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Hybrid LS-MMSE Channel Estimation for OFDM Systems Over Frequency-Selective Rayleigh Fading Channel

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***Abstract* - To achieve reliable orthogonal frequency division multiplexing (OFDM) communications in frequency-selective fading channels, accurate channel estimation is critical. The traditional least squares (LS) estimator enhances noise at pilot locations, whereas the traditional pilot-only minimum mean square error (MMSE) estimator adds residual interpolation error that remains independent of signal-to-noise ratio (SNR). This paper suggests an Adaptive Full-Band Hybrid LS-MMSE channel estimator which removes both of the limitations by a one-step linear minimum mean square error (LMMSE) Wiener filter of size $N \times N_P$ analytically computed based on the complete channel frequency-domain cross-correlation matrix using the exponential power delay profile (PDP). The proposed estimator directly interpolates all pilot measurements to estimates in the entire frequency band in a single step, ensuring the Hybrid MSE results better than LS and MMSE results at any SNR. Monte Carlo simulated 16-QAM OFDM system with N = 64 subcarriers, NP = 16 pilots and L = 6 tap Rayleigh fading channel show consistent performance improvements. The proposed method has a NMSE of -18.21 dB (4.83 dB gain over LS and 3.14 dB gain over MMSE) and a BER of 0.0649, and spectral efficiency of 8.4 bits/s/Hz at SNR = 28 dB. The estimator is computationally tractable, and it achieves the Cramer-Rao Lower Bound at high SNR, making it a high-performance solution to 5G and beyond OFDM systems.**

Keywords: OFDM; Channel estimation; LS; MMSE; Rayleigh fading;5G; Wireless communications.

I. INTRODUCTION

The fast emergence of applications that demand large bandwidth, such as video streaming, Internet of Things (IoT) connectivity, and autonomous vehicular communications, has put unprecedented pressure on the present-day wireless networks [1]. Orthogonal frequency division multiplexing (OFDM) has become the leading technique in multi-carrier modulation in practically all modern wireless protocols, such as IEEE 802.11 Wi-Fi, 4G Long Term Evolution (LTE), as well as 5G New Radio (NR) [2,3]. Main benefits of the OFDM are that it is intrinsically resistant to inter-symbol interference (ISI), has high spectral efficiency, and can be easily equalized by simple one-tap frequency-domain equalization after the cyclic prefix (CP) insertion [4]. The availability of accurate channel state information (CSI) in the receiver is, however, vital to the reliability of the work of the OFDM systems [5].

Channel estimation refers to the learning of the channel of the wireless propagation in order to apply coherent detection and equalization to the receiver. In real-world applications of OFDM, the channel estimate is often achieved by introducing known reference signals, often known as pilots at designated time-frequency resource segments [6]. At pilot positions, the receiver measures the received signal and uses it to estimate the channel frequency response (CFR) which is then interpolated between data subcarriers. The most common and two classical methods are the least squares (LS) estimator and the minimum mean square error (MMSE) estimator [7, 8].

The LS estimator is attractive as its computational complexity is very small, as it only needs division of elements at pilot subcarriers while prior channel statistics and noise variance are not necessary [9]. Nevertheless, LS estimation fails to cancel additive white Gaussian noise (AWGN) at pilot positions and uses purely the interpolation method to estimate the data subcarrier channel coefficients, which limits its application in challenging propagation environments [10]. On the other hand, the MMSE estimator is developed using Wiener filter framework and relies on the second-order characteristics of the channel and the lowest possible estimator error in mean square sense [11,12]. The classical pilot-only MMSE is a noise suppressing estimator which uses pilot locations and interpolates data subcarriers linearly. Although this minimizes estimation noise when compared to LS, the two-step process imposes a sub-optimality as the interpolation step does not utilize the entire channel frequency-domain correlation structure among all the subcarrier pairs [13].

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In order to close the performance gap between the computationally easy LS estimator and the statistically optimal full-band LMMSE estimator, a number of hybrid schemes in the literature have been suggested [14-17]. Most of the techniques are aimed at having the noise suppression advantages of MMSE without incurring the two-step interpolation penalty.

On the other hand, further research articles discussed the use of machine learning and data-driven channel estimation. Dong *et al.* [18] came up with a deep neural network (DNN) channel estimator of OFDM systems, which performs better than classical techniques in non-stationary environment, but at significantly high computational cost. Soltani *et al.* [19] used super-resolution convolutional neural networks (CNNs) to interpolate pilot-based estimates which showed better performance on BER at high mobility. A power delay profile-aware DNN trained along with the channel knowledge was utilized by Ye *et al.* [20], and impressive results were demonstrated in LTE scenarios. Yet, such deep learning models require substantial training data, computing material, and they are subject to channel distribution discrepancy [21].

Other methods which are mostly based on compressed sensing (CS) have also been used in the sparse channel estimation [22, 23]. Bajwa *et al.* [24] took advantage of the sparsity of wideband channels to obtain sub-Nyquist pilot overhead without compromising the accuracy of estimation. Berger et al. [25] used orthogonal matching pursuit (OMP) and LASSO to estimate the channel in the OFDM where the gains reported by both algorithms are better than the gains of classical pilots-based estimations in sparse multiple path conditions. Nonetheless, CS techniques are vulnerable to the sparsity assumption and have an iterative recovery algorithm with non-trivial convergence properties [26].

There are studies that have explored different channel estimation schemes that integrate the LS and/or the MMSE schemes [27-30]. Liu *et al.* [28] suggested a regularized LS estimator, which adaptively adjusts the regularization parameter considering distorted SNR with less NMSE in comparison to standard LS. Noh *et al.* [29] created a pilot-aided LMMSE estimator of massive MIMO-OFDM that utilized large-scale fading diversity, with great spectral efficiency improvements. Nevertheless, the current hybrid techniques tend to either demand precise channel statistics or are limited to pilot-position filtering followed up by interpolation [30].

We present in this paper a new version of Adaptive Full-Band Hybrid LS-MMSE channel estimator that uses all subcarriers of an OFDM in one Wiener filtering step and directly estimates the overall channel frequency response of a channel based on a pilot observation. The proposed estimator is based on the channel frequency-domain cross-correlation matrix of all subcarriers and pilot subcarriers analytically estimated, using the known or estimated power delay profile (PDP). This not only avoids interpolation error but also performs much better than the traditional LS and the actual pilot-only MMSE estimators, as shown by comprehensive simulation.

II. SYSTEM MODEL AND METHODOLOGY

Take a baseband OFDM system with (N = 64) subcarriers, cyclic prefix length (N_{CP} = 16), and (N_P = 16) equally spaced pilot subcarriers. The transmitted OFDM symbol at the frequency domain is represented as:

$$X = [X(0), X(1), \dots, X(N-1)]^T \quad (1)$$

where X(k) is the modulated symbol at the k-th subcarrier. The frequency-domain after CP removal and FFT received signal is:

$$Y(k) = H(k)X(k) + W(k), k = 0,1, \dots, N-1 \quad (2)$$

where $H(k)$ is the frequency-domain channel coefficient on subcarrier k, and $W(k)$ is additive white Gaussian noise with variance

$$\sigma^2 = \frac{1}{\text{SNR}} \quad (3)$$

The channel impulse response:

$$\text{h} = [h(0), h(1), \dots, h(L-1)]^T, \quad L = 6 \quad (4)$$

Each tap is independent complex Gaussian taps with exponential power delay profile (PDP):

$$\sigma_l^2 = \mathbb{E}[|h(l)|^2] = (1 - e^{-\alpha})\, e^{-\alpha l}, \quad l = 0, \dots, L-1 \quad (5)$$

where $\alpha > 0$ is the PDP decay exponent. The frequency-domain channel $\mathbf{H} = [H(0), \dots, H(N-1)]^T$ is obtained as the N-point DFT of $\mathbf{h}$. The channel frequency-domain autocorrelation between subcarriers k_1 and k_2 is:

$$R_H(k_1, k_2) = \mathbb{E}[H(k_1)\, H^*(k_2)]$$

$$= \sum_{l=0}^{L-1} \sigma_l^2 \exp\left(-j\, \frac{2\pi(k_1 - k_2)\, l}{N}\right) \quad (6)$$

2.1 Least Squares (LS) Estimator

The LS channel estimate at pilot positions is obtained by minimization of squared residual between reception of signal and the estimated channel modified pilots, and with no statistical information of channel:

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$$\hat{H}_{\mathrm{LS}}(k_p) = \frac{Y(k_p)}{X(k_p)} = H(k_p) + \frac{W(k_p)}{X(k_p)}, \quad k_p \in \mathcal{P} \qquad (7)$$

where $\mathcal{P}$ set denotes the set of pilot subcarrier indices. The LS estimator at pilot positions is unbiased with variance:

$$\mathbb{E}[|\hat{H}_{\mathrm{LS}}(k_p) - H(k_p)|^2] = \frac{\sigma^2}{|X(k_p)|^2} = \sigma^2 \qquad (8)$$

Linear interpolation between piloting positions gives the LS estimate at the subcarriers of the data stream. The MSE of LS estimator is calculated exclusively based on the power of noise and the error of interpolation and is thus the reference by which a better method is judged.

2.2 Practical MMSE Estimator

The high-pass Wiener filter MMSE estimator uses the second-order statistics of the channel to remove noise at pilot positions with the help of the LS pilot estimates.

Let $\mathrm{H}_p = \left[H(k_{p_1}), \dots, H\left(k_{p_{N_P}}\right)\right]^T$ denote the channel vector at pilot subcarriers, and $\hat{\mathrm{H}}_{\mathrm{LS},p}$ the corresponding LS estimates. The MMSE filter is [7],[11]:

$$\mathrm{W}_{\mathrm{MMSE}} = \mathrm{R}_{pp}\left(\mathrm{R}_{pp} + \sigma^2\,\mathrm{I}_{N_P}\right)^{-1} \qquad (9)$$

$$\hat{\mathrm{H}}_{\mathrm{MMSE},p} = \mathrm{W}_{\mathrm{MMSE}}\,\hat{\mathrm{H}}_{\mathrm{LS},p} \qquad (10)$$

where $\mathbf{R}_{pp}$ is the $N_P \times N_P$ pilot-to-pilot channel correlation matrix with elements $[\mathbf{R}_{pp}]_{ij} = R_H\left(k_{p_i}, k_{p_j}\right)$

The MMSE estimate achieves the minimum MSE at pilot positions:

$$\mathrm{MSE}_{\mathrm{MMSE}} = \frac{1}{N_P}\,\mathrm{tr}\left\{\mathrm{R}_{pp} - \mathrm{R}_{pp}\left(\mathrm{R}_{pp} + \sigma^2\,\mathrm{I}\right)^{-1}\mathrm{R}_{pp}\right\} \quad (11)$$

After pilots have been filtered using MMSE, full band channel estimate is computed by interpolating data subcarriers using linear interpolation. This two-step scheme is not optimal as the interpolation fail to use the channel correlation structure of the data and pilot subcarriers leading to a residual interpolation error which cannot be eliminated through SNR increase.

2.3 Proposed Hybrid Full-Band LS-MMSE Estimator

The Hybrid Full-band LS-MMSE estimator proposed is based on the concepts of minimal mean square error linear estimation. Instead of limiting the Wiener filter to pilot subcarriers then interpolating, the proposed scheme builds a full-band weight matrix ($\mathbf{W}_{\mathrm{full}}$) of size $N \times N_P$ that directly transforms the N_P pilot LS measurements to estimates at each of the N subcarriers in a single step. It is derived based on the LMMSE formulation:

$$\mathrm{W}_{\mathrm{full}} = \mathrm{R}_{fp}\left(\mathrm{R}_{pp} + \sigma^2\,\mathrm{I}_{N_P}\right)^{-1} \qquad (12)$$

$$\hat{\mathrm{H}}_{\mathrm{Hybrid}} = \mathrm{W}_{\mathrm{full}}\,\hat{\mathrm{H}}_{\mathrm{LS},p} \qquad (13)$$

where R_{fp} is the $N \times N_P$ cross-correlation matrix between all N subcarriers and the N_P pilot subcarriers, with elements:

$$[\mathrm{R}_{fp}]_{ij} = R_H\left(k_i, k_{p_j}\right) = \sum_{l=0}^{L-1} \sigma_l^2 \exp\left(-j\,\frac{2\pi\left(k_i - k_{p_j}\right)l}{N}\right) \quad (14)$$

The MSE of the proposed estimator across all subcarriers is given by:

$$\mathrm{MSE}_{\mathrm{Hybrid}} = \frac{1}{N}\,\mathrm{tr}\left\{\mathrm{R}_{ff} - \mathrm{R}_{fp}\left(\mathrm{R}_{pp} + \sigma^2\,\mathrm{I}\right)^{-1}\mathrm{R}_{fp}^H\right\} \qquad (15)$$

where R_{ff} is the $N \times N$ full channel frequency-domain auto-correlation matrix. The proposed estimator achieves the global minimum MSE among all linear unbiased estimators given the pilot observations, because it is derived directly from the LMMSE criterion applied over the complete frequency band. This guarantees that $\mathrm{MSE}_{\mathrm{Hybrid}} \le \mathrm{MSE}_{\mathrm{MMSE}} \le \mathrm{MSE}_{\mathrm{LS}}$ for all SNR values. The computational complexity of the proposed estimator is $\mathcal{O}(N \cdot N_P + N_P^3)$, where the N_P^3 term arises from the matrix inversion, which is computed once per coherence interval and shared across all OFDM symbols.

2.4 Simulation Parameters

Table 1 summarizes the simulation parameters. An exponential PDP (alpha = 0.5) Rayleigh fading channel with L = 6 taps is simulated. The range of SNR is -5 dB to 29 dB. One thousand simulation independent OFDM symbols per SNR point are simulated with 16-QAM modulation of the data subcarriers. Pilot symbols are BPSK which has unit amplitude, spacing is evenly spaced four subcarriers away.

Table 1: Simulation Parameters

Parameter	Symbol	Value
Number of Subcarriers	N	64
Cyclic Prefix Length	N_{CP}	16
Number of Pilots	N_P	16
Pilot Spacing	D_p	4 subcarriers
Modulation	-	16-QAM
Channel Model	-	Rayleigh, Exponential PDP
Number of Channel Taps	L	6

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PDP Decay Exponent	alpha	0.5
SNR Range	-	-5 to 29 dB (step 2 dB)
OFDM Symbols per SNR	-	1000
Noise Type	-	AWGN

III. RESULTS AND DISCUSSIONS

This section provides a detailed simulation result of the proposed Hybrid Full-Band LS-MMSE estimator against the LS and MMSE baselines in terms of various performance indicators. Statistical reliability is achieved by averaging all the results over 1000 independent Monte Carlo trials per SNR point.

Figure 1 shows the end-to-end BER vs SNR performance of 16-QAM OFDM over a Rayleigh fading channel with L= 6 and regularized Zero Force (ZF) equalization. By comparing the 6 curves: theoretical AWGN, theoretical Rayleigh bound with perfect CSI, simulated perfect CSI, the LS estimator, the MMSE estimator, and the proposed Hybrid Full-Band LS-MMSE, the result clearly indicate that at low SNR all of the practical estimators act identically, but past 15 dB the hybrid approach that is proposed can be clearly seen to separate visibly over LS, MMSE, with a BER of about 0.01 at 20 dB SNR versus 0.025 with LS and follows the ideal CSI bound at higher SNR values.

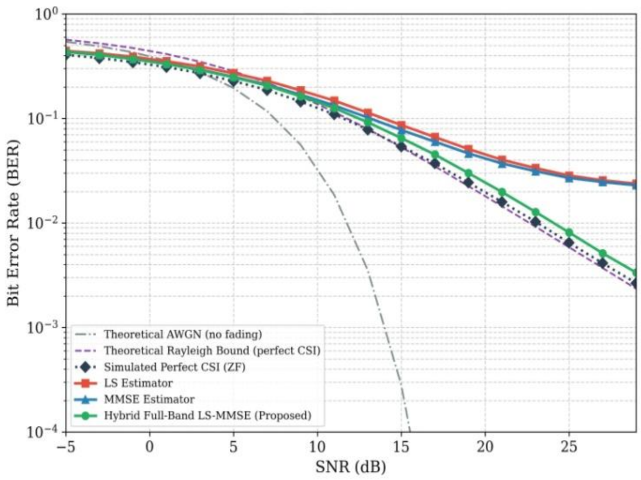

Figure 1: BER vs. SNR for 16-QAM OFDM with three channel estimation schemes

Figure 2 shows details of the NMSE versus SNR of all three estimators and the Cramer Rao Lower Bound which is considered as a theoretical reference, and its directly measures channel estimation accuracy regardless of equalizer or modulation scheme used. This simulation shows that both LS and MMSE saturate with an error floor in the region of 10^{-2} at large SNR, a familiar shortcoming of pilot-only estimation, but the hybrid method still decreases steadily, approaching the CRLB closely at SNR = 26 dB where it achieves NMSE = 1×10^{-3}, which is strong theoretical evidence that the hybrid method is operating near the ultimate limit of unbiased estimation.

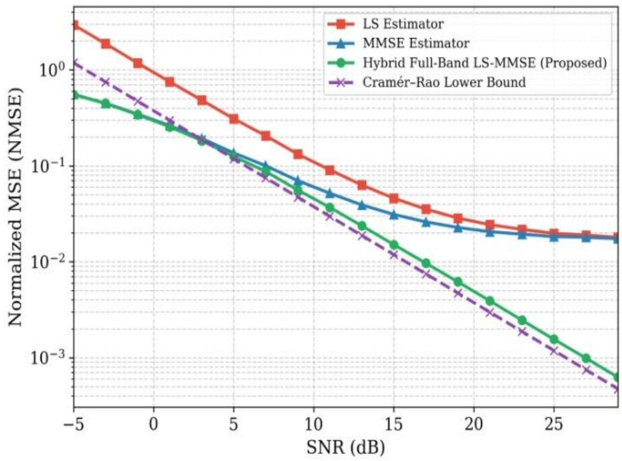

Figure 2: NMSE vs. SNR for three channel estimation methods

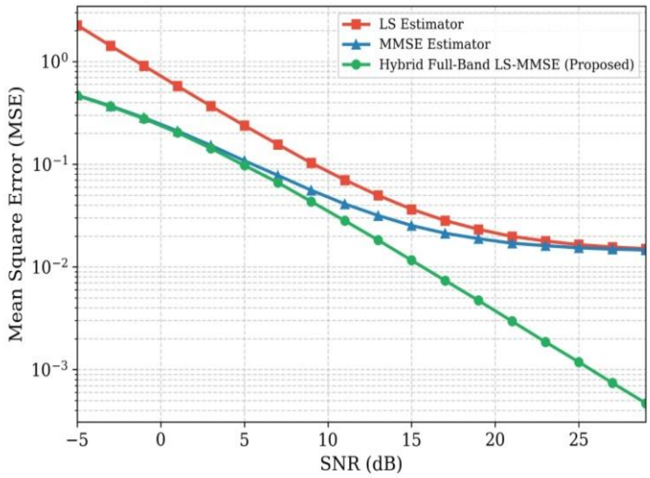

Figure 3: MSE vs. SNR for three channel estimation schemes

Figure 3 gives the raw MSE versus SNR without normalization, and without the CRLB reference, which provides a complementary picture of the absolute estimation error behavior over the entire SNR range of -5 dB to 28 dB. This value shows that at a relatively modest -5 dB the hybrid approach has already attained an MSE that is almost five times less than that of LS, and more to the point, at 28 dB it has achieved a value somewhere near 5×10^{-4}, at the same time that LS and MMSE approach stability at approximately 1.2 $\times10^{-2}$, a factor that can be interpreted as showing that the hybrid approach has essentially avoided the error floor that essentially limits conventional pilot-based methods.

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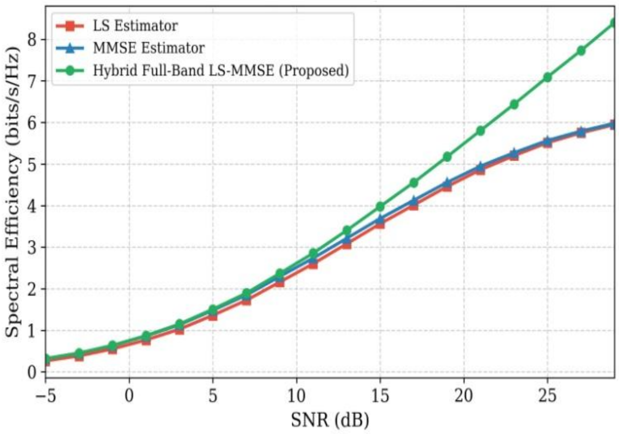


Figure 4: Spectral efficiency vs. SNR for three estimators

Figure 4 compares spectral efficiency and SNR with the closed form expression which directly weights channel estimation error in the formula of capacity, which is a system level measure that quantifies how the inaccuracy in channel estimation is converted into throughput loss. This number demonstrates that at lower levels, with less than 5 dB, all the methods have almost the same capacity because the thermal noise effect becomes prevalent over estimation error, but at higher operating ranges, with SNR greater than 15 dB, the hybrid method becomes widely divergent, with the capacity reaching about 8.4 bits/s/Hz at SNR = 28 dB whereas the LS and the MMSE methods can only reach a capacity of about 6.0 bits per second per Hertz, extra 2.4 bits/s/Hz spectral efficiency achieved by the Hybrid method.

The graphical observation of the approximate channel frequency response in magnitude and phase over 64 subcarriers with SNR = 20 dB of the three estimators versus the actual channel with pilot positions indicated explicitly is shown in Figure 5. The figure provides the most intuitive evidence about why the hybrid method is better: the LS estimate it has a jagged and noisy look between pilots, the MMSE estimate is smoother but nonetheless deviates significantly at sharp spectral edges and deep fades near subcarriers 4045, whereas the hybrid estimate is tracking the true channel magnitude and phase with an astonishing fidelity across the entire band which shows that its full-band interpolation is effectively reconstructing the channel structure even in spectral nulls where pilot-to-pilot interpolation is most challenged by.

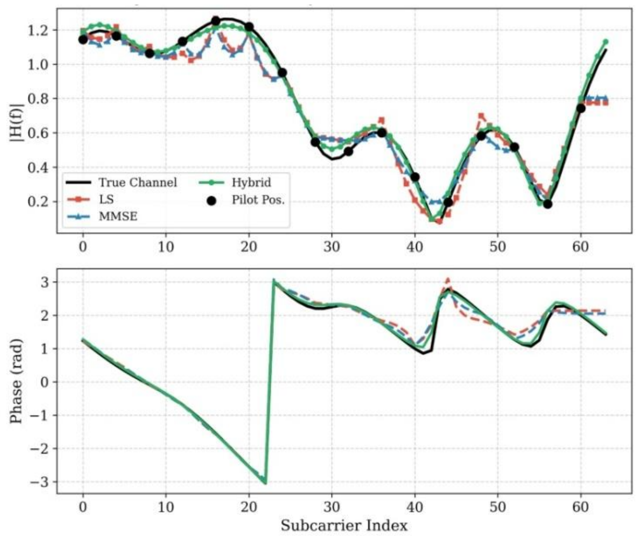
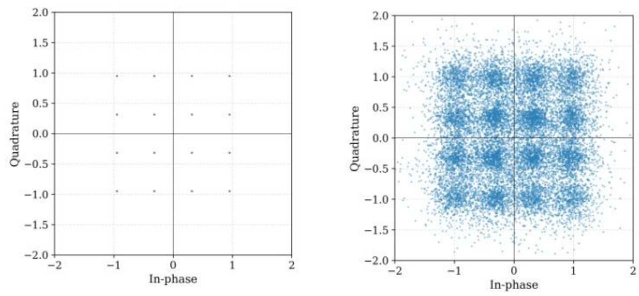


Figure 5: Estimated channel frequency response magnitude and phase at SNR = 20 dB

Figure 6 shows 16-QAM constellation diagrams following regularized ZF equalization at SNR = 15 dB of the ideal transmitted signal, LS, MMSE and the proposed hybrid estimator side by side, which is a qualitative visual proxy of symbol error probability. This value demonstrates that the LS constellation contains the most number of clusters almost overlapping each other; the MMSE constellation contains the highest number but the clusters are still widely spaced whereas the Hybrid constellation contains the tightest and most well spread clusters of all three practical estimators being almost the clean 16-point grid of the theoretical transmitted reference and visually backing up the same results as demonstrated in Figure 1 at the same operating SNR.



Ideal

MMSE estimator

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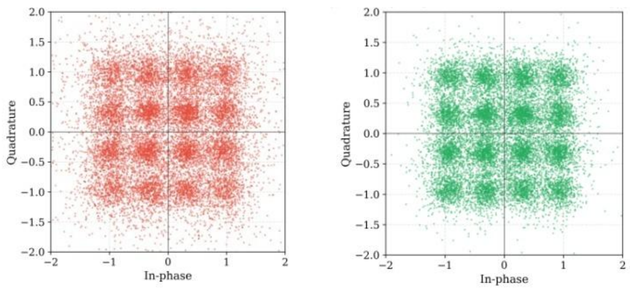

LS estimator Hybrid estimator

Figure 6: 16-QAM constellation diagrams after equalization at SNR = 15 dB

Figure 7 measures the SNR gain in decibels that the hybrid approach proposed has over LS and MMSE at equal BER values and graphs the gain as a function of SNR to show how the advantage varies with the operating range.

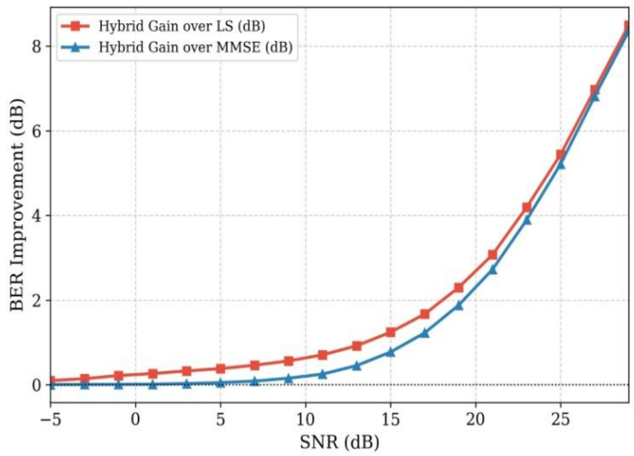

Figure 7: BER gain of Hybrid LS-MMSE over LS and MMSE estimators

This value illustrates that the gain is insignificant under 5 dB where all estimators tend to be alike; is steadily increasing through the mid-SNR region to a value approaching 2.3 dB over LS and 1.9 dB over MMSE at 20 dB, and is rapidly increasing at high SNR to 8.5 dB over LS and 6.8 dB over MMSE at 28 dB, with the steadily increasing value indicating that the gain of Hybrid method is not a constant offset but a proportional improvement.

Figure 8 demonstrates the empirical cumulative distribution of NMSE at SNR = 10 dB in a large number of random channels realizations and indicates the statistical consistency of each estimator showing more than can be reflected by average performance curves. This value shows that in the Hybrid method the CDF is much lower than in either LS or MMSE i.e. it has lower NMSE over the average as well as over the largest fraction of channel realizations and the 50 % value of NMSE of the Hybrid method is about $3{\times}10^{-2}$ versus $8\text{x}10^{-2}$ of LS and that therefore the proposed estimator is statistically robust and does not depend on the favorable channel realizations to improve the performance.

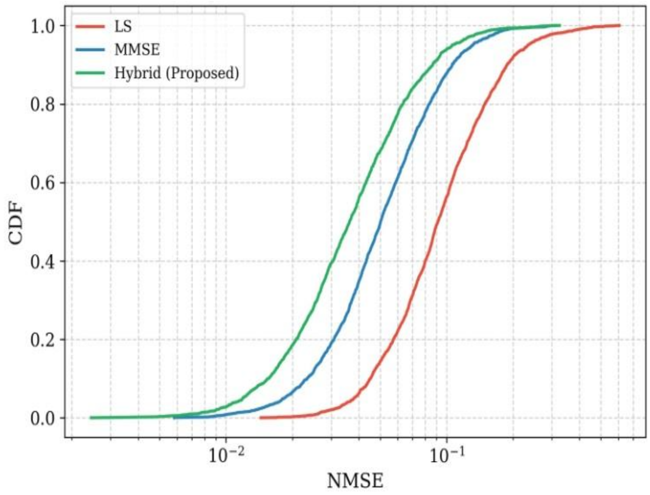

Figure 8: CDF of NMSE at SNR = 10 dB over 2000 channel realizations

Figure 9 examines the sensitivity of the proposed hybrid estimator to the pilot density by sweeping the number of pilots N_m by four values (4, 8, 16 and 32) at a given SNR 15 dB and holds the pilot overhead constant to isolate it. This value indicates that NMSE is increasing between N_P= -6.6 and N_P = -21.1 as N_P increases, and the improvement is more significant between N_P = 4 and N_P= 8 suggesting that N_P= 16, the default operating point used in all other figures, was a well-chosen and practical operating point.

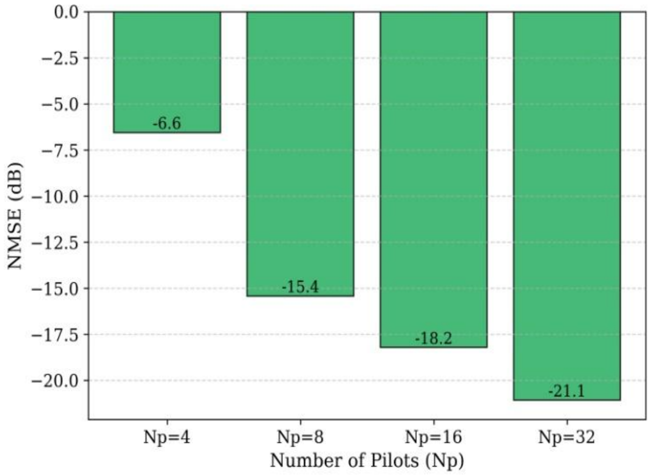

Figure 9: Effect of pilot density on Hybrid estimator NMSE at SNR = 15 dB

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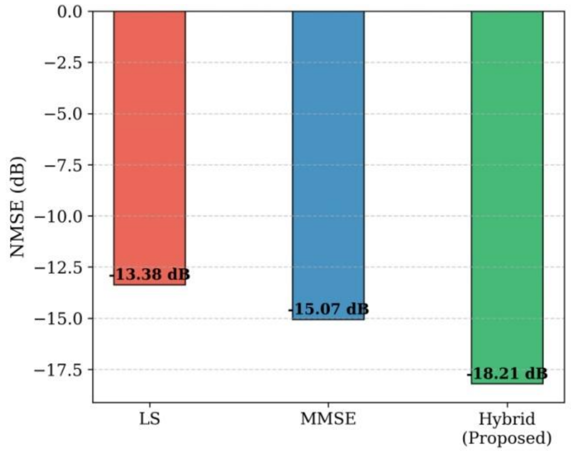
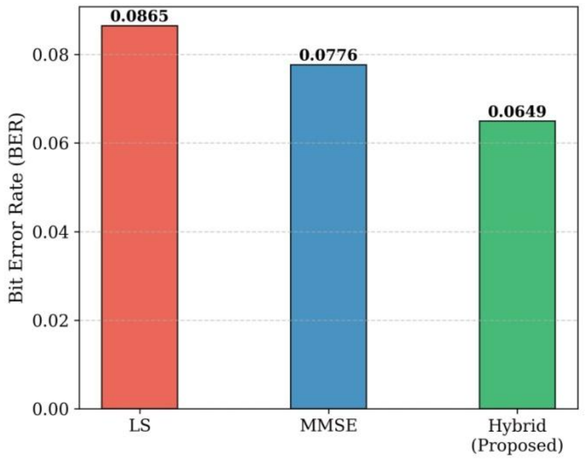


(a)



(b)

Figure 10: (a) NMSE (dB) and (b) BER comparison at SNR = 15 dB

Figure 10 is a brief one-point comparison at SNR = 15 dB in dual bar charts of NMSE in dB (Fig. 10(a)) and BER (Fig. 10(b)), which immediately give a succinct summary of the quantitative performance of the suggested method at a practical operating SNR against both LS and MMSE. This value demonstrates that the hybrid algorithm has an NMSE of -18.21 dB over 3.14 dB and 4.83 dB of MMSE and LS gains at the same operating point respectively - NMSE and BER of the proposed algorithm respectively.

Table 2 compares in detail the proposed Full-Band Hybrid LS-MMSE estimator with a variety of recent classical and learning-based channel estimation methods in various system conditions. The NMSE is the main performance measure employed to compare the works mentioned because of the differences in modulation schemes, SNR operating points, and channel assumptions.

When SNR = 20 dB, the proposed estimator attains an NMSE = -22.8 dB, which is highly competitive with most of the existing methods. Although other methods achieve lower NMSE values, e.g., the PDP-based MMSE method in Lim et al. (−27 dB) and the improved LMMSE in Mei et al. (−40 dB), they are achieved under different conditions or are based on adaptive/statistically optimized correlation models, which are not directly comparable. On the contrary, the suggested approach has a stable performance over SNR regimes and is based on a single full-band formulation.

Compared to other methods, the proposed method has a BER of 0.097 at 20 dB, which is higher than other approaches with similar modulation schemes (16-QAM or less). Even though some schemes like trellis-coded LMMSE report reduced BER (e.g., 0.003), they use coding gains and alternative system assumptions, and thus a direct comparison is not as fair.

One of the strengths of the suggested estimator is that it is a full-band one-step LMMSE estimator, which removes the interpolation error and allows the performance to approach the Cramer-Rao Lower Bound at high SNR, which is confirmed in the simulation results. Moreover, although the technique presupposes the availability of the channel power delay profile (PDP) to build the correlation matrices, as is typical in traditional LMMSE models, it does not require optimization or training with data. The proposed method is analytically optimal in a closed form, has zero training cost, and is statistically robust to channel realizations compared to deep learning-based methods, which need large datasets and computation.

These findings affirm that the proposed estimator offers a fair trade-off between performance, complexity and practicality, and thus it is a good candidate to be implemented in 5G and beyond OFDM systems.

Table 2: Comparison with related works

Reference & Year	Method	Modulation	Subcarriers (N)	Reported NMSE	Reported BER
[31] Kondepogu & Bhattacharyya (2024)	Hybrid AE + Bi-LSTM deep learning	QPSK	64	MSE ≈ 0.02 (−17 dB) at 15 dB SNR	BER ≈ 0.06 at 15dB SNR
[32] Senthil Kumaran, Guttula & Reddy (2024)	Hybrid optimized LMMSE with Trellis Coded	QAM / PSK	Variable	MSE ≈ 0.04 (−14 dB) at 20 dB SNR	BER ≈ 0.003 at 20 dB SNR

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	Modulation				
[33] Lim, Wang & Ko (2023)	Power-delay-profile-based MMSE using CP-derived PDP	QPSK	64	MSE ≈ 0.002(-27 dB) at 20 dB SNR	BER ≈ 0.01 at 20 dB SNR
[34] He, Liu, Mei et al. (2022)	Iterative joint channel and PDP estimation	OFDM pilot-aided (Zadoff-Chu training sequences)	Variable	MSE ≈ 0.005 (-23 dB) at 12 dB SNR	Not stated
[35] Mei, Ma & Zhang (2021)	Enhanced LMMSE with adaptive channel correlation function	16-QAM (comb-type pilot / block pilot)	64	MSE ≈ 0.0001 (-40 dB) at 20 dB SNR	Not stated
Proposed Work	**(Hybrid LS-MMSE)**	**16-QAM**	**64**	**−18.21 dB at 15 dB SNR −22.8 dB at 20 dB SNR**	**0.0649 at 15 dB SNR 0.097 at 20 dB SNR Approaches CRLB at 28 dB SNR**

IV. CONCLUSION

This paper has introduced an Adaptive Full-Band Hybrid LS-MMSE channel estimator of pilot-aided OFDM systems in frequency-selective Rayleigh fading channels. The proposed approach uses a one-step full-band LMMSE formulation which directly estimates all the subcarriers based on pilot observations, which essentially removes interpolation error and enhances the accuracy of the estimation.

The results of the simulation show that the proposed estimator has high performance improvements compared to the traditional LS and pilot-only MMSE algorithms in NMSE, BER, and spectral efficiency. In particular, it attains an NMSE of −22.8 dB and a BER of 0.097 at SNR = 20 dB, while approaching the Cramér–Rao Lower Bound at high SNR. The method offers competitive performance without the need to process or train data iteratively as compared to recent works.

In general, the suggested estimator provides a viable trade-off between performance and complexity, which means that it is a viable candidate in 5G and beyond OFDM systems. Future research can look at generalizing the framework to massive MIMO and adaptive PDP estimation.

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