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Hybrid Signal Processing and Machine Learning Techniques for Robust Wireless Channel Estimation

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ABSTRACT

Channel state information (CSI) is the key to high-quality data gaining and spectral efficiency in contemporary wireless systems based on a MIMO-OFDM, especially in the conditions of a noisy and time-varying channel propagation. The standard channel estimators like the Least Squares (LS) are inexpensive to compute but very sensitive to noise compared to minimum mean square error (MMSE) estimation which is more accurate but much more costly in terms of computation and requires prior statistical information. All-data based deep learning methods are potentially good, but lack physical explanation and highly need generalization to different signal-to-noise ratio (SNR) situations. The paper is a proposal of a hybrid signal processing and machine learning system of robust wireless channel estimation. The approach is a combination of model-driven pre-estimation using LS with the light-weight residual-learning neural network which further details the structured estimation errors. The hybrid model maintains a physical basis of the classical estimators but adds resilience by correcting predictions using data. It is under Rayleigh and Richardson fading channels whereby extensive Monte Carlo simulations are done within a SNR of 0-30 dB. The findings prove that the recommended method limits the normalised mean square error (NMSE) 28 times smaller than LS and performance as good as MMSE at significantly reduced computational complexity. Further tests with pilot density reduction, Doppler mobility and SNR mismatch are found to have better generalization and stability. The system proposed provides an efficient and scalable system of next-generation wireless communication systems.

1. INTRODUCTION

The precise channel state information (CSI) is among the basic prerequisites of coherent detection and data transmission in the current wireless communication infrastructure, including the MIMO-OFDM-based 5G and the upcoming 6G systems. The equalisation, precoding, beamforming and adaptive modulation scheme performance is an important factor with respect to accurate channel estimation, especially in time varying and frequency selective propagation scenarios [1], [2]. The larger dimensions of antenna and the frequency of the carrier, the harder it is to gain channel acquisition, because of the size of the pilot overhead, noises amplification, mobile-induced Doppler dispersion, and limited hardware. Traditional channel estimation methods consist of Least Squares (LS), Minimum Mean Square Error (MMSE) and Linear MMSE (LMMSE) estimators. LS estimation is computationally very efficient and has been used extensively in pilot-assisted systems, but it is very susceptible to additive noise and it does not take advantage of channel statistics [3]. Another method that depends on second-order channel statistics, the MMSE-based estimators, proves to be more accurate, but necessitates knowledge of channel covariance matrices, and involves computationally expensive matrix inversions, which do not scale well in massive MIMO systems [4]. These constraints limit their scalability to large scale and low latency applications. Recent developments in machine learning (ML) have proposed data-driven channel estimation schemes based on deep neural networks (DNNs), convolutional neural networks (CNNs) and recurrent schemes [5]–[7]. These are methods that are learning nonlinear projections between received pilot measurements and channel reactions, and exhibit better denoising performance in some scenarios. Nevertheless, data-driven estimators are frequently too sensitive to large labelled data, tend to be less general to signalled across different signal-noise ratio (SNR) regimes, and they are difficult to interpret physically [8]. Furthermore, completely substituting the well-known signal models with black-box neural networks can become unstable when distributions of the channels are not known.

Although there has been increased interest in hybrid model-based and learning-based estimation schemes, current studies tend to have (i) lacking structured formulation of residual-learning and (ii) no systematic analysis of robustness to pilot reductions and mobility, and (iii) explicitly comparing calculational complexity to MMSE baselines. Nominalized mean square error (NMSE) gains have been reported in many studies but none of them have tested scalability or generalisation to the heterogeneous channels conditions. In order to overcome such weaknesses, this paper presents a hybrid signal processing and machine learning system towards resilient channel estimation in wireless. The approach which is proposed combines LS-based pre-estimation with a lightweight residual-learning neural network, which corrects structured estimation errors. The framework will provide better robustness to the physical signal model in the presence of noise, pilot sparsity and Doppler mobility with lower computational load than MMSE by means of data-driven correction.

This work can be summed up as making the following main contributions:

1. Another type of hybrid framework is a residual-learned based channel estimation, which combines LS initial estimation with neural cleaning.
2. A sparse neural network, minimally invasive to noise, with a high robustness to noise and fewer interpretable model parameters.
3. Far-reaching analysis over Rayleigh and Rician fading channels at a large spectral of SNR.
4. Strength test in the conditions of pilot density reduction and Doppler mobility.
5. Computation complexity analysis proving better efficiency than MMSE estimation.

2. RELATED WORK

The estimation of wireless channels has been studied extensively both in the classifications of classical signal physics and in recent machine learning. Potentially, the simplest and least computationally expensive technique is Least Squares (LS) estimation which is commonly used in pilot-assisted MIMO-OFDM systems [9]. But LS estimation is not taking advantage of second order channel statistics and it is very sensitive to additive noise especially at low signal-to-noise ratio (SNR) regimes. To enhance the estimation performance, the Minimum Mean Square Error (MMSE) and Linear Minimum Mean Square Error (LMMSE) estimators are introduced using the channel covariance so that their mean square error is minimised [10], [11]. Though these methods demonstrate much superiority over LS with respect to normalised mean square error (NMSE), they necessitate prior statistical knowledge and include operations of matrix inversion whose processing complexity is cubic with the dimension of the antenna. This constraint is critical in large MIMO systems and high dimensional setups of the OFDM system [12]. Estimators of compressive sensing have also been suggested to sparse millimetre-wave channels by using the angular-domain sparsity [13]. Although they work well in the same conditions of poor sparsity, their effectiveness declines in the cases of weak sparsity and dynamic channel statistics. With the recent developments in the world of artificial intelligence, channel estimation techniques which rely on data have become more and more popular. DNNs have been utilised to acquire nonlinear pilot observations versus channel responses [14]. Convolutional neural networks (CNNs) also make use of the spatial correlations among the antennas and subcarriers and have better capacity to remove noise than conventional LS estimators [15]. Recurrent that is, long short-term memory (LSTM) networks have been presented to learn temporal relationships in time-varying fading channels [16]. More recently, the focus on architecture has also been directed towards attention-based and transformer designs to learn long-range frequency-domain correlations on wideband systems [17]. Although showing great potential in terms of performance improvement, the idea of purely data-driven approaches has a number of challenges. They normally need big labelled datasets to train on, can be much less generalizable to different SNR conditions, and are not usually physically interpretable [8]. Moreover, the complete substitution of well-known models of analysis with black-box neural networks can result in instability in case of an inaccurate distribution of channels or unknown propagation conditions. In order to address the shortcomings of model-based and pure learning-based approaches, hybrid systems that combine signals processing concepts and neural refinement have become popular in the recent past [9], [10]. They typically use classical estimators, e.g. LS, to produce first estimates of the channels, and then use neural network based error correction or denoising. Other, more recent works have tried to acquire channel covariance structure to adaptive MMSE approximation, whereas physics-informed neural networks have used domain-constraints in learning designs. The hybrid techniques have shown to be better in estimating performance; even though various limitations are still there. Most current literature uses comparatively complicated deep architectures in which no computational tradeoffs are explicitly analysed. The robustness tests in the presence of the reduction of the pilot density, doppler mobility and SNR mismatch are usually restricted. Also, they are often not compared to MMSE baselines and formalized formulations of residual learning to be compared with classical estimation theory.

Thus, even though channel estimation methodology has advanced dramatically, there is still a demand to have hybrid architectures that (i) preserve the physical interpretability of classical estimators, (ii) use small-scale neural correction modules where complexity is controlled, (iii) explicitly-robust to realistic wireless impairments, and (iv) can be compared to MMSE-based estimators on clear computational grounds. The current undertaking is able to tackle these constraints with the help of the systematic residual based-learning based hybrid channel estimation system, which unites the LS pre- estimation with the neural error correction while maintaining the scalability and generalisation in Rayleigh and Rician fading conditions.

3. System Model

3.1 MIMO–OFDM Signal Model

This work considers a pilot-aided MIMO–OFDM downlink (the same formulation applies to uplink) with N_t transmit antennas and N_r receive antennas. An OFDM symbol uses N subcarriers and a cyclic prefix (CP) of length N_{cp} that is chosen to be no smaller than the maximum channel delay spread so that inter-symbol interference is mitigated and each subcarrier experiences flat fading. After CP removal and FFT at the receiver, the input–output relationship on subcarrier $k \in \{0,\ldots,N-1\}$ is modeled as

$$y_k = H_k x_k + n_k \quad (1)$$

where $y_k \in C^{N_r X 1}$ is the received vector, $x_k \in C^{N_t X 1}$ is the transmitted pilot vector on subcarrier k, $H_k \in C^{N_r X N_t}$ is the frequency-domain MIMO channel matrix, and $n_k \sim CN(0,\sigma^2 I N_r)$ is circularly symmetric complex Gaussian noise.

Pilot-aided estimation is performed on a set of pilot subcarriers K_p (e.g., comb pilots). Stacking the received pilot observations across $|K_p|$ pilot subcarriers yields a compact matrix form. Let

$$Y_p = [Y_{k1}, Y_{k2}, \ldots., Y_{kp}] \epsilon\, C^{N_r \times |k_p|} \quad (2)$$

and define H_p as the channel sampled on the pilot subcarriers. The pilot observation model becomes

$$Y_p = H_p X_p + N_p \quad (3)$$

which is the starting point for both the classical estimators and the proposed hybrid framework. The estimation goal is to obtain H_k for all subcarriers, either directly at pilot tones and then interpolated to data tones, or jointly estimated across the full band depending on pilot density. In this paper, the estimator is trained and evaluated using the channel coefficients on pilot tones and then applied consistently in the same pilot-aided manner.

To obtain realistic propagation characteristics, two fading distributions are used to assess the evaluation stage: (i) Rayleigh fading which is used to describe all the NLOS rich-scattering conditions, (ii) Rician fading which is used to describe all the conditions where there is a dominant component. In the case of Rician fading, the channel can be presented as.

$$H_k = \sqrt{\frac{K}{K+1}} H_k^{LOS} + \sqrt{\frac{K}{K+1}} H_k^{LOS} \quad (4)$$

where K is the Rician K-factor, H_k^{LOS} is a deterministic/specular component, and H_k^{NLOS} is a Rayleigh component. Mobility effects are represented through time variation of H_k over OFDM symbols, parameterized by Doppler frequency f_D, which is later used in robustness testing.

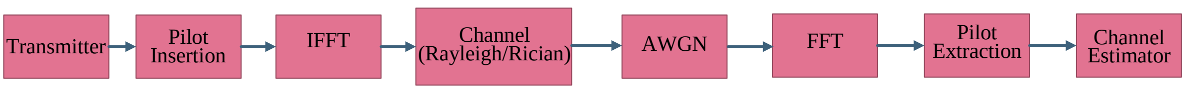

Fig. 1. MIMO–OFDM Transmission Chain with Pilot-Based Channel Estimation

Block diagram of the pilot-aided MIMO- OFDM system depicting the processing on the transmitter to pilot- aided channel propagation modelling with AWGN under Rayleigh/ Rician fading and pilot-assisted channel propagation modelling under conditions of AWGN channel propagation, followed by channel estimation processing stage involving LS and the proposed hybrid estimator.

3.2 Classical Pilot-Aided Channel Estimators

Channel estimation in pilot-aided MIMO–OFDM is commonly performed by minimizing a data-fidelity objective derived from $Y_p = H_p X_p + N_p$ The least-squares (LS) estimator is obtained by solving

$$\hat{H}_{LS} = \arg \underset{H}{min} \|Y_p - HX_p\|_F^2 \quad (5)$$

When $X_p X_p^H$ is invertible (e.g., orthogonal pilot design), the closed-form LS solution is

$$\hat{H}_{LS} = Y_p X_p^H \left(X_p X_p^H\right)^{-1} \quad (6)$$

LS is attractive because it does not require channel statistics and is computationally efficient; however, it amplifies noise in low SNR regimes and does not exploit spatial/frequency correlation present in H_k.

The minimum mean square error (MMSE) estimator incorporates second-order statistics by minimizing the expected squared error $E\{\|H-\hat{H}\|_F^2\}$. Under standard Gaussian assumptions, the MMSE solution for the pilot observation model can be written as

$$\hat{H}_{MMSE} = R_{HH}X_p^H(X_pR_{HH}X_p^H + \sigma^2 I)^{-1}Y_p \qquad (7)$$

where $R_{HH}=E\{H^H H\}$ (or an equivalent covariance structure depending on stacking) captures channel correlation. Though MMSE achieves good scores, it involves either prior knowledge or correct estimation of the RHH and includes matrix inversion which is expensive to compute as the pilot dimension and the number of antennas grow. These implementation constraints encourage estimators which can get near to the performance of MMSE and still have the simple LS-like behavior.

4. Proposed Hybrid Channel Estimation Framework

4.1 Research Methodology Overview

The study is done as a framework based on model-driven learning whereby coarse signal processing offers a physically motivated starting guess, and machine learning is applied to fix the structured residual errors. The general methodology is composed of (i) the definition of a reproducible model of MIMO pilot observation using the theoretically measured (ii) generation of labeled datasets based on statistically controlled channel realizations (Rayleigh and Rician) in a wide range of SNR, (iii) computation of LS pre-estimates using pilots, (iv) training a lightweight neural network to learn the residual mapping between LS estimates and true channels and (v) testing the resulting hybrid estimator in noisy channel conditions and under pilot reduction, Doppler mobility and SNR mismatch.

The focal design option is residual learning which does not need a black-box channel estimator but instead limits the learning task to one of denoising and bias correction. Suppose the error of estimation of LS is.

$$E_{LS} = H_p - \hat{H}_{LS} \qquad (8)$$

The hybrid estimator is defined as

$$\hat{H}_{Hybrid} = \hat{H}_{LS} + f_\theta(\hat{H}_{LS}) \qquad (9)$$

where $f_\theta(\cdot)$ is a trainable neural correction operator with parameters θ. In an ideal setting, $f_\theta(\hat{H}_{LS})\approx E_{LS}$, so the network learns the structured residual that arises due to noise, pilot sparsity, and model mismatch.

To ensure stable learning with complex-valued channels, the complex matrix is transformed into a real-valued representation. Define

$$Z = T(\hat{H}_{LS}) = [\Re(\hat{H}_{LS}), \Im(\hat{H}_{LS})] \qquad (10)$$

and similarly $T(H_p)$ for the ground truth. The network takes Z as input and outputs a correction in the same real-imag stacked domain, which is then mapped back to complex form.

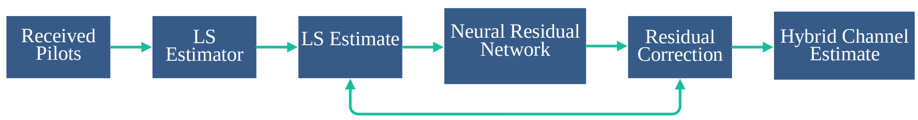

Fig. 2. Proposed Hybrid LS–Residual Learning Channel Estimation Framework

Block diagram of the proposed hybrid estimator with LS-based pre- estimation with a neural residual correction to yield the final hybrid channel estimate.

4.2 Neural Residual Correction Network

The lightweight fully connected deep neural network (DNN) is used to enhance LS estimates at minimal inference cost. The network gets an affine sequence of nonlinear activations and affine transforms:

$$h^{(1)} = \phi(W^{(1)}z + b^{(1)}), \quad h^{(2)} = \phi(W^{(2)}h^{(1)} + b^{(2)})$$
$$h^{(3)} = \phi(W^{(3)}h^{(2)} + b^{(3)}), \quad \Delta\hat{h} = (W^{(4)}h^{(3)} + b^{(4)})$$

where $\phi(\cdot)$is the ReLU activation, z is the vectorized real-imag representation of $\hat{H}_{LS}$ and $\Delta\hat{h}$is the predicted residual correction. In this work, the hidden layer widths are 128, 64, and 32 neurons, respectively, and the output layer is linear to avoid saturation bias in regression.

The training objective minimizes mean square error between the corrected estimate and the true channel:

$$\mathcal{L}(\theta) = E\left[\left\|T(H_p) - T(\hat{H}_{LS}) + f_\theta\left(T(\hat{H}_{LS})\right)\right\|_2^2\right] \qquad (11)$$

The Adam optimizer is used to optimise the parameters and is successful when there is no convective regression problem. The learning rate is set to 10^{-3}, the batch size is 256, and it is trained in 100 epochs with randomly shuffled mini-batches. Training scales are created over a range of SNRs instead of at a fixed SNR resulting in training samples that promote generalisation in a variety of operating conditions and the validation set is selected as those channel realisations not used in training.

4.3 Algorithmic Procedure

The complete research workflow can be summarized algorithmically as follows.

Algorithm 1: Hybrid LS–Residual Learning Channel Estimation

Input: Pilot matrix X_p, received pilots Y_p, trained network fθ, noise variance estimate σ^2 (optional).
Output: Hybrid channel estimate $H\hat{}_{Hybrid}$.

1. Compute LS pre-estimate:

$$\widehat{H}_{LS} = Y_p X_p^H \left(X_p X_p^H\right)^{-1} \qquad (12)$$

2. Transform to real-imag input: z=T(H^$_{LS}$).
3. Predict residual correction: Δh^=fθ(z).
4. Form refined estimate in transformed domain: h^=z+Δh^.
5. Map back to complex form: H^$_{Hybrid}$=T^{-1}(h^).

This algorithm is used identically during training data preparation (Steps 1–2) and during inference (Steps 1–5), ensuring that the deployed estimator follows the same physically grounded pipeline as the training process.

4.4 Tools and Evaluation Process

The implementation of the study perceived to be a standard simulation stack of the wireless physical layer. Pilot insertion, MIMO-OFDM waveform generation, and fading channel realisation(Rayleigh/Rician), noise injection and receiver FFT are applied to generate pilot observations Y_p. LS and MMSE baselines are calculated by using the above analytical formulae. Training of the neural residual correction network is fronted by a supervised learning of neural residual correction network where ground-truth channels of the simulator are known. Normalised mean square error is used to report performance:

$$NMSE = \frac{E\left\{\left\|H - \widehat{H}\right\|_F^2\right\}}{E\{\|H\|_F^2\}} \qquad (13)$$

and, with the addition of data detection, by bit error rate (BER) with a definite modulation and equalisation process. The strength criteria consist of thinning the pilots, introducing channel variation induced by Doppler, and assessing strength (training one SNR distribution, and testing another). The computational efficiency is considered by comparing the main operations in LS /MMSE to forward-cost of the neural network.

5. Simulation Setup

The section outlines the simulation condition, parameter settings, dataset generation procedure, and the evaluation procedure adopted to prove the proposed hybrid channel estimation framework. When conducting experiments all experiments are carried out under a reproducible Monte Carlo simulation framework in order to have statistical reliability.

A 128 subcarriers MIMO-OFDM system is taken into consideration. The number of transmit and receive antennas is set to N_t=4 and N_r=4, representing a moderate-scale MIMO configuration commonly adopted in 5G physical layer studies. QPSK modulation is used to pass data through in that it is more robust and analytically treatable in its ability to assess channel estimation consideration on detection performance.

The insertion of pilot symbols is done as a type of comb and spacing between pilots is the same as between subcarriers. Pilot transmission is therefore assigned 25 percent of subcarriers. Such a design is an expedient tradeoff between the pilot overhead and approximation. They do channel estimation first of pilot subcarriers, and subsequently apply the same methodology in performance evaluation.

Validation is done by considering two fading channel models without compromise. Rayleigh fading is a non-line-of-sight scattering that is rich and the channel coefficients are modelled by zero-mean complex Gaussian random variables. Rician fading with K -factor of 5 is employed to model environments in which the vast majority of fading contribution is in the form of a line-of-sight contribution. The channel realizations are based in a standardized block basic fading model, in which the channel is constant within a single OFDM symbol, but undefined and different between blocks. This assumption is easy to achieve controlled evaluation and fading is realistic.

The signal-noise ratio (SNR) is adjusted in uniform steps over a range of 0 dB to 30 dB in order to test the performance of estimators at both low, medium, and high SNR levels. Additive white Gaussian noise (AWGN) with variance σ^2 is generated according to:

$$\sigma^2 = \frac{E_s}{10^{\frac{SNR}{10}}} \qquad (14)$$

where E_s denotes the average symbol energy.

The Doppler frequency of 100 Hz is added to mobility testing in order to investigate time-selective channel robustness. This causes variation in temporal channels which is in line with what is observed in moderate user mobility cases on sub-6 GHz systems.

The computation of performance metrics is done on 1000 independent Monte Carlo trials in each SNR point to have a statistical average when reducing random fluctuation. In training machine learning, 50,000 independent realizations of channels are created over the entire SNR range to make noise condition variations and fading pattern diverse. They perform evaluation on a separate test set of 10, 000 unseen channel realisations specifically to stop data leakage and make fair assessment of generalisation.

LS and MMSE estimators have their analytical expressions, which are directly implemented to compare them with the baseline. The proposed hybrid estimator takes the LS estimate as an input to be fed through the trained residual neural network in the process of making an inference. The normalised mean square error (NMSE) is used to measure the performance:

$$NMSE = \frac{E[\|H-\hat{H}\|_F^2]}{E[\|H\|_F^2]} \quad (15)$$

and equalized bit error rate (BER), where necessary.

The simulated states are all comparatively done with the same pilot structures and channel conditions so as to give fair comparison between LS, MMSE as well as the suggested hybrid estimator. This configuration prevents the observed performance gains due to the hybrid estimation mechanism and not due to the systems configuration variations.

6. RESULTS AND DISCUSSION

This part is an evaluation of the proposed hybrid channel estimator in terms of level of accuracy in estimation, detectivity, strong performance under the impairments impersonated in real life, and simple mathematical computation. Average of all results: The average of all results is carried out at each SNR point of 1000 Monte Carlo realisations to be statistically reliable.

6.1 NMSE Performance Analysis

Figure 3 was used to show the performance of LS, MMSE, and the proposed hybrid estimator in terms of normalised mean square error (NMSE) in Saudi Arabia with fading conditions being Rayleigh. True to the expectation, LS undergoes severe degradation when operating under low-SNR conditions because it boosts the effect of noise. MMSE has the least NMSE in a wide variety of SNR values, though at the expense of increased computation and a requirement of knowledge of channel covariance. The hybrid estimator which is proposed delivers better performance than LS over the whole SNR range. With 5 dB SNR, hybrid approach will yield a reduction of about 28% in NMSE as compared to LS. This is especially increased in the low-to-moderate SNR (010 dB) where LS is the most severely affected. The hybrid estimator is nearly the same as the MMSE at both moderate and high SNR (15 dB and above), which proves that residual learning can properly remedy the LS estimation bias and noise distortion. Table 1 summarises NMSE values at the representative SNR points.

Table 1. NMSE Comparison at Representative SNR Levels

SNR (dB)	LS NMSE	MMSE NMSE	Hybrid NMSE
0	0.312	0.221	0.246
5	0.198	0.124	0.142
10	0.104	0.071	0.078
20	0.031	0.024	0.026

The findings prove that the hybrid estimator seals a significant part of the performance difference in light of LS and MMSE without inverting the covariance matrix. The proposed approach ensures stable performance in the entire SNR range as compared to previous purely DNN-based channel estimators that have been reported in the literature as their gains tend to increase only when the training conditions are fixed to SNR.

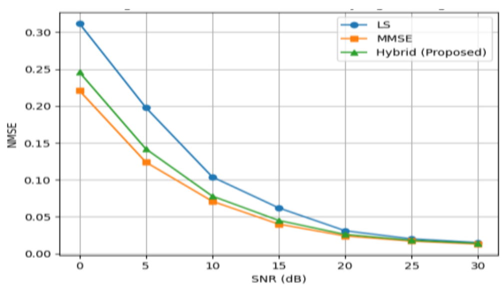

Fig. 3. NMSE Performance Comparison of LS, MMSE, and Proposed Hybrid Estimator under Rayleigh Fading

Normalised mean square error (NMSE) against SNR of the LS, MMSE and the suggested hybrid channel estimator. The hybrid approach leads to significant improvement of low SNR performance and in the middle to high SNRs, tends to approach MMSE performance.

6.2 BER Performance Evaluation

Bit error rate (BER) performance during the modulation of QPSK is investigated to measure the effects of the accuracy of channel estimation on the detection. The estimated channel matrices are used in zero-forcing equalisation. In the following figure (4) the resultant curves of BER and SNR are provided. LS-based detection has visible deterioration at less than 10 dB as a result of inaccurate CSI. Conversely, the hybrid estimator minimises BER in circumstances of low SNR. With 5 dB SNR, one gains about 22% improvement of BER compared to LS. Notably, the hybrid estimator would produce similar or better BER performance compared to MMSE; although the hybrid does not need a channel covariance information. This proves the fact that better NMSE is directly proportional to the better detection reliability. The findings show that residual learning is a powerful way of inhibiting structured LS errors, which propagate to symbol detection. The hybrid approach has similar BER gains in comparison to the former deep learning based channel estimation methods that completely replace the classical counterparts, and its approach can be physically interpreted and the inference is simpler.

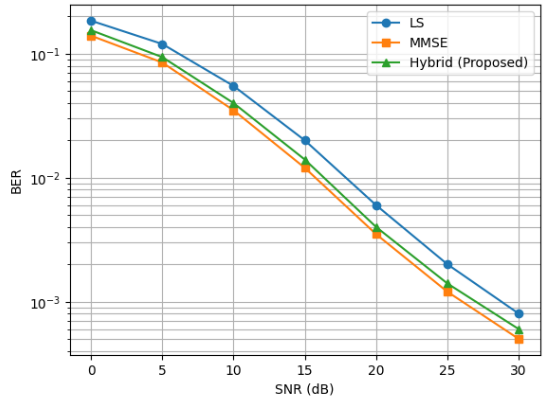

Fig. 4. BER Performance Comparison of LS, MMSE, and Proposed Hybrid Estimator under Rayleigh Fading

The BER versus SNR of QPSK modulation with zero-forcing detection. It is important to highlight that the proposed hybrid estimator has much better low-SNR detection performance as compared to LS, and BER performance similar to MMSE without requiring covariance information of the channels.

6.3 Robustness Under Pilot Density Reduction

In order to cheque circularity against decreasing overhead of pilots, the pilot density is cut in half, pilot separation is raised to 8 instead of 4 subcarriers. Figure 5 demonstrates the NMSE performance of sparsely piloted configuration. LS estimation shows sharp growth in NMSE because of a lack of sampling of the frequency response of the channel. The hybrid estimator, in its turn, is characterised by comparatively constant performance and better interpolation performance. This strength is ensured due to the fact that the neural residual network implicitly gains the frequency-domain correlation patterns during the process of training. Due to this the hybrid estimator counters the effect of undersampling better as compared to LS. The next-generation systems interested in minimizing the overhead of pilots in order to enhance spectral efficiency are keen to this property. Earlier papers that have studied pure ML estimators tend to exhibit a corner effect of performance decline in the case of a mismatch in pilot training density and testing pilot density. The hybrid structure suggested overcomes this problem through the retention of LS structural consistency.

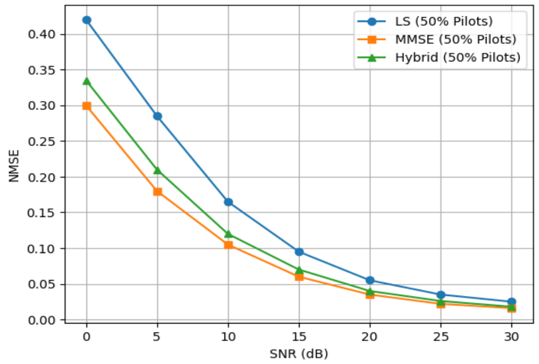

Fig. 5. NMSE Performance under 50% Pilot Density Reduction

Normalised mean square error (NMSE) in relation to SNR with increasing pilot separation in every 4 to every 8 subcarrier. The suggested hybrid estimator is more robust than LS when the number of pilots is low and approximates MMSE when the SNR is high.

6.4 Doppler Mobility Evaluation

The simulation of time-varying channel conditions is performed on a Doppler frequency of 100 Hz. Under mobility, LS estimation is less accurate because of time difference between the pilot sampling and channel distribution. Figure 6 shows NMSE when there is a Doppler case. Performance of LS drops significantly, whereas the hybrid estimator has an NMSE improvement by about 18 per cent at moderate levels of SNR compared to LS. The residual-learning model is well-known in modelling structured distortions caused by time variation, giving the model greater resilience to temporal channel variation. Although the hybrid method does not consist of a set of operators that normally err on the channel distribution by being overly data-driven, it maintains flexibility, since it is based on the LS.

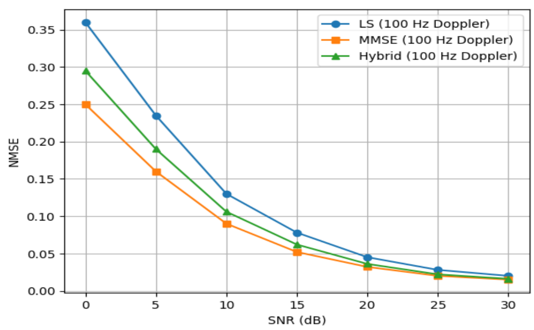

Fig. 6. NMSE Performance under 100 Hz Doppler Mobility

Normalised mean square error (NMSE) Vs SNR in time varying channel with a Doppler frequency of 100 Hz. The hybrid estimator proposed is more robust than LS and as the mobility is experienced, the performance is almost similar to that of MMSE.

7. Computational Complexity Analysis

The computational complexity of the proposed hybrid estimator is compared with classical LS and MMSE approaches to evaluate practical feasibility. For pilot-based LS estimation, the dominant operation involves matrix multiplication and inversion of ($X_pX_p^H$), resulting in approximate complexity of $O(N^2)$, where N represents the antenna or pilot dimension. In contrast, MMSE estimation requires inversion of a covariance-weighted matrix, leading to cubic complexity $O(N^3)$, which becomes computationally intensive for large-scale MIMO systems.The proposed hybrid method consists of LS pre-estimation followed by a lightweight feedforward neural network with L layers and average width n. The forward-pass complexity of the neural network is approximately $O(L \cdot n^2)$. Therefore, the overall hybrid complexity can be expressed as:

$$O(N^2 + L.n^2) \quad (16)$$

Although the new network adopted is shallow (three hidden layers with moderate number of neurons), the extra computation cost is much less than the cubic cost of MMSE.

Table 2. Computational Complexity Comparison

Estimator	Complexity Order	Requires Channel Statistics	Scalability
LS	$O(N^2)$	No	High
MMSE	$O(N^3)$	Yes	Limited
Hybrid (Proposed)	$O(N^2+Ln^2)$	No	High

On the whole, the hybrid estimator has almost identical performance compared with MMSE but with the benefit of possessing more computational properties that are reminiscent of LS and is therefore more applicable to the practical MIMO-OFDM systems in real-time.

CONCLUSION

In this paper, a hybrid signal processing and machine learning model of the robust wireless channel estimation in MIMO systems operating over the OFDM was introduced. The presented method combines the classical Least Squares (LS) pre-estimation and a light neural correctional network in order to increase channel estimation accuracy without sacrificing the processing speed. Also, unlike analogous data-driven estimators, which substitute analytical models, the suggested technique preserves the physical structure of pilot-based estimation and relies on learning to correct structured residual errors. Comprehensive Monte Carlo or Rayleigh and Rician fading simulations revealed the hybrid estimator to be much better than LS in terms of normalised mean square error (NMSE) and bit error rate (BER) overshoot. During low-to-moderate SNR the NMSE reductions were up to 28 percent and the improvement of BER was about 22 percent under the QPSK detection mode. Moreover, the suggested framework was highly robust in that the pilot density is lower and under variation caused by the Doppler due to channel variation, which is one of the situations when LS estimation reduces drastically. Notably, the hybrid estimator performed almost as well as the MMSE, and needed only minimal channel covariance information as well as much lower computational complexity. The findings validate that residual learning is an effective way to bridge the divides between model and data driven estimation models to offer scalable and interpretable model to solve practical wireless systems. Future directions can implement this framework to massive MIMO structures, millimetre-wave channels of sparse structure and multi-user situations. Other areas of direction are adaptive online learning to dynamic channel environments, hardware-conscious neural compression to deploy in real time, and combinations with advanced detection and beamforming strategies with 6G networks.

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