Research Article BEU Fen Bilimleri Dergisi 15(1): 408-422 (2026) DOI: 10.17798/bitlisfen.1831126

BİTLİS EREN UNIVERSITY
FEN BİLİMLERİ DERGİSİ
ISSN: 2147-3129 / e-ISSN: 2147-3188

DMOA-DRIVEN CHANNEL ESTIMATION FOR OFDM: ROBUST PERFORMANCE ACROSS MODULATION ORDERS, PILOT DENSITIES AND 3GPP FADING MODELS

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Article Info

Received: *November 27, 2025*
Revised: *February 23, 2026*
Accepted: *February 25, 2026*

Keywords
Channel estimation,
Dwarf mongoose optimization algorithm,
Metaheuristic optimization,
OFDM,
Wireless communications.

ABSTRACT

This work proposes an innovative channel estimation technique for OFDM systems using the Dwarf Mongoose Optimization Algorithm (DMOA) without requiring any channel statistics. In this technique, the DMOA algorithm is used to search for the optimal parameters of the effective SNR, RMS delay spread, and Doppler frequency to minimize the pilot domain estimation error. Unlike the conventional MMSE method, which requires channel correlation matrices to be known in advance, this method adaptively estimates the parameters using the metaheuristic search algorithm. Simulation results prove that the proposed method consistently performs better than the conventional LS method in all modulation formats (QPSK, 16-QAM, 64-QAM, and 256-QAM), pilot densities (1/3, 1/6, 1/9, and 1/12), and 3GPP channel models (TDLC-300, EPA, EVA, and ETU). The results are particularly significant in the medium to high SNR region, in which the LS method shows significant error floor. In addition, the proposed method shows robust results in sparse pilot environments and effectively reduces the degradation caused by increasing pilot spacing. In all scenarios, DMOA achieves near-optimal results compared to the ideal MMSE method without requiring any statistical information. The proposed method also shows better results compared to PSO and DE in terms of stable convergence and reduced estimation error for the entire range of SNR. This shows DMOA to be a potential method for channel estimation in future OFDM systems.

1. INTRODUCTION

In fact, Orthogonal Frequency Division Multiplexing (OFDM) is one of the essential components of many popular wireless communication systems such as IEEE 802.11, LTE, and 5G technologies [1]. The ability of OFDM to cope with frequency selective fading stems from its ability to split a high-speed data stream into many orthogonal sub-carriers to achieve higher spectral efficiency with minimal inter-symbol interference [2]. Nevertheless, the effectiveness of any OFDM system still depends on the degree of precision associated with channel state information acquisition techniques. The wireless communication channel is constantly changing due to multipath delay spread, Doppler spread, and shadowing effects, making channel estimation a complex task that has to be constantly updated to cope with these channel dynamics [3].

The conventional method of channel state information acquisition through pilot-based channel estimation has been widely accepted because the known pilot symbols embedded within the OFDM frame provide adequate information to the receiver to estimate the frequency response of the channel [4]. Although conventional channel estimation techniques such as Least Squares (LS) and Minimum Mean Square Error (MMSE) are still widely employed because of their analytical tractability and simple application to practical problems [5, 6], these techniques are still limited by poor performance associated with low signal-to-noise ratio values or pilot sparsity, whereby LS fails to exploit any statistical information associated with the channel [7,8]. Although the MMSE estimator has been shown to provide better estimation accuracy than LS, its effectiveness still depends on the availability of accurate second-order channel statistics, which are difficult to obtain or estimate in many practical scenarios [9]. These limitations have resulted in many research studies on pilot-based channel estimation using metaheuristics such as various bio-inspired algorithms such as Particle Swarm Optimization (PSO) [10], Artificial Bee Colony (ABC) [11], Grey Wolf Optimizer (GWO) [12], Harmony Search (HS) [13], the Firefly Algorithm [14], Elephant Herding Optimization (EHO) for large MIMO systems [15], among many others, which have shown that these algorithms can be useful in channel estimation problems to enhance pilot design to achieve better channel estimation accuracy.

The latest developments in metaheuristics and machine learning have sparked renewed research into other adaptive channel estimation techniques that are capable of coping with channel dynamics without any prior channel models [16-26]. Among various metaheuristic approaches, the Dwarf Mongoose Optimization Algorithm (DMOA) has drawn interest because it offers a good balance between exploration and exploitation, uses a relatively simple set of parameters, and performs well on non-convex optimization problems [27, 28]. Unlike PSO, which relies on velocity-based updates that can lead to premature convergence when particles cluster around suboptimal solutions, and DE, whose differential mutation may struggle in landscapes with multiple local minima, DMOA employs a structured three-phase search mechanism. The alpha group maintains broad exploration to preserve population diversity, the scout group performs intensive local refinement in promising regions, and the babysitter exchange mechanism replaces stagnant candidates to prevent convergence to local optima. This hierarchical organization provides inherent robustness against the rugged cost function landscape encountered in channel estimation, where effective Signal to Noise Ratio (SNR), delay spread, and Doppler parameters interact in a highly nonlinear manner. Consequently, DMOA is particularly well-suited to the OFDM channel estimation problem, offering more stable convergence and higher estimation accuracy than conventional metaheuristics without requiring problem-specific parameter tuning.

Inspired by the above-mentioned arguments, the DMOA algorithm is employed to solve a wider and more practical set of OFDM conditions. The proposed algorithm is assessed using different QPSK, 16-QAM, 64-QAM, and 256-QAM modulations, different pilot spacing values such as 1/3, 1/6, 1/9, and 1/12, and a variety of 3GPP channel models, including the Tapped Delay Line Channel with 300 ns delay spread (TDLC-300), Extended Pedestrian A (EPA), Extended Vehicular A (EVA), and Extended Typical Urban (ETU). In order to better evaluate the convergence and accuracy of the DMOA algorithm, the proposed algorithm is also comparatively evaluated using the PSO and DE algorithms. Simulation results show that the DMOA algorithm-based estimator considerably outperforms the LS algorithm and achieves near-MMSE accuracy without using the channel statistics, making the DMOA algorithm a viable and reliable channel estimation algorithm for future OFDM systems.

2. MATERIALS AND METHODS

This section describes the proposed DMOA-based channel estimation framework developed for OFDM systems. It begins by introducing the system model and defining the channel estimation problem. A brief summary of the DMOA algorithm follows, after which the optimization-based estimation method is explained together with remarks on its computational aspects.

2.1. OFDM System Model

Consider an OFDM system with N subcarriers, where the transmitted frequency-domain symbol vector is

$$X = [X_0, X_1, \dots, X_{N-1}]^T \tag{1}$$

Among the subcarriers, a subset P is reserved for pilot symbols, while the remaining set carries data. After removing the cyclic prefix and applying the DFT, the received symbols are given by

$$Y_k = H_k X_k + W_k, k = 0, \dots, N-1, \tag{2}$$

where H_k denotes the channel frequency response of the k-th subcarrier and W_k is additive white Gaussian noise.

The frequency-domain channel response H_k is related to the time-domain channel impulse response through the DFT. Let $h[n]$ denote the discrete-time baseband equivalent channel with L resolvable multipath components:

$$h[n] = \sum_{l=0}^{L-1} \alpha_l \, \delta[n - \tau_l], n = 0,1, \dots, N-1 \tag{3}$$

where α_l and τ_l represent the complex gain and discrete delay of the l-th path, respectively. The frequency-domain channel response at the k-th subcarrier is then obtained as

$$H_k = \sum_{n=0}^{N-1} h[n] \, e^{-j2\pi kn/N} = \sum_{l=0}^{L-1} \alpha_l \, e^{-j2\pi k\tau_l/N} \tag{4}$$

The channel vector $H = [H_0, H_1, \dots, H_{N-1}]^T$ thus captures the complete frequency-selective fading characteristic of the wireless channel.

For pilot positions, X_k is known, enabling estimation of the frequency response H_k. The overall objective of channel estimation is to reconstruct the channel vector

$$H = [H_0, H_1, \dots, H_{N-1}]^T \tag{5}$$

with minimal error.

2.2. Channel Estimation Problem Formulation

For pilot subcarriers, the relationship

$$Y_k = H_k X_k + W_k, k \in P \tag{6}$$

holds. The classical LS estimator computes

$$\widehat{H}_k^{LS} = \frac{Y_k}{X_k}, \tag{7}$$

which is then interpolated over the data subcarriers. Although computationally simple, LS does not incorporate channel statistics and thus exhibits degraded performance under low-SNR or sparse-pilot conditions.

The MMSE estimator improves accuracy by exploiting second-order channel statistics through

$$\widehat{H}^{MMSE} = R_{HP}(R_{PP} + \sigma_w^2 I)^{-1} \widehat{H}^{LS} \tag{8}$$

It is important to note that the MMSE estimator employed as a benchmark in this study assumes perfect knowledge of the channel correlation matrices R_{HP} and R_{PP}, as well as the noise variance σ_w^2. Since such information is rarely available or accurate in realistic wireless deployments, MMSE serves as a theoretical lower bound on estimation error rather than a practically achievable target. Any estimator that approaches MMSE performance without requiring explicit channel statistics therefore represents a significant practical advancement. This observation motivates the development of the proposed DMOA-based approach, which seeks to achieve near-MMSE accuracy through adaptive parameter optimization. In practice, the problem becomes a non-convex multi-parameter optimization task in which effective SNR behavior, Root Mean Square (RMS) delay spread, and Doppler frequency jointly determine estimation accuracy. These characteristics make metaheuristic optimization a suitable approach.

2.3. Dwarf Mongoose Optimization Algorithm (DMOA)

DMOA is a population-based metaheuristic inspired by the cooperative foraging behavior and adaptive social structure of dwarf mongooses [21, 22]. The algorithm progresses through three main phases:

• **Alpha Group (Exploration):** Individuals search the solution space more broadly to maintain diversity and reduce the likelihood of premature convergence.

• **Scout Group (Local Improvement):** Scout members carry out focused local searches to refine candidate solutions in areas that appear promising.

• **Babysitter Exchange (Diversity Maintenance):** Candidates that make little progress over several iterations are replaced with new ones, allowing the algorithm to retain its exploratory capability.

The strength of DMOA largely stems from its ability to keep a workable balance between exploration and exploitation, allowing it to navigate complex and highly non-convex search spaces with a fair degree of stability. Another practical benefit is that the method needs only minimal parameter adjustment, which makes it relatively straightforward to use in real implementations.

2.4. DMOA-Based Channel Estimation Procedure

The channel estimation problem is cast as an optimization task in which DMOA searches for the parameter vector

$$\theta = [\theta_1, \theta_2, \theta_3]^T, \tag{9}$$

representing the effective SNR, the RMS delay spread, and the maximum Doppler frequency. These parameters define an MMSE-inspired estimator that does not rely on explicit channel statistics. The rationale for choosing these three parameters is based on their direct relationship to the fundamental components of the MMSE filter framework. The effective signal-to-noise ratio (θ_1) plays an important role in controlling the amount of noise regularization within the Wiener filter, thereby balancing noise reduction and signal preservation. The RMS delay spread (θ_2) determines the frequency correlation of the channel, specifying the rate at which the channel varies subcarrier to subcarrier due to multipath propagation effects. The maximum Doppler frequency (θ_3) determines the time correlation of the channel, specifying the rate at which the channel varies due to mobility effects. These three parameters are sufficient to characterize the second-order statistics of the channel necessary for the MMSE estimator, namely, the channel autocorrelation matrix and the noise variance.

The objective function is given by the squared error between the received pilot symbols and the pilot-domain channel response generated from a candidate parameter vector:

$$f(\theta) = \| \ Y_P - H(\theta) \ \odot \ X_P \ \|^2, \tag{10}$$

where $\odot$ denotes element-wise multiplication and $H(\theta)$is the channel response computed from the candidate parameters. The physical intuition behind this cost function is that the pilot subcarriers are known points at which the actual channel response is observable via the received signal. By minimizing the error at these points, the optimization procedure ensures that the parametric channel model H(θ) accurately models the observed frequency-domain channel characteristics at these points. The parameters θ are physically meaningful in that they define a correlation structure that affects the channel response over the entire frequency band. Therefore, an accurate modeling of the channel characteristics at the pilot points implies an accurate modeling of the channel characteristics at the intervening data subcarriers as well. The cost function effectively transforms the problem of blind channel estimation into that of supervised parameter fitting, where the observations at the pilot points are used to direct the optimization procedure toward the optimal MMSE filter configuration. The smoothness of the channel is used to our advantage in that if the parametric channel model accurately models the underlying channel characteristics at the pilot points, then it will do so at the intervening data points as well.

The parametric channel estimation $H(\theta)$ is defined within the framework of a Wiener filter, as motivated by the principles of MMSE estimation. In detail, by letting the parameter vector be defined as $\theta = [\theta_1, \theta_2, \theta_3]^T$, the channel estimation across all the subcarriers is given by

$$\widehat{H}(\theta) = R_{HH}(\theta_2, \theta_3) \left[R_{HH}(\theta_2, \theta_3) + \frac{1}{\theta_1} I \right]^{-1} \widehat{H}^{LS} \tag{11}$$

where the parameter θ_1 represents the effective signal-to-noise ratio used for noise suppression, and the parametric correlation matrix $R_{HH}(\theta_2, \theta_3)$ follows a structure depending on the RMS delay spread θ_2 and the maximum Doppler shift θ_3. Under the assumption of an exponential power delay profile and the Doppler spectrum proposed by Jakes, the entry of the correlation matrix $R_{HH}(\theta_2, \theta_3)$ corresponding to the m^{th} and n^{th} subcarriers is modeled as

$$[R_{HH}]_{m,n} = \frac{1}{1 + j2\pi\theta_2\Delta f(m-n)} \cdot J_0(2\pi\theta_3 T_s) \tag{12}$$

where Δf is the subcarrier spacing, T_s is the OFDM symbol duration, and $J_0(\cdot)$ is the zeroth-order Bessel function of the first kind.

Through the minimization of the cost function $f(\theta)$ as defined in Eq. (10), DMOA performs an effective search for the optimal combination of parameters that most accurately explains the observed pilot measurements, thereby providing a channel estimate that closely approximates the MMSE solution without explicit knowledge of the actual channel statistics.

The DMOA-based estimation procedure operates in the following sequence:

1. Pilot symbols are extracted from the received OFDM frame.
2. A population of candidate parameter vectors θ_i is initialized.
3. For each candidate, a channel estimate is generated using the MMSE-inspired parametric model.
4. The objective function f_i is evaluated for every candidate.
5. The population is updated through the alpha, scout, and babysitter phases of DMOA.
6. This process is repeated until convergence or until a preset maximum number of iterations is reached.
7. The best solution θ^*, corresponding to the minimum objective value, is selected.
8. The final channel estimate is obtained using θ^*.

This optimization-based framework allows the estimator to adaptively select suitable parameter values without relying on prior channel statistics, which in turn enhances robustness under different propagation conditions and pilot densities.

2.5. Computational Complexity and Implementation Considerations

The computational complexity of the proposed DMOA-based channel estimation technique is discussed with regard to conventional channel estimation techniques.

LS Estimation: The pilot-based least squares estimation step has a computational complexity of $O(N_p)$. The interpolation step adds another term, $O(N)$, to the overall complexity, which becomes $O(N)$.

MMSE Estimation: The MMSE-based channel estimation technique involves a computational complexity of $O(N_p^3)$ for the matrix inversion step and another term, $O(N \times N_p)$, for the matrix multiplication step, giving a total computational complexity of $O(N_p^3 + NN_p)$.

DMOA Estimation: The computational complexity of the DMOA-based channel estimation technique is dominated by the population size N_{pop}, the maximum number of iterations I_{max}, and the MMSE-based filtering step used in each iteration of the DMOA optimization technique. The overall computational complexity can be stated as

$$O\left(I_{max} \times N_{pop} \times \left(N_p^3 + NN_p\right)\right) \tag{13}$$

The DMOA-based channel estimation technique, although computationally more complex than the least squares-based technique, offers better estimation accuracy compared to the least squares technique. Moreover, the proposed technique does not require any statistical information about the channel, which is difficult to obtain in practice and can vary with time in wireless communication systems. The proposed technique can operate with or without channel statistical information, which makes it more feasible for practical implementation, with fewer parameters to be optimized, thereby providing better performance over a wide range of channel conditions.

Implementation Considerations. The real-time feasibility of the proposed DMOA-based estimator is naturally subject to the computational capabilities of the receiver and the latency constraints of the target application. Under the simulation parameters considered in this study ($N_{pop} = 30$, $I_{max} = 50$), the algorithm requires 1.5×10^3 fitness evaluations per OFDM symbol. Each fitness evaluation involves computing the pilot domain error through matrix operations with a computational complexity of $O(N_p^2)$. This operation is highly parallelizable and can be efficiently implemented on current digital signal processor (DSP) or graphics processing unit (GPU) technology.

For a system with $N_p = 170$ pilots (resulting in a 1/6 pilot spacing with 1024 subcarriers), a single fitness evaluation involves approximately 10^4 floating-point operations. With 1.5×10^3 fitness evaluations per symbol, the total computational complexity is approximately 1.5×10^7 operations per OFDM symbol. Given that current DSP technology allows for throughputs of over 10^{10} operations per second, the DMOA-based estimator is able to process each OFDM symbol in a fraction of a millisecond. This is well within the symbol duration of 5G systems, e.g., 33.3 μs with a 30 kHz subcarrier spacing.

For systems with even tighter latency constraints, several complexity reduction methods can be employed. The most important ones are (i) reducing the population size and number of iterations with a small performance penalty, (ii) exploiting temporal correlation in the channel estimation problem through initialization of the optimization with the previous symbol's solution, and (iii) performing the optimization once every coherence time and reusing the parameters across several successive OFDM symbols.

2.6. Simulation Setup and Performance Evaluation

This section describes the simulation framework employed to evaluate the performance of the proposed DMOA-based channel estimation approach. The OFDM system is designed with parameters appropriate for a real 5G scenario but still enabling detailed statistical analysis. The main parameters of the system are given in Table 1. An FFT of 1024 is employed along with a 256 sample cyclic prefix. The sub-carrier spacing is fixed at 30 kHz. Pilot symbols are inserted periodically in the frequency domain with spacings of 1/3, 1/6, 1/9, and 1/12. This allows the robustness of the channel estimation approach to be evaluated. To examine the performance of the channel estimation approach with different levels of complexity in the constellation, four different modulation schemes are employed: QPSK, 16-QAM, 64-QAM, and 256-QAM.

Table 1. Simulation parameters

Parameter	Value
FFT size	1024
Cyclic prefix length	256 (1/4 of FFT)
Subcarrier spacing	30 kHz
Symbol duration	1/30 kHz
Pilot spacing	3, 6, 9, 12
Number of pilots	1024 / pilot spacing
Modulation order	QPSK / 16-QAM / 64-QAM / 256-QAM
Channel models	TDLC-300, 3GPP EPA, EVA, ETU
Noise model	AWGN added after multipath convolution
Number of OFDM symbols per run	100
Number of independent Monte-Carlo runs	10
SNR range	0-30 dB (step = 5 dB)
Channel estimation methods	LS, MMSE, DMOA
Sample rate	1024 × 30kHz = 30.72 MHz

The parameters of the DMOA were determined based on preliminary analyses of the convergence of the algorithm. A population size of $N_{pop} = 30$ and a maximum number of iterations $I_{max} = 50$ were determined through systematic experiments. In fact, for the channel conditions tested, the algorithm was observed to converge within 30-40 iterations, with no significant improvement in the cost function for 50 iterations or more. Furthermore, the sensitivity analysis showed that a population size of 20 resulted in an increase of 5% in the mean squared error, whereas an increase in population size to 50 resulted in an improvement of less than 1%. This implies that a population size of 30 provides a good balance between accuracy and computational complexity.

Furthermore, the choice of 10 runs for the Monte Carlo analysis was validated based on a comparison with 50 runs, which showed that the mean bit error rate and mean squared error values were almost identical, with a slightly tighter confidence interval.

To guarantee realistic channel propagation conditions, simulations are performed over a number of standardized 3GPP channel models, such as TDLC-300, EPA, and EVA, each of which has different delay spreads, multipath profiles, and levels of frequency selectivity. For the sake of comparison, three baseline methods are considered. The first is the traditional LS method with linear interpolation. The second is the MMSE method with ideal channel statistics. The third is a pair of metaheuristic methods based on PSO and DE. The variety of methods included allows the estimation performance as well as algorithm robustness to be tested.

The performance of the methods is tested in terms of different metrics. The Bit Error Rate (BER) is a measure of the overall reliability of the communication system. The Mean Square Error (MSE) is a direct measure of the channel estimation accuracy. The statistical reliability of the methods is guaranteed through a robust Monte Carlo simulation framework. For each value of SNR and channel model, 10 independent simulations are performed. Each simulation uses a different channel realization and noise sequence. In each simulation run, 100 OFDM symbols are sent. The BER and MSE are estimated based on the results of each simulation run. The overall performance metrics are the sample mean of the results from the 10 independent simulation runs.

To evaluate the statistical fluctuations, 95% confidence intervals are used, and these are computed based on the Student's t-distribution. In this case, for a given performance measure with a mean value $\bar{x}$ and a standard deviation s, computed from $n = 10$ runs, the confidence interval is given by:

$$CI = \bar{x} \pm t_{0.025,\,9} \cdot \frac{s}{\sqrt{n}} \tag{14}$$

where $t_{0.025,9} \approx 2.262$, representing the critical value of the t-distribution with 9 degrees of freedom and a confidence level of 97.5%. This equation considers the limited number of runs and provides a very conservative estimate of the actual mean value of the system's performance. The choice of 10 runs for the Monte Carlo simulations was verified with preliminary experiments, where increasing the number of runs to 50 results in almost the same mean values, with only a small improvement in the confidence intervals. This verifies that 10 runs are indeed sufficient to ensure statistical stability for the given comparisons. To ensure a fair comparison, the same channel and noise realizations are used for all estimation algorithms in each run.

Together, this simulation framework provides a comprehensive platform for evaluating the effectiveness of the proposed DMOA-based estimator across different channels, pilot configurations, and modulation schemes.

3. RESULTS AND DISCUSSION

This section presents the entire set of simulation results that verify the effectiveness of the proposed method of channel estimation via DMOA optimization. The results are presented in such a manner that the trends of bit error rates (BER) and mean squared errors (MSE) are emphasized with different modulation types, pilot spacings, and standardized 3GPP channel models, while at the same time allowing for direct comparisons with other optimization methods of the metaheuristic type. All of the results are obtained via the statistical evaluation method, where 100 OFDM symbols are used with 10 different Monte Carlo simulations for each value of the signal to noise ratio (SNR). For each curve, 95% confidence intervals are used to ensure the results' reliability.

3.1. BER and MSE Performance over TDLC-300 Channel

Figures 1 and 2 show the performance comparison of the BER and MSE for the least squares, DMOA, and MMSE channel estimators for the TDLC-300 channel with pilot spacing equal to 1/6, and for QPSK, 16-QAM, 64-QAM, and 256-QAM modulations. From these figures, it is clearly demonstrated that the performance of the DMOA estimator is better than that of the LS estimator and close to that of the MMSE estimator.

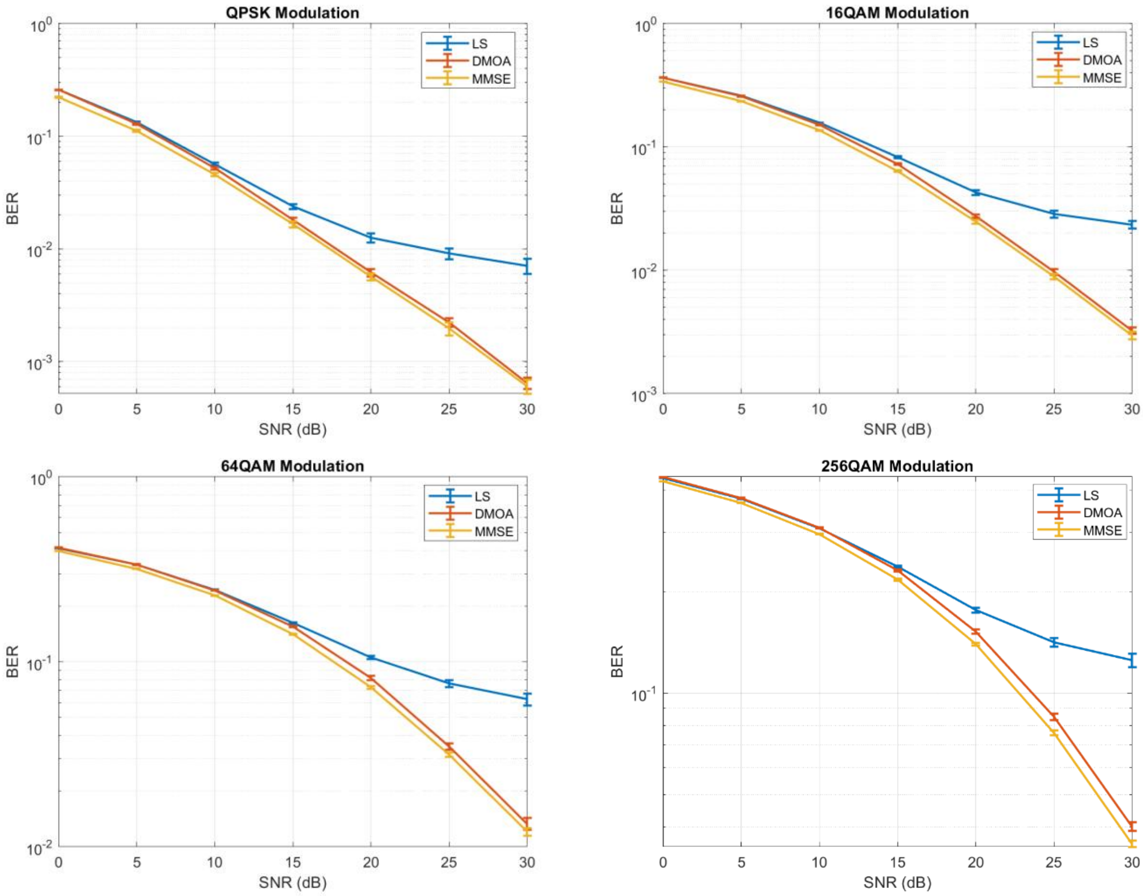

Figure 1. BER vs. SNR performance of LS, MMSE, and DMOA estimators for QPSK, 16-QAM, 64-QAM, and 256-QAM over the 3GPP TDLC-300 channel (pilot spacing 1/6).

In the case of QPSK, improvements from DMOA are found to be marginal at very low values of SNR, where noise is dominant and all estimators show comparable BER performance. However, once the SNR crosses 10 dB, the optimization capability of DMOA starts to show its effects. Over the range of 10 to 20 dB, which is the range of interest, DMOA shows significant performance improvement in terms of BER, achieving about half of that of the least squares (LS) approach at around 15 to 20 dB, while still being within a small margin of the MMSE bound. At higher values of SNR, around 25 to 30 dB, the performance of LS is found to saturate due to interpolation effects and pilot density, while that of DMOA continues to improve, closely approaching the MMSE curve and showing improvements of over one order of magnitude over that of the LS approach at 30 dB.

Similar trends are noted for 16-QAM and other higher-order constellations. For 16-QAM, although minimal or no improvement is noted at low SNR (0 to 5 dB), the effectiveness of the proposed method becomes more apparent at higher SNR levels. For the medium-SNR region (15 to 20 dB), the proposed method reduces the BER by 30 to 40% compared to the LS method, with DMOA always being between the LS method and the MMSE method. For high SNR levels, the difference between the proposed method and the LS method becomes more apparent, with the proposed method effectively eliminating the BER floor of the LS method.

The benefits of DMOA are seen even more clearly in the case of 64-QAM and 256-QAM, as these are more prone to inaccuracies in channel estimation. In such cases, it is clear that LS has error floors even at relatively high SNR levels, while DMOA maintains a much steeper bit-error-rate (BER) decline and closely tracks the performance of the MMSE receiver. For example, in the SNR range of 25-30 dB, DMOA has a BER reduction factor of two to three compared to the LS receiver for 64-QAM and 256-QAM, while still closely tracking the performance of the MMSE receiver.

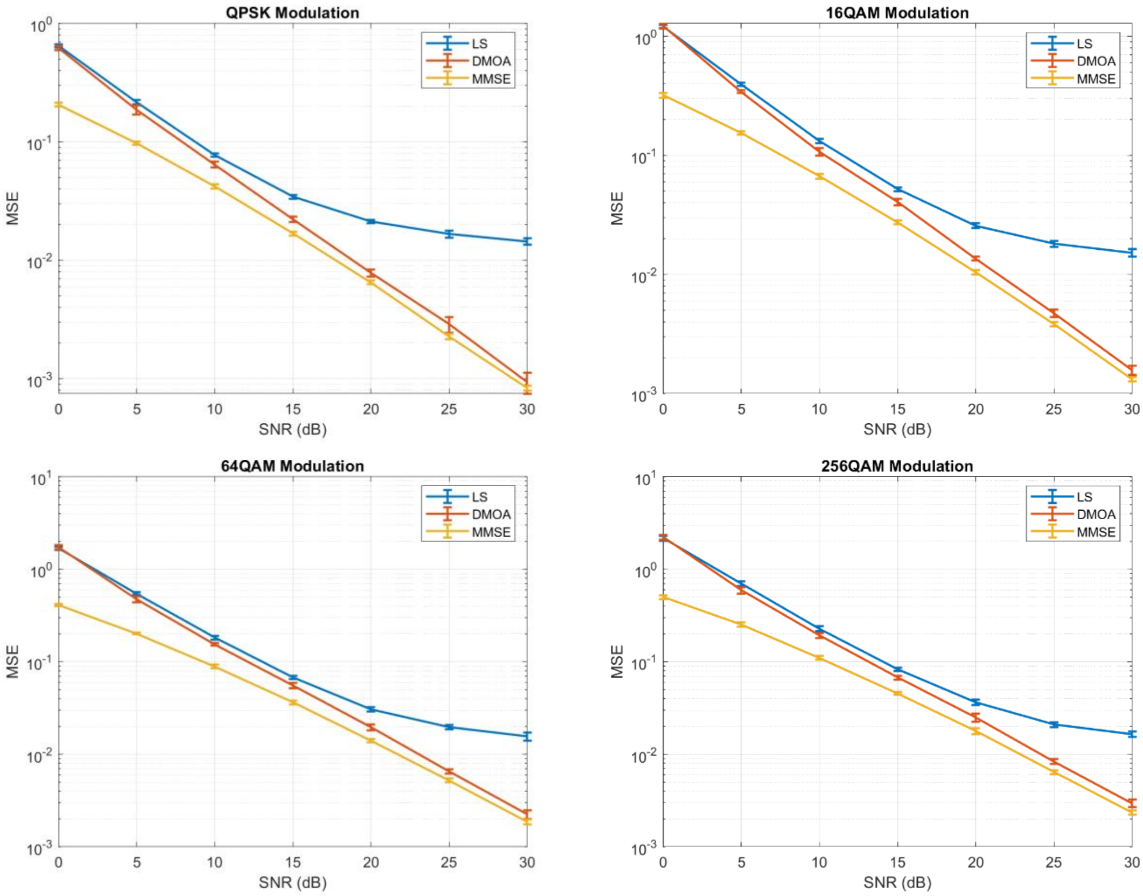

Figure 2. MSE vs. SNR performance of LS, MMSE, and DMOA estimators for QPSK, 16-QAM, 64-QAM, and 256-QAM over the 3GPP TDLC-300 channel (pilot spacing 1/6).

The MSE results provided in Figure 2 verify that the improvements in the bit error rate indeed come from the improvements in the accuracy of the channel estimation. In all cases, the proposed DMOA algorithm has lower MSE than the least squares estimator for all values of the signal to noise ratio. The improvements, although moderate at low values of the signal to noise ratio, become significant as the signal to noise ratio increases, verifying the ability of the DMOA algorithm to follow the actual channel response as the noise limitations decrease. In the case of 16-QAM and other high-order modulations, the proposed algorithm shows significant improvements, sometimes by tens of percent, over the least squares estimator, and the minimum mean square error estimator acts as a lower bound. The confidence intervals of all the results are narrow, verifying the stability of the optimization.

3.2. Impact of Pilot Spacing under TDLC-300 Channel

To evaluate the sensitivity of the proposed estimator to pilot density, Figures 3 and 4 investigate the BER and MSE performance for different pilot spacings of 1/3, 1/6, 1/9, and 1/12 in the frequency domain. The effect of pilot spacing is most clearly visible for 64-QAM, where the system exhibits the highest sensitivity to channel estimation errors.

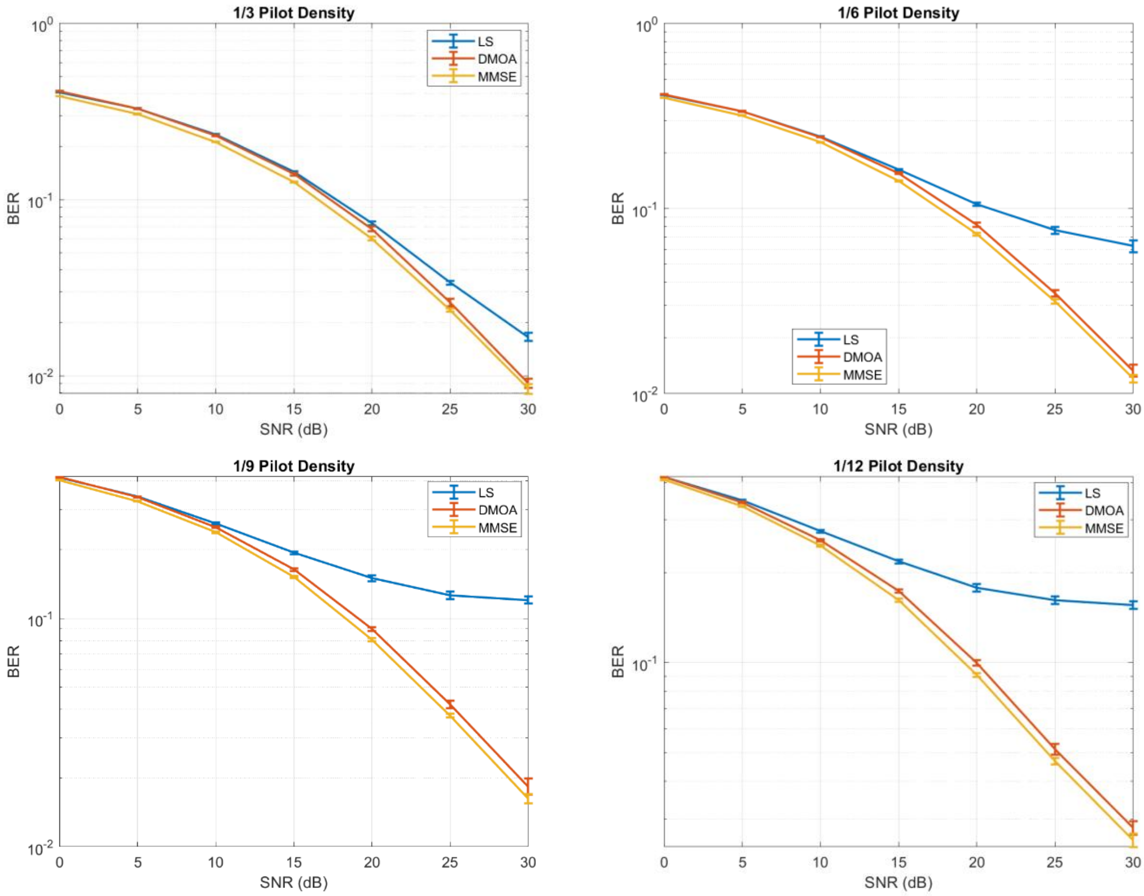

Figure 3. BER vs. SNR performance of LS, MMSE, and DMOA estimators for QPSK, 16-QAM, 64-QAM, and 256-QAM under different pilot spacings (1/3, 1/6, 1/9, 1/12) over the 3GPP TDLC-300 channel.

In this dense pilot environment, where pilots are spaced at 1/3, LS benefits from a relatively good operating environment due to the short interpolation distances between pilots. Under this environment, DMOA provides significant, albeit moderate, improvements over LS. For example, at high SNR, the BER of DMOA is about 40-50% lower than that of LS, while its gap to MMSE is still moderate. However, when the pilot spacing increases to 1/6, 1/9, and 1/12, the performance of LS suffers substantially, especially at medium to high SNR levels, where interpolation errors become the dominant performance degradation mechanism. On the other hand, both DMOA and MMSE show much slower performance degradation. Under the sparest pilot spacing, i.e., 1/12, DMOA enjoys a large BER reduction over LS, while still closely tracking the MMSE performance. At an SNR range of 25-30 dB, the curve for DMOA is substantially below that of LS, by more than four times, while closely tracking MMSE.

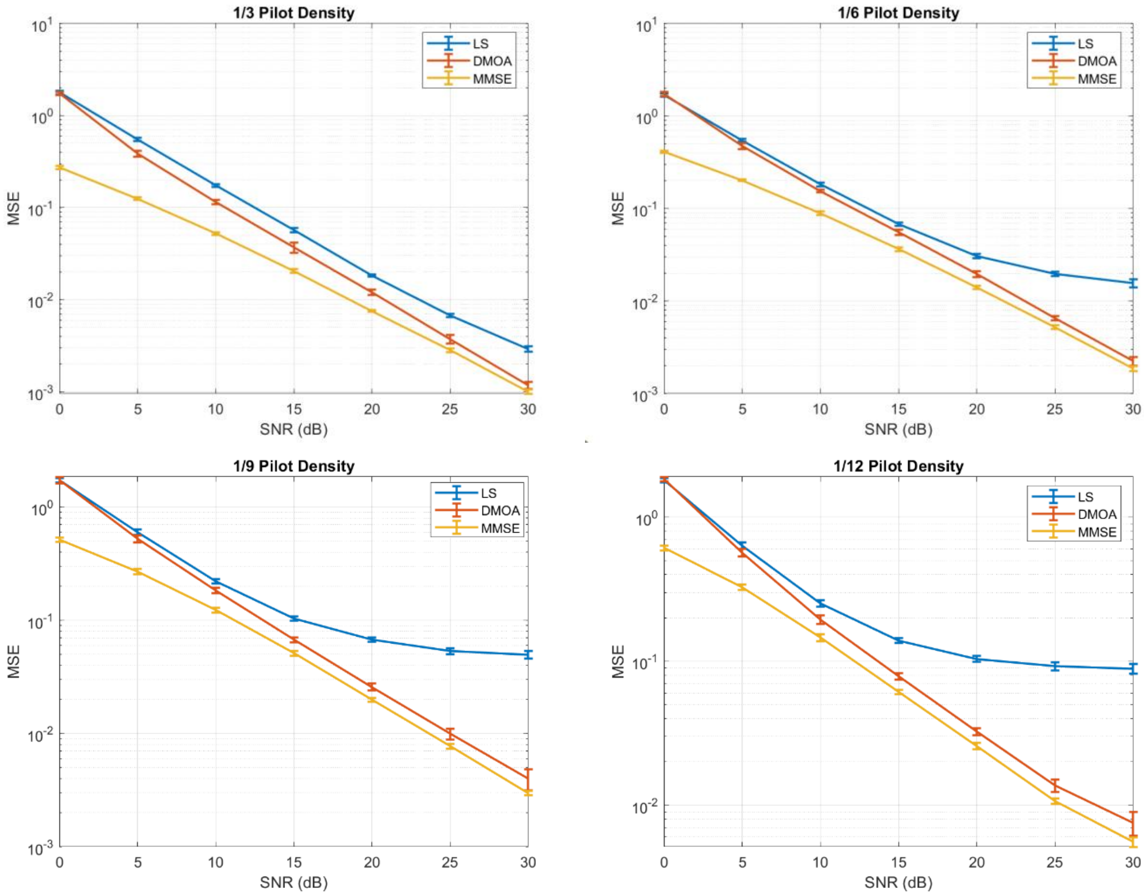

Figure 4. MSE vs. SNR performance of LS, MMSE, and DMOA estimators for QPSK, 16-QAM, 64-QAM, and 256-QAM under different pilot spacings (1/3, 1/6, 1/9, 1/12) over the 3GPP TDLC-300 channel.

Further, the mean squared error results provided by Figure 4 offer some further insight into the behavior. As the distance between the pilots increases, the least squares estimator shows a sharp rise in MSE due to the lack of adequate sampling of the frequency-selective channel. In contrast, the DMOA method shows lower MSE values as the distance between the pilots increases, as the adaptive adjustment of the correlation parameters, inspired by the MMSE method, compensates for the lack of sampling. In the case of 64-QAM, the relative MSE improvement of the DMOA method over the LS method is significant, especially at 1/9 and 1/12, which indicates that the DMOA method is especially beneficial when the overhead of the pilot arrangement needs to be minimized. While the actual values of the MSE vary between the different modulation methods, the qualitative behavior is the same: the DMOA method compensates for the degradation due to sparse pilot arrangements and reduces the performance gap to the MMSE method.

The findings in these experiments point to an important practical consequence: high pilot density inherently leads to reduced interpolation error, which, in turn, makes optimization-based estimators less competitive. However, DMOA becomes more beneficial in low-overhead scenarios, where classical LS estimation experiences significant interpolation errors.

3.3. Performance over Different 3GPP Fading Models

Figure 5 assesses how robustly the proposed DMOA-based estimator performs against different standard 3GPP channel models. For this test case, 16-QAM transmission with pilot spacing of 1/6 is employed through the EPA, EVA, and ETU models, which represent pedestrian, vehicular, and highly dispersive urban environments, respectively. For all three models, DMOA significantly outperforms LS estimation while closely tracking the MMSE estimator.

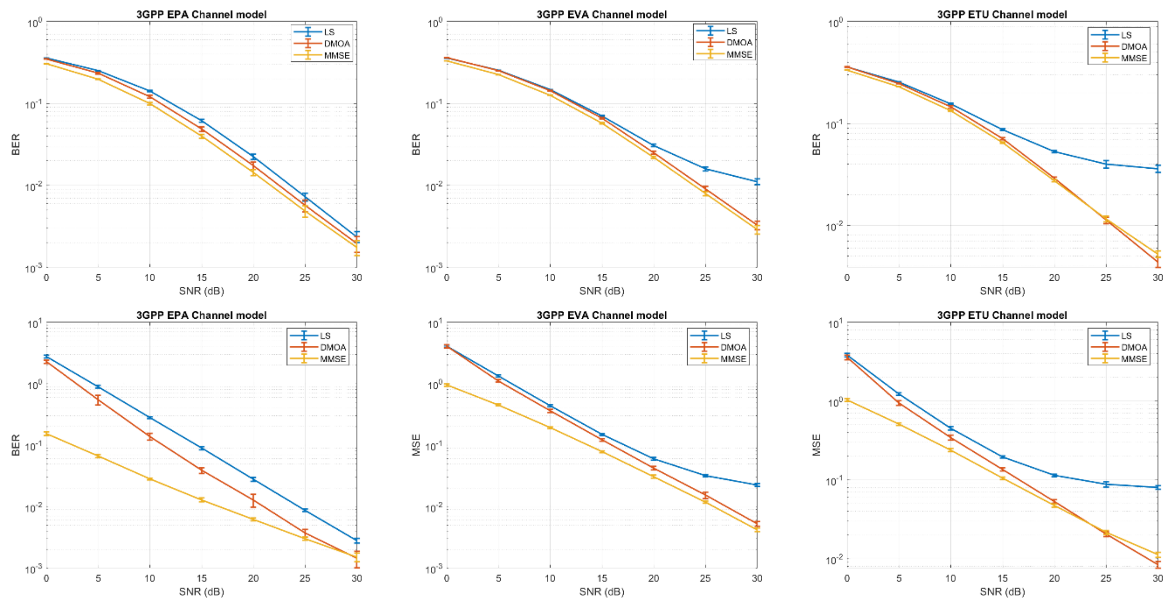

Figure 5. BER and MSE performance of LS, MMSE, and DMOA estimators for 16-QAM over the 3GPP EPA, EVA, and ETU channel models with 1/6 pilot spacing.

For the EPA channel with mild delay spread, DMOA's performance gain over LS is evident but moderate. For the entire range of SNR values, DMOA's improvement over LS is reflected by a 5 to 10% improvement in BER at low to medium SNR values, with increasing gains at higher SNR values where DMOA's performance is closer to the MMSE estimator's performance. At 20 to 25 dB SNR values, DMOA's BER performance is significantly better than LS's while remaining close to the MMSE estimator.

For the EVA channel with higher delay spread and frequency selectivity, DMOA's performance gain over LS is even clearer. For all SNR values, DMOA's BER performance is significantly better than LS's, with the BER performance curve shifting downward to indicate better performance.

For the ETU channel with the most extreme delay spread and higher Doppler components, LS's performance is significantly worse than DMOA's, especially at medium to high SNR values with extreme frequency selectivity. DMOA's performance gain over LS is evident at all SNR values, with DMOA's performance significantly better than LS's at medium to high SNR values.

In summary, the performance of DMOA across the three channel models with varying delay spreads and Doppler components confirms DMOA's robustness to channel environments with varying characteristics while remaining close to the MMSE estimator's performance without any prior knowledge of channel statistics. The confidence intervals show that the improvements are statistically significant and not merely due to random fluctuations.

3.4. Comparison with Alternative Metaheuristic Estimators

In Figures 6, a comparative analysis of the proposed DMOA-based estimator with other two metaheuristics, i.e., PSO and DE, is provided for 16-QAM transmission over the EPA channel with pilot spacing equal to 1/6. As shown, all three metaheuristics optimize the same cost function based on the MMSE criterion but have different search strategies.

From the BER plots shown in Figure 6a, it can be seen that all three optimization-based estimators perform better than the LS estimator. Moreover, DMOA has the lowest BER among all three metaheuristics for the entire range of SNRs. At medium to high SNRs, DMOA has better stability compared to PSO and DE, resulting in better convergence to the desired solution compared to the other two metaheuristics. These results are also reflected in the MSE plot shown in Figure 6b, where DMOA has the lowest MSE among all three metaheuristics, followed by PSO and DE, while the LS estimator has the worst performance.

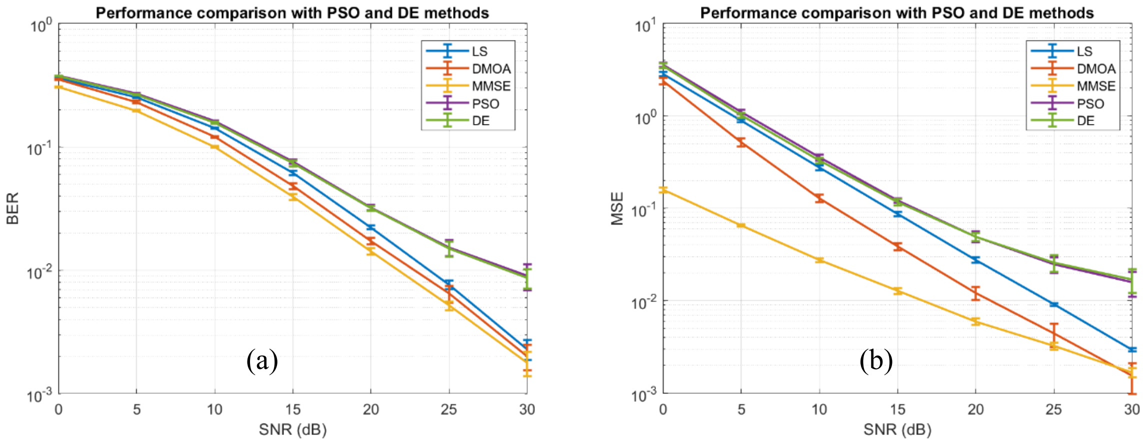

Figure 6. BER and MSE performance of LS, MMSE, DMOA, PSO, and DE estimators for 16-QAM over the 3GPP EPA channel model with 1/6 pilot spacing.

The results suggest that while PSO and DE-based estimators perform better than the LS estimator for channel estimation over the EPA channel, DMOA has a better exploration/exploitation tradeoff for channel estimation problems. As a result of its highly efficient population update mechanisms, DMOA has a better tradeoff between stability and precision than PSO and DE-based estimators for channel estimation problems, resulting in lower BER and MSE for the entire range of SNRs.

3.5. Comparison with Alternative Metaheuristic Estimators

In this subsection, a comparative evaluation of the proposed DMOA-based estimator with respect to two popular evolutionary-based optimization techniques, namely, Particle Swarm Optimization (PSO) and Differential Evolution (DE), as well as the traditional LS and ideal MMSE estimators, is presented for the case of 16-QAM modulation in the presence of the 3GPP EPA fading channel with a pilot spacing of 1/6. The numerical results, in terms of BER and MSE with 95% confidence intervals, are presented in Figure 6a and Figure 6b, respectively.

From Figure 6a, it is clear that the DMOA-based approach provides the optimal results among all metaheuristic-based techniques for the entire range of signal-to-noise ratio (SNR). In the case of low SNR levels, i.e., between 0 dB and 5 dB, all techniques present similar trends in their BER curves due to noise effects; however, a slight improvement of the DMOA-based estimator with respect to the traditional LS estimator, as well as worse performance of PSO and DE, is observed. In the case of higher SNR levels, i.e., above 10 dB, the gap between the curves of the different techniques becomes clearer. Specifically, for an SNR of 15 dB, the DMOA-based estimator presents a BER of 4.8×10-2, whereas the traditional LS estimator presents a BER of 6.1×10-2, a significant improvement in terms of error rate reduction. In contrast, PSO and DE present a BER of 7.3×10-2, a weaker convergence behavior of these two techniques. In addition, the traditional LS estimator presents a significant error floor for high SNR levels, whereas the DMOA-based estimator continuously decreases the BER and approaches the ideal MMSE estimator.

The MSE values in Figure 6b also confirm the better estimation accuracy of DMOA. In all SNR values, DMOA is seen to follow the ideal MMSE curve very closely, with MSE values significantly lower than those of the competing methods, such as LS, PSO, and DE. For example, when SNR=20 dB, DMOA has an MSE of 1.2×10-2. This is more than double the MSE of the LS method, with the metaheuristic methods having MSE values even higher, above 4.5×10-2. The MSE values of PSO and DE are even larger when SNR is high, such as 30 dB, where DMOA has an MSE of 1.5×10-3. PSO and DE methods, although better than the LS method, show lower convergence dynamics, which leads to larger error values and wider confidence intervals.

4. CONCLUSION

This paper proposes a framework for channel estimation based on the DMOA algorithm for OFDM systems, which does not require any information on channel statistics. The simulation results show that the proposed scheme outperforms the LS estimator for all modulation schemes, pilot spacings, and 3GPP channel models. In the case of the TDLC-300 channel, DMOA improves the BER and MSE performance of the system for QPSK, 16-QAM, 64-QAM, and 256-QAM modulation schemes. The improvement in system performance is significant, especially at medium and high SNRs, where the LS estimator fails to provide an improvement due to the limitations of interpolation-based methods. It is also observed that the DMOA estimator provides good performance for sparse pilot configurations and minimizes the adverse effects of pilot spacing on the system, which are inherent in the LS estimator.

Further simulations with EPA, EVA, and ETU channels are performed, and it is observed that the proposed estimator provides good performance for different channel environments, approaching the ideal MMSE estimator without any information on channel statistics. In addition, the proposed estimator outperforms PSO and DE in terms of convergence characteristics and provides lower BER and MSE for all SNR values. Based on the simulation results, it can be inferred that the DMOA estimator provides good channel estimation capabilities and can be used for channel estimation in future wireless systems, especially in environments where there are requirements for low pilot overhead and no information on channel statistics.

Acknowledgment

This study did not receive any funding or support from any institution or organization.

Statement of Research and Publication Ethics

The study is complied with research and publication ethics.

Artificial Intelligence (AI) Contribution Statement

This manuscript was entirely written, edited, analyzed, and prepared without the assistance of any artificial intelligence (AI) tools. All content, including text, data analysis, and figures, was solely generated by the author.

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