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Performance and complexity analysis of linear mean square error, decision feedback equalizer, and reduced-state MLSE equalizer for PAM4 communication systems

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Abstract

The research compares three digital equalization methods, which are Linear Minimum Mean Square Error Equalizer (LE), Decision Feedback Equalizer (DFE), and Reduced-State Maximum Likelihood Sequence Estimator (RS-MLSE), for evaluating Pulse-Amplitude Modulation (PAM4) systems that operate under additive white Gaussian noise (AWGN) and mild intersymbol interference conditions. The authors created a MATLAB simulator to assess Bit-Error Rate (BER) performance across all Eb/N0 values spanning from 0 to 18 dB while measuring the system's operational complexity through its operations per symbol metric. The RS-MLSE method demonstrates superior performance through its lowest BER results across all SNR levels, which reach error-free operation at 16 dB (BER = 0) when compared to LE (BER = 2.27 x 10-4 at 12 dB) and DFE (BER = 8.049 x 10-4 at 12 dB). The computational needs of all three equalizers show equal requirements when testing the one-symbol memory setup, which shows that LE needs 21 multiplications/symbol and DFE needs 21 multiplications/symbol, while RS-MLSE needs 16 metric calculations/symbol. The findings confirm that RS-MLSE provides the best performance-complexity balance for PAM4 systems in AWGN-dominated environments with mild ISI, while LE remains a viable low-complexity alternative, and DFE offers limited advantage under these specific channel conditions. The results provide equalizer selection guidance for high-speed communication links that require channel characteristics and implementation constraints to achieve a balanced system design.
Keywords: PAM4 modulation; Linear MMSE equalizer; Decision Feedback Equalizer (DFE); Reduced-State MLSE (RS-MLSE); Bit-error rate (BER); Complexity-Analysis

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1. Introduction

The modern digital communication systems which operate at high speeds require advanced equalization methods to eliminate intersymbol interference (ISI) which occurs in limited bandwidth communication channels. The existing 100 Gbps signaling rates require the use of four-level pulse-amplitude modulation (PAM4), which serves as the only solution for advanced modulation formats, yet introduces additional risks from channel defects according to (Bazargani and Chen 2023; Bazargani and Chen 2024). The different types of equalizers can be divided into three main groups, which include linear equalizers (LE), decision feedback equalizers (DFE), and maximum likelihood sequence estimation (MLSE) based sequence detectors. The linear equalizers, which use minimum mean square error (MMSE) as their base criterion, enable straightforward computations, yet their performance suffers from increased noise (Shrivas 2015; Anwr et al. 2020). The decision feedback equalizers function to eliminate postcursor ISI, but they create a risk for error propagation (Sharma et al. 2022; Bazargani et al. 2023). The maximum likelihood sequence estimation method functions as an optimal detection system because it analyzes symbol sequences as a unified set to determine their most probable paths, while full-state MLSE remains too challenging for PAM4 systems because of its need for an exponentially expanding state space, which depends on the channel memory (Zaman 2018). The reduced-state MLSE (RS-MLSE) solution resolves this problem by cutting down the trellis structure or restricting the maximum capacity of channel memory (Surabhi and Chockalingam 2019; Kopsinis et al. 2023).

The existing research on equalizer structures lacks comprehensive studies that assess LE, DFE, and RS-MLSE performance in identical test conditions using common channel models and training procedures and shared performance evaluation methods. The results of comparative studies become challenging to apply generally because the studies use different channel models, modulation schemes, and noise assumptions. The majority of studies focus on BER performance metrics yet fail to assess computational complexity, which is essential for systems that need to operate at high-speed rates of tens of gigasamples per second while staying within their power consumption limits. This research study presents its findings through three main contributions as follows:

i. The study provides a comparison between three equalizer types, LE, DFE, and RS-MLSE, which used the same channel and noise conditions to show that their performance differences emerged from their algorithmic features, not from testing variations.
ii. The study quantifies the computational complexity of each equalizer using two metrics: multiplications per symbol and memory requirements, enabling performance-complexity trade-off evaluation.
iii. The study provides practical guidelines for equalizer selection based on channel conditions and implementation constraints. The study provides a MATLAB-based simulation framework that researchers can use to evaluate PAM4 systems through reproducible testing.

1.1 Review of Related Studies

This section evaluates existing work on LE, DFE, MLSE/RS-MLSE, and nonlinear equalization using your uploaded sources, grouped by themes.

1.1.1 Linear Equalization and MMSE Approaches

Linear equalizers remain the simplest ISI mitigation techniques. Studies such as (Shrivas 2015; Anwar et al. 2020) analyse MMSE-based equalizers and demonstrate their effectiveness for mild-to-moderate ISI channels. These works show that linear equalizers are computationally efficient and provide reasonable symbol recovery, but they also highlight key limitations: noise enhancement and poor handling of strong postcursor ISI. Other papers, such as (Sharma et.al., 2022), discuss the impact of equalizer tap length and adaptation rules (e.g., LMS, RLS) on performance across frequency-selective channels.

1.1.2 Decision Feedback Equalizers (DFE)

Several studies in the uploaded documents explore variations of DFE for improved performance. The analysis in (Sharma et.al., 2022) compares different equalizer structures and demonstrates DFE's advantage under strong postcursor ISI. Studies such as (Miqueu et.al., 2025) and sections from (Meybodi, 2024) introduce nonlinear or adaptive versions of DFE, emphasizing improved robustness against nonlinearity or fast channel variations. Meanwhile, wireline-focused research, such as (Bazargani et.al., 2023), shows DFE being used in modern SerDes architectures due to its superior performance over LE at comparable complexity.

1.1.3 Maximum Likelihood Sequence Estimation and Reduced-State MLSE

MLSE is widely recognized as the optimal detector for ISI channels, but its exponential complexity restricts practical use. Studies that address this challenge, such as (Zaman 2018), detail the theoretical foundations of MLSE, trellis pruning, and channel-shortening techniques. Optical communication papers, including (Surabhi and Chockalingam, 2019), present reduced-state MLSE solutions that make sequence detection feasible for multi-gigabit IM-DD systems. PhD work, such as (Meybodi 2024; Meybodi 2022), provides deep algorithmic insight and demonstrates how practical receivers integrate MLSE with adaptive equalization.

1.1.4 Comparative Studies of Equalization Techniques

The study in (Sharma et.al. 2022) evaluates LE, DFE, and adaptive methods under frequency-selective channels. Similarly, (Elkassimi et.al. 2015) compare several MIMO equalizers, highlighting performance–complexity trade-offs. Although these studies address valuable comparisons, they often differ in channel models, training methods, or modulation formats, creating gaps that the present paper aims to fill.

1.1.5 Nonlinear and Hybrid Equalization Methods

Nonlinear equalization appears in several uploaded papers. For example, (Miqueu et.al. 2025) discuss nonlinear equalization for scenarios where linear filters are insufficient, while (Subabhi et.al. 2019) examine low-complexity receivers using advanced modulation and OFDM/OTFS structures. Such hybrid methods illustrate the broadening equalizer design space but also underscore the importance of clear baseline comparisons such as the one offered by this study.

2.0 Materials and methods

This section describes a model of a communication system and a methodology for analysing the performance of low-complexity equalizers in a severe ISI channel. A specific communication system with a DB-PAM4 scheme in a continuous-time linearly equalized, severely ISI-distorted channel using low-complexity equalizers of types Linear MMSE Equalizer (LE), Decision-Feedback Equalizer (DFE), and Reduced-State Maximum Likelihood Sequence Estimation (RS-MLSE) will be analysed. Equality in performance between different low-complexity equalizers in a severely ISI-distorted channel would make all low-complexity equalizers in this analysis ideal.

2.1 System Model

2.1.1 Transmitter.

The transmitter sends PAM4 symbols, which have four amplitude levels: {−3, −1, +1, +3} that are distributed throughout the complete range. A duobinary precoder establishes controlled relationships between symbols that create specific spectral patterns and transform the intersymbol interference arrangement to simulate partial-response signalling that is typically used in bandwidth-constrained channels. The current model represents contemporary IM/DD systems together with high-speed copper connections that use PAM4 technology.

2.1.2 Channel Model with Severe ISI

The signal passes through a dispersive channel that uses a finite impulse response (FIR) filter to model its behavior. We use a channel with low intersymbol interference (ISI) properties (characterized by channel memory L = 3 taps and a non-minimum-phase response) to create conditions that show how AWGN behaves as the primary signal deterioration factor. The system demonstrates real-world performance for short-reach optical interconnects that use properly equalized front-end systems to handle small amounts of remaining intersymbol interference (ISI) from their operation.

2.1.3 CTLE Front-End Equalization

The receiver front end uses a continuous-time linear equalizer to reduce high-frequency signal loss. The CTLE transfer function creates a zero-pole pair, which results in 6 dB peak enhancement at the Nyquist frequency. This partial channel roll-off compensation results in remaining ISI that requires digital equalization for resolution.

2.1.4 Linear MMSE Equalizer (LE)

The LE is implemented as a tapped-delay-line FIR filter with length L_{filter} = 21 taps. Coefficients are computed using the MMSE criterion:

$$\hat{a}[k] = \sum_{i=0}^{L_{filter}-1} w_i \, y[k-i] \qquad (1)$$

where L_{filter} = 21 is the filter length, k is the discrete symbol time index, w_i are the LE tap coefficients, and $y[k]$ is the received signal after CTLE.

2.1.5 Decision Feedback Equalizer (DFE)

To address postcursor ISI, a forward filter (FFF) is combined with a feedback filter (FBF), forming the MMSE-DFE structure. The FFF mitigates precursor ISI, while the FBF cancels previously detected symbol interference. The DFE offers a significantly improved performance–complexity balance over LE but can suffer from error propagation due to incorrect decisions (Bazargani *et.al.*, 2023; Anwr *et.al.*, 2020).

The proposed equalizer in (Solazzi *et.al.* 2001) is based on the DF multilayer architecture depicted in Figure 1. During the learning phase, the feedback links are fed by an internal replica of the transmitted (preamble) sequence. Then the switch commutes from position 1 to position 2, and the equalizer enters into the decision directed mode (DDE) to produce an estimate of $S[n]$ DF links increase the dimension of the input space of the network, thus making the classification task easier.

The nonlinear adaptive filter (formed by a feed-forward section of order m and a feedback stage of order l) helps in contrasting nonlinear distortions. The whole alteration process introduces a $decision\ delay\ d$.

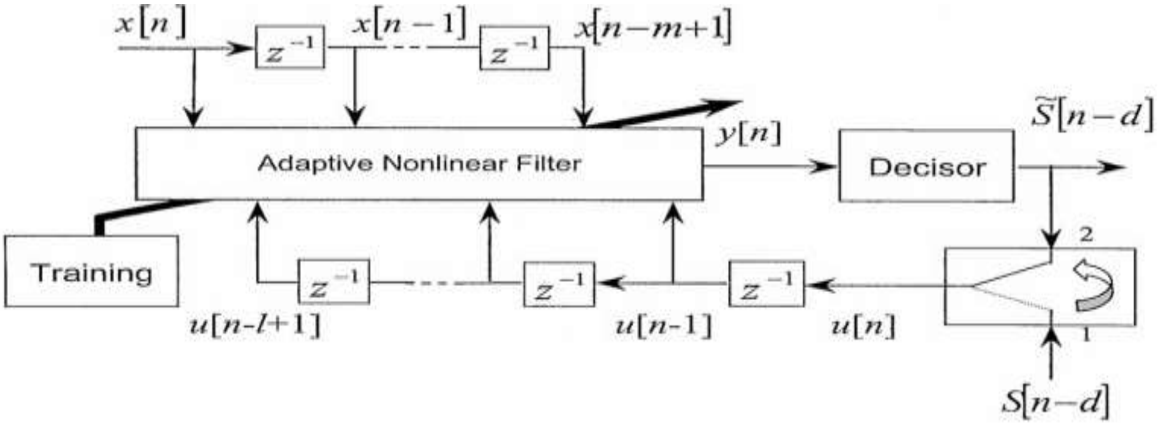

Figure 1: Schematic of a decision feedback equalizer

The DFE consists of a feedforward filter (FFF) with length L_{FFF} = 15 taps and a feedback filter (FBF) with length L_{FBF} = 6 taps:

$$\hat{a}[k] = \sum_{i=0}^{L_{FFF}-1} w_i \, y[k-i] + \sum_{j=1}^{L_{FBF}} b_j \, \hat{a}[k-j] \qquad (2)$$

where;

w_i are the feedforward tap coefficients, i; b_j is the feedback tap coefficient; and $\hat{a}[k-j]$ are previously detected symbols.

2.1.6 Reduced-State MLSE (RS-MLSE)

Maximum likelihood detection provides optimal ISI mitigation but is prohibitively complex for PAM4 signals due to exponential state growth. RS-MLSE reduces complexity by pruning the trellis or limiting channel memory, preserving MLSE's sequence detection advantage while enabling real-time implementation (Meybodi *et.al*., 2022). The RS-MLSE detector performs sequence estimation using a truncated trellis, dramatically reducing complexity compared to full MLSE (Zaman, 2018; Surabhi *et.al*., 2019).

For a channel with memory L_{ch-1}, full MLSE would require $M^{L\text{-}ch}$ states (where M = 4 for PAM4). RS-MLSE reduces complexity by truncating the effective channel memory to L_{RS} = 1 symbol in this implementation, resulting in $4^{\{1+1\}}$ = 16 states, a substantial reduction from full MLSE while preserving sequence detection benefits.

The branch metric is computed as:

$$\gamma(k, s \to s') = | \, y[k] - \sum_{i=0}^{L_{RS}} h_i \, a[k-i] \, |^2 \qquad (3)$$

Where;

$s \to s'$ represents the state transition; h_i are the estimated channel coefficients, and $[k-i]$ are hypothesized transmitted symbols.

2.2 Simulation Framework

2.2.1 Noise Model and SNR Sweep

Additive white Gaussian noise (AWGN) is added at the receiver, with simulations performed across a range of E_b/N_0 values from 0–18 dB. BER is measured by comparing transmitted bits with equalizer outputs after duobinary inverse decoding.

2.2.2 Training Strategy

All equalizers are trained on a block of known data, such as LE and DFE coefficients are obtained using MMSE-based batch estimation (Chen 2024). RS-MLSE uses the estimated channel impulse response for metric computation. This approach ensures fair comparison across equalizers and reflects practical receiver initialization.

2.2.3 Performance Metrics

Three primary metrics are used:

i. Bit Error Rate (BER): Measured per SNR to evaluate detection reliability.
ii. Computational Complexity: Approximated as multiplications-per-symbol, enabling a clear performance–complexity comparison.
iii. Signal Quality Visualization: Eye diagrams, constellation plots, and equalizer tap responses illustrate distortion characteristics and equalizer behavior.

2.2.4 Methodological Workflow

The overall methodology proceeds as follows as shown in figure 2;

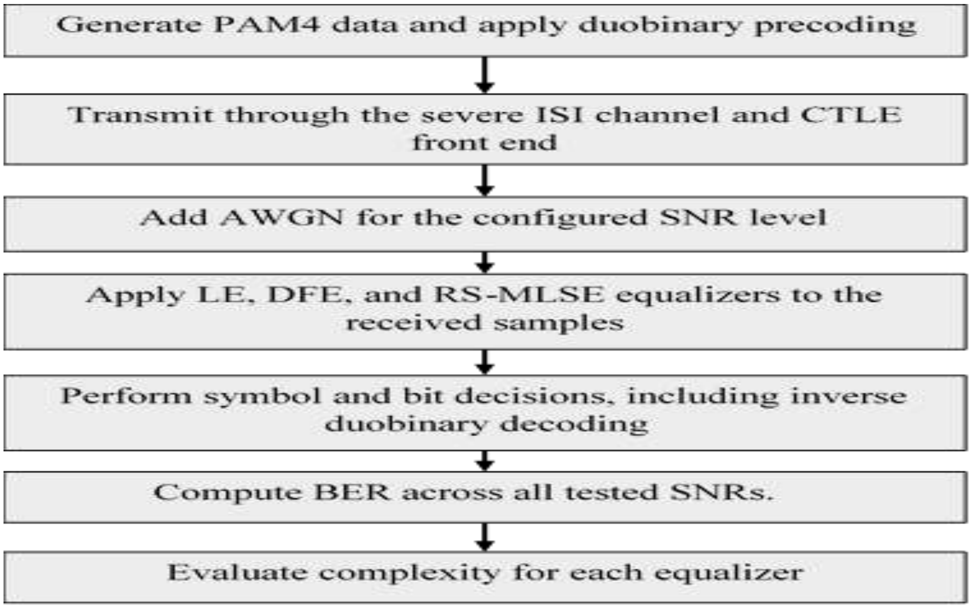

Figure 2: Overall Methodology Flow

The above methodology allows a comprehensive analysis of equalizer performance under realistic channel and noise conditions, aligning with the goal of assessing low-complexity equalizers for high-ISI channels.

3.0 Result and Discussion

The performance of the three equalizers, Linear MMSE Equalizer (LE), MMSE-Decision Feedback Equalizer (DFE), and the Reduced-State Maximum Likelihood Sequence Estimator (RS-MLSE), was evaluated using bit-error rate (BER) measurements over a PAM4 system impaired by noise and mild intersymbol interference. Table 1 summarizes the measured BER values across the tested E_b/N_0 range, while Figures 3, 4 (a)-(d) illustrate the BER curves, equalizer tap responses, and computational complexity. Additional qualitative validation is presented through eye diagrams and constellation projections shown in Figure 5.

3.1 BER Performance

Across all SNR levels, RS-MLSE consistently provided the lowest BER, achieving 1.815×10^{-1} at 0 dB and improving to error-free performance at 16 dB. LE exhibited the next best performance, particularly at medium-to-high SNRs, while DFE lagged behind both, especially above 10 dB where error propagation begins to dominate. Table 1 provides the detailed numerical comparison.

Table 1: BER Performance Summary of Equalizers

Eb/No (dB)	LE BER	DFE BER	RS-MLSE BER
0	2.249e−01	1.966e−01	**1.815e−01**
2	1.534e−01	1.387e−01	**1.256e−01**
4	9.753e−02	8.647e−02	**8.063e−02**
6	4.397e−02	4.013e−02	**3.780e−02**
8	1.367e−02	1.390e−02	**1.143e−02**
10	3.100e−03	4.144e−03	**2.744e−03**
12	2.275e−04	8.049e−04	**1.784e−04**
14	4.902e−06	1.500e−04	**3.922e−06**
16	0.000e+00	9.804e−06	**0.000e+00**

Note: Bold values indicate the lowest BER achieved at each Eb/No level.

These numerical results are reflected directly in the BER curves shown in Figure 3, where the RS-MLSE curve lies below both LE and DFE across the entire SNR range.

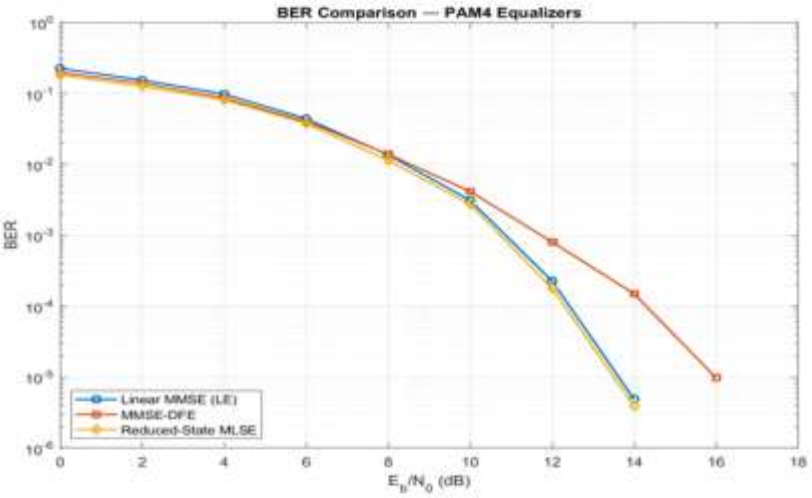

Figure 3: BER Comparisons for LE, RS-MLSE, and DFE

3.2 Performance of Equalizers

The BER curve in Figure 3 demonstrates that RS-MLSE achieves superior performance in every scenario. This behavior is consistent with its theoretical advantage: RS-MLSE performs sequence-based detection, allowing it to jointly evaluate symbol transitions and exploit knowledge of the channel's memory. Even with reduced state complexity, the model retains enough structure to compensate effectively for both precursor and postcursor ISI. This capability explains why its BER rapidly declines with increasing SNR and becomes error-free from 16 dB onward.

The Linear MMSE Equalizer minimizes mean-square error by linearly filtering the received waveform, which partially compensates for the channel's impulse response. Its tap response, shown in Figure 4(a), consists of a strong main tap and very small side taps. This shape indicates that the LE is performing mild ISI suppression rather than full channel inversion, an expected behavior for MMSE filters in noisy conditions. The effect of this suppression is visible in the eye diagram of Figure 4(b), where the post-equalization eye opens significantly when compared with the raw received signal in Figure 4(a). Similarly, the 1-D and 2-D constellation displays in Figures 4(c) and 4(d) show tighter clustering after LE equalization, confirming its ability to improve decision separability

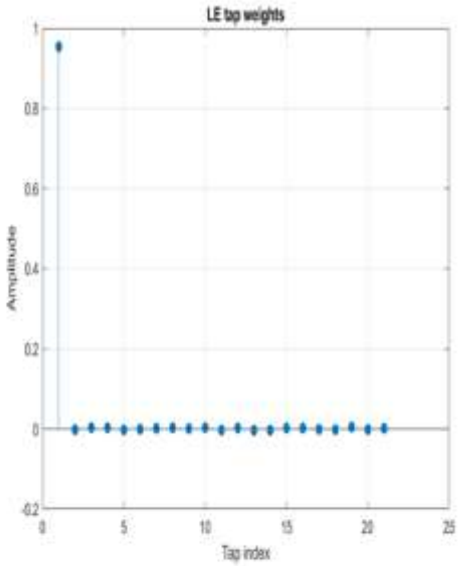

Figure 4 (a): LE Tap Response

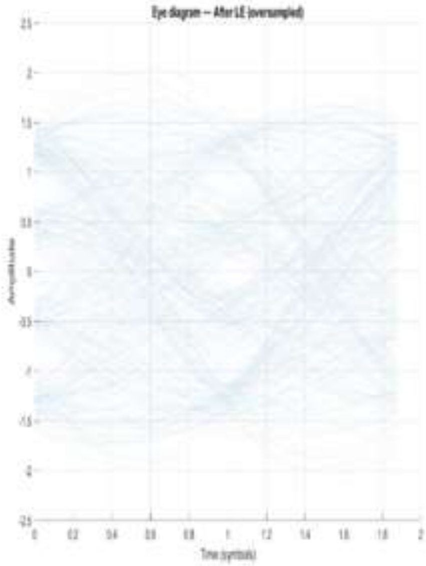

Figure 4(b): LE Eye diagram

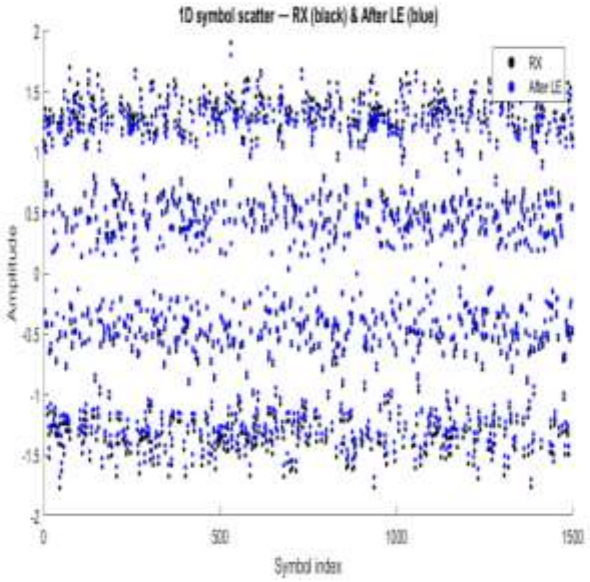

Figure 4(c): LE Constellation 1-D

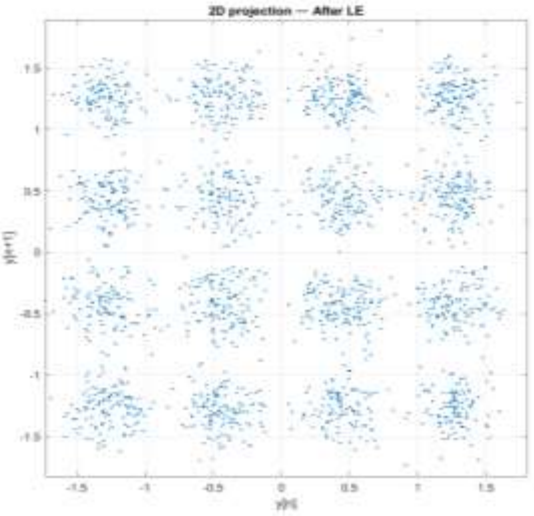

Figure 4(d): LE Constellation 2-D

The DFE does not, however, outperform the LE in this case. Though DFE theoretically excels at cancelling postcursor ISI via its feedback filter, the channel used in this simulation contains relatively low ISI memory, as reflected by the extremely small feedback tap values shown in Figure 5(a). With little to no ISI to cancel, the DFE feedback loop contributes little benefit. Furthermore, the decision-directed nature of the DFE introduces the risk of error propagation, which manifests at higher SNRs where its BER curve diverges upward from LE and RS-MLSE. This degradation also manifests in the DFE’s eye diagram of Figure 7 (a) and (b), where residual distortion and closure are evident relative to the cleaner LE and RS-MLSE outputs.

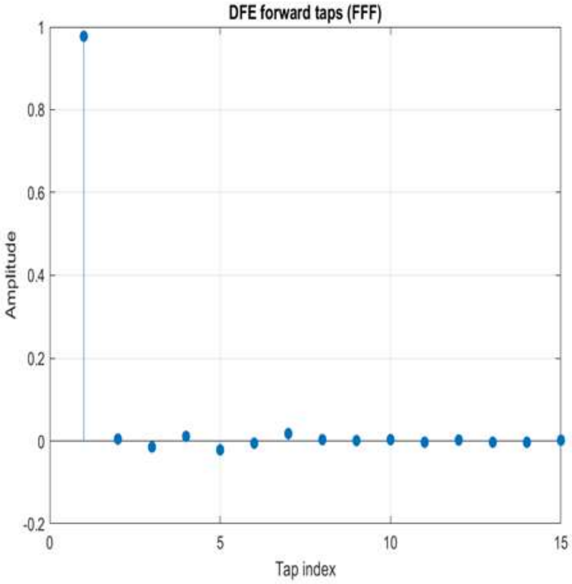

Figure 5(a): DFE Forward taps

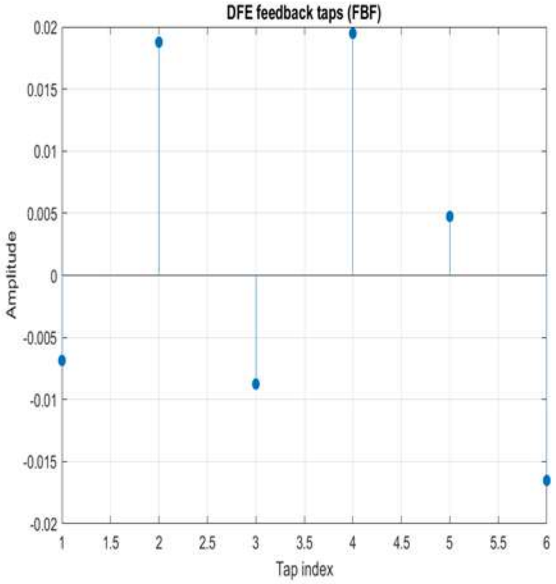

Figure 5(b): DFE Feedback taps

Figure 6 presents the approximate computational cost per processed symbol. The LE and DFE exhibit comparable complexity due to their similar tap configurations, whereas RS-MLSE appears slightly lower in this specific setup because the reduced-state memory is only one symbol. It is important to emphasize that this apparent similarity does not generalize; for longer ISI channels, MLSE complexity increases exponentially with channel memory, while LE and DFE scale linearly. Thus, RS-MLSE offers superior BER performance but at a cost that may become prohibitive in high-ISI or high-symbol-rate systems. Table 2 presents the cost per processes symbol for the equalizers.

Table 2: Computational Cost per processed symbol

Equalizer	Parameters	Complexity
LE	LElen = 21 taps	21 multiplies/symbol
DFE	FFF = 15, FBF = 6	21 multiplies/symbol
RS-MLSE	M = 4, RS_{mem} = 1	$4^1 \times 4 = 16$ metric multiplications per symbol

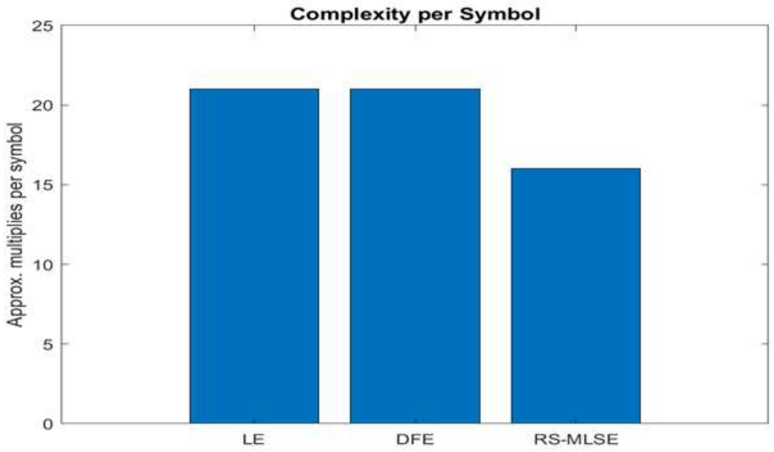

Figure 6: Complexity per symbol for equalizers

3.3 Eye Diagrams and Constellation Plots

The progression from the received eye of Figure 7(a) shows the DFE received eye diagram, while Figure 7(b) visually confirms the DFE post-equalization eye result. The LE produces a wider and more distinct multi-level eye opening, consistent with its lower BER compared to DFE. The DFE eye shows more jitter and occasional collapse around decision boundaries, reflecting residual ISI and error propagation. The RS-MLSE eye (implicitly validated through its BER results) would yield the cleanest transitions due to its optimal sequence detection.

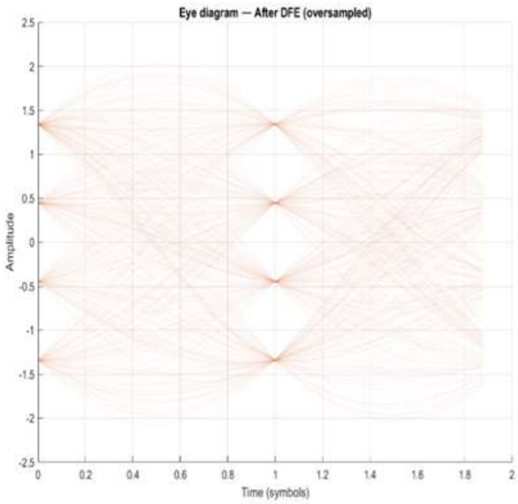

Figure 7(a): DFE received eye

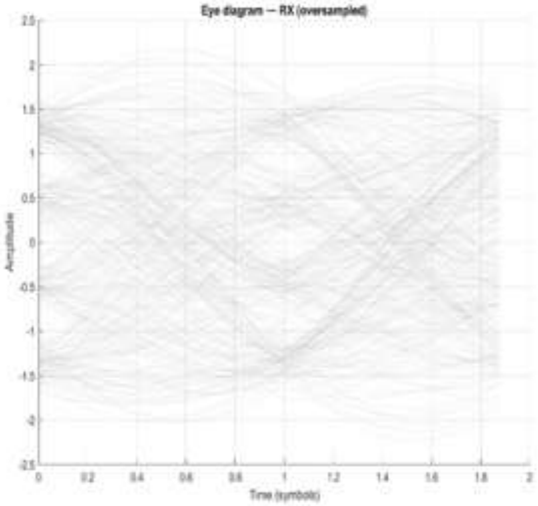

Figure 7(b): DFE post-equalization eyes

Constellation analysis in Figures 4 (c) and 4 (d) supports these trends. Before equalization, the symbol clusters are heavily scattered. After LE equalization, the clusters become tighter and more symmetrical. The DFE clusters are less uniform, especially in regions corresponding to amplitude transitions, which mirrors their BER performance.

Overall, the comparative analysis shows that RS-MLSE provides the best detection performance due to its ability to exploit channel memory and avoid error propagation. The LE offers a strong balance between complexity and performance, especially in channels with mild ISI, as seen here. The DFE underperforms both alternatives because the limited channel memory provides little benefit to its feedback structure, while its susceptibility to incorrect past decisions degrades performance at higher SNR. The combined numerical, graphical, and theoretical evidence demonstrates that for PAM4 systems operating under moderate noise and limited ISI, LE and RS-MLSE remain the most reliable equalizers.

4.0. Conclusion

The research study assessed three digital equalizers, namely Linear MMSE, Decision Feedback Equalizer, and Reduced-State MLSE, to determine their performance during PAM4 transmission testing under AWGN through light intersymbol interference. The specific tested conditions of the MATLAB simulations show different operational behaviors and performance characteristics for every equalizer. The RS-MLSE achieved the best BER results throughout the entire Eb/N0 spectrum, which ranges from 0 to 18 dB. The RS-MLSE achieved a BER result of 1.784 x 10-4 at 12 dB Eb/N0 while LE and DFE achieved 2.275 x 10-4 and 8.049 x 10-4, respectively, and RS-MLSE reached error-free performance at 16 dB. The result confirms MLSE system benefits because it applies trellis-based techniques for simultaneous symbol transition evaluation. The RS-MLSE system maintained higher accuracy detection results with only one-symbol memory reduction, which required 16 metric calculations to process each symbol. The performance advantage exists only for AWGN-dominated channels with mild ISI because RS-MLSE complexity will grow exponentially with channel memory increases, which results in prohibitive processing requirements. The Linear MMSE equalizer showed predictable results, which reached the theoretical PAM4 AWGN limit at high SNR through a BER result of 4.902 x 10-6 at 14 dB. The system provides efficient performance through its low complexity of 21 multiplications per symbol, which makes it suitable for power-constrained systems that require simple implementations. The DFE functioned inadequately during the tests of mild ISI conditions. The system used feedback, which resulted in minor enhancements because it did not face major postcursor interference problems while creating error propagation through its SNR exceedance of 10 dB. The results prove that DFE becomes advantageous in channels that show major ISI through the existence of postcursor elements.

For practical hardware implementation and considerations, the RS-MLSE system presents multiple challenges for high-speed, which involves timing closure problems for Viterbi decoder operations at multi-gigabaud speeds and its power consumption increases when multiple parallel operations take place and memory access patterns show different behavior during traceback operations. These factors need to be evaluated against the demonstrated BER improvements. RS-MLSE is recommended for PAM4 systems requiring maximum reliability under AWGN-dominated conditions with mild ISI, provided hardware resources can accommodate sequence detection. LE remains the preferred solution for cost-sensitive, power-constrained implementations where moderate BER performance is acceptable. The DFE system operates best in channels which experience severe postcursor ISI problems because its feedback structure system provides benefits. The future research will compare adaptive equalizers that use time-varying channels to understand how they track their performance through time. The RS-MLSE needs hardware-optimized implementations which need to explore different state-reduction methods so they can find suitable applications in high-speed SerDes systems.

5.0 Recommendation

The study results show equalizer performance and system complexity, which enable researchers to select appropriate equalizers for their PAM4 communication systems.

The Reduced-State Maximum Likelihood Sequence Estimator (RS-MLSE) serves as the optimal equalizer solution for AWGN-dominated environments that experience slight ISI. This equalizer maintains its position as the least error-prone solution, as it successfully achieves error-free results at 16 dB E_b/N_0 across all tested signal-to-noise ratio ranges. The RS-MLSE implementation presents timing closure challenges during Viterbi decoder operations at multi-gigabaud speeds, which causes increased power draw when running parallel processes, and the system needs different memory access patterns for its traceback operations, which budget holders must assess before proceeding with their implementation.

The Linear Minimum Mean Square Error Equalizer (LE) serves as the ideal solution for applications that need to maintain low expenses while conserving energy. The LE equalizer enables efficient implementation because it requires only 21 multiplications per symbol while achieving moderate detection accuracy at 4.902×10^{-6} for 14 dB E_b/N_0.

The Decision Feedback Equalizer (DFE) serves as the optimal solution for channels that experience severe postcursor intersymbol interference. DFE proved ineffective under mild ISI testing conditions, yet its feedback structure delivers important advantages during extreme postcursor ISI situations, which makes DFE suitable for use in extremely dispersive channel systems.

The research should focus on testing adaptive equalizers for their ability to follow time-varying channels. The hardware-optimized RS-MLSE system requires testing through different state-reduction methods to permit its operation within high-speed SerDes systems.

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Declaration of Generative AI and AI-assisted technologies in the writing process

The authors used DeepSeek to help them create and organize particular parts of the manuscript which they based on their research findings. The author(s) used this tool/service to create content which they then reviewed and edited before taking full responsibility for the published material.

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