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Improved Minimum Variance Channel Estimation Techniques for OFDM Systems

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ABSTRACT

Orthogonal frequency division multiplexing (OFDM) systems face challenges in channel estimation due to noise, variability, and the doubly dispersive nature of wireless channels, which degrade performance. To address these challenges, a multichannel minimum variance double dispersive channel estimator is proposed. The method employs a hybrid approach that combines subspace and minimum variance techniques, optimizing the filter bank output power under a signal-to-noise ratio (SNR) constraint. This design preserves the desired signal while effectively suppressing disturbances, achieving robust performance with reduced computational complexity compared to existing methods. Simulation results demonstrate that the proposed estimator outperforms subspace and asymptotic methods in terms of normalized mean square error (NMSE) and bit error rate (BER), particularly under low SNR and frequency-selective conditions. These findings highlight its potential for enhancing spectral efficiency and data integrity in advanced OFDM-based communication systems..

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INTRODUCTION

Multicarrier modulation is considered a promising technique for broadband wireless networks(H. Liu & Li, 2005). The most representative multicarrier technology is orthogonal frequency division multiplexing (OFDM) which has been widely used in wireless communications such as wireless LAN and digital video broadcasting - terrestrial (DVB-T) (D. Liu *et. al.*, 2022) . The third-generation partnership project (3GPP) launched 5G (fifth-generation mobile technology), a new standard for cellular networks in 2018 to replace the previous standards of 3G, 4G and 4G LTE (Jin *et. al.*, 2023). Its goal was to define a new set of standards for devices and applications compatible with 5G networks. Like its predecessors, 5G uses radio waves to transmit data (Sarwar *et. al.*, 2023). However, because of improvements in latency, throughput and bandwidth, 5G networks can reach much faster download and upload speeds, giving it a much wider range of applications (Chen *et. al.*, 2023). 5G release 17 achieves theoretical data rates for downlink (DL) and uplink (UL) of up to 100 Gbps and 1 Gbps respectively (Boodai *et. al.*, 2023). OFDM is used in DL and UL because of its ability to suppress frequency and time selectivity of the channel (Ji *et. al.*, 2018). The basic idea of OFDM is to split high-speed data to low-speed parallel channels. It is a well-known multiplexing and modulation scheme that has been widely employed in wireless broadband systems in the previous decade to combat frequency-selective type fading in wireless channels(Rani & Singal, 2023). For coherent detection, the channel state information (CSI) of the underlying frequency-selective channel has to be estimated at the receiver. Channel estimates may be obtained by exploiting training symbols (Manasa & Venugopal P, 2022), or by blind schemes (Hussein *et. al*., 2023). A popular class of blind channel estimators for OFDM systems are subspace schemes that were considered in several studies (Alayyan *et. al*., 2009; Amleh & Li, 2008; García-Naya *et. al*., 2017; Li, 2003; Rani & Singal, 2023; Tang, 2023). It is well known that OFDM systems are sensitive to various interference (Shafin *et. al*., 2018) . When the covariance of the interference can be reliably estimated at the receiver, pre-whitening can be invoked before applying subspace channel estimation(Wang et al., 2018). However, when there is insufficient information about the interference so that pre-whitening cannot be performed, subspace channel estimation is in general inaccurate(Mehrabani *et. al*., 2023).

To maximize the performance of OFDM systems reliable identification and equalization of doubly dispersive channel is desired(Šimko et al., 2010). Currently the channel identification and equalization techniques used require a major fraction of the channel capacity to send training sequences over channels(Puja Astawa et al., 2021). There are however practical situations where it is not feasible to utilize a training sequence. In fast varying channels (Alayyan *et. al*., 2009) it is extremely difficult to use training sequences to identify and equalize the channel (Neinavaie & Kassas, 2023) . Using blind channel identification techniques, the OFDM receiver can identify the doubly dispersive channel characteristics and equalize it, all based on the received signal and no training sequences needed. This saves the channel capacity by increasing bandwidth efficiency.

Blind identification and equalization of channels for OFDM systems have been a very attractive area of research during the past decade(Alayyan *et. al*., 2009; Amleh & Li, 2008; Du et al., 2012; Mehrabani *et. al*., 2023; Vilas Boas *et. al*., 2022; Wang et al., 2018) and references therein. The known algorithms are mostly based on second order statistics (SOS) due to their spectral properties (Mehrabani *et. al*., 2023). Subspace (SB) based algorithms are the subset of the SOS algorithm using the Multiple Signal Classification (MUSIC) concept to a relation between the channel impulse responses and the noise subspace associated with covariance matrix of the system output (Zhu *et. al*., 2023). SB methods enjoy their deterministic property, where the channel parameters can be recovered perfectly in the absence of noise, using only a finite set of data samples, without any statistical assumptions over the input data. The use of the SB-based method has been suggested in (Yang *et. al*., 2020) to accomplish blind MIMO channel identification in OFDM systems. In (Alayyan *et. al*., 2009) an improved subspace method is presented using minimum noise subspace (MNS) decomposition concept. The work in (Kawasaki & Matsumura, 2022) proposes semi-blind channel estimation method for orthogonal precoded OFDM. The proposed method can be applied regardless of radio frequency. However, the pilot symbols degrade throughput performance in highly changing channels. Despite their high identification efficiency, SB-based method can also be computationally very intensive, which may be unrealistic or too costly to implement in real time, especially for large sensor array systems (Zhang *et. al*., 2023).

In this paper an improved multichannel minimum variance algorithm is presented for channel estimation. The channel estimation is obtained by designing an equalizing filter bank that preserves the desired signal components and suppressing the overall disturbances. The channel estimate is obtained by directly maximizing the filter bank output power through a combination of subspace and minimum variance method by lower bounding the filter bank output power in terms of signal to noise power ratio (SNR). Therefore, the method is the hybrid of the subspace and asymptotic lower bound (SNR) of filter bank output power. The contributions include analysis of the proposed improved minimum variance blind channel estimation in OFDM systems. This method exploits the statistical properties of the received signal and redundancy in the transmitted signal to track and estimate the channel. As the blind channel estimation technique, it eliminates the need for dedicated pilot symbols or tones, leading to more efficient use of bandwidth. This reduction in overhead allows for higher data rates and increased robustness against channel impairments without sacrificing spectral efficiency. An added advantage of the proposed hybrid method is its potential to enhance privacy and security in communication systems using OFDM technology by reducing the reliance on pilot symbols, thereby minimizing the exposure of signaling information. Detailed mathematical analysis is given to show how the subspace and asymptotic techniques are combined to obtain the proposed hybrid method. A comparison of existing algorithms is done, to obtain the channel estimation capability in error rate performance. The error rate performance is assessed in terms of bit mean squared error to noise power ratio. These results are obtained using simulation platform, MATLAB®. To test for the performance of the hybrid method AWGN and double dispersive wireless channel environments are used. The channel models used are from (Ling & Proakis, 2017) and (Mattera *et. al.*, 2021) for AWGN and double dispersive channel respectively. The selected channel models, derived from (Ling & Proakis, 2017) and (Mattera *et. al.*, 2021), are widely recognized for their accuracy in representing AWGN and doubly dispersive channel characteristics, making them suitable benchmarks for evaluating the robustness and practical applicability of the proposed estimator.

MATERIALS AND METHODS

OFDM System Model

Considering the simplified block diagram of a general multicarrier system in Figure 1; the information symbols $a(n)$ are first serial to parallel (S/P) converted to N x 1 vectors $a(i) \triangleq [a(iN)\ a(iN+1)\ ...\ a(iN+N-1)]^T$. N is usually the number of subcarriers used or the FFT matrix size and $i \in 0,1,2,3,\dots N-1$. These vectors are modulated by J x 1 matrix $\mathbf{F}$. $\mathbf{F} = [\bar{\mathbf{F}}_1{}^{\mathrm{T}},\ \bar{\mathbf{F}}^{\mathrm{T}}]^{\mathrm{T}}$, where $\bar{\mathrm{F}}$ is the N x N Inverse Fast Fourier Transform (IFFT) matrix with entries $[\bar{\mathbf{F}}]_{k,l} \triangleq \mathrm{N}^{-1/2}\exp\,(j2\pi(k-1)(l-1))$ for k row and l column. $\bar{\mathbf{F}}_1$ is the J-N x N matrix formed from the last J-N rows of $\bar{\mathbf{F}}$. J is chosen to avoid multipath – induced inter symbol interference (ISI) i.e. $\mathrm{J} \geq \mathrm{N} + \mathrm{L}$ and L is the channel length.

Technically the block with function **F** performs the IFFT and cyclic prefix (CP) insertion automatically i.e. $s(i) = \mathbf{F}a(i)$. These data symbols (blocks), $s(i)$, are then parallel to serial (P/S) converted and sent through a doubly dispersive channel with impulse response h(n). At the receiver the received samples $y(n)$ are S/P converted to J x 1 vectors $y(i) \triangleq [y(iJ)\ y(iJ+1)\ ...\ y(iJ+J-1)]^T$ and then equalized by the J x N matrix $\mathbf{G}$ to form $\hat{a}(i) = \mathbf{G}^H y(i)$.

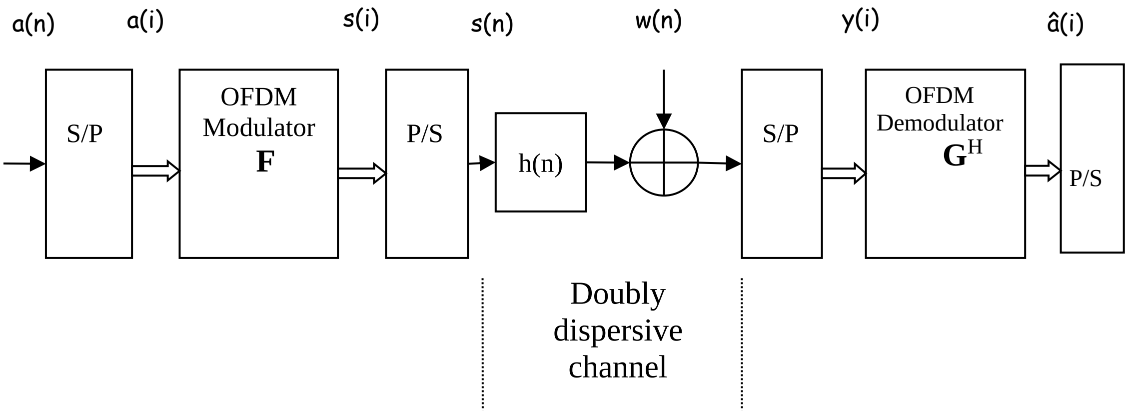

Figure 1: Baseband discrete time model of a general multicarrier system.

Effectively the block with function **G** performs the CP removal and FFT (Fast Fourier Transform) on the received signal vector. An alternative method to counter for ISI is to use zero padding (ZP) (Rebouh et al., 2023), which amount to choosing $\mathbf{F} \triangleq [\bar{\mathbf{F}}^{\mathrm{T}}, \mathbf{O}_{(\mathrm{J-N})\mathrm{x\,N}}{}^{\mathrm{T}}]^{\mathrm{T}}$ where $\mathbf{O}_{(\mathrm{J-N})\mathrm{x\,N}}$ is an all zero J-N x N matrix. It is shown in (Ali *et. al.*, 2004) that ZP guarantees symbol recovery irrespective of the zero locations. Using CP transmission, the received vector $y(i)$ is given as:

$$y(i) = \mathbf{H}\bar{\mathbf{F}}\mathrm{s(i)} + \mathrm{w(i)} \qquad (1)$$

where **H** is the J x N Toeplitz channel matrix with first column $[h(0)\ h(1)\ \ldots h(L)\ \mathbf{O}_{1\mathrm{x}\,(\mathrm{J-L-1})}]^T$ and first row $[h(0)\,, \mathbf{O}_{1\mathrm{x}\,(\mathrm{N-1})}]$ and $w(i)$ is the additive white Gaussian noise with zero mean and unit variance i.e. $\sigma_w{}^2 = 1$. The problem is to estimate the channel coefficients $\{h(n)\}_{n=0}^{L}$ from the measurements $\{y(n)\}$ only without any prior information of the transmitted symbols.

Minimum Variance Algorithm

Using the multichannel minimum variance principle an equalizing filter bank of **N** finite impulse response filters $\mathbf{G}_{\mathbf{J\,x\,N}}$ is designed. These filters are of unity gain passing only the frequency of interest f_k, $i \in 0, 1, 2, \ \ . \ . \ . \ , N-1$ and completely annihilate the other **N-1** interfering symbols. By using multichannel minimum variance principle, a bank of band pass filters $g_i(n)$ is designed as shown in Figure 2, with center frequency ω_i so that each filter rejects the maximum amount of out-of-bound power while passing the signal component at frequency ω_i with no distortions. The filter bank is represented by $\mathbf{G} \in \mathbb{C}^{\mathrm{J\,x\,N}}$ matrix as:

$$\mathbf{G} = [g_1(n)\ \ g_2(n)\ \ \ldots\ \ g_N(n)] \qquad (2)$$

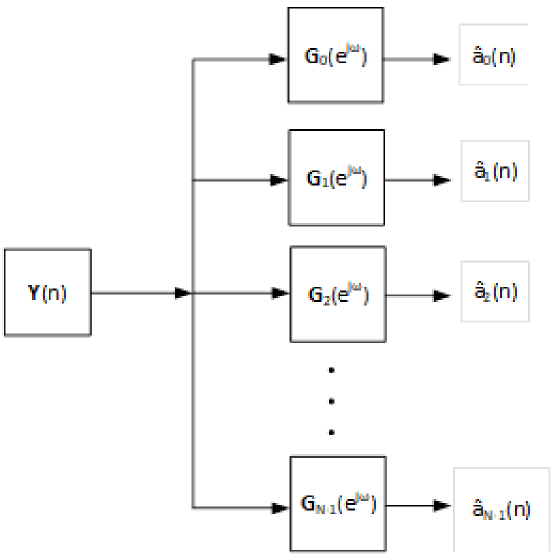

Figure 2: Bank of band pass filter with minimum variance output.

where $g_i(n)$, $n \in 1, 2, 3, \ldots\ \ \mathrm{J}$, is a J x 1 column vector containing the coefficients of the ideal band pass filter with bandwidth Δ and center frequency ω_i.

The gain of the filters at their center frequencies ω_i is unity.i.e.,

$$|G_i(e^{j\omega})| = \begin{cases} 1, & |\omega - \omega_i| < \Delta/2 \\ 0, & otherwise \end{cases} \quad (3)$$

Then, after $u(n)$ is filtered with $g_i(n)$, the power of the output of the filter i will be

$$E\{|y_i(n)|^2\} = \frac{1}{2\pi}\int_{\omega_i-\Delta/2}^{\omega_i+\Delta/2} P_a(e^{j\omega})d\omega \quad (4)$$

Since $G_i\left(e^{j\omega}\right) = \sum_{n=0}^{J} g_i(n)e^{-jn\omega_i}$, then each filter i can be represented as $G_i(\omega) = \mathrm{g_i}^{\mathrm{H}}\mathbf{e}_{\mathrm{i}}$, for $\mathbf{e}_{\mathrm{i}} = [1 \;\; e^{j\omega_i} \;\; e^{j2\omega_i} \;\; \ldots \;\; e^{j(J-1)\omega_i}]$. Substituting the filter's response into (4), it yields

$$E\{|y_i(n)|^2\} = {g_i}^H R_{aa} g_i \quad (5)$$

where $R_{aa} \triangleq E\{a(i)a(i)^H\}$ is the covariance matrix of input signal.
However, R_{aa} is not known to the receiver, therefore, from (5) it can be estimated as

$$R_{aa} \triangleq E\left\{G^H y(i)y(i)^H G\right\} \approx G^H R_{yy} G \quad (6)$$

For equation (6) to hold, the condition $G^H H\bar{F} = I_N$ must hold and also $GH^H\bar{F}^H = I_N$. Then, the filter output power will be obtained as

$$E\{|y_i(n)|^2\} = {g_i}^H R_{aa} g_i \quad (7)$$

To find the filters g_i that will minimize the ${\sigma_y}^2 = E\{|y_i(n)|^2\}$ the optimization problem can be reduced to

$$g_i = \min_{g_i} \; E\{|y_i(n)|^2\} \quad (8)$$

subject to $g_i\mathbf{e} = 1$

Therefore:

$$g_i = \min_{g_i} \; E\left\{\left|y_i(n)\right|^2\right\} = \frac{1}{\mathbf{e}_i{}^H R_{aa}\mathbf{e}_i} \quad (9)$$

where $g = \frac{{R_{aa}}^{-1}\mathbf{e}}{\mathbf{e}^H {R_{aa}}^{-1}\mathbf{e}}$. Substituting equation (9) into (8) yields

$$G = \min_{G} \; E\{|y(n)|^2\} = \frac{1}{G^H\mathbf{e}{R_{yy}}^{-1}G\mathbf{e}} \text{ subject to } G^H H\bar{F} = I_N \quad (10)$$

The index i is dropped since these estimates are valid for all frequencies. From the computational point of view the minimum variance principle requires inversion of covariance matrix R_{yy} . Then, the quadratic form $G^H\mathbf{e}{R_{yy}}^{-1}G\mathbf{e}$ must be evaluated. The products of $G^H\mathbf{e}_i{}^H$ and $G\mathbf{e}_i$ are directly the IFFT and FFT of the filter bank respectively. In this case $G^H\mathbf{e}_i{}^H = \bar{G}^H$ and $G\mathbf{e}_i = \bar{G}$ will be used to formulate the optimization problem as

$$\min_{G} \; E\{|y(n)|^2\} = \bar{G}^H R_{yy}\bar{G} \quad (11)$$

Solving for the quadratic equation (11) for solution that will minimize (10), is finding $\bar{G}$ that will minimize the sums of the terms along the main diagonal (Gruber & Hayes, 1997). Hence the optimization problem is now presented as:

$$\bar{G} = \arg\min_{\bar{G}} \; tr\left(\bar{G}^H R_{yy}\bar{G}\right) \text{ with condi} = I_N \quad (12)$$

From (Stoica & Randolph, 1997) p. 283 the solution of (12) is given as $\bar{G} = {R_{yy}}^{-1}H\bar{F}(\bar{F}^H H{R_{yy}}^{-1}H\bar{F})^{-1}$. Hence, to minimize the filter bank output power

$${\sigma_y}^2 = tr\left\{\left(H^H {R_{yy}}^{-1}H\right)\right\} \quad (13)$$

It is shown in (Li, 2003) that maximizing ${\sigma_y}^2$ is asymptotically equivalent to

$$\hat{\mathrm{h}} = \arg\min_{\|h\|^2=1} \; tr\left\{H^H {R_{yy}}^{-1}H\right\} \quad (14)$$

However, ${R_{yy}}^{-1}$ is a full rank matrix and hence decomposable using the EVD as follows:

$${R_{yy}}^{-1} = S\Lambda S^H + \sigma^2 WW^H \quad (15)$$

where S is the signal subspace and $W$is the noise subspace. Since the noise subspace is orthogonal to signal subspace (Gruber & Hayes, 1997) and assuming that $N \geq L$, the matrix H is full rank giving

$$W^H H F^H = 0 \qquad (16)$$

The knowledge of the column space of $W^H H F^H = 0$ characterizes H up to a scalar constant because

$$Q_\omega = E\{\omega(n)\omega(n)^H\} = \sigma^2 I_\omega \qquad (17)$$

the autocorrelation of noise samples, is also a full rank matrix. The filter coefficients $\{h(i)\}_{i=0}^{L}$ can be identified from the knowledge of the range of the signal part of the whitened covariance matrix. Then, substituting (15) into (14) yields

$$\hat{h} = \arg \min_{\|h\|^2=1} tr\{H^H(S\Lambda S^H + \sigma^2 W W^H)H\} \qquad (18)$$

but due to (16) the equation (18) becomes:

$$\hat{h} = \arg \min_{\|h\|^2=1} tr\{H^H(S\Lambda S^H)H\} \qquad (19)$$

It is well known (Forney, 1975) that W can be uniquely spanned by basis of N vectors $V_n = [V_{W(1)} \;\; V_{W(2)} \;\; . \;\; . \;\; . \;\; V_{W(N)}]$. Therefore (16) can be represented as

$$V_n{}^H H F^H = h^H E F^H \qquad (20)$$

E is L x N-L block hankel matrix with first column $\left[V_{W(1)}{}^T \;\; V_{W(1)}{}^T \ldots V_{W(L)}{}^T\right]$ and last row $\left[V_{W(L)}{}^T \;\; V_{W(1)}{}^T \ldots V_{W(N)}{}^T\right]$.

Using (20) the optimization problem in (19) can be represented as:

$$\hat{h} = \arg \min_{\|h\|^2=1} tr\{\mathbf{h}^H \mathbf{A}\mathbf{h}\} \qquad (21)$$

where $\mathbf{A} = \mathbf{E}\mathbf{E}^{\mathbf{H}}$.

This quadratic optimization criterion allows unique estimation of **h** up to a scale factor and is thus obtained as the eigenvector associated with the minimum eigenvalue of **E**.

EXPERIMENTAL RESULTS

Parameters Settings

In this section, the parameters for simulation and numerical analysis of the proposed channel estimation algorithm based on the improved minimum variance algorithm are presented. The proposed method is compared with the asymptotic (AS) (Adeogun, 2018) and subspace (SB) (Rekik *et. al.*, 2024) blind channel estimators. Table 1 shows the system and channel experimental conditions based on the 3GPP standard in the numerical experiments.

Table 1: Simulation and numerical experimental conditions

Parameter	Value
OFDM symbol duration	$\frac{1}{30}$ ms
FFT-points N	512
Carrier frequency	2.15GHz
Sampling interval T_s	72 µs
Modulation	QPSK, 64QAM
CP length T_g	$\frac{9}{128}$ T_s
Subcarrier mapping ($\boldsymbol{K \leq N}$)	$-\frac{K}{2}, -\frac{K}{2}+1, \ldots\ldots, \frac{K}{2}-1$
Transmission bandwidth	5 MHz 10 MHz

As a metric of the channel estimation accuracy, the normalized mean square error (NMSE) is choses. The choice of NMSE as a performance metric is based on its ability to provide a normalized and scale-independent measure of the channel estimation accuracy. In this work it is defined as

$$NMSE = E\left\{\frac{\|\hat{h} - h\|^2}{\|h\|^2}\right\} \qquad (22)$$

For simulation, 5000 random symbols are generated and the system utilizes the IDFT transform with QPSK and 64QAM constellations. The channel is simulated as a L+1=51 tap FIR channel and is assumed that the channel taps are independent and identically distributed (i.i.d.) and correlate in time.

Results and Discussion

Figure 3 depicts the comparison between the proposed hybrid method with asymptotic (AS) and subspace (SB) methods presented in references (Adeogun, 2018) and (Rekik et al., 2024) respectively. The comparison is also done with ideal channel for benchmarking where all transmitted OFDM symbols are assumed to be known and used for channel estimation using the cost function in equation (22). Performance parameters in Table 1 are used in this experiment. The figure presents the NMSE against SNR for all the methods considered. Several observations can be drawn from this experiment. Comparing AS and SB methods under AWGN channel, they demonstrate the same estimation performance in low SNR values up to 20dB. Beyond 20dB the AS outperforms SB due to derived bounds which eliminate the need for repeated computation and dependence on channel parameters. However, the proposed hybrid method outperforms the AS and SB methods due to existence of equalizing filter bank that preserves the transmitted signal components by suppressing the overall disturbances. It can be observed that there is an average improvement of 5dB at any given error rate for the proposed method is compared to AS and SB methods. It is also observed that analytical performance coincides with the proposed method's performance, making it visually indistinguishable in Figure 3.

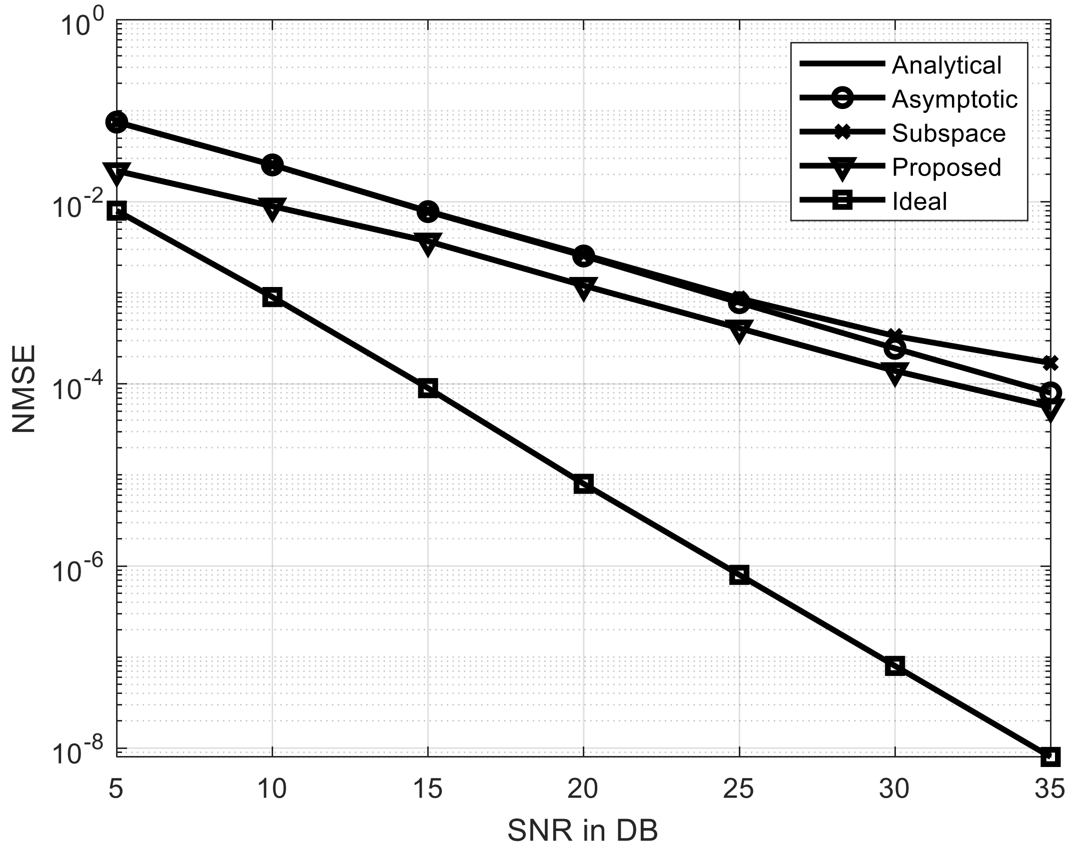

Figure 3: NMSE vs SNR for ideal, analytical, proposed, asymptotic and subspace methods under AWGN channel.

Figure 4 shows the NMSE performance of the proposed system in frequency selective channel. Comparison with existing AS and SB shows improved performance at lower SNR values. Results in Figure 4 shows that there is at least 5dB estimation improvement of the proposed method compared to the existing AS and SB methods. The bit error rate (BER) performance of the OFDM system in an additive white Gaussian noise (AWGN) channel was evaluated for the proposed hybrid method and compared with the Asymptotic (AS) and Subspace (SB) methods as shown in Figure 5. The results demonstrate that the hybrid method achieves a lower BER across a range of SNR levels, highlighting its improved robustness against noise. The hybrid method consistently outperforms the AS and SB methods, particularly at higher SNRs, where the reduction in errors is more significant. In a frequency selective channel, the BER performance of the hybrid method was analyzed and compared with the AS and SB methods as shown in Figure 6. The frequency selective channel introduces multipath fading, which poses additional challenges. The hybrid method shows a marked improvement in BER performance over the AS and SB methods, effectively mitigating the effects of multipath fading. The results indicate that the hybrid method provides better resilience against frequency selectivity, maintaining a lower BER.

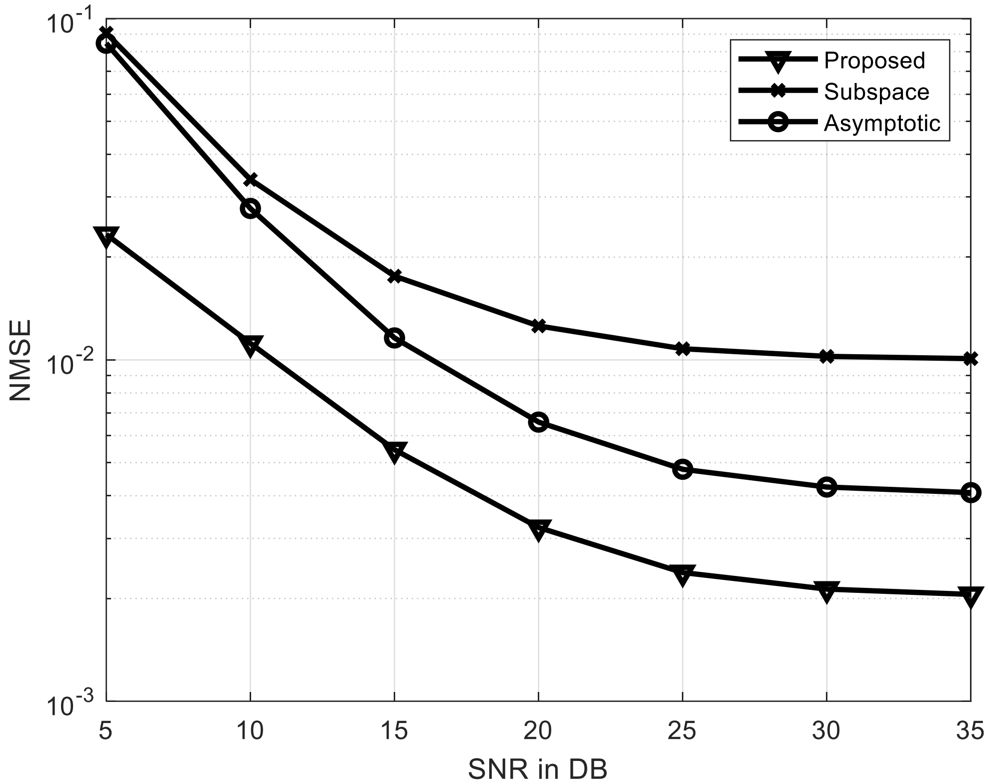

Figure 4: NMSE vs SNR for proposed, asymptotic and subspace methods under frequency selective channel.

The performance of different MIMO configurations was compared using the hybrid method, AS method, and SB method as shown in Figure 7 and Figure 8. The hybrid method demonstrates superior performance across all configurations, offering enhanced diversity and spatial multiplexing gains. The trade-offs between performance and complexity were also considered, with the hybrid method showing a balanced approach that maximizes BER performance while managing complexity. Results show that a 4x4 MIMO system outperforms the 2x2 system in terms of BER, particularly at lower SNRs, where the additional diversity helps in combating fading and noise.

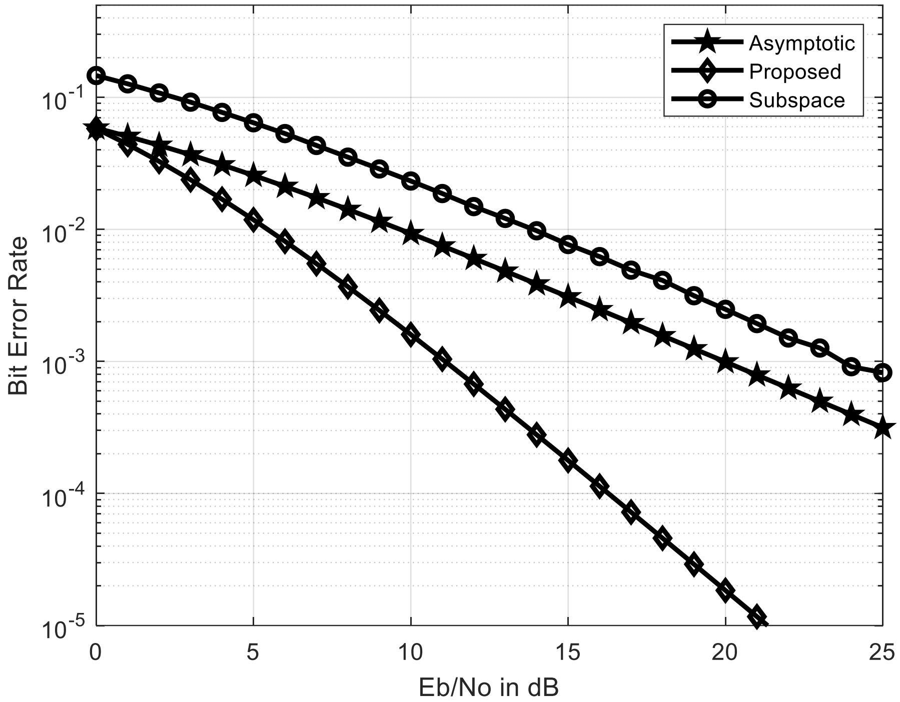

Figure 5: BER vs SNR for proposed, asymptotic and subspace methods under awgn channel.

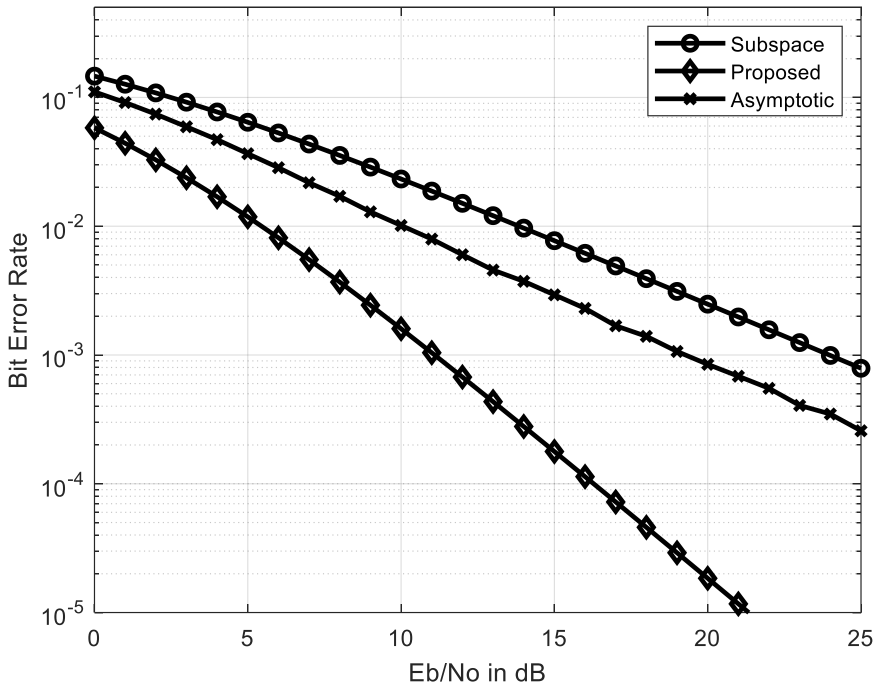

Figure 6: BER vs SNR for proposed, asymptotic and subspace methods under frequency selective channel.

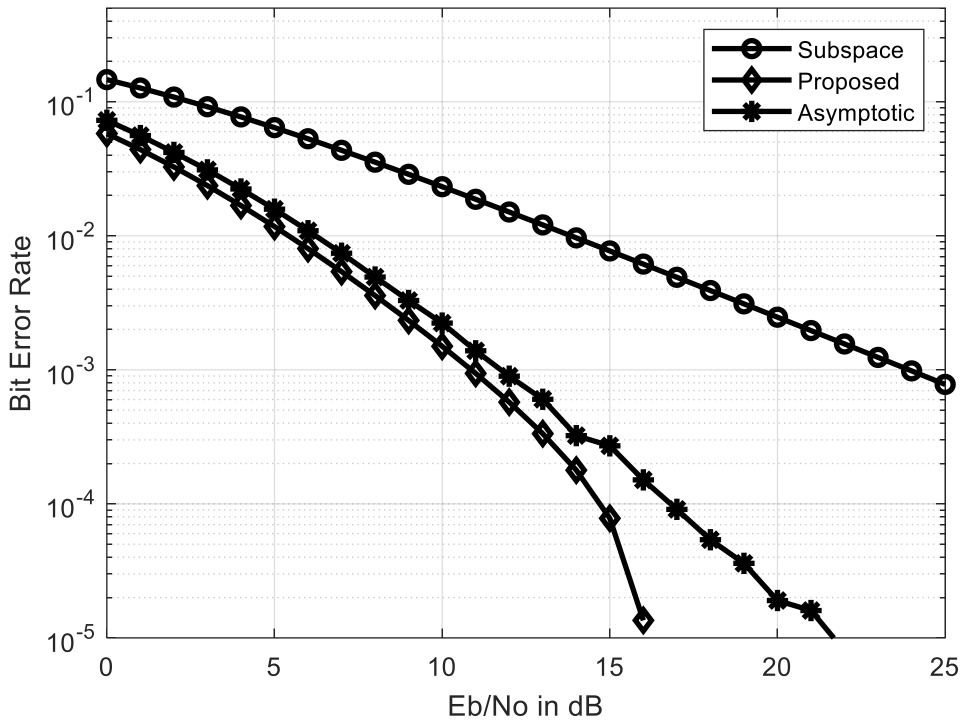

Figure 7: BER vs SNR for Proposed, Asymptotic and Subspace Methods using 2x2 MIMO Configuration.

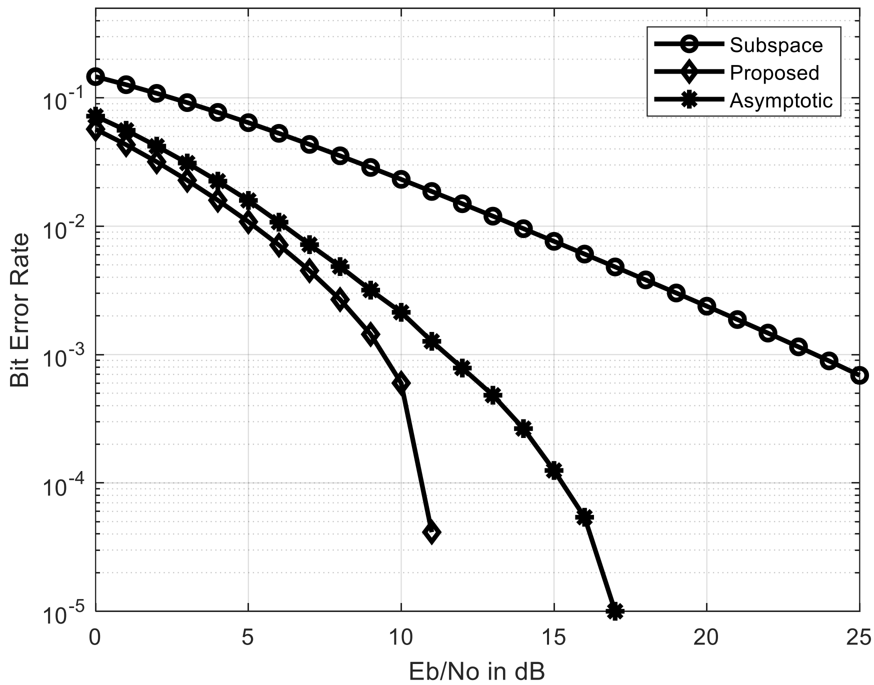

Figure 8: BER vs SNR for proposed, asymptotic and subspace methods using 4x4 MIMO configuration.

For fair comparison between proposed and existing blind channel estimation schemes, the computational complexity is presented in Table 2. The complexity in this study is defined as of the number of multiplications, additions, matrix inversions and computational resources needed to complete each estimation. N_S is the number of symbols, N_{CP} is the CP length, G is the filter bank matrix, E is hankel matrix, N is the number of subcarriers and R^{-1} is the inverse of received signal covariance matrix.

Table 2: Complexity of channel estimators

Method	Complexity	Processing Time [ms]
Subspace (Rekik et al., 2024)	$O(NN_S(N+N_{CP}))*E*R^{-1}$	14.20
Asymptotic (Adeogun, 2018)	$O(N_{CP}N_S(N+N_{CP})*E*R^{-1})$	11.80
Proposed	$O(N_{CP}N_SN)*R^{-1}+O(N)*E*G$	10.02

The processing time is the average estimation time of 10,000 trials in the simulation environment presented in Table 1. As observed in Table 2, the proposed method converges faster than existing methods with low computational complexity. Unlike subspace methods, which require computationally intensive operations such as eigenvalue decomposition and inversion of the covariance matrix R^{-1} , the proposed hybrid method avoids double matrix multiplication by leveraging a simplified filter bank design. This results in reduced computational complexity, making it more efficient for real-time implementation in practical systems.

Channel estimation and equalization are critical for the performance of MIMO OFDM systems. The hybrid method's channel estimation accuracy and equalization effectiveness were compared with the AS and SB methods as shown in Figure 9. The hybrid method provides more accurate channel estimates, resulting in significant BER improvements when Zero Forcing (ZF) equalization was applied in Frequency Selective channel. It is observed that AS method outperform SB as ZF equalization tends to amplify noise, especially in subspace methods leading to degradation in performance. Furthermore, the SB method is more sensitive to inaccuracies in channel estimation, which ZF equalization exacerbates. This sensitivity leads to higher Bit Error Rates (BER). The proposed hybrid and AS methods outperform the SB method under ZF equalization primarily due to their better channel estimation accuracy, robustness to noise, and overall efficiency in processing. The hybrid method's ability to combine the strengths of both AS and SB methods provides an additional edge in performance.

The presented simulation results for the hybrid method, AS method, and SB method have practical implications for real-world MIMO OFDM systems. The hybrid method's ability to maintain low BER in both AWGN and frequency selective channels makes it suitable for various applications, including wireless broadband and 5G networks. The findings guide the design of robust communication systems and highlight the hybrid method's practical advantages over the AS and SB methods

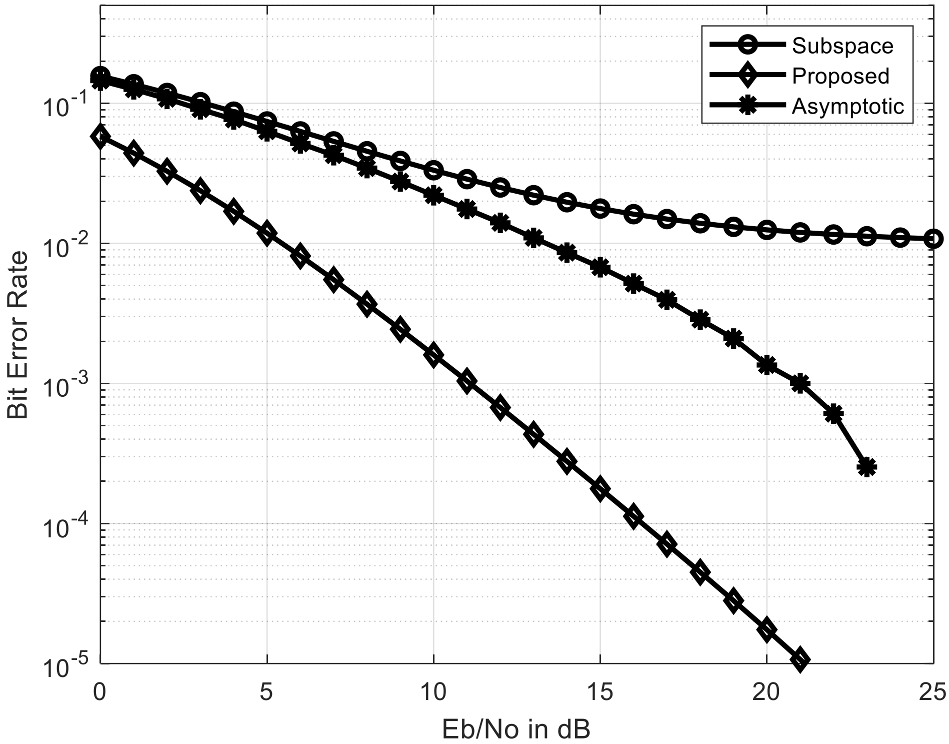

Figure 9: BER vs SNR for zero forcing equalizer under frequency selective channel.

CONCLUSION

In this paper, a minimum variance channel estimator is proposed and compared to other fast fading channel estimators. The estimator used multichannel minimum variance principle by designing an equalizing filter bank that preserved the desired signal components while suppressing the overall disturbances. The channel estimate was obtained by directly maximizing the filter bank output power through a combination of subspace and minimum variance methods by lower bounding the filter bank output power in terms of SNR. So, the method was a hybrid of the subspace and asymptotic lower bound (SNR) of filter bank output power. By integrating the beneficial aspects of AS and SB, the hybrid method is shown to achieve better channel estimation and noise mitigation. The hybrid method adapts to varying channel conditions more effectively, leveraging the advantages of both AS and SB under different scenarios. The hybrid method is observed to be more robust against channel impairments and noise, as it balances the trade-offs that each individual method might face when used alone. Future research can explore further enhancements to the hybrid method, including advanced channel estimation and equalization techniques. Investigating higher-order MIMO configurations and optimizing system parameters for specific applications are promising areas. Integrating emerging technologies such as machine learning for adaptive parameter tuning can provide additional performance gains. Addressing the limitations of the current study, such as the assumption of perfect synchronization, will be crucial for future advancements.

REFERENCES

Adeogun, R. O. (2018). Asymptotic performance bound on estimation and prediction of mobile MIMO-OFDM wireless channels. *IEEE Wireless Communications and Networking Conference, WCNC, 2018-April*. 1-5. doi:10.1109/WCNC.2018.8377005

Alayyan, F. O., Shubair, R. M., Zoubir, A. M., & Leung, Y. H. (2009). Blind channel identification and equalisation in OFDM using subspace-based methods. *Journal of Communications*, **4**(7), 472-484. doi:10.4304/jcm.4.7.

Amleh, K., & Li, H. (2008). Blind-channel estimation and interference suppression for single-carrier and multicarrier block transmission systems. *IEEE Transactions on Vehicular Technology*, **57**(5), 2779 - 2791 . doi:10.1109/TVT.2008.915497

Boodai, J., Alqahtani, A., & Frikha, M. (2023). Review of Physical Layer Security in 5G Wireless Networks. *Applied Sciences (Switzerland)*, **13**(12), 122-129. doi:10.3390/app13127277

Chen, W., Lin, X., Lee, J., Toskala, A., Sun, S., Chiasserini, C. F., & Liu, L. (2023). 5G-Advanced Toward 6G: Past, Present, and Future. *IEEE Journal on Selected Areas in Communications*, **41**(6), 1592 – 1619 doi:10.1109/JSAC.2023.3274037

Du, J., Xiao, P., Wu, J., & Chen, Q. (2012). Design of isotropic orthogonal transform algorithmbased multicarrier systems with blind channel estimation. *IET Communications*, **6**(16), 2695-2704. doi:10.1049/iet-com.2012.0029

Forney, G. D. (1975). Minimal Bases of Rational Vector Spaces, with Applications to Multivariable Linear Systems. *SIAM J Control*, **13**(3), 345 – 357. doi:10.1137/0313029

García-Naya, J. A., Heath, R., Kaltenberger, F., Rupp, M., & Vía, J. (2017). Experimental evaluation in wireless communications. *Eurasip Journal on Wireless Communications and Networking*, **17**(1), 1-3. doi:10.1186/s13638-017-0842-2

Gruber, M. H. J., & Hayes, M. H. (1997). Statistical Digital Signal Processing and Modeling. *Technometrics*, **39**(3), 335-336. doi:10.2307/1271141

Hussein, W., Audah, K., Noordin, N. K., Kraiem, H., Flah, A., Fadlee, M., & Ismail, A. (2023). Least Square Estimation-Based Different Fast Fading Channel Models in MIMO-OFDM Systems. *International Transactions on Electrical Energy Systems*, **2023**(1), 1-23. doi:10.1155/2023/5547634

Ji, H., Park, S., Yeo, J., Kim, Y., Lee, J., & Shim, B. (2018). Ultra-Reliable and Low-Latency Communications in 5G Downlink: Physical Layer Aspects. *IEEE Wireless Communications*, **25**(3), 124-130. doi:10.1109/MWC.2018.1700294

Jin, H., Liu, K., Zhang, M., Zhang, L., Lee, G., Farag, E. N., Zhu, D., Onggosanusi, E., Shafi, M., & Tataria, H. (2023). Massive MIMO Evolution Toward 3GPP Release 18. *IEEE Journal on Selected Areas in Communications*, **41**(6), 1-7. doi:10.1109/JSAC.2023.3273768

Kawasaki, H., & Matsumura, T. (2022). Semi-Blind Channel Estimation by Subspace Method for Orthogonal Precoded OFDM Systems. *2022 IEEE 33rd Annual International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC)*, 451–456. doi:10.1109/PIMRC54779.2022.9977787

Li, H. (2003). Blind channel estimation for multicarrier systems with narrowband interference suppression. *IEEE Communications Letters*, **7**(7), 45-47. doi:10.1109/LCOMM.2003.814030

Ling, F., & Proakis, J. (2017). Synchronization in Digital Communication Systems. In *Synchronization in Digital Communication Systems*. 60-93 doi:10.1017/9781316335444

Liu, D., Luo, Y., Li, Y., Wang, Z., Li, Z., Zhang, Q., Zhang, J., & Li, Y. (2022). An LDPC Encoder Architecture with Up to 47.5 Gbps Throughput for DVB-S2/S2X Standards. *IEEE Access*, *10*, 19022 -19033. doi:10.1109/ACCESS.2022.3151086

Liu, H., & Li, G. (2005). OFDM-Based Broadband Wireless Networks: Design and Optimization. Chapter in a Book: *OFDM-Based Broadband Wireless Networks: Design and Optimization*, Print ISBN:9780471723462, 450-475. doi:10.1002/0471757195

Manasa, B. M. R., & Venugopal P. (2022). A systematic literature review on channel estimation in MIMO-OFDM system: Performance analysis and future direction. *Journal of Optical Communications*, **45**(3), 589-614. doi:10.1515/joc-2022-0033

Mattera, D., Tanda, M., & Bellanger, M. (2021). Comparing the performance of OFDM and FBMC multicarrier systems in doubly-dispersive wireless channels. *Signal Processing*, **179**(10), 1-9. doi:10.1016/j.sigpro.2020.107818

Mehrabani, M. R., Abolhassani, B., Haddadi, F., & Tellambura, C. (2023). Second-Order Statistics-Aided Channel Estimation for Multipath Massive MIMO-OFDM Systems. *IEEE Access*, **11**(1), 2569-2582**.** doi:10.1109/ACCESS.2023.3247662

Neinavaie, M., & Kassas, Z. M. (2023). Unveiling Starlink LEO Satellite OFDM-Like Signal Structure Enabling Precise Positioning. *IEEE Transactions on Aerospace and Electronic Systems*, **60**(2), 2486 - 2489. doi:10.1109/TAES.2023.3265951

Puja Astawa, I. G., Hidayah, N., & Sudarsono, A. (2021). Channel estimation using MMSE based DFT for OFDM system. *Proceedings - 2021 IEEE 5th International Conference on Information Technology, Information Systems and Electrical Engineering: Applying Data Science and Artificial Intelligence Technologies for Global Challenges During Pandemic Era, ICITISEE***,** 1-5. doi:10.1109/ICITISEE53823.2021.9655775

Rani, M., & Singal, P. (2023). Perceptron for channel estimation and signal detection in OFDM systems. *Journal of Optics (India)*, **52**(1), 69-76. doi:10.1007/s12596-022-00924-x

Rebouh, D., Djebbar, A. B., & Besseghier, M. (2023). Blind joint CFO and STO estimation for FBMC/OQAM systems. *IEEE Communications Letters*, **27**(9), 2422-2426. doi:10.1109/LCOMM.2023.3293392

Rekik, O., Aliyu, K. N., Tuan, B. M., Abed-Meraim, K., & Trung, N. L. (2024). Fast Subspace-based Blind and Semi-Blind Channel Estimation for MIMO-OFDM Systems. *IEEE Transactions on Wireless Communications*, **23**(8), 10247-10257. doi:10.1109/TWC.2024.3370720

Sarwar, M. S., Ahmad, M., & Shin, S. Y. (2023). Subcarrier Index Modulation for Spectral Efficient Frequency Division Multiplexing in Multi-Input Multi-Output Channels. *IEEE Transactions on Vehicular Technology*, **72**(2), 2678 - 2683. doi:10.1109/TVT.2022.3213011

Shafin, R., Liu, L., Ashdown, J., Matyjas, J., & Zhang, J. (2018). On the channel estimation of multi-cell massive FD-MIMO systems. *IEEE International Conference on Communications*, *2018-May*, 1-5. doi:10.1109/ICC.2018.8422128

Šimko, M., Mehlführer, C., Wrulich, M., & Rupp, M. (2010). Doubly dispersive channel estimation with scalable complexity. *2010 International ITG Workshop on Smart Antennas, WSA 2010*, 251-256. doi:10.1109/WSA.2010.5456443

Stoica, P., & Randolph, M. (1997). *Introduction to spectral analysis* (1st ed.). Prentice Hall, Upper Saddle River, N.J., ©1997, 1-319.

Tang, Z. (2023). OFDM communication system based on FPGA. *Proceedings - 2023 3rd Asia-Pacific Conference on Communications Technology and Computer Science, ACCTCS 2023*, 1-5. doi:10.1109/ACCTCS58815.2023.00126

Vilas Boas, E. C., Silva, J. D. S., de Figueiredo, F. A. P., Mendes, L. L., & de Souza, R. A. A. (2022). Artificial intelligence for channel estimation in multicarrier systems for B5G/6G communications: a survey. In *Eurasip Journal on Wireless Communications and Networking*, **2022**(116), 1-63. doi:10.1186/s13638-022-02195-3

Wang, H., Liao, J., Xu, L., & Wang, X. (2018). Blind channel estimation for FBMC/OQAM systems based on subspace approach. *Information (Switzerland)*, **9**(3), 1-14. doi:10.3390/info9030058

Yang, R. N., Zhang, W. T., & Lou, S. T. (2020). Adaptive Blind Channel Estimation for MIMO-OFDM Systems Based on PARAFAC. In *Wireless Communications and Mobile Computing*, **2020**(5), 1-17 doi:10.1155/2020/8396930

Zhang, G., Li, P., Wang, X., Xia, Y., & Yang, J. (2023). Flexible Battery-Free Wireless Sensor Array Based on

Functional Gradient-Structured Wood for Pressure and Temperature Monitoring. *Advanced Functional Materials*, **33**(2), 1-12. doi:10.1002/adfm.202208900

Zhu, P., Lin, H., Li, J., Wang, D., & You, X. (2023). High-Performance Channel Estimation for mmWave Wideband Systems With Hybrid Structures. *IEEE Transactions on Communications*, **71**(4), 2503 - 2516. doi:10.1109/TCOMM.2023.3245657