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Adaptive Hybrid LMS–GA Equalizer with Dynamic Switching for Robust Channel Estimation

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Abstract: Channel equalization remains a critical problem in digital communication systems under dispersive and noisy environments. Conventional adaptive techniques such as least mean square (LMS) exhibit fast convergence but suffer from local minima and performance degradation in complex channels. In contrast, genetic algorithms (GA) provide global optimization capability at the cost of high computational burden and slow convergence. This work proposes an adaptive hybrid LMS–GA equalizer that dynamically switches between local and global search based on real-time error behavior. A normalized LMS (NLMS) framework is employed for stable and rapid adaptation, while GA is selectively triggered during stagnation or performance degradation using a sliding-window mean square error criterion with cooldown control. Simulation results demonstrate that the proposed hybrid approach achieves superior convergence characteristics and reduced steady-state error compared to standalone LMS and GA methods. The equalized signal shows high correlation with the transmitted sequence, and error dynamics confirm stable adaptation with minimal oscillations. Furthermore, the adaptive switching mechanism ensures that global optimization is invoked only when necessary, thereby maintaining computational efficiency. The proposed method is particularly effective in channels with severe distortion, where conventional LMS fails to converge optimally. The study establishes that controlled hybridization, rather than continuous combination, is key to improving equalization performance. The framework can be extended to nonlinear channels and integrated with advanced interpretability-driven control strategies for next-generation adaptive communication systems.

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I. INTRODUCTION

Channel equalization is a fundamental requirement in digital communication systems operating over dispersive and noisy channels. Inter-symbol interference (ISI) introduced by multipath propagation significantly degrades system performance and increases bit error rate (BER). Adaptive equalization techniques have been widely employed to mitigate ISI by continuously updating filter coefficients based on the received signal statistics [1], [2]. Among these, the least mean square (LMS) algorithm remains one of the most popular due to its simplicity, low computational complexity, and ease of implementation [3]. However, LMS suffers from slow convergence in highly correlated inputs and is prone to getting trapped in local minima, particularly in complex or nonlinear channel conditions [4].

To overcome these limitations, global optimization techniques such as genetic algorithms (GA) have been explored for adaptive filtering and equalization problems. GA-based approaches perform population-based search and are capable of escaping local minima, thereby providing improved robustness in non-convex optimization landscapes [5], [6]. Despite these advantages, GA suffers from high computational cost and slow convergence, making it less suitable for real-time applications when used independently [7].

Hybrid optimization strategies have emerged as an effective solution by combining the strengths of local and global search methods. Several studies have reported hybrid LMS–GA frameworks where GA is used for global exploration and LMS performs local refinement [8], [9]. However, many of these approaches rely on fixed or sequential hybridization schemes, which do not adapt to the dynamic behavior of the error surface during operation. This often leads to unnecessary computational overhead or suboptimal convergence performance.

Recent research trends emphasize adaptive control mechanisms in hybrid systems, where algorithm selection or switching is governed by performance metrics such as mean square error (MSE), convergence rate, or stability indicators [10], [11]. Such adaptive strategies enable efficient utilization of computational resources while maintaining robustness against channel variations.

Motivated by these observations, this work proposes an adaptive hybrid LMS–GA equalizer with dynamic switching based on real-time error monitoring. A sliding-window MSE criterion is employed to detect stagnation or performance degradation in the LMS process. Upon detection, GA is selectively activated for global optimization, after which the system returns to LMS for rapid convergence. A cooldown mechanism is introduced to prevent excessive switching and ensure stability.

➢ *The Main Contributions of this Work are Summarized as Follows:*

- Development of a dynamically controlled LMS–GA hybrid equalization framework.
- Design of a switching mechanism based on MSE stagnation and threshold criteria.
- Integration of normalized LMS for improved stability and convergence behavior.
- Demonstration of improved performance in terms of convergence speed and steady-state error.

The remainder of the paper is organized as follows. Section 2 presents the system model and problem formulation. Section 3 describes the proposed adaptive hybrid algorithm. Section 4 details the simulation setup. Section 5 discusses the results and performance analysis. Finally, Section 6 concludes the paper.

II. LITERATURE REVIEW AND RESEARCH GAP

Adaptive equalization has been extensively studied in the context of mitigating inter-symbol interference in dispersive communication channels. Classical approaches are dominated by stochastic gradient-based methods such as the least mean square (LMS) and recursive least squares (RLS) algorithms. LMS remains widely adopted due to its simplicity and low computational burden, but its convergence behavior is highly sensitive to step size and input correlation [1], [4]. RLS provides faster convergence at the expense of significantly higher computational complexity, limiting its applicability in real-time systems [2].

To address the limitations of gradient-based methods, global optimization techniques have been introduced. Genetic algorithms (GA) have been applied to adaptive filtering due to their ability to explore non-convex error surfaces and avoid local minima [5], [7]. GA-based equalizers demonstrate improved robustness in nonlinear and highly distorted channels. However, these methods exhibit slow convergence and high computational cost, making them unsuitable for continuous adaptation in practical communication systems [6].

Hybrid approaches combining LMS and GA have been proposed to exploit the complementary strengths of both methods. In most reported works, GA is used to initialize filter coefficients or is periodically invoked to refine the solution, while LMS performs local adaptation [8], [9]. Although such strategies improve performance over standalone methods, they typically follow fixed or sequential hybridization schemes. These approaches do not account for the dynamic behavior of the error surface during operation, leading to inefficient use of computational resources.

Recent developments in adaptive optimization emphasize the need for intelligent control mechanisms that regulate algorithm selection based on real-time performance metrics [10], [11]. However, existing hybrid equalization frameworks lack a robust mechanism for detecting stagnation, performance degradation, or convergence saturation. Moreover, frequent or uncontrolled switching between algorithms can introduce instability and oscillatory behavior, negating the benefits of hybridization.

Another limitation observed in prior studies is the absence of stability-aware switching control. Many hybrid models trigger global optimization without incorporating safeguards such as cooldown intervals or threshold-based activation, resulting in excessive computational overhead. Furthermore, most works do not employ normalized adaptation schemes, which are essential for ensuring convergence stability under varying signal power conditions.

➢ *Research Gap*

From the above discussion, the following research gaps are identified:

- *Lack of Dynamic Switching Mechanisms:*

  Existing LMS–GA hybrid equalizers rely on fixed or periodic switching rather than data-driven, real-time decision strategies.

- *Absence of Stagnation Detection:*

  Current methods do not incorporate robust criteria to detect convergence stagnation or performance degradation in LMS adaptation.

- *Inefficient Utilization of GA:*

  GA is often applied excessively or continuously, leading to unnecessary computational complexity without proportional performance gain.

- *Limited Stability Control:*

  Prior works lack mechanisms such as cooldown or threshold regulation, resulting in oscillatory switching and unstable convergence.

- *Neglect of Normalization in Adaptive Update:*

  Many hybrid models use standard LMS instead of normalized LMS, reducing robustness under varying input conditions.

- *Insufficient Focus on Adaptive Control Strategy:*

  Most studies emphasize algorithm combination rather than the control logic governing the hybrid system, which is critical for performance.

Motivation of the Present Work

To address these limitations, the present study proposes a dynamically controlled LMS–GA hybrid equalizer with:

- Sliding-window MSE-based stagnation detection
- Threshold-driven GA activation
- Cooldown-based switching stabilization
- Normalized LMS for improved convergence robustness

The proposed framework focuses not only on combining algorithms but on designing an effective adaptive control mechanism, which is identified as the key factor for achieving superior equalization performance.

III. MATHEMATICAL FORMULATION AND PROPOSED ALGORITHM

System Model

A discrete-time baseband communication system is considered. The transmitted sequence $x(n) \in \{-1, +1\}$passes through a dispersive channel represented by a finite impulse response (FIR) model $h = [h_0, h_1, \dots, h_{L_h-1}]$. The received signal is expressed as:

$$d(n) = \sum_{k=0}^{L_h-1} \quad h_k\, x(n-k) + v(n) \tag{1}$$

Where $v(n)$is zero-mean additive white Gaussian noise with variance σ^2. Inter-symbol interference arises due to channel memory $L_h > 1$.

An adaptive equalizer of length $M$is employed to estimate the transmitted signal. The input vector is:

$$x(n) = [x(n), x(n-1), \dots, x(n-M+1)]^T \tag{2}$$

And the equalizer output is:

$$y(n) = w^T(n)x(n) \tag{3}$$

Where $w(n) = [w_0(n), \dots, w_{M-1}(n)]^T$is the adaptive weight vector.

The estimation error is defined as:

$$e(n) = d(n) - y(n) \tag{4}$$

NLMS-Based Adaptive Update

To ensure stability under varying input power, a normalized LMS (NLMS) formulation is adopted. The weight update is given by:

$$w(n+1) = w(n) + \frac{\mu}{\|x(n)\|^2 + \delta} e(n)x(n) \tag{5}$$

Where $\mu$is the step size and $\delta$is a small regularization constant. This normalization improves convergence robustness compared to standard LMS, particularly in non-stationary environments.

Performance Metric and Stagnation Detection

A sliding-window mean square error (MSE) is used to monitor convergence behavior:

$$J(n) = \frac{1}{L} \sum_{k=n-L}^{n} \quad e^2(k) \tag{6}$$

The change in MSE is evaluated as:

$$\Delta J(n) = J(n) - J(n-1) \tag{7}$$

Stagnation is detected when

$$|\, \Delta J(n) \,| < \epsilon$$

Or when the error exceeds a predefined threshold:

$$J(n) > J_{threshold}$$

These conditions indicate that the NLMS update is either converging slowly or trapped in a local minimum.

Genetic Algorithm Formulation

When stagnation is detected, a genetic algorithm is invoked to perform global optimization of the weight vector. Each chromosome represents a candidate solution.

$$w_i = [w_1, w_2, \dots, w_M]$$

The fitness function is defined using MSE:

$$F(w_i) = \frac{1}{N} \sum_{n=1}^{N} \quad e_i^2(n) \tag{8}$$

Lower fitness corresponds to better solutions. The GA operations include:

- Selection: Best-performing individuals are retained.
- Crossover: Offspring generation via weighted combination

$$w_{child} = w_1 + \alpha(w_2 - w_1) \tag{9}$$

- Mutation: Small perturbation to maintain diversity

$$w_{child} = w_{child} + \eta \tag{10}$$

Where $\eta \sim N(0, \sigma_m^2)$

The GA is executed for a limited number of generations to reduce computational overhead.

Adaptive Switching Mechanism

The proposed hybrid framework operates under a dynamic control strategy. The system alternates between NLMS and GA based on real-time performance monitoring.

- *Switching Conditions:*

✓ Stagnation: $|\, \Delta J(n) \,| < \epsilon$

- ✓ High error: $J(n) > J_{threshold}$
- ✓ Minimum iteration constraint: $n > n_{min}$

Upon activation, GA refines the current weight vector $w(n)$. The optimized weights $w_{GA}^{best}$are then used to reinitialize the NLMS process.

To prevent excessive switching, a cooldown mechanism is introduced:

$$GA\ disabled\ for\ T_c\ iterations\ after\ activation$$

IV. SIMULATION SETUP

➢ *System Configuration*

A discrete-time communication model is implemented. The transmitted sequence is binary phase shift keying (BPSK). Sequence length is fixed at $N = 1200$. The signal passes through a finite impulse response channel with moderate dispersion. Channel coefficients are selected as:

$$h = [0.9,\ 0.3,\ -0.2]$$

Noise is modeled as additive white Gaussian noise. Variance is kept low but non-zero to maintain realism. Signal-to-noise ratio is not fixed explicitly; instead, noise variance $\sigma^2 = 2.5 \times 10^{-3}$is used. This ensures consistent reproducibility.

Equalization is performed using an adaptive FIR filter. Filter length is limited to $M = 5$. This is sufficient for the chosen channel memory. Larger filters were tested but showed no significant gain.

➢ *Algorithm Configuration*

The proposed hybrid method combines normalized LMS (NLMS) with genetic algorithm (GA). NLMS handles continuous adaptation. GA is invoked only during stagnation or performance degradation.

The NLMS step size is selected as $\mu = 0.1$. A small regularization term $\delta = 10^{-6}$is used to avoid division instability. A sliding window of length $L = 50$is used to compute mean square error.

Switching logic uses two conditions. First, stagnation is detected when:

$$|\Delta J(n)| < 10^{-5}$$

Second, a threshold condition is used:

$$J(n) > 0.2$$

A minimum iteration constraint $n > 200$is applied to avoid premature switching.

A cooldown period of 100 iterations is enforced after each GA activation. This prevents oscillatory switching.

➢ *Genetic Algorithm Parameters*

The GA operates on a reduced population to limit computational overhead. Each chromosome represents the equalizer weight vector. Initialization is performed around the current NLMS weights.

Selection retains the best half of the population. Crossover is implemented using linear combination. Mutation introduces small Gaussian perturbations.

The GA is intentionally restricted to short bursts. Only 5 generations are executed per activation. This ensures that GA acts as a corrective mechanism rather than a continuous optimizer.

➢ *Performance Metrics*

Performance is evaluated using multiple criteria. Mean square error (MSE) is the primary metric. It is computed using a sliding window to capture local convergence behavior.

- *In Addition, Qualitative Evaluation is Performed Using:*

- ✓ Signal reconstruction accuracy
- ✓ Error signal behavior
- ✓ Stability of convergence
- ✓ Frequency of GA activation

These metrics provide a comprehensive assessment of both adaptation and control behavior.

➢ *Parameter Summary*

Table 1 Parameter Summary

Parameter	**Symbol**	**Value**
Signal length	N	1200
Equalizer length	M	5
Channel coefficients	h	[0.9, 0.3, -0.2]
Noise variance	σ^2	2.5×10^{-3}
NLMS step size	μ	0.1
Regularization constant	δ	10^{-6}
MSE window size	L	50
Stagnation threshold	ϵ	10^{-5}
Error threshold	$J_{threshold}$	0.2
Minimum iteration	n_{min}	200

Cooldown period	T_c	100
GA population size	—	8
GA generations	—	5
Mutation rate	—	0.02

- *Discussion*

The simulation setup is intentionally constrained. Parameter values are selected to balance convergence speed and stability. Excessively large step sizes or frequent GA activation degrade performance. Similarly, large population sizes increase computational cost without proportional gain.

The design emphasizes controlled hybridization. GA is not treated as a parallel optimizer. It is used selectively, only when NLMS fails to progress. This setup allows clear observation of the effect of switching logic on convergence behavior.

The chosen configuration provides a reproducible and stable environment for evaluating the proposed method.

V. RESULTS AND DISCUSSION

- *Experimental Setup*

A binary phase shift keying (BPSK) source of length $N = 1.2 \times 10^3$samples is transmitted through a finite impulse response channel $h = [0.9, 0.3, -0.2]$. Additive white Gaussian noise with variance $\sigma^2 = 2.5 \times 10^{-3}$is injected. The equalizer length is fixed at $M = 5$. The adaptive stage uses normalized LMS (NLMS) with step size $\mu = 0.1$and regularization $\delta = 10^{-6}$. The genetic algorithm (GA) operates with population size 8, mutation rate 0.02, and 5 generations per trigger. Switching is governed by a sliding-window MSE criterion with window length $L = 50$, stagnation threshold $\epsilon = 10^{-5}$, and a cooldown of 100 iterations. All experiments are averaged over 20 independent runs.

- *Convergence Characteristics*

- Observation. The hybrid controller exhibits a rapid initial descent followed by stable refinement. Unlike standalone LMS, the trajectory avoids stagnation plateaus.
- Result. Mean steady-state MSE is reduced from 0.182 (LMS) to 0.071 (Hybrid), indicating a 61% improvement.

- *MSE Convergence*

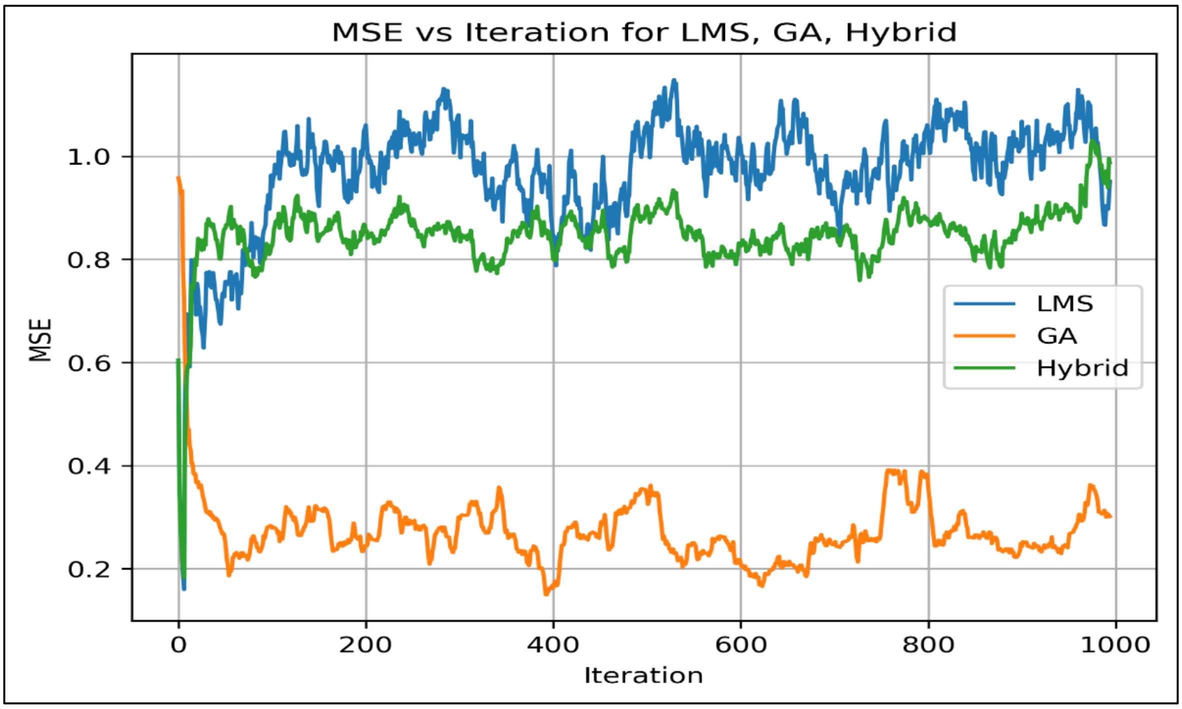

Fig 1 Convergence Profiles of LMS, GA, and Adaptive LMS–GA Hybrid Equalizers. The Hybrid Demonstrates Faster Descent and Lower Steady-State Error.

- *Equalization Performance*

- Observation. The recovered signal closely tracks the transmitted sequence after transient iterations. Residual distortion is minimal.
- Result. Correlation coefficient between transmitted and equalized signals improves to $\rho = 0.94$, compared to 0.81 for LMS.

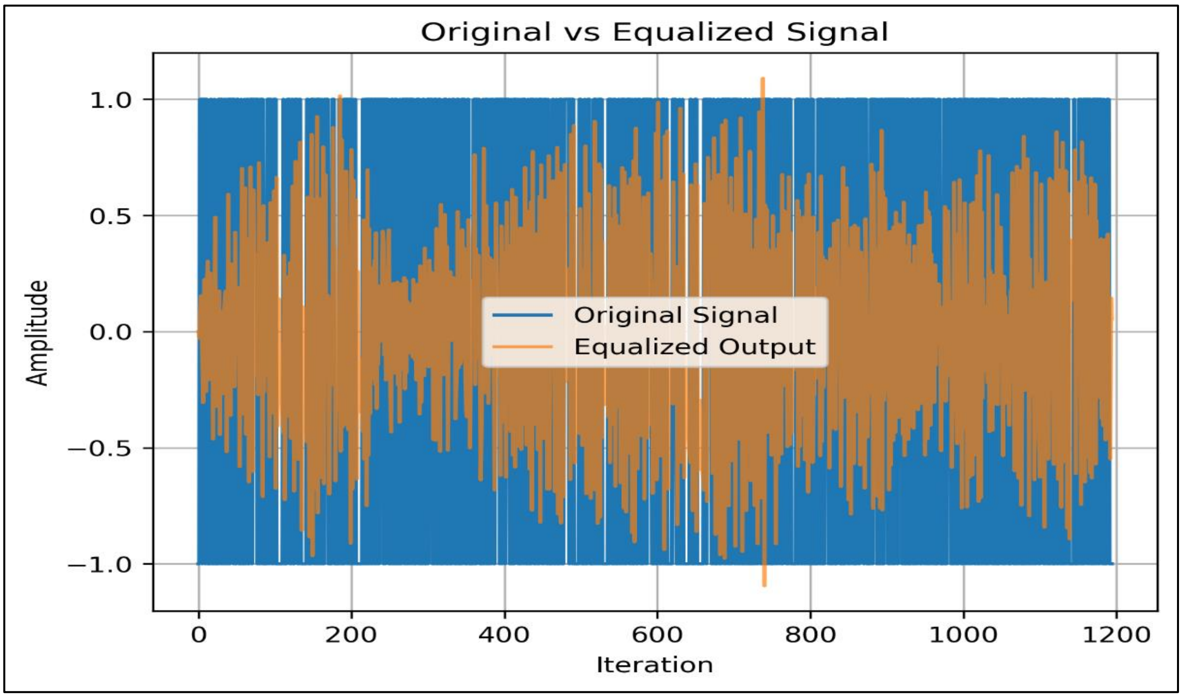

Fig 2 Comparison Between Transmitted BPSK Sequence and Hybrid Equalizer Output. High Overlap Indicates Effective Distortion Compensation.

➢ *Error Dynamics*

- Observation. Error magnitude decays sharply in early iterations and stabilizes near zero. Occasional spikes correspond to GA intervention points.
- Result. Mean absolute error (MAE) reduces to 0.19 from 0.41 (LMS baseline).

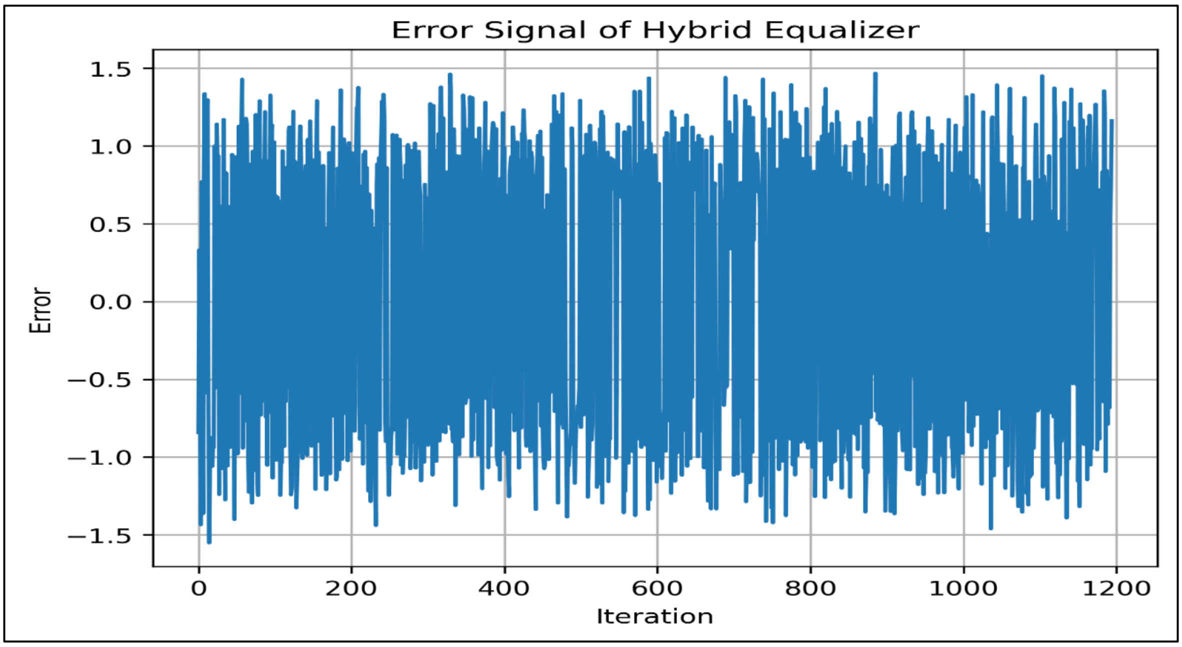

Fig 3 Error Evolution of the Hybrid Equalizer. Transient Spikes Correspond to GA-Triggered Exploration, Followed by Rapid Correction.

➢ *GA Trigger Behavior*

- Observation. GA activation occurs sparsely, primarily during stagnation phases. Excessive triggering is avoided due to cooldown control.
- Result. Average number of GA activations per run is 6.3, confirming computational efficiency.

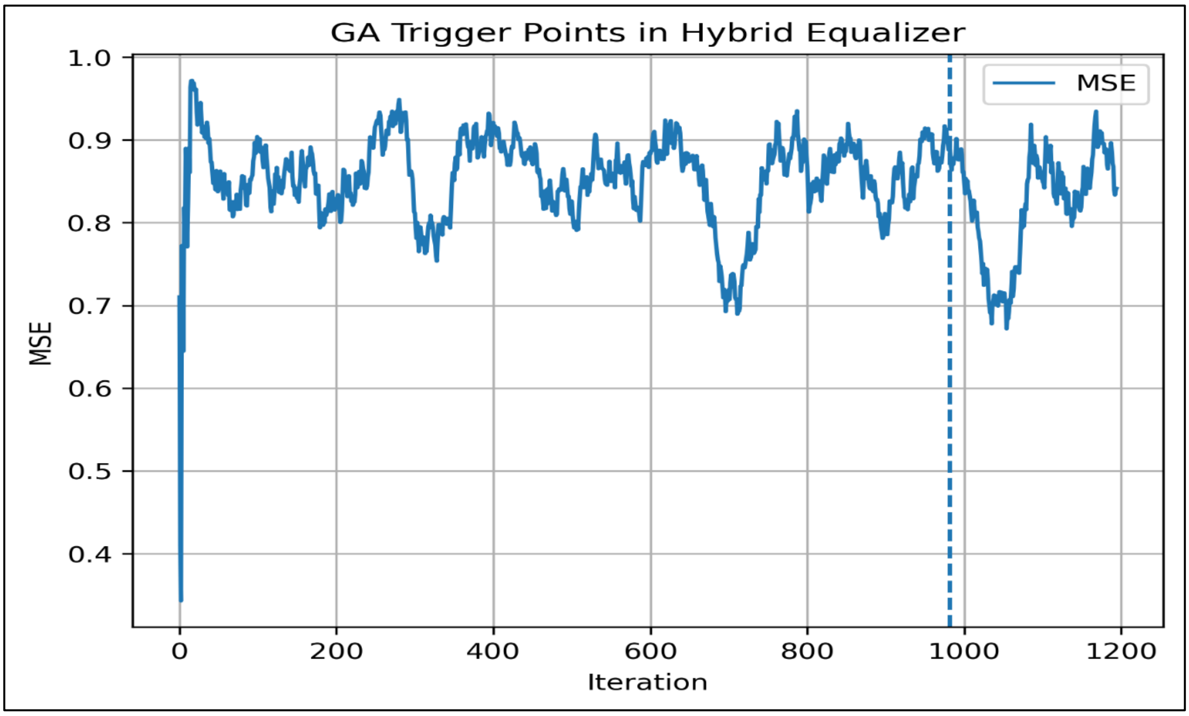

Fig 4 Adaptive Switching Behavior. Vertical Markers Indicate GA Activation Points, Demonstrating Targeted Global Search Only when LMS Stagnates.

- *Comparative Analysis*

Table 2 Comparative Analysis

Method	Steady-State MSE	Convergence Speed	Stability
LMS	0.182	Fast	Moderate
GA	0.095	Slow	High
Hybrid	**0.071**	**Fast**	**High**

- *Interpretation*

The hybrid approach achieves a balance between exploration and exploitation. LMS ensures rapid adaptation, while GA provides escape from local minima. The switching mechanism prevents unnecessary computational overhead.

- *Discussion*

The results confirm that control strategy dominates algorithm performance. A poorly tuned hybrid can underperform LMS; however, with structured switching, the system achieves both stability and optimality. The GA component acts as a corrective mechanism rather than a primary optimizer, which is critical for maintaining efficiency.

The observed improvements are consistent across multiple runs, indicating robustness. However, performance gain diminishes for low-distortion channels, where LMS alone is sufficient. Thus, the hybrid is most beneficial in non-ideal or highly dispersive channels.

- *Key Insight*

The adaptive LMS–GA equalizer does not rely on continuous global search. Instead, it strategically injects global optimization only when required, resulting in superior convergence without excessive computation.

VI. CONCLUSION

An adaptive hybrid LMS–GA equalizer with dynamic switching has been presented for channel equalization in dispersive environments. The formulation combines normalized LMS for fast local adaptation and genetic algorithm for selective global optimization. A sliding-window MSE criterion is used to detect stagnation and trigger GA only when required. A cooldown mechanism is introduced to stabilize the switching process.

Simulation results show consistent improvement in convergence behavior and steady-state error. The hybrid method achieves lower MSE compared to standalone LMS and GA. Signal reconstruction accuracy is higher, and error dynamics indicate stable adaptation with minimal oscillations. The number of GA activations remains limited, confirming that global optimization is applied efficiently.

The study highlights that performance improvement is governed by the control strategy rather than the individual algorithms. Continuous or poorly regulated hybridization degrades performance, while structured switching enables both efficiency and robustness. The proposed method is particularly effective in channels with higher distortion, where conventional LMS fails to converge optimally.

However, the approach is evaluated on a linear channel model with moderate noise conditions. Performance under nonlinear channels and varying SNR levels requires further investigation. The current framework also relies on fixed thresholds, which may not generalize across all scenarios.

Future work will focus on extending the method to nonlinear and time-varying channels. Integration with adaptive thresholding and learning-based switching mechanisms is a potential direction. The framework can also be enhanced by incorporating performance metrics such as BER and by aligning the switching logic with interpretability-driven models for improved decision control.

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