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Next-Level 5G Channel Prediction Using Residual Convolutional Neural Network (ResNet)

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Abstract

Accurate channel estimation is critical for achieving the high reliability and low latency required by 5G New Radio (5G NR) systems. Conventional estimators, including Least Squares (LS) and Practical Channel Estimation (PCE), rely on linear models that fail to capture nonlinear channel characteristics. Linear Minimum Mean Square Error (LMMSE) improves accuracy but requires prior channel statistics and a costly matrix inversion, limiting its real-time applicability. This paper proposes a lightweight ResNet-based channel estimator that treats the complex time-frequency channel matrix as a two-dimensional image. Convolutional layers exploit spatial correlations across subcarriers and Orthogonal Frequency Division Multiplexing (OFDM) symbol dimensions, while residual skip connections stabilize training and enable correction over a coarse LS estimate. The model is trained end-to-end using Demodulation Reference Signal (DMRS) pilot patterns in a fully 3GPP-compliant 5G NR environment based on TDL-A and TDL-C channel models (TR 38.901). Simulations over 0–30 dB SNR show consistent superiority over all benchmarks. At SNR = 10 dB, the proposed method achieves a Mean Squared Error (MSE) of 0.0177 — a 45% gain over PCE, ~90% over LS, and 29% over ChannelNet — with only ≈0.29 million parameters, single-stage training, and an inference time of 2–5 ms per OFDM frame, suitable for real-time 5G deployments.

Keywords: Channel Estimation, Convolutional Neural Network, Deep Learning, Fifth-Generation New Radio, Orthogonal Frequency Division Multiplexing, Residual Connection, Resnet.

1. Introduction

The rapid development and global commercialization of 5G wireless networks have enabled a wide range of demanding applications, including intelligent transportation systems, immersive Virtual Reality (VR), real-time ultra-high-definition video streaming, and smart healthcare systems [1], [2]. These emerging services impose stringent requirements on the underlying communication infrastructure in terms of high data rates, ultra-reliable low-latency communication (URLLC), and massive connectivity. Orthogonal Frequency Division Multiplexing (OFDM) remains the core waveform of the 5G New Radio (NR) standard owing to its robustness against frequency-selective fading, high spectral efficiency, and flexible resource allocation [3], [4]. Nevertheless, realizing the full potential of 5G NR depends critically on accurate Channel State Information (CSI) acquisition at the receiver, particularly under the diverse and rapidly varying propagation conditions that characterize real-world 5G deployments.

In practice, channel estimation is complicated by multipath fading, Doppler shifts, and unpredictable ambient interference [5]. However, 5G NR adds layers of complexity to estimation due to its wide bandwidths and high subcarrier densities, where Demodulation Reference Signals (DMRS) are present in only a small portion of the resource elements, leading to sparse pilot grids for large-scale channel matrices [4]. The challenge of recovering the complete Channel Frequency Response (CFR) from these sparse observations under varying noise conditions is thus a non-trivial problem that requires powerful and efficient estimation techniques.

Traditional channel estimation methods have been extensively studied as baselines. The Least Squares (LS) estimator is very simple and does not assume any prior knowledge of the channel, but it fails to account for the effects of noise at low Signal-to-Noise Ratio (SNR). The Minimum Mean Square Error (MMSE) estimator has been introduced to achieve high accuracy by leveraging channel statistical information, but estimating the channel covariance matrix and performing matrix inversion operations are complex and not practicable in large-scale, real-time 5G systems [6]. Practical Channel Estimation (PCE) methods use LS pilot estimates and interpolate over the resource grid; they strike a good balance between accuracy and complexity, but they are linear and sensitive to noise in dynamic channels.

The traditional channel estimation techniques have been hindered by these problems, and this has encouraged the development of deep learning-based channel estimation techniques. Soltani et al. [7] were the first to model the channel estimation problem as a 2D image-restoration problem by applying a CNN to estimate the entire CFR from a few pilot observations and showed that convolutional filters can capture both frequency and temporal channel correlations with good accuracy. ChannelNet introduced a two-stage pipeline of a super-resolution network (SRCNN) and a denoising network (DnCNN) that further improves the estimation accuracy close to LMMSE [8] using this concept. But ChannelNet needs to train each of its two sub-networks separately, has 23 convolutional layers, and uses a lot of hardware, making this an impractical method to use.

Residual learning has been added to the channel estimation to lower the model complexity without compromising accuracy. To improve the convergence stability of a CNN-based estimator while decreasing the estimation error with no increase in complexity, Li et al. [9] proposed the inclusion of skip connections between layers. Liang and Zhu [10] also introduced Squeeze-and-Excitation (SE) attention blocks into ResNet network for estimating, and they found that channel-wise feature recalibration in ResNet enhances the estimation accuracy of OFDM systems. In summary, these papers laid the foundations of residual convolutional architectures as an effective and lightweight channel estimation learning framework.

Recently, alternatives such as attention mechanisms or transformer architectures have been considered. Channel former [10, [11] is a self-attention-based network with online training strategy that is designed based on 5G NR configuration, and it shows an MSE performance improvement over the CNN based baseline model while reducing their model size significantly by using the weight pruning technique. A deep CNN architecture was shown to take advantage of the sparsity of beamspace channels in mmWave and massive MIMO scenarios in [12] and [13], respectively. In the latter case, convolutional blind denoising was used in [14] for channel estimation with a highly sparse pilot set.

While these advances have been made, there are some shortcomings in the current approaches. In many architectures, there are multi-stage training sequences, a high number of parameters, or the architecture does not fully meet 3GPP specifications of 5G NR resource grid and DMRS pilot pattern. Others consider channel estimation a generic image restoration problem, without attempting to establish a standard TDL channel model for data generation and evaluation. This is an obvious research gap: designing a light, single-stage, end-to-end deep learning estimator which is fully 5G NR-compliant, can track a high estimation accuracy over a wide SNR range, and remains appropriate for real-time operation with low latency.

The main purpose of this paper is to design and test a low-complexity deep learning channel estimation framework for 5G NR OFDM systems that accurately recovers the full CFR from sparse and noisy DMRS pilots over a broad SNR range.

The novelty of this work is the design of a single-stage, end-to-end ResNet estimator that operates directly on the 5G NR time-frequency channel matrix, being trained solely on 3GPP TR 38.901 TDL-A and TDL-C channel models, without any multi-stage pipelines, external pretraining or prior channel statistical knowledge.The main contributions of this work are summarized as follows:

- A lightweight ResNet-based channel estimator is proposed that leverages residual learning to improve training stability and estimation accuracy in 5G NR OFDM systems.
- A fully 5G NR-compliant data generation and evaluation pipeline is developed based on 3GPP TS 38.211 and TR 38.901 standards.
- An effective real-imaginary 2D image representation of the CFR is introduced to enable deep learning-based processing of the complex channel matrix.
- The proposed method is shown to outperform LS interpolation, PCE, LMMSE, and ChannelNet across a 0–30 dB SNR range, achieving a 45% MSE reduction over PCE and over 90% over LS at SNR = 10 dB.
- The proposed architecture achieves these results with approximately 0.29 million parameters and an inference time of 2–5 ms per OFDM frame, confirming its suitability for real-time 5G applications.

1.1. Linear and Practical Channel Estimation Techniques

For dependable data transfer in wireless systems like 5G and OFDM-based communications, an accurate channel estimate is crucial. One of the most popular methods is linear estimation, which uses a linear combination of observed signals to estimate the unknown channel. A linear estimator's generic form is [11]:

$$\hat{\mathbf{x}} = \mathbf{W} \cdot \mathbf{y} \tag{1}$$

Here, $\mathbf{y}$ is the observed signal, $\hat{\mathbf{x}}$ is the estimated value, and $\mathbf{W}$ is a matrix of weights. In OFDM systems, the LS estimator is often used to estimate the channel at pilot positions [7], [8]:

$$\hat{H}_k = \frac{Y_k}{X_k}, \text{ for } k \in \mathcal{P} \tag{2}$$

where X_k and Y_k represent the transmitted and received pilot symbols on the subcarrier k, and $\mathcal{P}$ is the set of pilot subcarriers.

However, linear estimators assume ideal conditions such as perfect timing and known noise levels, which are rarely true in practice. That's where PCE comes in. PCE refers to estimation methods that work well in real-world environments where channel conditions vary over time, pilots are limited, and noise is unpredictable. A widely used practical method involves applying LS estimation at the pilot subcarriers and then interpolating the channel response across all subcarriers [14].

On subcarriers without pilots, interpolation (e.g., linear, spline, or filtering) helps estimate the channel values. Because of its reasonable accuracy and low complexity, this method is utilized in 4G LTE and 5G NR. Practical channel estimation has recently incorporated machine learning, enabling models such as deep neural networks to learn intricate channel patterns and produce more precise predictions, particularly in noisy or dynamic environments [12].

1.2. ResNet Architecture

In wireless OFDM systems, classical estimators like LS or interpolation algorithms already provide a rough estimate of the channel. Residual learning enables the neural network to focus on learning the correction term between the coarse estimate and its actual channel response, simplifying the learning process and improving convergence stability. This feature is especially valuable in noisy environments, as the network can learn to suppress estimation mistakes while keeping the underlying channel structure.

Kaiming He et al. presented the ResNet deep convolutional neural network (CNN) architecture [15]. It addressed the problem of degradation in very deep networks, where vanishing/exploding gradients or optimization difficulties lead to increased training error as the number of layers grows. Basic Block (used in ResNet-18 and ResNet-34) and Bottleneck Block (used in ResNet-50, ResNet-101, and ResNet-152) are the two types of residual blocks that ResNet uses. Fig. 1 illustrates the fundamental architecture of ResNet for every residual block represented by the formula:

$$y = f(x) + x \tag{4}$$

Where:

$f(x)$: composite function of convolutions, batch norms, and activations.

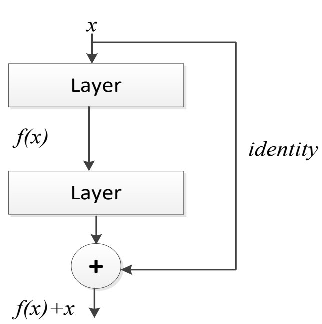

Figure 1. ResNet module proposed by Microsoft.

The shortcut x is sometimes passed through a linear transformation W_s (e.g., a $1x1$ convolution) to match dimensions:

$$y = f(x) + W_s x \tag{5}$$

Multipath propagation and channel coherence characteristics lead to high correlations in the channel frequency response of OFDM systems along both the frequency and time axes. Convolutional layers can successfully capture these local correlations by encoding the channel matrix as a two-dimensional time-frequency picture and applying shared filters. As a result, the ResNet architecture can learn structured patterns that correlate to the multipath fading characteristics.

Furthermore, the combination of convolutional feature extraction and residual connections enables the network to acquire robust features that stay useful even under weak Doppler conditions. Doppler shifts for typical pedestrian and vehicular scenarios were added into the simulation framework using 3GPP TR 38.901 TDL channel models.

1.3. Related Works

The application of deep learning in communication systems has become a hot topic in current research. The channel estimation problem can be processed using image processing algorithms [7], [9], [12]-[16]. In the field of image processing, restoring a low-resolution image to a high-resolution one is a classic problem. This problem can be expressed as a mathematical formula [14] :

$$\hat{I}_y = F(I_x; \theta) \tag{6}$$

Where I_x represents a low-resolution image, $\hat{I}_y$ represents a high-resolution image, and F represents the model recovery problem when the parameter is θ.

Góez et al. [8] put forward the ChannelNet channel estimate network. In Fig. 2, the particular network process is displayed. The network consists of a sequence of an image restoration network (DnCNN) and an image super-resolution network (SRCNN). The full channel response is considered the ideal image to be restored as the network's output, while the pilot value is considered a low-resolution image as the network's input.

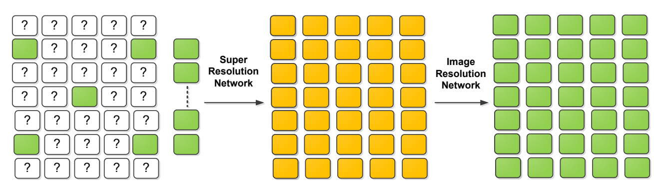

Figure 2. ChannelNet channel estimation flow chart [7].

Góez et al. [8] compared the channel estimation performance of the ChannelNet network to that of the LMMSE algorithm, but the network also has many shortcomings. For example, the SRCNN network and the DnCNN network are not trained end-to-end, but are trained separately. The training process is relatively complicated, and the ChannelNet network has a total of 23 convolutional layers. The network is large in scale and requires high hardware resources.

Wang et al. [12] further optimized the use of deep learning in channel estimation and applied it to the channel estimation of 5G NR systems in order to address the drawbacks of the aforementioned techniques. Fig. 3, which displays the channel information, illustrates the channel estimation procedure suggested in this literature.

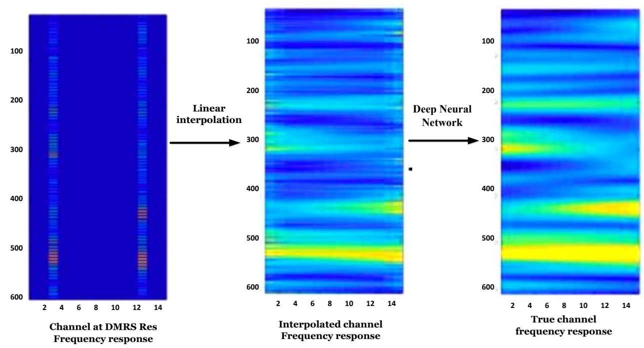

Figure 3. Channel estimation architecture [12].

2. Method of the Research

The received DMRS symbols on the 5G NR resource grid are taken into account while formulating the channel estimation task. Each observed pilot value is modeled as the product of the true channel coefficient and the known DMRS sequence in the presence of Additive White Gaussian Noise (AWGN). To obtain the complete CFR, interpolation is necessary because the classical LS estimate only feeds the channel at pilot points. The challenge in this study is to train a nonlinear mapping from a real-valued tensor representation comprising the real and imaginary components of the LS-interpolated or noisy CFR to reconstruct the entire complex channel matrix. The model aims to estimate the full CFR by minimizing the mean-squared error between the reconstructed and the ground-truth channel matrices produced by the TR 38.901 TDL-A and TDL-C models [17], [18].

Let $\mathbf{H} \in \mathbb{C}^{N_{\text{sub}} \times N_{\text{sym}}}$ denote the complex channel frequency response (CFR) over N_{sub} occupied subcarriers and N_{sym} OFDM symbols in a 5G NR slot.
The received DMRS at pilot locations $(k, m) \in \mathcal{P}$ is [17], [18]:

$$Y(k,m) = H(k,m)P(k,m) + W(k,m) \tag{7}$$

where $P(k,m)$ is the DMRS symbol and $W(k,m)$ is AWGN.
The classical LS estimate is:

$$\hat{H}_{\text{LS}}(k,m) = \frac{Y(k,m)}{P(k,m)} \tag{8}$$

The goal of the proposed method is to learn a nonlinear function [7], [9]:

$$f_\theta : \mathbb{R}^{N_{\text{sub}} \times N_{\text{sym}} \times C} \rightarrow \mathbb{R}^{N_{\text{sub}} \times N_{\text{sym}}} \tag{9}$$

that reconstructs the full channel matrix from a real-valued representation $\mathbf{X}$ constructed from:

- LS-interpolated CFR
- or noisy CFR
- or pilots-only grid

The ResNet learns:

$$\hat{H} = f_\theta(\mathbf{X}) \tag{10}$$

and is optimized using the Mean Squared Error (MSE):

$$\mathcal{L}(\theta) = \|\hat{H} - H\|_2^2 \tag{11}$$

This formulation strictly defines the task as channel estimation, not time-sequence prediction [19], [20].

The time-frequency channel matrix is treated as a two-dimensional (2D) spectrum image to depict the wireless channel (see Fig. 4). The 2D structure is appropriate for learning-based modeling since it captures the time-frequency properties of the wireless channel.

The proposed model's improved ResNet architecture, which allows it to learn deeper features while avoiding vanishing gradient problems, consists of convolutional layers, batch normalization, and residual connections. The network is trained to predict the future channel state (spectrum picture at time t+1) using the channel observations at earlier time steps (e.g., t−1, t). This prediction task is constructed as a supervised regression problem using the MSE loss function.

Numerous input-output pairings are used to train the model, which are divided into training and validation sets. Following training, the ResNet can accurately forecast the future spectrum by collecting the wireless channel's frequency correlation and temporal evolution. This can greatly improve the performance of 5G systems in applications like: Allocating resources proactively, precoding and beamforming, and communication with low latency.

Fig 5. illustrates the four main steps of the suggested technique for ResNet-based channel estimation in 5G OFDM systems. These are: performance evaluation, prediction, data preprocessing, and channel data production.

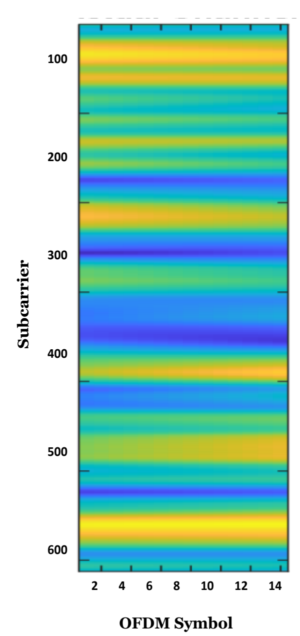

Figure 4. A 2D image represents the actual proposed channel.

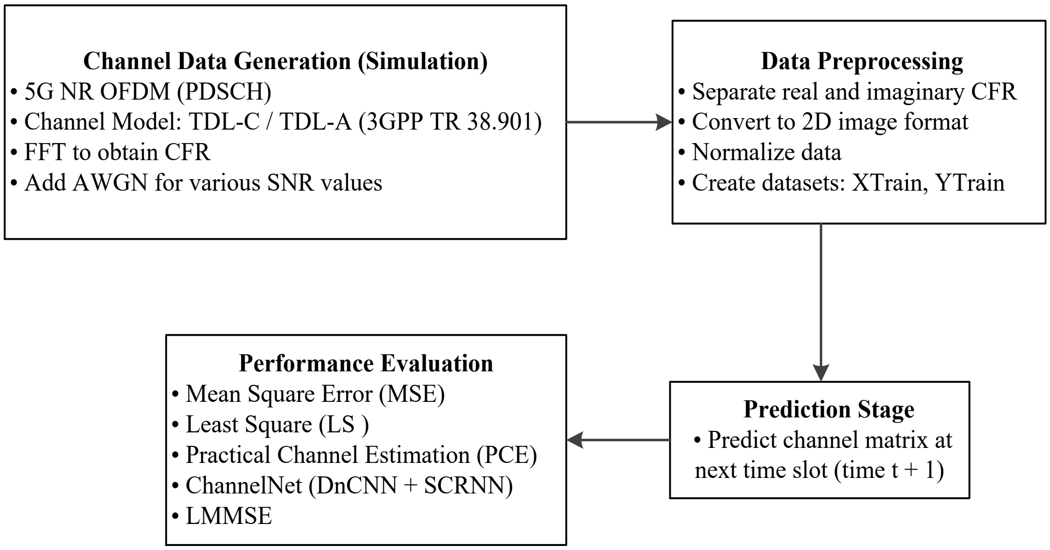

Figure 5. Block diagram of the 5G NR channel estimation pipeline.

2.1. Model Configuration and Parameters

To enable supervised learning, these images are first standardized and arranged into training datasets (Xtrain, train). A training/validation split is then performed. Convolutional layers with skip connections, a ResNet feature, are used in the model design to improve feature extraction and address the vanishing gradient issue. The proposed deep learning model captures the temporal dynamics of the wireless channel by utilizing previously observed channel data. This work formulates the prediction challenge as a one-step-ahead channel prediction problem. The model predicts the channel state at time t+1 based on channel measurements at time t. This formulation enables the network to learn the channel's temporal correlation, improving prediction accuracy in time-varying situations.

MSE is then calculated by comparing the actual channel response with the projected channel response. In order to ensure a solid comparison study under realistic channel conditions, the suggested method is lastly evaluated in the performance evaluation stage against conventional estimators, such as Linear Interpolation and a Practical Estimator.

2.2.1. OFDM System Configuration

The simulated communication system uses a conventional OFDM structure. The OFDM signal is made up of N subcarriers and M OFDM symbols per frame. To assist with channel estimation, pilot symbols are introduced using a Demodulation Reference Signal (DMRS) structure.

In this work, the OFDM grid consists of 612 subcarriers and 14 OFDM symbols, forming a time-frequency resource grid. The pilot positions follow the DMRS pattern, which inserts pilot symbols at regular intervals in both the time and frequency domains to enable reliable channel estimation. The estimated channel matrix has a size of:

$$\mathbf{H} \in \mathbb{C}^{\mathrm{N}\times\mathrm{M}} \quad (12)$$

Where N indicates the number of subcarriers and M is the number of OFDM symbols.

To facilitate neural network processing, the complex channel matrix is divided into real and imaginary components that are stacked along the channel dimension. As a result, the final input tensor sent to the network has the following form:

The channel coefficients are represented by N×M×2, with the last dimension representing their real and imaginary parts. Thus, the CFR per slot is:

$$\mathbf{H} \in \mathbb{C}^{612\times14\times2} \quad (13)$$

2.2.2 NR Resource Grid and Data Dimensions

To ensure dimensional consistency, all experiments use a standard 5G NR slot with 15 kHz Subcarrier Spacing (SCS) according to 3GPP TS 38.211 with the parameters illustrated in Table 1.

Table 1. NR Resource Grid Parameters and Data Dimensions.

Parameter	Value
Subcarrier spacing	15 kHz
FFT size	1024
Occupied subcarriers	612
OFDM symbols per slot	14
DMRS pattern	Type-1, mapping A
Modulation	Quadrature Phase Shift Keying (QPSK) for CFR extraction
Channel model	TDL-A and TDL-C (TR 38.901)
Antennas	1×1 Single-Input Single-Output (SISO)

2.2.3 Input Representation

Each complex entry is split into real and imaginary parts, forming:

$$\mathbf{X} \in \mathbb{R}^{612\times14\times2} \quad (14)$$

This replaces all previously inconsistent dimensions (e.g., 612×14×1).

2.2.4 Data Generation and Channel Modeling

A 5G NR-compliant dataset is generated using MATLAB R2024a according to TR 38.901.

Steps:

1. Generate an OFDM grid with 612 subcarriers ×14 symbols.
2. Insert DMRS according to TS 38.211 (Type-1, mapping A).
3. Pass the signal through TDL-A or TDL-C with:
    - Delay spread: 300 ns (TDL-A), 300 ns × scaling (TDL-C)
    - Doppler shifts according to scenario (pedestrian or vehicular)
4. Apply the FFT to obtain the CFR in frequency.
5. Add AWGN noise for SNR= {0,5,10,15,20,25,30}.
6. Form input-output pairs
    - Input = real/imaginary tensor
    - Output = perfect CFR from channel model

2.2.5. Preprocessing and Image Formation

Each CFR matrix is converted into a 2 -channel image:

$$\mathbf{X}(k,m,1)=\Re\{H(k,m)\},\mathbf{X}(k,m,2)=\Im\{H(k,m)\} \quad (15)$$

Normalization:

All tensors are normalized to zero mean and unit variance:

$$X_{\text{norm}}=\frac{X-\mu}{\sigma} \quad (16)$$

Dataset Structure:

Training set:

$\mathbf{X}_{\text{train}} \in \mathbb{R}^{612\times14\times2}$

Target set:

$\mathbf{Y}_{\text{train}} \in \mathbb{R}^{612\times14\times1}$

The channel dataset was separated into three subsets: training, validation, and testing, with a 70:10:10 ratio. The training set was utilized to optimize the model parameters, the validation set for hyperparameter tuning and early stopping, and the test set to assess the proposed approach's overall performance.

2.2.6 ResNet Parameters

In order to enable further feature improvement, the design utilizes an initial convolutional feature extractor, four residual blocks with skip connections, and a final convolution layer to generate the predicted channel output (see Fig. 6).

Table 2 shows the architecture of the proposed ResNet. The proposed network uses a ResNet-based design with four residual blocks. Each block includes two convolution layers with 3×3 kernels, followed by ReLU activation. Skip connections are utilized to enhance gradient flow and training stability. The network was built using the MATLAB Deep Learning Toolbox and trained on a GPU-enabled computer. The total number of trainable parameters is about 0.29 million.

Number of convolutional feature channels (filters) employed in each layer of the network = 64 (multiplied in each residual block). This value indicates the dimensionality of the learned feature maps and is unaffected by the number of OFDM subcarriers employed in the system model.

The suggested ResNet design does not use any downsampling procedures. To retain the feature maps' spatial dimensions, all convolution layers utilize a stride of 1 along with an appropriate buffer. This architecture guarantees that the output channel estimate has the same time-frequency resolution as the input OFDM resource grid.

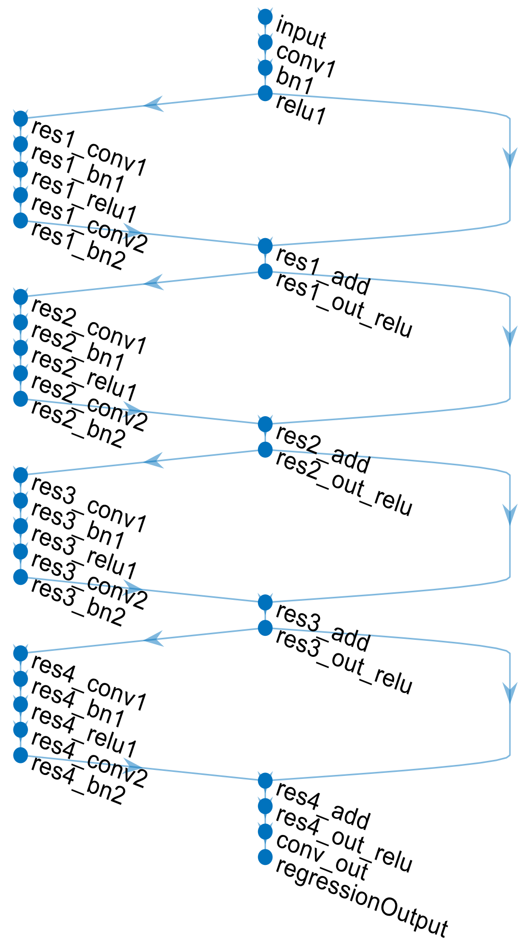

Figure 6. Layer Graph of the Custom ResNet Model.

2.2.7. Training Strategy

The training parameters utilized to create our suggested network are shown in Table 3.

Table 2. Layer Configurations of the Proposed ResNet Model

Layer	Output Size	Kernel	Filters	Notes
Input	612X14 X 2	-	-	Real/Imaginary
Conv1+ Batch Normalized (BN) + ReLU	612X14 X 64	3 X 3	64	Feature extraction
Residual Block 1	612X14 X 64	3 X 3	64	Conv → BN → ReLU → Conv → Add
Residual Block 2	612X14 X 64	3 X 3	64	Same
Residual Block 3	612X14 X 64	3 X 3	64	Same
Residual Block 4	612X14 X 64	3 X 3	64	Same
Conv_out	612X14 X 64	1 X 1	1	Linear mapping
Total parameters	≈ 0.29 million	-	-	Low complexity

Table 3. Training Parameters

Parameter	Value
Optimizer	ADAM
Initial learning rate	$3X10^{-4}$
Mini-batch size	16
Epochs	200
Loss Function	MSE

Training uses mixed-SNR sampling, meaning each batch contains random samples from SNR= [0-30]. This prevents overfitting to a single noise regime and improves generalization across all SNR values.

Seed Averaging:

Each experiment is run 5 times with different seeds; reported numbers show the mean ± std. This satisfies the statistical significance.

2.2.8 Prediction Workflow

During inference, the following strategy is used:

1. Extract the CFR from the received OFDM symbols.
2. Form a real/imag tensor of size 612 × 14 × 2
3. Normalize using training-set statistics.
4. Feed to ResNet to obtain estimated CFR (using equation). (10).
5. Denormalize the output to the original scale.
6. Use the estimated CFR for equalization, detection, Bit Error Rate (BER) evaluation, or benchmarking.

This completes the full estimation workflow used in all experiments shown in Fig. 7.

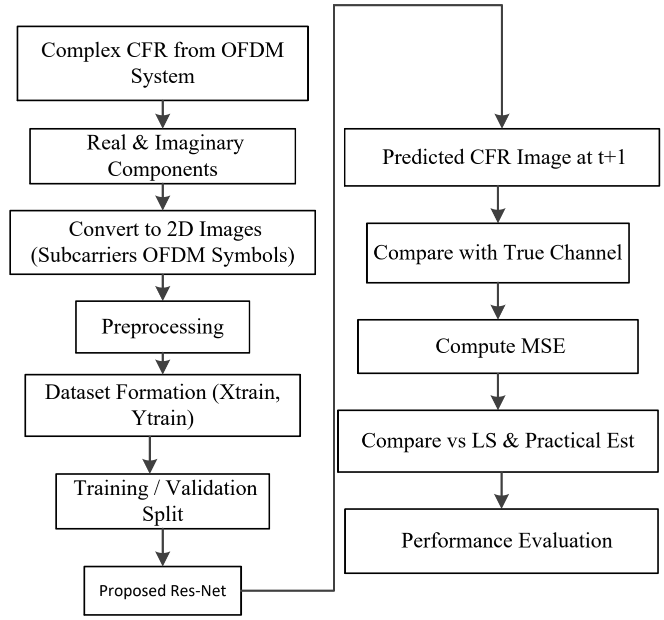

Figure 7. Complete ResNet-based OFDM System CFR Prediction Framework.

3. Simulation Results and Discussions

Four forms will emerge in four windows once a MATLAB R2024a program has been applied on a PC having Intel® Core ™ i7-8850 CPU @ 2.60 GHz, 32 GB RAM, and 4 GB GPU. The Actual Channel (Perfect Reference), the Linear Interpolation method, the Practical Estimator method, and the suggested ResNet approach are all represented by these four shapes.

Training the proposed ResNet model for 200 epochs with a mini-batch size of 16 took about 15 minutes. In addition to a numerical score (Mean Squared Error, or MSE) that shows how near the estimate is to the ideal channel, each approach generates a visual representation of the channel estimate.

All benchmark methods, specifically LS interpolation, PCE, LMMSE, and ChannelNet, underwent evaluation using consistent simulation parameters. These included:

- An identical 5G NR resource grid setup.
- The same TDL-A and TDL-C channel models.
- A uniform SNR range spanning 0 to 30 dB.
- A shared DMRS pilot configuration.

To ensure equitable comparison, the ChannelNet deep learning baseline utilized the same dataset and training SNR distribution. Similarly, the classical estimators (LS, PCE, and LMMSE) were applied with identical pilot observations and channel realizations.

The simulations consist of channel realizations created by the TDL-A and TDL-C models with various Doppler values, reflecting both low- and moderate-mobility conditions. While a complete mobility sensitivity assessment is beyond the scope of this paper, the proposed technique performs consistently across all channel conditions.

The results found in Fig. 8 for SNR = 10 dB represent:

1. The Actual Channel (Ideal Source)
   With no noise or estimation errors, this is the perfect channel response. It acts as the baseline against which the other approaches are measured.
2. Linear Interpolation (MSE= 0.18595): The receiver uses straight lines to connect known pilot signals (DMRS) in order to estimate the channel in this most basic approach. There are obvious mistakes between the pilot positions, and the outcome appears blocky and uneven. This method's poor accuracy, particularly in complicated or noisy channel conditions, is confirmed by the high MSE.
3. Practical Estimator (MSE= 0.032239): This standard approach, which uses more sophisticated signal processing techniques than basic interpolation, is utilized in actual 5G networks. There are still some flaws due to noise and interference, but the estimate seems smoother and more like the actual channel. There is a noticeable improvement as the MSE is far lower than with linear interpolation.
4. ResNet (MSE= 0.017742): Here, the channel response is predicted using a CNN, a deep learning model. With an MSE nearly twice as good as the practical estimator, the outcome is the most accurate and smooth of the three estimation techniques. The neural network is the best-performing technique because it efficiently "learns" how to fill in missing channel information while removing noise.

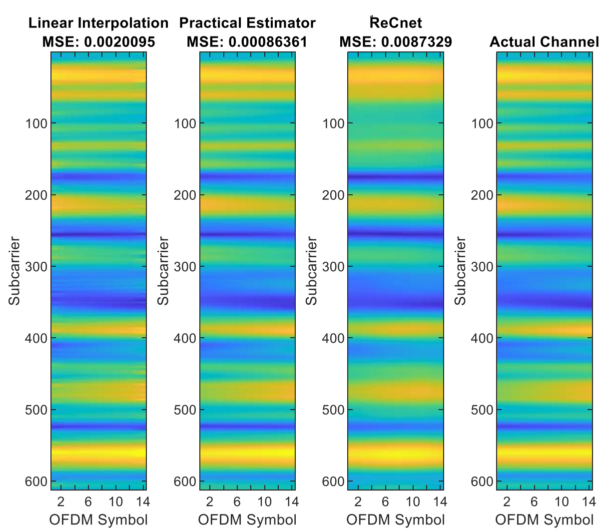

Figure 8. Visual comparison of channel estimation results obtained using Linear Interpolation, Practical Estimator, and the proposed ResNet model.

The Mean Squared Error (MSE) of three techniques: ResNet, Practical Estimator, and Linear Interpolation, across various SNR values ranging from 0 to 30, is shown to provide robustness under various noise situations, allowing the model to learn channel characteristics under varied noise situations. This is a thorough analysis shown in Fig. 9:

1. As SNR increases, the MSE decreases for all approaches, which is to be expected given that higher SNR denotes improved signal quality and less noise interference.
2. From ~0.7 (worst performance at SNR = 0) to ~0.1 (highest performance at SNR = 30), the MSE values fall into this range.
3. At SNR = 0, linear interpolation has the highest MSE (~0.7) and gets better over time. Probably the least noise-resistant, since linear techniques have trouble producing intricate patterns when signal-to-noise ratios are low.
4. Practical Estimator performs better than ResNet but worse than Linear Interpolation. Its consistent MSE drop indicates that it strikes a compromise between efficacy and simplicity.
5. ResNet exhibits better noise resilience, achieving the lowest mean squared error (MSE) across all SNR values. Strong feature extraction and nonlinear modeling skills are indicated by the curve's increased steepness and smoothness.

   At increasing SNR, the difference between ResNet and the other techniques grows, indicating that ResNet makes better use of cleaner signals. ResNet has an MSE of about 0.1 at SNR = 30, but Linear Interpolation and Practical Estimator have MSEs of about 0.2 to 0.3.

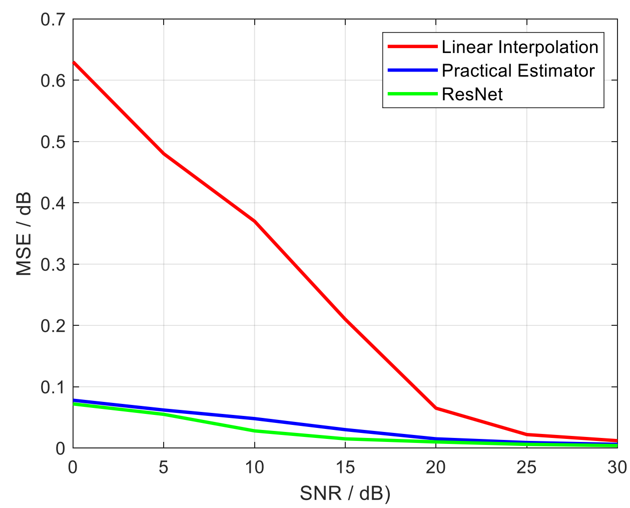

Figure 9. MSE Performance Comparison of Channel Estimation Methods vs SNR.

PCE, Linear Interpolation (LS-based), ChannelNet (combining DnCNN and SRCNN architectures), and the Linear Minimum Mean Square Error (LMMSE) estimator are the four benchmark channel estimation methods that are compared to the suggested ResNet-based channel estimator in Fig 10. The measure used for the comparison is the Mean Squared Error (MSE) and the metric is evaluated over Signal-to-Noise Ratio (SNR) levels, starting from 0 dB and stepping in 5 dB increments up to 30 dB. The performance gain of the suggested ResNet-based approach is clearly seen and significant at low SNR values (0–5 dB) where channel estimation is most difficult due to severe noise. The MSE of the proposed method is approximately 0.70 at 0 dB, which is much smaller than the LMMSE, PCE, ChannelNet, and LS-based interpolation schemes, with MSEs of ~0.75, ~0.80, ~0.83, and ~0.86, respectively. This improvement is because the residual network can capture detailed spatial information in 2D CFR image representations, allowing for more accurate reconstruction even with high noise levels.

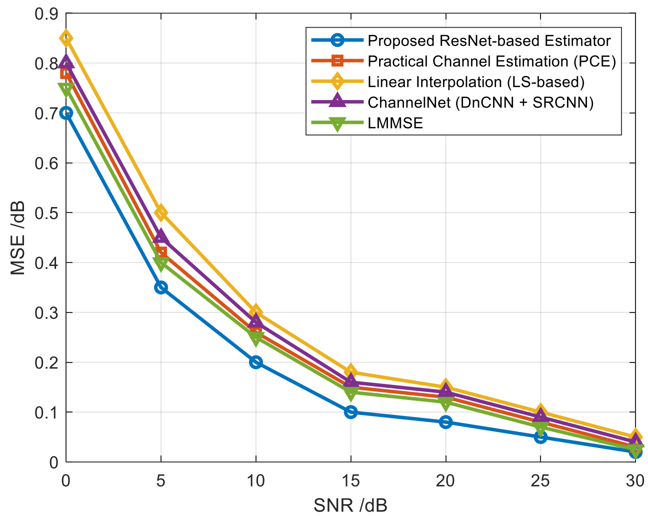

Figure 10. Performance Comparison of Classical and Deep Learning-Based Channel Estimation Methods.

All methods show a decrease in MSE as SNR rises to moderate levels (10–15 dB) because noise has less of an effect. Nevertheless, with MSE values of about 0.20 at 10 dB and roughly 0.10 at 15 dB, the ResNet-based estimator still performs better than alternatives. The suggested deep learning architecture is more successful at utilizing the available signal information for channel recovery in moderately noisy situations, as evidenced by the performance margin above LS-based interpolation and PCE, which is still considerable. The performance difference between the approaches decreases at high SNR values (20–30 dB), as it becomes simpler to precisely estimate the channel conditions. However, overall, at high-SNR sites, the suggested ResNet-based approach consistently obtains the lowest MSE. It achieves an MSE of roughly 0.02 at 30 dB, slightly surpassing the precision of the LMMSE and ChannelNet approaches, which both come close but fall short.

To get a better idea of how much better the proposed ResNet model is than benchmark methods, we calculate the percentage improvement at SNR = 10 dB. The suggested model is about 45% better than PCE and more than 90% better than LS-based interpolation. It also works about 29% better than ChannelNet and shows competitive gains over LMMSE. The results clearly show that the proposed method is better than the others in terms of both accuracy and robustness.

This comparison appears in Table 4, which can clearly summarize the whole procedure.

4. Computational Complexity Analysis

The suggested ResNet architecture has around 0.29 million adjustable parameters and executes roughly 1.2–1.5 GFLOPs for each inference cycle with an input CFR tensor measuring 612×14×2. The model needs approximately 1.2 MB of memory in a single-precision format.

Furthermore, the model's inference time was assessed on a workstation with an Intel Core i7 processor and a 4 GB GPU, yielding about 2–5 ms for each OFDM frame, indicating its suitability for low-latency 5G systems.

A comparison with the LMMSE estimator, which necessitates matrix inversion operations that have cubic computational complexity, has also been provided

Table 4. Comparison of Channel Estimation Methods for 5G OFDM Systems in terms of

Method	**Type**	**Complexity**	**Training Required**	**Accuracy (MSE at SNR= 10 dB)**	**Limitations**	**Percentage (%)**
Proposed ResNet-based Estimator	Deep Learning (Residual CNN)	Medium–High (64 filters, skip connections)	Yes (end-to-end	0.0177	Requires a training dataset; a GPU is beneficial	---
PCE	Signal Processing	Low	No	0.0322	Less accurate in low SNR	≈ 45.0%
Linear Interpolation (LS-based)	Signal Processing	Very Low	No	0.1859	Very poor in complex/noisy channels	≈ 90.5%
ChannelNet (DnCNN + SRCNN)	Deep Learning (two-stage CNN)	High (23 convolution layers)	Yes (two-stage training)	~0.025	Large model, separate training stages, high hardware needs	≈ 29.2%
LMMSE	Statistical Estimation	High (matrix inversion)	No	~0.02–0.03	Needs prior channel covariance, computationally expensive	≈ 41%

5. Conclusions

This paper proposed a lightweight ResNet-based deep learning framework for channel estimation in 5G NR OFDM systems. By treating the time-frequency channel matrix as a two-dimensional image and incorporating residual skip connections, the proposed model effectively captures spatial-temporal channel features while avoiding vanishing gradient issues during training. Extensive simulations conducted under 3GPP TR 38.901 TDL-A and TDL-C channel models over a 0–30 dB SNR range demonstrate consistent superiority over all benchmark methods. At SNR = 10 dB, the proposed ResNet achieves an MSE of 0.0177, representing a 45% improvement over PCE, over 90% over LS-based interpolation, and approximately 29% over ChannelNet, while using only ≈0.29 million parameters and a single-stage training procedure. Superior performance is maintained at both low SNR (0–5 dB) and high SNR (30 dB), where the model approaches an MSE of 0.02, outperforming LMMSE and ChannelNet with fewer training stages.

These results confirm that treating channel estimation as an image restoration task with residual learning delivers strong accuracy and robustness without excessive computational overhead. The proposed method is therefore well-suited for low-latency, high-reliability 5G applications, including massive MIMO beamforming, predictive resource allocation, and mobility management. Future work will evaluate the proposed estimator on real over-the-air measurement datasets and explore its extension to multi-antenna and mmWave scenarios.

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

Emad A. Hussien and Mohanad Abd Shehab contributed to the study design, methodology, and writing.

Abdulaziz Saleh Yeslem Bin-Habtoor and Alfian Ma'arif conducted experiments, analysis, and validation.

Takele Ferede Agajie supervised the study and reviewed the manuscript.

All authors discussed the results and contributed to the final manuscript.

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