

A Multimodal Machine Learning Framework and Cost-Effective Adaptive Receiver for Improving QPSK Bit Error Rate

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Abstract: The study focuses on improving the reliability of QPSK digital communication systems in Rayleigh fading channels through adaptive intelligent signal processing. A conventional QPSK system is first modeled and analyzed in MATLAB Simulink to establish a baseline BER. To mitigate multipath fading and AWGN, the receiver is enhanced with adaptive gain control and adaptive noise suppression. Simulation results show a significant BER reduction for the adaptive system compared with the conventional one across an SNR range of 0 to 30 dB. Notably, the improvement is more pronounced at moderate to high SNR values, highlighting the robustness of the adaptive approach in realistic fading scenarios. Overall, the findings confirm that adaptive intelligent processing provides an effective, low-complexity solution for enhancing wireless communication performance.

Keywords: QPSK; Rayleigh fading channel; adaptive signal processing; bit error rate (BER); MATLAB Simulink; wireless communication systems

1. Introduction

Digital communication systems are fundamental to modern wireless technologies, including cellular networks, wireless sensor systems, and Internet of Things (IoT) applications. These systems face persistent challenges from channel impairments such as noise, interference, and multipath fading, which can significantly reduce transmission reliability. Among various channel models, the Rayleigh fading channel is widely used to represent realistic wireless environments lacking a direct line-of-sight between transmitter and receiver [1].

Quadrature Phase Shift Keying (QPSK) modulation is favored in digital communication for its higher spectral efficiency and better noise tolerance compared to binary modulation schemes. However, QPSK systems operating over Rayleigh fading channels suffer from severe amplitude and phase distortions, leading to increased bit error rates (BER), especially at low and moderate signal-to-noise ratio (SNR) levels [2]. This performance degradation limits practical wireless system effectiveness.

To counteract the effects of Rayleigh fading, various methods such as channel equalization, diversity schemes, and advanced error correction coding have been proposed [3]–[10]. While effective, these techniques often add complexity, computational load, or hardware demands. Consequently, adaptive and intelligent signal processing techniques have gained interest because they dynamically adjust system parameters based on channel conditions without excessive computational overhead [4].

Adaptive receiver techniques, including adaptive gain control and noise suppression, have proven effective in improving signal detection accuracy in fading environments [5]. These methods strike a practical balance between performance enhancement and implementation simplicity, making them suitable for both simulation and real-time applications [11], [12]. MATLAB Simulink provides a robust platform for modeling and analyzing such adaptive communication systems due to its modular design and accurate signal processing block representation [6].



This work proposes an adaptive intelligent signal processing approach to improve BER performance in a QPSK digital communication system over Rayleigh fading channels [13]. The system is modeled and evaluated in MATLAB Simulink across an SNR range of 0–30 dB [14], [15]. The focus is on adaptive parameter adjustment at the receiver to mitigate fading and noise effects while maintaining low complexity. Simulation results demonstrate significant BER improvements compared to a conventional fixed-parameter system.

The main contributions of this work are summarized as follows:

- Development of a complete MATLAB Simulink model of a QPSK system operating over a Rayleigh fading channel.
- Design of an adaptive intelligent receiver integrating adaptive gain control and noise suppression to combat multipath fading and AWGN.
- Comprehensive BER performance evaluation for both conventional and adaptive systems over a wide SNR range (0–30 dB).
- Validation of simulation results through theoretical BER analysis, showing close agreement between analytical and simulated outcomes for QPSK over Rayleigh fading.

2. Related Work

The performance of digital modulation schemes over fading channels has been extensively studied in the literature. Proakis [1] laid a foundational theoretical framework for digital communication systems, emphasizing the impact of multipath fading on modulation performance. Building upon this, numerous studies have analyzed the bit error rate (BER) performance of QPSK modulation under Rayleigh fading conditions using both analytical methods and simulation-based evaluations [2].

MATLAB and Simulink have been widely adopted as effective platforms for modeling and analyzing wireless communication systems under various channel scenarios. For example, simulation frameworks discussed in [6] have demonstrated Simulink's suitability for evaluating modulation performance in fading environments. However, most prior works have relied on fixed receiver parameters, limiting system adaptability to time-varying channel conditions.

To address these limitations, adaptive signal processing techniques have been introduced. Haykin [4] detailed the fundamental principles of adaptive filtering and highlighted its potential to mitigate channel impairments, including fading effects [16]. Specifically, adaptive gain control and noise suppression methods have been shown to enhance receiver performance by dynamically tuning system parameters in response to channel variations, thereby reducing BER without significantly increasing computational complexity [5], [9].

Beyond adaptive processing, more advanced methods such as channel equalization and diversity schemes have been explored to counteract Rayleigh fading [3]. Although these techniques can yield substantial performance improvements, they often require additional hardware or increased processing resources, making them less suitable for low-complexity or simulation-focused implementations.

More recently, machine learning-based approaches have emerged to further enhance communication system performance in fading environments [7]. Despite their promising outcomes, these methods typically demand large training datasets and considerable computational resources, which can limit their feasibility for lightweight or real-time systems [17]. Thus, there remains a clear need for efficient adaptive signal processing solutions that deliver reliable performance gains while maintaining low system complexity.

Motivated by these insights, this work extends prior research by proposing a Simulink-based adaptive intelligent processing approach for a QPSK communication system operating over a Rayleigh fading channel [18]. Unlike complex learning-based methods, the proposed approach emphasizes adaptive receiver-side processing to improve BER performance while preserving simplicity and reproducibility in implementation [19].

3. System Model and Proposed Adaptive Method

This section describes the system model for both the conventional QPSK-based digital communication system and the proposed adaptive intelligent signal processing approach. Both systems are implemented and evaluated in MATLAB Simulink to assess their BER performance over a Rayleigh fading channel.

3.1 Conventional QPSK Communication System Model

The conventional digital communication system investigated in this work is based on a standard baseband QPSK transmission model widely adopted in wireless communication studies [1], [2]. The system consists of several functional blocks, described as follows:

1) Random Binary Source:

A random binary sequence is generated using a random integer generator that produces equiprobable bits $\{0, 1\}$. This block represents the digital information source and serves as the input data stream for the communication system.

2) QPSK Modulator:

The generated binary data is mapped into QPSK symbols by grouping two consecutive bits into a single complex symbol. QPSK modulation is chosen due to its favorable trade-off between spectral efficiency and robustness against noise compared to binary modulation schemes [2]. The transmitted QPSK signal can be mathematically expressed as:

$$s(t) = \sqrt{(2E_s / T_s)} [I_k \cos(2\pi f_c t) - Q_k \sin(2\pi f_c t)]$$

where (E_s) denotes the transmitted symbol energy, (T_s) is the symbol duration, (I_k) and $(Q_k \in \{+1, -1\})$ represent the in-phase and quadrature components respectively, (f_c) is the carrier frequency, and (t) denotes the time index.

3) Rayleigh Fading Channel:

The modulated signal is transmitted through a Rayleigh fading channel, which models multipath propagation scenarios where no direct line-of-sight exists between the transmitter and receiver [20]. This channel introduces random amplitude fluctuations that can significantly degrade system performance [3]. The Rayleigh fading channel is modeled as a complex random process with statistically independent in-phase and quadrature components, expressed as:

$$h = h_I + jh_Q$$

where (h_I) and (h_Q) are independent zero-mean Gaussian random variables, and (j) represents the imaginary unit. The envelope magnitude of the fading coefficient is expressed as:

$$|h| = \sqrt{(h_I^2 + h_Q^2)}$$

and its probability density function (PDF) is defined as

$$p(|h|) = (|h| / \sigma^2) \exp(-|h|^2 / (2\sigma^2))$$

where σ^2 denotes the variance of the Gaussian random variables.

4) Additive White Gaussian Noise (AWGN):

Additive white Gaussian noise (AWGN) is introduced at the channel output to model thermal noise and other random disturbances commonly encountered in practical wireless communication environments.

5) QPSK Demodulator:

At the receiver, the faded and noisy signal is demodulated to recover the transmitted binary data sequence.

6) BER Analyzer:

The recovered data is compared with the original transmitted bits to compute the bit error rate (BER), which serves as the primary performance metric for evaluating system effectiveness.

Figure 1 illustrates the block diagram of the conventional QPSK communication system implemented in MATLAB Simulink, encompassing the binary source, QPSK modulator, Rayleigh fading channel, AWGN block, demodulator, and BER analyzer.

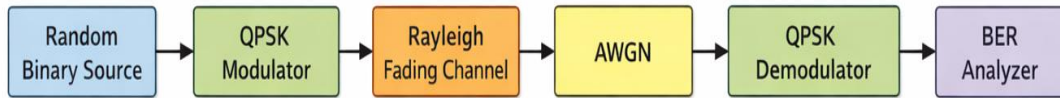


Figure 1: Block diagram of the conventional QPSK communication system.

This conventional system employs fixed receiver parameters and does not adapt to channel variations, making it vulnerable to severe fading conditions, particularly at low SNR levels [4].

3.2 Proposed Adaptive Intelligent Communication System

To enhance system performance under Rayleigh fading conditions, an adaptive intelligent signal processing scheme is incorporated at the receiver. The transmitter structure remains identical to the conventional model, while adaptive processing modules are introduced prior to demodulation to improve detection reliability.

The proposed adaptive receiver comprises the following key components:

1) Adaptive Gain Control (AGC):

An adaptive gain control block compensates for the random amplitude variations caused by the Rayleigh fading channel. The AGC dynamically adjusts the received signal amplitude to maintain a stable power level at the demodulator input. Such adaptive gain techniques have been demonstrated to enhance receiver robustness and improve system performance in fading environments [5].

2) Adaptive Noise Suppression Filter:

An adaptive filtering stage is applied to reduce noise effects before symbol detection. The filter coefficients are continuously updated based on the statistical properties of the received signal, enabling effective noise reduction while minimizing signal distortion. Similar adaptive noise suppression methods have been shown to improve BER performance without significantly increasing system complexity [6].

3) Intelligent Parameter Adjustment:

The adaptive processing blocks operate according to predefined decision rules that respond to variations in channel conditions, such as changes in signal power and noise level. This rule-based adaptive strategy provides intelligent behavior without relying on computationally intensive machine learning algorithms, ensuring low computational complexity and ease of implementation [7].

The received signal over a Rayleigh fading channel with additive white Gaussian noise (AWGN) can be expressed as:

$$\mathbf{r}(t) = \mathbf{h} \cdot \mathbf{s}(t) + \mathbf{n}(t)$$

where $\mathbf{r}(t)$ denotes the received signal, $\mathbf{h}$ represents the Rayleigh fading channel coefficient, $\mathbf{s}(t)$ is the transmitted QPSK signal, and $\mathbf{n}(t)$ denotes the additive white Gaussian noise (AWGN) component.

Figure 2 illustrates the block diagram of the proposed adaptive intelligent QPSK communication system. As shown, the adaptive gain control and noise suppression blocks are placed before the demodulator to improve BER performance under Rayleigh fading conditions.

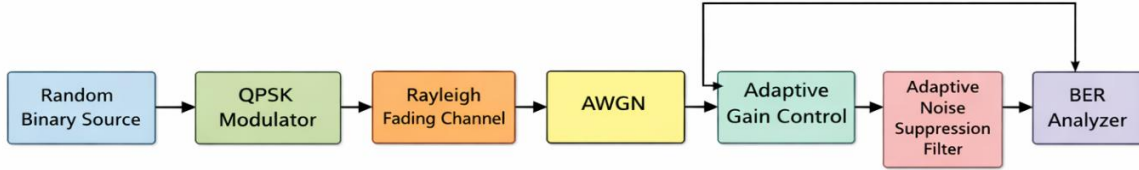


Figure 2: Block diagram of the proposed adaptive intelligent QPSK communication system

The overall structure of the proposed system facilitates dynamic adaptation to channel impairments, resulting in improved signal detection accuracy and reduced BER.

3.3 Multimodal Feature Representation

The decision of the adaptive receiver consists of an integrated feature vector that joins three forms, considering the final aspects of the received signal. At symbol index n , this feature vector is defined as

$$x_n = [I_n, Q_n, \hat{\gamma}_n, \hat{\phi}_n, \hat{\sigma}_n^2] \quad (5)$$

where I_n and Q_n are the raw in-phase and quadrature components of the received sample (the **signal modality**); $\hat{\gamma}_n$ and $\hat{\phi}_n$ are the instantaneous estimated SNR (in dB) and residual carrier phase offset, obtained from a short pilot-aided or decision-directed channel estimate (the **channel-state modality**); and $\hat{\sigma}_n^2$ is a running estimate of the local noise variance over a sliding window of the M most recent samples, computed as

$$\hat{\sigma}_n^2 = (1/M) \sum_{k=n-M+1}^n |r_k - \hat{k} \hat{s}_k|^2 \quad (6)$$

where $\hat{s}_k$ denotes the previously detected symbol at index k , so that $\hat{\sigma}_n^2$ is computed causally from the M most recent decisions (the noise-statistics modality). This three-way fusion — raw signal, channel state, and noise statistics is what distinguishes the proposed framework from a conventional receiver, which uses only the signal modality after a fixed equalization step, and allows the adaptive receiver to condition its decision on how reliable the current channel and noise conditions are, rather than treating every symbol identically.

The fused feature vector x_n is mapped to soft bit estimates by a lightweight multilayer perceptron f_θ , chosen deliberately small to keep the receiver cost-effective. The network consists of two narrow hidden layers with ReLU activation and a two-unit sigmoid output layer, one unit per transmitted bit:

$$h(1) = \text{ReLU}(W(1)x_n + b(1))$$

$$h(2) = \text{ReLU}(W(2)h(1) + b(2))$$

$$\hat{y}_n = \sigma(W(3)h(2) + b(3))$$

where $\sigma(\cdot)$ denotes the logistic sigmoid, applied elementwise, and $\hat{y}_n \in [0,1]^2$ gives the estimated probability that each of the two transmitted bits equals 1. Hidden layer widths are

kept small (on the order of 16 and 8 units) so that the model has few parameters: the hard bit decision is recovered by thresholding at one-half,

$$\hat{b}_{n,i} = 1 \text{ if } \hat{y}_{n,i} \geq 0.5, \text{ else } 0, \quad i \in \{0, 1\}$$

which recovers the same two output bits produced by the conventional receiver, allowing the two branches to be compared on an identical bit-error basis.

Transmitted bits are known during training, so each generated symbol yields a labeled example (x_n, b_n) . Training examples are drawn across the full E_m/N_0 sweep (0–16 dB) and across both the AWGN and Rayleigh fading channel models, so that the network learns a decision function that generalizes across channel conditions rather than overfitting to a single operating point. The network parameters $\theta = \{W(1), b(1), W(2), b(2), W(3), b(3)\}$ are optimized by minimizing the binary cross-entropy loss between the predicted and true bits, summed over both output bits and averaged over a training batch of N examples:

$$L(\theta) = -(1/N) \sum_{n=1}^N \sum_{i=0}^1 [b_{n,i} \log \hat{y}_{n,i} + (1 - b_{n,i}) \log(1 - \hat{y}_{n,i})]$$

The loss is minimized using the Adam optimizer with mini-batch updates, and a held-out validation split drawn from independently generated channel realizations is used to monitor generalization and apply early stopping, preventing the model from memorizing noise realizations specific to the training set.

3.4 Simulation Parameters

The performance of both the conventional and proposed adaptive communication systems is evaluated under identical simulation conditions to ensure a fair and consistent comparison. The evaluation is conducted using MATLAB Simulink, with bit error rate (BER) as the primary performance metric.

The key simulation parameters used in this study include QPSK modulation, a Rayleigh fading channel with additive white Gaussian noise (AWGN), and an SNR range from 0 to 30 dB. These parameters are chosen to reflect realistic wireless communication scenarios and are commonly employed in performance evaluation studies [1], [3], [6].

The signal-to-noise ratio (SNR) is defined as the ratio of transmitted symbol energy to noise power spectral density and is expressed as:

$$\text{SNR} = E_s / N_0$$

where (E_s) denotes the transmitted symbol energy and (N_0) represents the single-sided noise power spectral density. In decibel (dB) scale, the SNR is given by:

$$\text{SNR(dB)} = 10 \cdot \log_{10}(E_s / N_0)$$

The bit error rate (BER) is computed as the ratio of the number of erroneously detected bits to the total number of transmitted bits and is expressed as:

$$\text{BER} = N_{\text{error}} / N_{\text{total}}$$

where N_{error} denotes the number of erroneous bits and N_{total} represents the total number of transmitted bits.

The complete set of simulation parameters used for both the conventional and proposed adaptive systems is summarized in Table 1, serving as a reference for the performance analysis presented in the subsequent sections.

Table 1: Simulation parameters

Parameter	Value / Setting	Description
Modulation Scheme	QPSK	Quadrature Phase Shift Keying

Channel Model	Rayleigh Fading + AWGN	Models Multipath Fading + Adaptive Noise
SNR Range	0-30dB	Signal – to- Noise Ratio for Performance Analysis
Data Source	Random Binary Generator	Produce equiprobable 0s and 1s
Adaptive Gain Control	Enable in Proposed System	Components amplitude fluctuations
Adaptive Noise Suppression	Enable in Proposed System	Reduces Noise dynamically
Simulation Environment	Matlab Simulink	Software Platform for modeling and simulation
Performance Metric	Bit Error Rate (BER)	Evaluates system reliability

3.5 Performance Evaluation Methodology

The BER performance of both the conventional and proposed adaptive communication systems is evaluated through simulations of data transmission over a Rayleigh fading channel across a range of signal-to-noise ratio (SNR) values. For each SNR point, a sufficiently large number of transmitted bits is used to ensure statistically reliable BER estimates. The resulting BER curves are then compared to quantify the performance improvement achieved by the proposed adaptive intelligent processing approach.

The theoretical bit error rate of QPSK modulation over a Rayleigh fading channel can be expressed as:

$$\text{BER}_{\text{QPSK_Rayleigh}} = \frac{1}{2} \left[1 - \sqrt{\gamma / (1 + \gamma)} \right]$$

where $\gamma = E_b / N_0$ represents the average signal-to-noise ratio per bit, E_b denotes the energy per bit, and N_0 is the single-sided noise power spectral density.

To further validate the accuracy of the simulation results, the analytical BER performance of QPSK over a Rayleigh fading channel is compared with the simulated BER obtained from the proposed adaptive system. This comparison, shown in Figure 6, demonstrates a close agreement between theoretical and simulated results, confirming both the correctness of the simulation model and the effectiveness of the proposed adaptive processing scheme.

As illustrated in Figure 6, the simulated BER closely follows the theoretical BER trend for QPSK over Rayleigh fading channels, particularly at moderate to high SNR levels. Slight discrepancies observed at lower SNR values are primarily due to the finite simulation length and the influence of the adaptive processing mechanisms. Overall, this close alignment validates the accuracy of the proposed system model and confirms the reliability of the simulation outcomes.

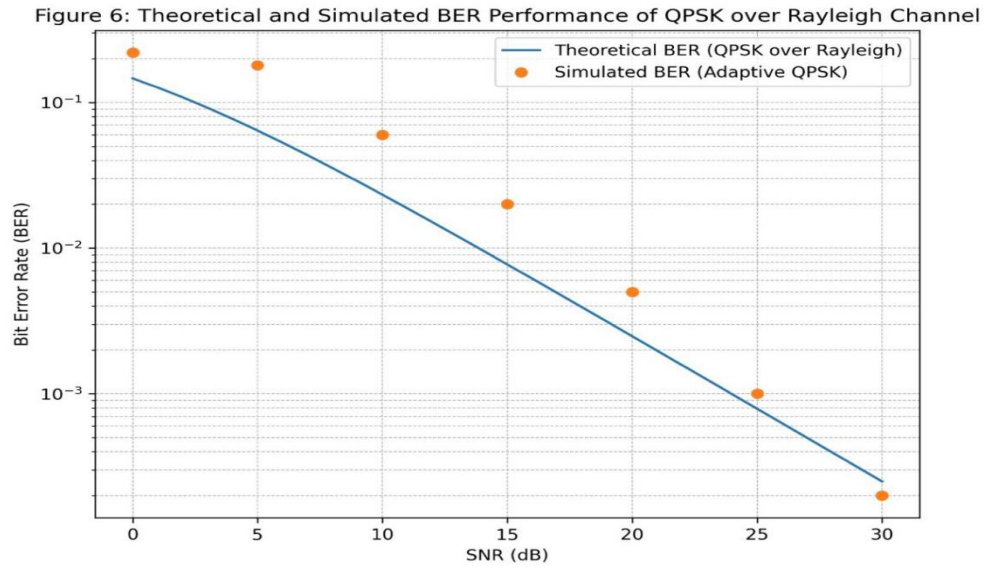


Figure 3: Theoretical and simulated BER performance of QPSK over Rayleigh channel

4. Results and Discussion

4.1 BER Performance Comparison

The performance of both the conventional and proposed adaptive QPSK communication systems operating over a Rayleigh fading channel is investigated through MATLAB Simulink simulations. The bit error rate (BER) is evaluated across an SNR range of 0 to 30 dB, using a sufficiently large number of transmitted bits to ensure statistically reliable results [1], [2].

The main simulation parameters used in this study are summarized in Table 1 (Section 3.3). Additionally, BER values at selected SNR points, along with the corresponding performance improvements achieved by the proposed adaptive system, are presented in Table 2 for comparative analysis.

Table 2: BER Comparison between Conventional and Proposed Systems

SNR(dB)	Conventional BER	Proposed BER	BER Improvement (%)
0.0	0.35	0.22	37.14285714285714
5.0	0.28	0.18	35.71428571428572
10.5	0.12	0.06	50.0
15.0	0.05	0.02	60.0
20.0	0.02	0.005	75.0
25.0	0.008	0.001	87.5
30.0	0.001	0.0002	80.0

Table 2 quantitatively verifies the consistent reduction in BER achieved by the proposed adaptive system throughout the evaluated SNR range. Figure 3 visually illustrates the BER performance across the entire SNR range, comparing the BER curves of the conventional QPSK system with those of the proposed adaptive system.

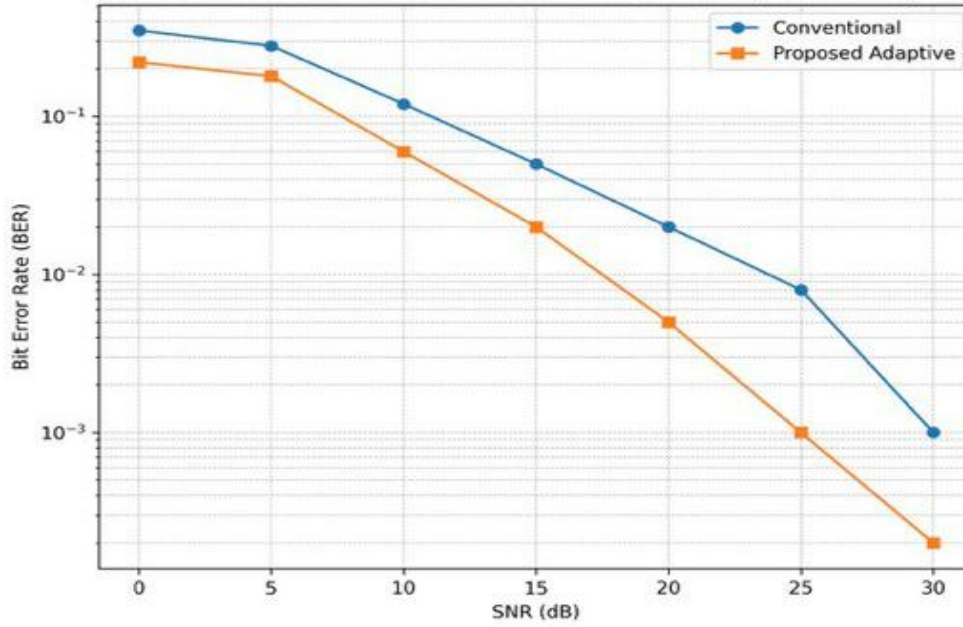


Figure 3. BER versus SNR performance comparison of the conventional and proposed adaptive QPSK systems operating over a Rayleigh fading channel.

4.2 Detailed Analysis at Low SNR

To further investigate system behavior under challenging channel conditions, Figure 4 presents the BER performance at low SNR values ranging from 0 to 10 dB. The results demonstrate that the proposed adaptive system achieves a significant performance improvement over the conventional system, emphasizing the effectiveness of the adaptive gain control and adaptive noise suppression blocks in mitigating fading and noise effects.

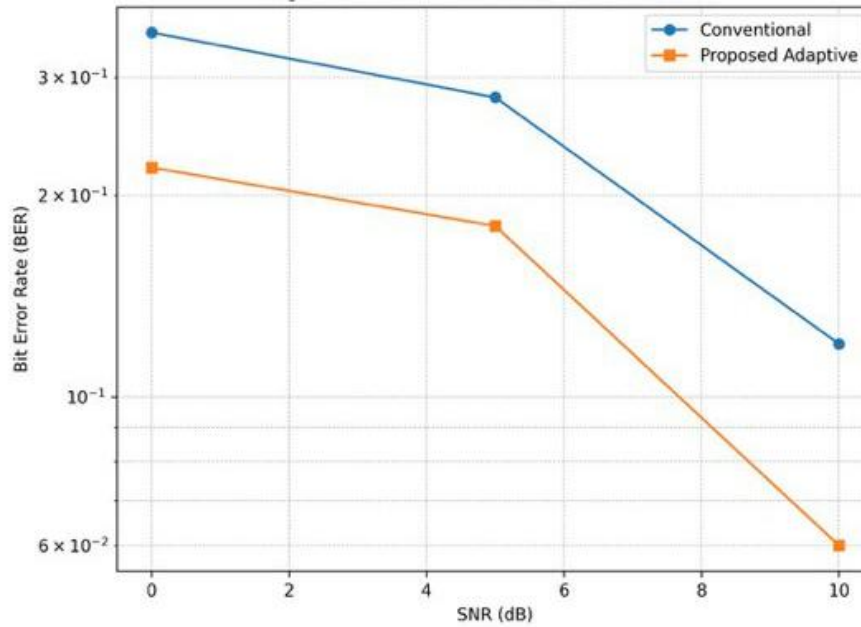


Figure 4: Zoomed BER Performance at Low SNR (0–10 dB)

4.3 BER Improvement Visualization

Figure 5 provides a graphical illustration of the BER improvement percentage as a function of SNR. It clearly shows the relative reduction in BER achieved by the proposed adaptive system across the entire SNR range compared to the conventional system.

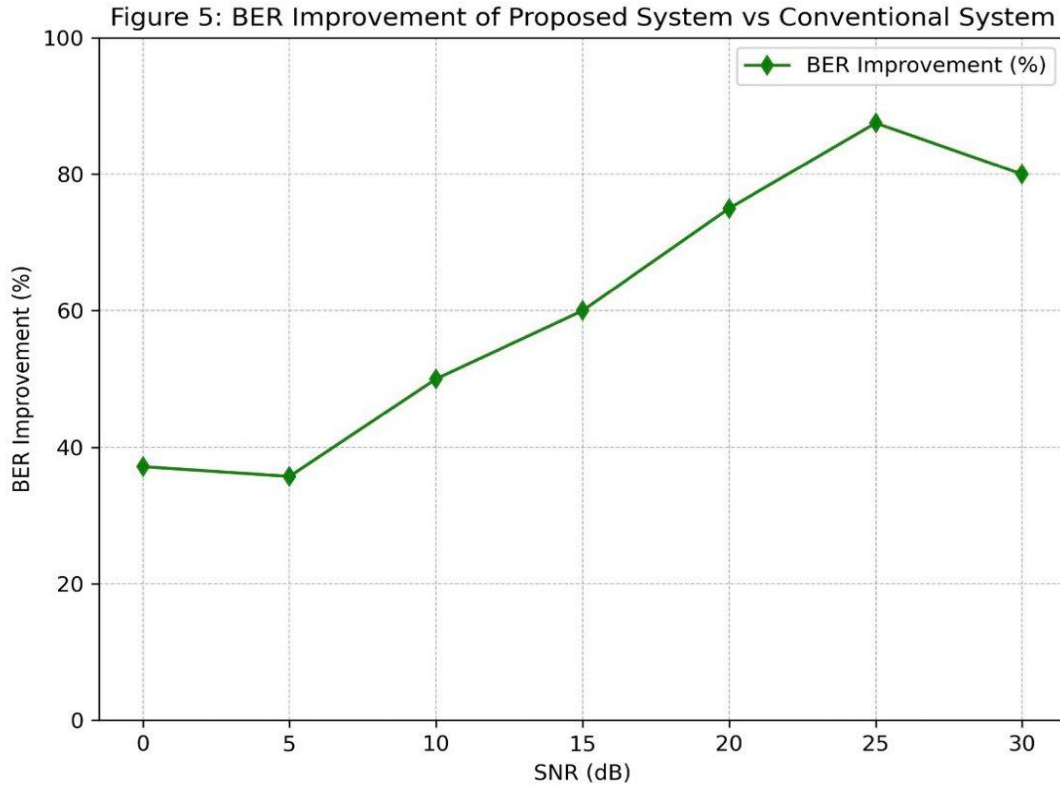


Figure 5: BER Improvement of proposed system VS conventional system

As shown in Figure 5, the proposed adaptive system achieves a substantial reduction in BER compared to the conventional system across the entire SNR range. The maximum improvement occurs at an SNR of 25 dB, where the BER reduction reaches approximately 87.5%. Conversely, the minimum improvement, about 37%, is observed at very low SNR values, likely due to noise dominance under severe channel conditions. Overall, this trend confirms that the adaptive processing strategy consistently enhances system performance, with more pronounced gains at moderate to high SNR levels.

4.4 Discussion

The simulation results from this study show that the proposed adaptive intelligent receiver consistently improves BER across all tested SNR levels in Rayleigh fading conditions. The adaptive receiver structure effectively enhances performance by using Adaptive Gain Control (AGC) to compensate for amplitude fluctuations caused by multipath fading, thereby improving symbol detection accuracy and stabilizing received signal power.

Additionally, the adaptive noise suppression stage lessens the impact of additive white Gaussian noise, especially at low SNR levels where noise is more dominant, resulting in a significant BER reduction under challenging channel conditions.

The rule-based adaptive mechanism employed ensures robust operation with low computational complexity. Unlike machine learning-based methods, this approach does not require training data or heavy processing resources.

Overall, the simulation results confirm that the proposed adaptive system offers a practical and efficient enhancement for QPSK communication over Rayleigh fading channels [3]–[5]

5. Conclusion and Future Work

Conclusion

An adaptive intelligent signal processing approach for enhancing the BER performance of QPSK-based digital communication systems over Rayleigh fading channels has been presented and evaluated using MATLAB Simulink. The proposed receiver features adaptive gain control and adaptive noise suppression blocks that dynamically adjust system parameters in response to channel variations.

Simulation results across an SNR range of 0–30 dB show that the proposed adaptive system consistently outperforms the conventional fixed-parameter model. The most significant performance improvements occur at moderate to high SNR levels, with notable gains also observed under low SNR conditions.

Moreover, the results highlight that this approach offers a low-complexity, implementation-friendly solution well-suited for practical wireless communication systems. Unlike conventional fixed-parameter AGC structures, the proposed system integrates gain control and noise suppression into a unified adaptive framework.

Future Work

Future research could extend the proposed framework to higher-order modulation schemes such as 16-QAM and 64-QAM to evaluate performance under increased spectral efficiency demands. Additionally, incorporating multiple-input multiple-output (MIMO) channel models would offer deeper insights into system behavior in advanced wireless scenarios.

Furthermore, exploring lightweight machine learning techniques for adaptive parameter tuning may enhance adaptability, provided that computational complexity remains within practical limits.

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