the number of samples per batch to 16 to determine the effect of batch size on model training effectiveness. These parameters were set to comprehensively evaluate the model performance and to find the best combination of parameters for accurate modeling of communication scenarios and efficient processing of received signals.

### 4.2 Simulation Analysis

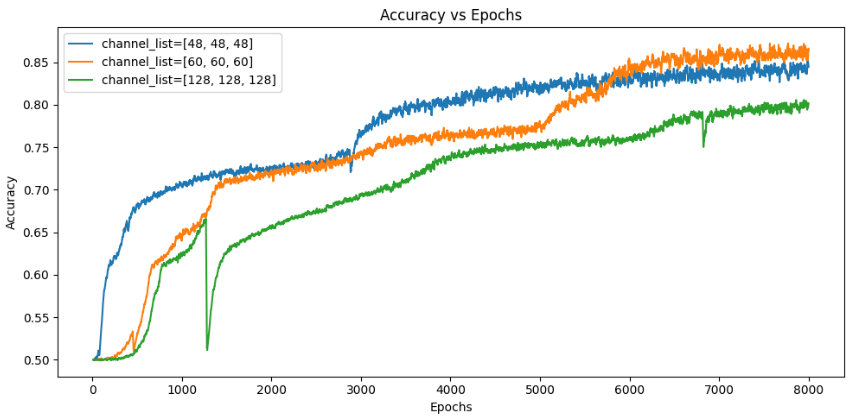


Fig. 6 Receiver data recovery accuracy with different channels

This section delves into a deep learning-based receiver efficiency scheme and simulates data recovery performance across various parameters. Three different channel configurations, namely [48, 48, 48], [60, 60, 60], and [128, 128, 128], were tested due to their significant impact on model performance. As depicted in Fig. 6, initial training stages show relatively low accuracy across all models, which gradually improves with increased training rounds. The model with 128 channels exhibits slower convergence but maintains stable and minimal fluctuations, highlighting its training stability. Conversely, models with 48 and 60 channels demonstrate faster convergence but with slightly less stability and more fluctuations. Taking into account training time and reception efficiency, the model with 60 channels is deemed optimal, showcasing shorter training time alongside commendable accuracy.

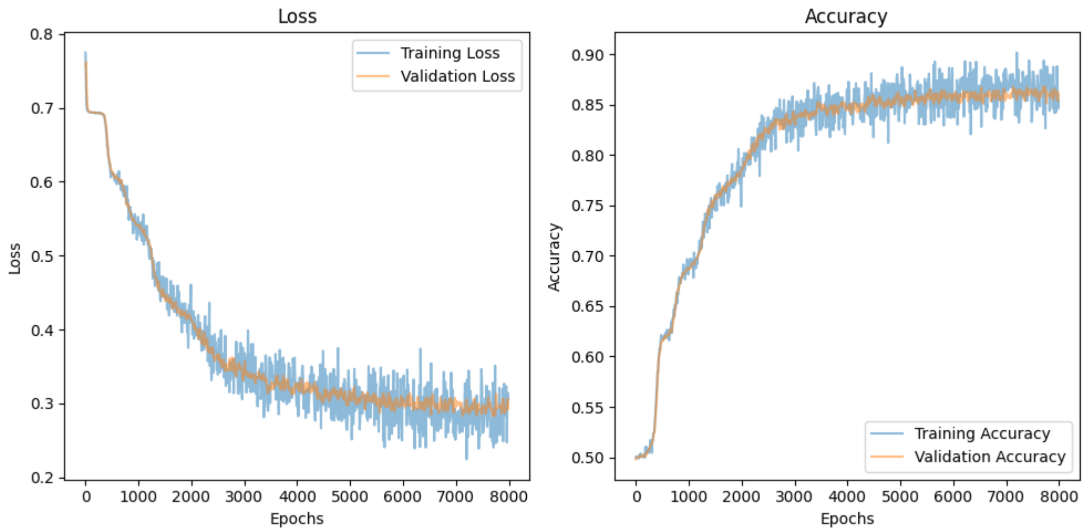


Fig. 7 Variation of data accuracy and loss during the training process

Fig. 7 illustrates the evolution of the data loss rate and accuracy rate throughout the training process. To enhance clarity, a moving average was applied to smooth the curves depicting verification accuracy and loss rate. Initially, theres a rapid decrease in loss rate and a corresponding increase in accuracy rate, indicating the models improved fit to training data and enhanced performance over time. Around the 2500-round mark, a noticeable inflection point occurs where the rate of change for both metrics slows down, likely due to increased training data necessitating more time and resources for learning and adaptation. Ultimately, the loss rate stabilizes around 0.28, while accuracy converges around 0.85, indicating commendable and stable model performance on the validation set.

Taken together, the data accuracy of the receiver model can reach about 0.85 through the adjustment of different parameters, indicating that our receiver scheme is feasible. In the case that the guide frequency does not occupy independent resources, a good reception effect can be achieved.

## 5. Conclusion

In this paper, we introduce a non-orthogonal frequency guide and data superposition transmission scheme for wireless communication systems, based on a deep learning method, to decode the superposition transmitted data at the receiver side. The effectiveness and feasibility of the scheme is verified through experimental and simulation analysis, and the decoding accuracy of the receiver model can reach up to 93%, which provides a new solution to improve the resource utilization and reception effect of the communication system.

## References

[1] Liu Weibo, Yan Biao, Shen Lin, et al. Massive MIMO channel state information feedback network based on AI communication [J]. Telecommunication Engineering, 2024, 64(1).

[2] Guo J, Li X, Chen M, et al. AI enabled wireless communications with real channel measurements: Channel feedback[J]. Journal of Communications and Information Networks, 2020, 5(3): 310-317.

[3] You Xiaohu, Zhang Chuan, Tan Xiaosi, et al. 5G technology based on AI—Research directions and examples [J]. Science in China: Information Science, 2018, 48(12): 1589-1602.

[4] He Xianwen, Dou Gaoqi, Gao Jun, et al. Channel estimation technology based on combined superposed pilots in OFDM cooperative network [J]. System Engineering and Electronic Technology, 2010, 39(11): 2580-2586.

[5] Cao Haiyan, Ye Zhenyu. Pilot optimization theory analysis and algorithm design in downlink channel estimation of massive MIMO systems based on compressed sensing theory [J]. Acta Physica Sinica, 2022, 5: 7-16.

[6] Zhao Chu. Research and simulation of efficient pilot transmission and detection technology[D]. University of Electronic Science and Technology of China, 2021.

[7] Xie Peng, Qian Rongrong, Ren Wenping. Channel estimation method based on wide-depth super-resolution network [J]. Telecommunication Engineering, 2024, 64(1)