Hybrid SNR-Adaptive Multiuser Detectors for SDMA-OFDM Systems

Uğur Yeşilyurt and Özgür Ertuğ

Multiuser detection (MUD) and channel estimation techniques in space-division multiple-access aided orthogonal frequency-division multiplexing systems recently has received intensive interest in receiver design technologies. The maximum likelihood (ML) MUD that provides optimal performance has the cost of a dramatically increased computational complexity. The minimum mean-squared error (MMSE) MUD exhibits poor performance, although it achieves lower computational complexity. With almost the same complexity, an MMSE with successive interference cancellation (SIC) scheme achieves a better bit error rate performance than a linear MMSE multiuser detector. In this paper, hybrid ML-MMSE with SIC adaptive multiuser detection based on the joint channel estimation method is suggested for signal detection. The simulation results show that the proposed method achieves good performance close to the optimal ML performance at low SNR values and a low computational complexity at high SNR values.

Keywords: Channel estimation, ML, ML-MMSE, MMSE-SIC, Multiuser detection, SDMA-OFDM.

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I. Introduction

The swift development of wireless communication technology has increased the demand for communication technologies to be faster and more reliable. OFDM and SDMA systems will play an important role in fulfilling the future requirements of wireless access systems [1]. OFDM is a parallel transmission scheme that modulates high-rate serial data streams with orthogonal subcarriers to separate low-data-rate substreams. If the channel delay spread is less than its inserted guard interval, OFDM can eliminate the inter-symbol interference caused by high data transmission [2]. On the other hand, SDMA-based techniques, as a subclass of multiple-input multiple-output (MIMO) systems, allow multiple users to share a frequency band simultaneously. Thus, SDMA techniques are a promising class of techniques to solve the capacity problem of wireless communication systems by achieving higher spectral efficiency. The multiple users in the SDMA systems can be differentiated by exploiting their unique user-specific spatial signatures [3].

At the receiver end of SDMA-OFDM systems, channel estimation and multiuser detection (MUD) plays an important role [4]. Traditional methods usually handle channel estimation and multiuser detection separately. Joint channel estimation and signal detection algorithms have recently received research attention [5]. Among the various conventional MUDs, ML and MMSE are the basic methods. ML detection has achieved the best performance, although this has the cost of substantially increased computational complexity, especially when there is a high number of users and in higher-order modulation schemes. Thus, its use is generally avoided in practical systems [6]. By contrast, MMSE MUD exhibits the lowest complexity at the cost of a limited performance due to multiple-access interference (MAI) [7]. The successive interference cancellation (SIC) technique has been recommended to improve the performance of the MMSE MUD [8]. MMSE with the SIC technique, which has a complexity comparable to the MMSE method achieves better BER performance than the MMSE method. Minimum BER and minimum symbol error rate MUDs directly minimize the probability of error rather than minimizing the mean square error (MSE) [9]. Genetic algorithm (GA)-assisted MMSE MUD attains suboptimal performance with decreased complexity [10]. The hybrid ML-MMSE adaptive multiuser detection technique was applied to SDMA-OFDM systems [11]. Joint ML and MMSE-SIC detection has been recommended for multi-cell network environments [12]. Most of these detectors assume that the channel is perfectly known at the receiver's end, whereas the proposed method estimates the channel state information.

In this paper, we proposed hybrid ML-MMSE with SIC adaptive multiuser detection based on joint channel estimation to ensure a tradeoff between complexity and BER performance. The new convergence includes channel estimation, effective SNR calculation obtained from the channel estimation result, and a routing module. Channel estimation is first performed, and the channel effective SNR value is calculated according to the channel state information obtained from the channel estimation. According to the channel effective SNR information, the routing module determines which method to select for efficient signal detection under various SNR conditions. Simulation results show that the hybrid ML-MMSE with SIC adaptive multiuser detection method can achieve good performance near optimal ML at low SNR values and a low computational complexity close to MMSE at high SNR values.

The rest of the paper is structured as follows. The SDMA-OFDM system model is described in Section II. In the Section III, the ML, MMSE, and MMSE-SIC detection methods are analyzed. In Section IV, the proposed hybrid ML-MMSE with SIC adaptive multiuser detection based on joint channel estimation method is described and exhaustively studied. Simulation results are comparatively presented in Section V, and finally, conclusions are provided in Section VI.

II. SDMA-OFDM System Model

1. SDMA-OFDM System

Figure 1 portrays the concept of SDMA systems, where a mobile station (MS) is equipped with a single transmission antenna, whereas the base station (BS) is equipped with an array of receiver antennas. Using a spatial signature constituted by the channel transfer function, the SDMA system provides simultaneous communication of multiple users in the same time and frequency domains.

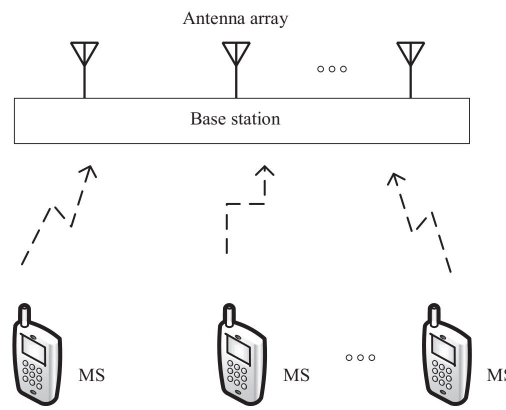

Fig. 1. Overview of SDMA system.

Figure 2 presents a block diagram of the SDMA-OFDM uplink (mobile station to base station) system model. In this figure, each of the L simultaneous mobile users employs a single transmit antenna, and the base station (BS) receiver employs R antenna array.

The received complex signal vector $\mathbf{y}[m, k]$ at the kth subcarrier of the mth OFDM block is constituted by the superposition of L independently transmitted user signals and contaminated by additive white Gaussian noise at each receiving antenna, expressed as

$$\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{n}, \tag{1}$$

where the $(R \times 1)$ dimensional vector $\mathbf{y}$ is the received signal, the $(L \times 1)$ dimensional vector $\mathbf{x}$ is the transmitted signal, and the $(R \times 1)$ dimensional vector $\mathbf{n}$ is the Gaussian noise signal with zero mean and σ_n^2 variance per element:

$$\mathbf{y} = [y_1, y_2, \dots, y_R]^T, \tag{2}$$

$$\mathbf{x} = [x^{(1)}, x^{(2)}, \dots, x^{(L)}]^T, \tag{3}$$

$$\mathbf{n} = [n_1, n_2, \dots, n_R]^T. \tag{4}$$

Here, the indices $[m, k]$ are omitted for the sake of convenience. The frequency-domain channel-transfer function matrix $\mathbf{H}$ is constructed by the set of channel-transfer function vectors of the L users, and $\mathbf{H}$ is given by

$$\mathbf{H} = [\mathbf{H}^{(1)}, \mathbf{H}^{(2)}, \dots, \mathbf{H}^{(L)}]^T, \tag{5}$$

where the $\mathbf{H}^{(l)}$ $(l = 1, \dots, L)$ is the vector of the channel transfer function associated with the channel links between the lth user's transmit antenna and each element of the R-element receiver antenna array, which is expressed as

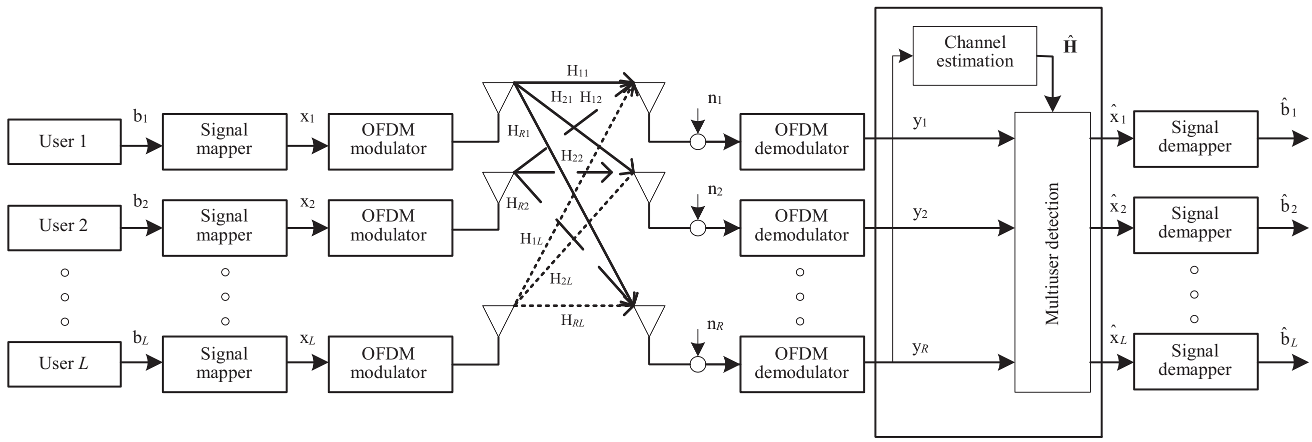

Fig. 2. Block diagram of uplink SDMA-OFDM system with L users and R receiving antennas.

$$\mathbf{H}^{(l)} = [\mathrm{H}_1^{(l)}, \mathrm{H}_2^{(l)}, \ldots, \mathrm{H}_R^{(l)}]^{\mathrm{T}}. \quad (6)$$

In (1) to (6), we assume that the lth user complex transmitted signal has zero-mean and σ_l^2 variance and the channel transfer function $\mathrm{H}_r^{(l)}$ of the different transmitters–receivers are independent, stationary, and complex Gaussian distributed processes with zero mean and unit variance [7].

In Fig. 3, we present the schematic of the OFDM modulator and demodulator. Once each user's serial data streams (b_l) are modulated using basic modulation techniques (BPSK, QPSK, or QAM), they are initially converted to parallel data streams in the OFDM modulator. This parallel data is subjected to inverse fast Fourier transform (IFFT) operation, and a cyclic prefix (CP) is added as a guard interval to prevent inter-symbol interference. These parallel data streams are then converted to serial data and transmitted to the base station over the SDMA-OFDM channel.

At the base station, each user's serial data added to the noise is converted back to parallel data, the CP is removed, and the FFT operation is performed. Finally, the parallel data is converted back to serial data.

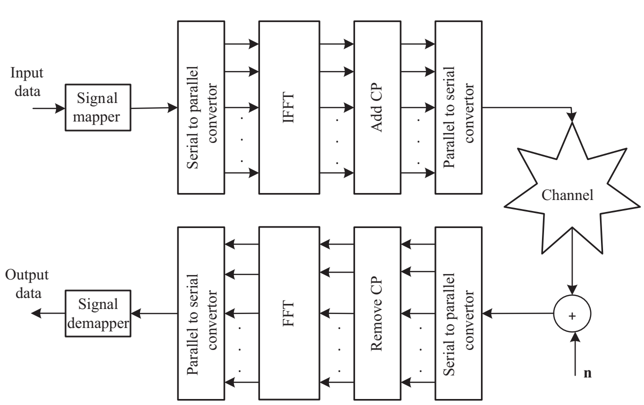

Fig. 3. Schematic of the OFDM modulator and demodulator.

III. Multiuser Detection Techniques

In SDMA-OFDM systems, noise and multiuser interference, where strong user signals may corrupt weak users are the major issues. To overcome these problems, the multiuser detection method, which is a receiver design technology is used. The detection algorithm can be expressed as

$$\hat{\mathbf{x}} = \mathbf{W}^{\mathrm{H}}\mathbf{y}, \quad (7)$$

where $\hat{\mathbf{x}}$ is the estimated signal vector, $\mathbf{W}$ is the $(R \times L)$ dimensional weight matrix, and $\mathbf{y}$ is the received signal vector.

1. Maximum Likelihood (ML) MUD

The highest complexity, nonlinear and highest optimum performance maximum likelihood (ML) MUD is based on other detection methods [13]. The ML detector calculates the minimum Euclidian distance by comparing all possible transmitted signal vectors with the received signal vector. The detected symbol $\hat{\mathrm{x}}_{\mathrm{ML}}$ is defined as

$$\hat{\mathrm{x}}_{\mathrm{ML}} = \arg\{\min||\mathbf{y} - \mathbf{H}\mathrm{x}_u||^2\}, \quad (8)$$

where x_u consists of the entire search space for the transmitted symbol, $u = 1, 2, \ldots, 2^{mL}$ is the set of the total matrix evaluations, and ||*|| means the norm of matrix *.

The ML detector supporting L simultaneous transmitting users has an exponentially increasing complexity with 2^{mL}, where m denotes the number of bits per symbol. Thus, as the number of users and the constellation size increase, the use of an ML detector becomes impractical in practice.

2. Minimum Mean Square Error (MMSE) MUD

The linear minimum mean square error (LMMSE) MUD achieves suboptimal BER performance, but it has lower computational complexity than the ML detector. The MMSE scheme assumes that the channel characteristic is known to the receiver because it requires noisy statistical knowledge to remove both the interference and the noise components. In (9), the weight vector is used to minimize the error value between the received signal and the corresponding transmitted signal, which is expressed as

$$\hat{\mathrm{x}}_{\mathrm{MMSE}} = \mathbf{W}^{\mathrm{H}}_{\mathrm{MMSE}}\mathbf{y}, \tag{9}$$

$$\mathbf{W}^{\mathrm{H}}_{\mathrm{MMSE}} = (\mathbf{H}\mathrm{H}^{\mathrm{H}} + 2\sigma_{\mathrm{n}}^{2}\mathbf{I})^{(-1)}\mathbf{H}, \tag{10}$$

where $\mathbf{H}$ is the $(R \times L)$ dimensional channel matrix, $\mathbf{I}$ is the R dimensional identity matrix, and $(.)^{\mathrm{H}}$ denotes the Hermitian operation "complex conjugate transpose."

3. Minimum Mean Square Error Successive Interference Cancellation (MMSE-SIC) MUD

The SIC technique is a suboptimal nonlinear effective technique for interference cancellation [14]. In comparison with the MMSE detector that detects signals in parallel, the MMSE-SIC detector detects signals one after another. In SIC implementation, the detection order is very important for the performance of the SIC detection scheme. To improve the performance of SIC, the layer with the highest signal-to-noise plus interference ratio (SINR) is selected. Subsequently, the interference effect of the signal in this layer is subtracted from the overall received signals. Similarly, the second strongest signal is perceived, and its effect is subtracted from the rest of the signals. This process continues until the final signal is obtained. This process is repeated $L - 1$ times in total [8].

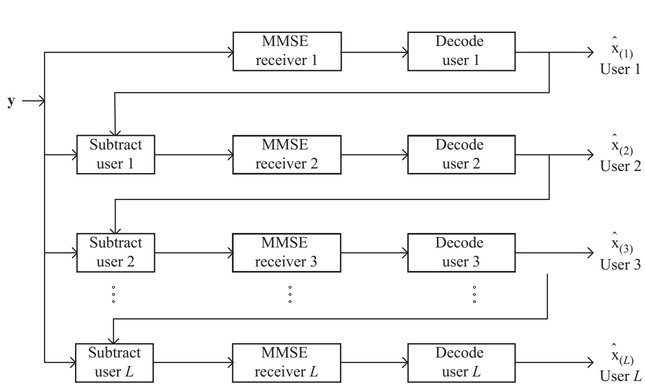

Fig. 4. MMSE-SIC receiver.

The MMSE-SIC detection technique uses an MMSE detector for symbol estimation. In the first stage, the signal $\hat{\mathrm{x}}_{(1)}$ determined by the MMSE method is subtracted from the received signal, and the remaining signal is obtained:

$$\widehat{\mathrm{y}}_{(1)} = \mathbf{y} - \mathrm{h}_{(1)}\widehat{\mathrm{x}}_{(1)} = \mathrm{h}_{(1)}\left(\mathrm{x}_{(1)} - \widehat{\mathrm{x}}_{(1)}\right) + \mathrm{h}_{(2)}\mathrm{x}_{(2)} + \mathrm{h}_{(L)}\mathrm{x}_{(L)} + \mathbf{n}. \tag{11}$$

If $\mathrm{x}_{(1)} = \hat{\mathrm{x}}_{(1)}$, the interference effect of this signal is cancelled in the second user's prediction $\mathrm{x}_{(2)}$. However, if $\mathrm{x}_{(1)} \neq \hat{\mathrm{x}}_{(1)}$, the calculation of $\mathrm{x}_{(2)}$ is wrong owing to error propagation. Figure 4 portrays the schematic of the MMSE-SIC receiver [1].

IV. Proposed Hybrid ML-MMSE with SIC SNR-Adaptive Multiuser Detection Based on Joint Channel Estimation

In SDMA-OFDM systems, channel estimation and multiuser detection are two important issues. They are often regarded as separate from each other. However, in the proposed method, channel estimation and multiuser detection work together. First, the channel estimator estimates the channel state information (CSI) and uses the estimated channel matrix $\mathbf{H}$ for effective SNR computation. According to the obtained effective SNR information, multiuser detection method is determined and the routing process is applied. The decision making operation is based on the threshold value.

1. Channel Estimation

Using both receiving and transmitting antennas, MIMO technology has advantages, such as higher data rates and greater mobility in wireless communication systems. Multiple signals are transmitted from different antennas at the transmitter using the same frequency band and different space. The channel state information (CSI) for data detection is required at the receiver. Therefore, channel estimation is a crucial task in MIMO systems [15], [16]. It is assumed that the channel is stationary during a block of communication process. The channel response of a block in the Rayleigh fading model is fixed within a block and changes from one block to another one.

In channel estimation, the channel matrix $\mathbf{H}$ is estimated with classic channel estimators including the least square (LS) estimator and the MMSE estimator. The rest of the study used the MMSE channel estimation method.

A. LS Channel Estimation

The LS channel estimator is an elementary channel estimator, whose purpose is to minimize the following squared error quantity:

$$\widehat{\mathrm{h}} = \arg\{\min||\mathbf{y} - \mathbf{x}\widehat{\mathrm{H}}_{\mathrm{LS}}||^2\}. \tag{12}$$

The LS-based channel transfer function $\widehat{\mathrm{H}}_{\mathrm{LS}}$ can be written as

$$\widehat{\mathrm{H}}_{\mathrm{LS}} = \mathbf{x}^{-1}\mathbf{y}. \tag{13}$$

This method has a disadvantage in terms of MSE performance since knowledge of channel statistics is not used, but it has very low computational complexity.

B. MMSE Channel Estimation

To minimize the mean square error, the MMSE channel estimator utilizes the second order channel statistics. Although the MMSE estimator achieves superior MSE performance, it has much higher computational complexity than the LS estimator. The MMSE estimate can be written as

$$\widehat{\mathrm{H}}_{\mathrm{MMSE}} = \mathbf{R}_{\mathrm{HH}}\left(\mathbf{R}_{\mathrm{HH}} + \sigma_{\mathrm{n}}^2(\mathrm{x}^{\mathrm{H}}\mathbf{x})^{-1}\right)^{-1}\widehat{\mathrm{H}}_{\mathrm{LS}}, \tag{14}$$

where $\mathbf{R}_{\mathrm{HH}}$ denotes the autocovariance matrix of $\mathbf{H}$, and $\sigma_{\mathrm{n}}{}^2$ denotes the noise variance. The $\mathbf{R}_{\mathrm{HH}}$ channel autocovariance matrix is defined by

$$\mathbf{R}_{\mathrm{HH}} = \mathrm{E}(\mathbf{H}\mathrm{H}^{\mathrm{H}}). \tag{15}$$

2. Effective SNR

The instantaneous channel effective SNR information is needed for our method of hybrid ML-MMSE with SIC adaptive multiuser detection based on joint channel estimation. From [17], the definition of effective SNR at the lth subcarrier can be expressed as,

$$\mathrm{SNR}_{\mathrm{eff}.l} = \frac{|H_m(k)|^2 S_u(k)}{|H_m(k)|^2 S_d(k) + N_0}\Big|_{k=l}, \tag{16}$$

where $H_m(k)$ is the estimated channel transfer function, k denotes the frequency, and $S_u(k)$ and $S_d(k)$ are the power spectral density (PSD) functions of the signal and Gaussian noise, respectively.

The instantaneous effective SNR is calculated based on the channel estimation. According to the instantaneous channel information, the threshold value is determined to ensure a tradeoff between performance and complexity. If the channel distortion effects are high, ML MUD with optimal performance is used, and if channel distortion effects are low, the MMSE-SIC MUD method is used. This threshold value is found after repeated simulations.

3. Threshold Value

The threshold value is crucial to provide a tradeoff between the signal detection performance and complexity. It is shown that ML detection can ensure much better mean square error performance than the MMSE and MMSE-SIC detection under an 8.5-dB channel effective SNR. MMSE and MMSE-SIC detection may be preferred with a channel effective SNR of 8.5 dB due to ML detection complexity and the acceptable BER performance of MMSE and MMSE-SIC. Therefore, we set the threshold value as 8.5 dB [18].

In data detection, although the ML method provides optimum performance, it has the disadvantage of high complexity. On the other hand, although the linear MMSE method has a simple structure, its BER performance is limited. Furthermore, the complexity of the MMSE-SIC method is lower than that of the ML method, and its BER performance is better than that of the MMSE method. Our proposed system is intended to achieve good performance and reduce complexity by combining the ML's optimum performance characteristic and the low complexity of nonlinear MMSE-SIC. As seen in Fig. 5, the receiver consists of a channel estimation module, an effective SNR calculator module, a routing module, and multiuser detection modules. According to the channel SNR information, the routing module routes either the MMSE-SIC detection method or the optimum ML detection method. All of the operations are summarized briefly below:

- First, channel estimation is performed, and channel matrix $\hat{\mathbf{H}}$ is obtained when one symbol frame is received.
- The effective SNR is computed using the $\hat{\mathbf{H}}$ estimated channel matrix.
- The effective SNR information is sent to the routing module, and the routing module decides which detection method to route at this stage:
  If SNR ≦ threshold value
  Apply ML MUD
  Else if SNR > threshold value
  Apply MMSE-SIC MUD
- The extracted signal is transmitted by using estimated channel matrix $\hat{\mathbf{H}}$ according to the selected multiuser detection method.
- The above steps are applied for all symbol frames in order.

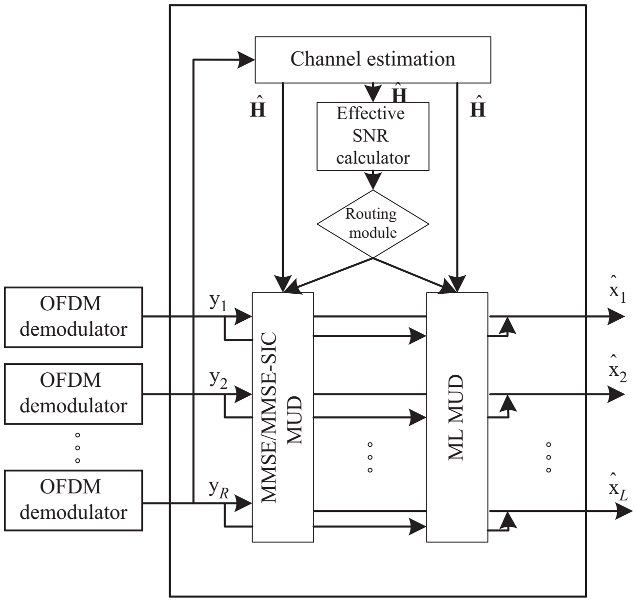

Fig. 5. Hybrid ML-MMSE with SIC method.

The proposed hybrid ML-MMSE with SIC method enhances the BER performance in poor SNR circumstances by using the optimal ML method. Under a high SNR condition, the hybrid ML-MMSE with SIC method reduces the complexity by using the nonlinear MMSE-SIC method.

V. Simulation Results

In this section, we analyze the BER performance and complexity of SDMA-OFDM systems with two receiver antennas and two transmitter antennas using the Matlab simulation program. We basically considered a full-load scenario in SDMA-OFDM Systems in Table 1. In a full-load scenario, the number of receiving antennas is equal to the number of users. Simulations are performed over 1,000 OFDM frames with 256 subcarriers and a cyclic prefix with a length of 64. Signals are separately modulated using 16-QAM modulation technique and transmitted in a one-tap Rayleigh fading channel.

1. Performance Analysis

Figure 6 shows a performance comparison in terms of BER versus SNR of the linear MMSE, optimal ML, nonlinear MMSE-SIC, and proposed hybrid ML-MMSE with SIC methods in SDMA-OFDM systems. It is also evident in the graph that the BER performance of the MMSE-SIC method is better than that of the MMSE method. As seen in Fig. 6, the MMSE-SIC method has

Table 1. Simulation parameters.

Parameter	Value
IFFT size	256
Cyclic prefix	64
Number of OFDM symbols	1,000
Number of users (L)	2
Number of received antennas (P)	2
Modulation technique	16-QAM
Channel	Rayleigh channel

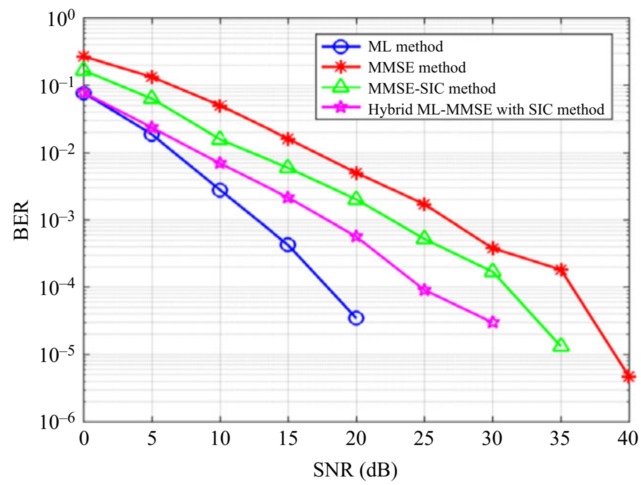

Fig. 6. BER performance versus SNRs of linear MMSE, optimal ML, nonlinear MMSE-SIC, and proposed hybrid ML-MMSE with SIC methods in SDMA-OFDM systems transmitting 16-QAM signals.

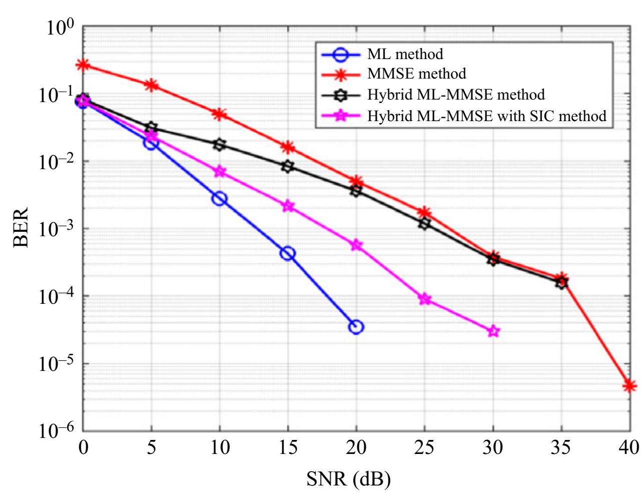

Fig. 7. BER performance versus SNRs of linear MMSE, optimal ML, hybrid ML-MMSE, and proposed hybrid ML-MMSE with SIC methods in SDMA-OFDM systems transmitting 16-QAM signals.

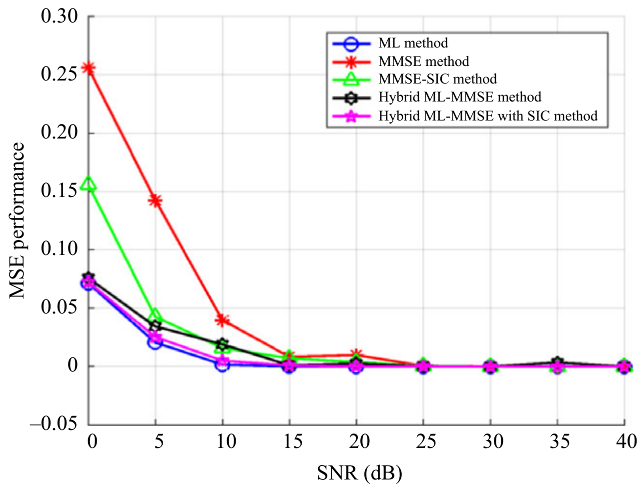

Fig. 8. MSE performance versus SNRs of linear MMSE, nonlinear MMSE-SIC, optimal ML, hybrid ML-MMSE, and proposed hybrid ML-MMSE with SIC methods in SDMA-OFDM systems transmitting 16-QAM signals.

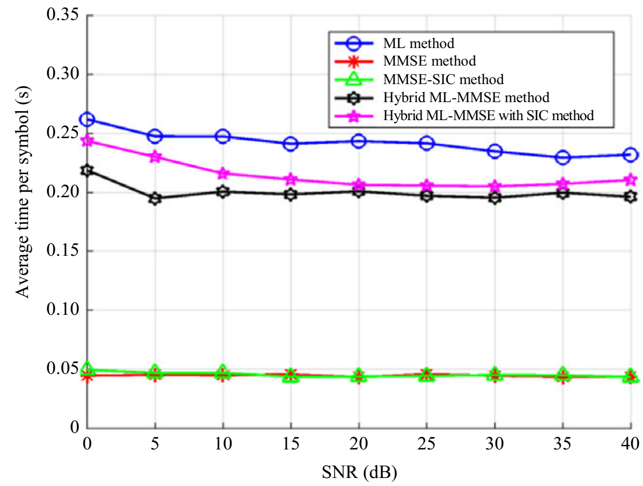

Fig. 9. Average detection time per symbol comparison of linear MMSE, nonlinear MMSE-SIC, optimal ML, hybrid ML-MMSE, and proposed hybrid ML-MMSE with SIC methods in SDMA-OFDM systems transmitting 16-QAM signals.

about 5 dB SNR gain over the MMSE method at a BER level of 10^{-3}.

The proposed hybrid ML-MMSE with SIC method can achieve good BER performance close to the optimal ML performance at low SNRs and a low computational complexity at high SNRs.

It can be inferred from Fig. 7 that the proposed hybrid ML-MMSE with SIC method has about 7 dB SNR gain over the hybrid ML-MMSE method at a BER level of 10^{-3}.

Figure 8 shows the mean square error (MSE) performance comparison of the traditional methods and the proposed method. MSE is a performance criterion that measures the average of the squares of errors. It is clear that the MSE performance of the hybrid ML-MMSE method and proposed hybrid ML-MMSE with SIC method is close to that of the optimal ML MUD method. It is clear that the ML, hybrid ML-MMSE, hybrid ML-MMSE with SIC, MMSE and MMSE-SIC detectors approach zero at about 10 dB, 15 dB, 10 dB, 15 dB and 15 dB SNR values, respectively.

In Fig. 9, the average elapsed time per symbol for linear MMSE, nonlinear MMSE-SIC, optimum ML, and the proposed methods are compared. It shows that the time required for signal detection in the proposed method is less than the time required for the optimal ML method with high complexity. Since the time required for signal detection is related to the computational complexity of the system, the proposed method appears to reduce the computational complexity. As the SNR value increases, a reduction in the time required for the proposed method is observed.

Table 2. Complexity analysis.

Methods	Complexity
ML C_{ML}	$o(2^{\mathrm{ML}})$
MMSE C_{MMSE}	$o(L^3)$
MMSE-SIC $C_{\mathrm{MMSE\text{-}SIC}}$	$o\{L^3(\frac{1}{2}N_t^2+\frac{1}{2}N_t)\}$
Hybrid ML-MMSE $C_{\mathrm{ML\text{-}MMSE}}$	$C_{\mathrm{ML}}\times\alpha+C_{\mathrm{MMSE}}\times(1-\alpha)$
Proposed hybrid ML-MMSE with SIC $C_{\mathrm{ML\text{-}MMSE\ with\ SIC}}$	$C_{\mathrm{ML}}\times\alpha+C_{\mathrm{MMSE\text{-}SIC}}\times(1-\alpha)$

2. Complexity Analysis

Note that the complexity of the MMSE detector is directly related to the transformation matrix that is computed by the matrix inversion. Thus, the complexity of the MMSE detector is $o(L^3)$. The SIC algorithm imposes a complexity such as multiplying by $\frac{1}{2}N_t^2+\frac{1}{2}N_t$, where the N_t is the transmit antenna. Thus, the complexity of the MMSE-SIC detector would increase to $o(L^3(\frac{1}{2}N_t^2+\frac{1}{2}N_t))$. The complexity of the ML detector with high complexity is $o(2^{\mathrm{ML}})$, where M is the order of modulation [19]. We determined as α the possibility of using ML in the systems we propose. The complexity of the hybrid ML-MMSE detector and the proposed hybrid ML-MMSE with SIC detector can be expressed as

$$C_{\text{ML-MMSE}} = C_{\text{ML}} \times \alpha + C_{\text{MMSE}} \times (1-\alpha), \tag{17}$$

$$C_{\text{ML-MMSE with SIC}} = C_{\text{ML}} \times \alpha + C_{\text{MMSE}-\text{SIC}} \times (1-\alpha), \tag{18}$$

where C_{ML}, C_{MMSE}, $C_{\text{ML-MMSE}}$, and $C_{\text{ML-MMSE with SIC}}$ express the complexity of the conventional detection methods and the proposed method. The complexity of these detectors is summarized in Table 2. Here, α is the measure of how much the signals suffer from severe noise interference and multipath fading. It is clear that the proposed method has lower complexity than the ML method because it has an alpha value of $\alpha \leq 1$ in most communication scenarios.

VI. Conclusion

In this paper, we proposed a method for hybrid ML-MMSE with SIC SNR-adaptive multiuser detection based on joint channel estimation in SDMA-OFDM systems. It is observed that the optimal ML detector has high complexity, and although the nonlinear MMSE-SIC detector has a simple structure with low complexity, its BER performance is limited. The BER performance of the MMSE-SIC method is better than that of the MMSE method. The MMSE method is less complex than the MMSE-SIC method, but the complexity of the MMSE-SIC method is at an acceptable level. The proposed method provides a tradeoff between complexity and BER performance. Based on the channel SNR condition, the proposed hybrid ML-MMSE with SIC method automatically routes either the nonlinear MMSE-SIC detector with a simple structure to reduce complexity or the ML detector with optimal BER performance to increase BER performance. By using the hybrid ML-MMSE, this method has the additional benefit of improving BER performance. Moreover, this method controls system complexity and maintains it at low levels.

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