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An Attention-driven BiLSTM Framework towards Computation of SEP in 6G Networks operating over Nakagami-m Fading Channels

Sarbeswar Samal[1], Sujata Chakravarty[1], Tanmay Mukherjee[2]*, Ayushee Das[1], Sasmita Parida[2]

[1]Department of Computer Science and Engineering, Centurion University of Technology and Management, Jatni, Bhubaneswar, 752050, Odisha, India.
[2]Department of Computer Science and Engineering, Siksha 'O' Anusandhan (Deemed to be) University, ITER College Road, Bhubaneswar, 751030, Odisha, India.
*Corresponding author(s): Tanmay Mukherjee, e-mail(s): utanmay10@gmail.com

Abstract

The recent emergence of 6G wireless networks has given rise to the demand for accurate channel characterization across the terahertz (THz) frequency band to capture the rapid fluctuations in signal propagation. Symbol error probability (SEP) acts as a crucial performance metric for communication systems operating over 6G fading environments. Analytical and approximate approaches to SEP computation are based on numerous mathematical simplifications, complex integrals, and models that are specific to the channel conditions, thus making SEP calculations intensive and less flexible to meet the requirements of new 6G paradigms as they evolve with nonlinear THz channel fading, high-density interference, and changing noise environments. This paper presents an intelligent, data-driven SEP estimator for Nakagami-m fading channels that utilizes an attention-guided bi-directional long short-term memory (AG-BiLSTM). This supervised AI-based estimation method reduces computational complexity and improves estimation accuracy compared to conventional Q-function-based estimators. Experimental results demonstrate that the AI-based estimation model has a Mean Absolute Error (MAE) of approximately 1.25×10^{-3}, averaged over all tested cases, and an R^2 value of 0.9707. Further, SEP performance for M-QAM signals over the AG-BiLSTM model is verified using Monte-Carlo simulations of order $O(10^6)$.

Keyword: Artificial Intelligence, Symbol error probability, Modulation, Fading, Performance Evaluation, 6G Networks

Introduction

The future of connectivity is being significantly transformed by the combination of wireless communication with artificial intelligence (AI), particularly in light of the increasing complexity of communication networks. Fading, which is defined as rapid variations in a signal's amplitude and phase due to multipath propagation, shadowing, user mobility, and dynamic channel conditions, is a major challenge in beyond 5G (B5G) and 6G wireless communication systems [1–4]. This phenomenon is even more severe in real-world applications, particularly in highly populated urban regions, vehicular communication contexts, and high-frequency bands like THz and millimeter-wave (mmWave). This leads to signal degradation, poor reliability, and inconsistent service quality, which calls for the creation of robust strategies to successfully reduce its effects.

In 6G communication systems, which leverage the terahertz (THz) frequency bands, achieving the lowest possible symbol error probability (SEP) is crucial for designing reliable and high-capacity wireless links [5]. SEP quantifies the likelihood of symbol misclassifications in the presence of noise and fading, thereby becoming a key performance indicator for evaluating and designing robust THz physical-layer architectures.

The traditional approach for evaluating SEP integrals across fading channels requires the exact approximation of the error function erf(.), the complementary error function erfc(.), and the Gaussian Q-function Q(.) [6]. In order to achieve this, researchers have created strict exponential bounds and numerical approximations for the Q-function. Among these are composite exponential models, which maintain analytical simplicity while providing good accuracy over a wide range of input values [7, 8]. In addition to being computationally efficient, these approximations significantly simplify closed-form performance analysis, particularly in realistic fading situations. It is well-known that fading scenarios in modern wireless systems are generally composite in nature, in which the communication channels are impacted by the simultaneous effects of multipath fading and shadowing [1, 9].

Additionally, these channels may not strictly follow the Gaussian noise assumptions by introducing non-Gaussian impulsive noise, including Additive Laplacian Noise, which has a substantial impact on Quality of Service (QoS) parameters and error performance [10]. In this setting, recent research has shed light on these complexities by creating SEP formulations under such composite fading and noise scenarios, along with validating the system performance using metrics such as outage probability and effective channel capacity [11].

Even though tighter approximations for SEP computation have been proposed in a number of works, these traditional approaches face a number of difficulties in complex fading situations. When obtaining closed-form solutions to SEP integrals, conventional approaches often encounter intractability. This occurs especially when dealing with composite or non-linear fading distributions [12–14]. Some real-time fading models take shadowing and multipath effects into account, resulting in multivariate integrals that require a complicated evaluation of SEP. Furthermore, emerging 6G wireless networks operate under highly dynamic propagation environments characterized by time-varying and frequency-selective fading, making accurate SEP evaluation increasingly challenging. In this study, Rayleigh fading is considered as the underlying channel model since it effectively captures small-scale fading in non-line-of-sight (NLoS) wireless environments and serves as a broadly accepted standard for evaluating SEP. Moreover, it provides a fundamental statistical framework for validating AI-based SEP estimation techniques before extending the framework to more complex 6G channel models. Consequently, SEP estimation techniques must adapt to these rapidly changing channel conditions while maintaining computational efficiency. In this setting, an AI-driven SEP estimation approach provides a promising alternative to conventional analytical methods.

The proposed AG-BiLSTM framework effectively learns complex nonlinear relationships directly from synthetically generated channel data for M-QAM modulation under Rayleigh fading, enabling it to model the interactions among the signal-to-noise ratio (SNR), modulation order, channel fading characteristics, and the corresponding symbol error probability with high accuracy. Additionally, there is a significant reduction in computational time compared to analytical integration methods. The results indicate that the AI-driven SEP estimation provides a robust, low-complexity, and high-accuracy alternative to real-time wireless performance evaluation in next-generation wireless systems.

1.1. Motivation(s)

The accurate computation of SEP in wireless fading scenarios is crucial because it quantifies the reliability of wireless links under pragmatic conditions. The conventional SEP evaluation techniques depend on critical mathematical formulations and approximations. Furthermore, despite their mathematical sophistication, traditional methods present several drawbacks when applied to real-world, data-driven, and dynamically varying wireless environments.

A major limitation is that the analytical formulations provide accurate results under ideal conditions; however, the results become impractical for time-varying conditions such as MIMO fading. Further, deriving new approximations for every fading model and modulation scheme increases complexity and reduces scalability. Artificial Intelligence (AI) and Machine Learning (ML) play a crucial role in modeling and optimization of wireless systems. Unlike conventional models, these models exploit the capability to identify non-linear patterns based on the characteristics of real or synthetic data. In this setting, the efficacy of AI models can be studied in current wireless systems, including channel estimation, modulation classification, and adaptive resource management. However, there has been limited study focusing on AI-based SEP prediction as an alternative to analytical computation.

1.2. Objective(s)

Based on the motivations stated above, this study mainly achieves the following objectives:

- To introduce a supervised deep learning regression framework in which an AG-BiLSTM model estimates SEP over Rayleigh fading channels.
- Integrating an attention mechanism with the BiLSTM framework, to capture nonlinear patterns among SNR, modulation order, and fading dynamics, while adaptively highlighting sensitive SNR regions where error probabilities vary rapidly.
- To train the model on a synthetically generated dataset under Rayleigh fading for M-QAM modulation scheme in order to obtain improved accuracy compared to conventional Q-function-based approaches.
- To validate the obtained AI-based SEP estimates against the analytical derivations using extensive Monte Carlo simulations of order $O(10^6)$.
- To analyze the performance of the proposed AI model using various metrics viz., accuracy, MAE, and R^2, along with a scatter plot to establish the relationship between the theoretical values and the obtained AI-based estimates for SEP.

1.3. Paper Layout

The research study is organized as follows. In Section 1, an overview of channel modeling over fading channels is given, illustrating the techniques used by researchers over the years to compute SEP over these channels. The motivations and objectives of the current research are also depicted in this section. Section 2 presents the relevant research in this area. The design of the proposed AI model for assessing the SEP in fading scenarios is covered in Section 3. Section 4 presents the analytical solution using Monte-Carlo simulation and illustrates the conventional model used for SEP evaluation. Section 5 presents the various results and discussions from the proposed AG-BiLSTM model to estimate the SEP. Finally, Section 6 presents the conclusion and future scope of the current research.

2. Related Work

This section portrays the different works carried out by researchers towards SEP evaluation over fading channels. Several approximations of the Gaussian Q-function have been reported in literature [15–18] for estimating SEP over fading channels. An accurate approximation was proposed in [15]; however, the resulting formulation lacks analytical tractability, limiting its suitability for SEP evaluation. In [16], the Q-function was approximated using two exponential terms, yielding high accuracy for large arguments but reduced precision for smaller inputs.

Loskot and Beaulieu in [17] propose a simple semianalytical method for evaluating average transmission error over slow-fading channels by fitting the conditional error probability with a Prony sum of exponentials. The approach is attractive because the average error can then be computed from the moment-generating function of the instantaneous input signal-to-noise ratio (SNR). Their numerical results show that using only a small number of conditional-error samples and just two exponential terms achieves high accuracy, with relative error below 6% in most tested cases.

The authors, Olabiyi and Annamalai, in [18] developed very tight invertible exponential-type approximations for the Gaussian Q(x) function and erfc(·), then used them to derive conditional symbol error probability formulas for several digital modulation schemes in a simple exponential form that is both analytically tractable and explicitly invertible. This proved to be important for SEP evaluation because invertibility helps map target error rates to required SNR in adaptive modulation and outage analysis [19]. Their framework also enables tight closed-form approximations for average SER over generalized fading channels through the moment generating function (MGF) approach, with accuracy validated against exact integral expressions. The authors in [20] used the Trapezoidal numerical integration technique with distinct values of n, i.e., $n = 3$ and $n = 4$, to estimate erf c(·) and provide tighter bounds to the Q-function. This exponential-based study provided a much closer fit and simple mathematical forms in contrast to the earlier approaches. However, the assumptions of ideal Nakagami-m fading, simplified noise models, and approximate analytical forms limit its usefulness.
In [21, 22], the authors proposed an additional approximate technique that makes it easier to calculate the SEP over the Fluctuating Beckmann (FB) fading channels, a popular channel model that includes a variety of fading types. While this study uses exponential forms to approximate the Gaussian Q-function and analyze the SEP, other research frequently ends by computing the PDF or MGF of FB fading. They make working with exponents easier by offering reliable and simple solutions. It is useful because it makes it possible to analyze SEP with modulation in FB fading, which was not previously discussed in the literature.
Further, the use of N-point Gauss-Hermite quadrature portrayed a closer approximation to the Gaussian Q-function [23]. Here, accuracy improved with increasing N, but at the expense of higher computational complexity. The SEP of Hexagonal-QAM (H-QAM) over Additive White Gaussian Noise (AWGN) channels using a two-dimensional Gaussian Q-function was examined in [24]. Their approximation was analytically tractable and exhibited a better fit than earlier approaches [15–18]. However, it failed to provide a tighter match for smaller signal-to-noise ratio (SNR) values.
Probabilistic shaping (PS), as described in [25], is used to introduce non-uniform symbol probabilities to improve symbol error performance in different channel environments. This results in a higher quality symbol error rate (SER) and SNR performance, especially in Rayleigh and log-normal fading channels. In both noise-limited and composite fading scenarios, this is a major advancement for next-generation adaptive communication systems. This method has many drawbacks, though, as it only takes SER performance into consideration without taking BER into account. It also ignores other realistic wireless circumstances, such as lognormal, Rayleigh, and AWGN fading channels.

3. System Model

The AG-BiLSTM architecture, as depicted in Fig. 1, integrates the bidirectional learning capability of BiLSTM with an attention mechanism, which highlights the most useful aspects of sequential input data in an adaptive manner. The BiLSTM component allows the model to understand the relationship between the parameters, viz., SNR, modulation order, and fading behavior in a time-dependent manner for characterizing wireless systems. The attention layer computes the dynamic weights over the BiLSTM hidden layers, enabling the model to select features that significantly impact SEP performance, thereby improving its robustness and interpretability under noisy or fluctuating channel conditions. The final dense layer then takes the attention-weighted feature vector and produces the predicted SEP values.

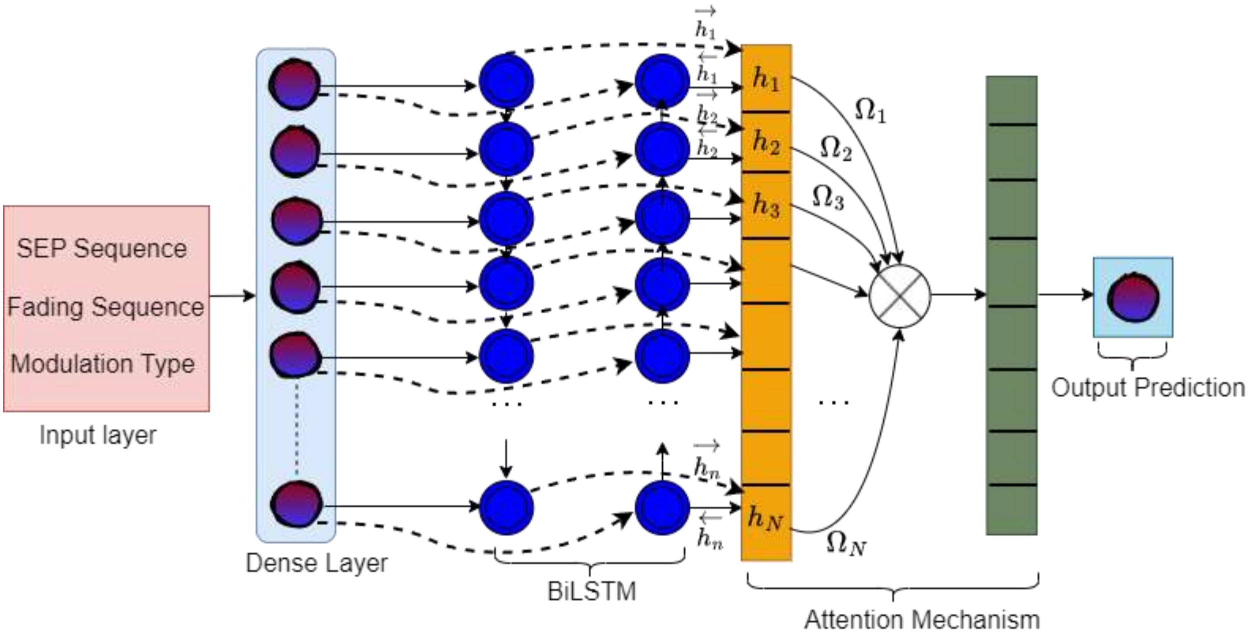

Fig. 1: Figure depicting the components of the proposed AG-BiLSTM model

The AG-BiLSTM model predicts SEP by learning the nonlinear mapping as [28]:

$f : \{SNR, M, h(t)\} \rightarrow P_e$ **(1)**

where, $h(t)$ is the time-varying Rayleigh fading factor and P_e is the predicted SEP.

The BiLSTM layer processes the input sequence in both forward and backward directions to capture dependencies among prior and subsequent SNR-fading interactions. The outputs of both directions are concatenated together to create a complete hidden state as:

$H_t = [\overrightarrow{h}_t ; \overleftarrow{h}_t]$ **(2)**

The attention mechanism assigns a weight Ω_t to each time step, highlighting the most relevant input characteristics [28], indicating how much that segment of the sequence contributes to final SEP prediction:

$e_t = v^T \tanh(W_h H_t + b_h), \quad \Omega_t = \exp(e_t) / \Sigma_{k=1}^{T} \exp(e_k)$ **(3)**

The context vector C_v is represented as the weighted sum of hidden states and is expressed as:

$C_v = \Sigma_{t=1}^{T} \Omega_t H_t$ (4)

The final SEP for a given SNR and modulation scheme (M-QAM) is predicted using the dense output layer as follows:

$P_e = \sigma(W_c C_v + b_c)$ **(5)**

where $\sigma(.)$ denotes the activation function.

4. Traditional/ Analytical Model

The above framework is validated using Monte-Carlo SEP results obtained with conventional techniques. In this approach, the SEP is evaluated upon averaging the instantaneous AWGN SEP expression of M-QAM modulation over the fading PDF [6]. The SEP expression conditioned on SNR κ for square M-QAM is obtained as [6]:

$P_a(\kappa) = 2(1 - 1/\sqrt{M})\, Q(\sqrt{[(3 \log_2 M)/(M - 1)\, \kappa]})$ **(6)**

where M is the constellation size. The Rayleigh fading PDF on instantaneous SNR κ is defined as [6]:

$\psi(\kappa) = (1/\bar{\kappa}) \exp(-\kappa/\bar{\kappa}), \quad \kappa \geq 0, \quad \bar{\kappa} = E[\kappa]$ **(7)**

Now, the average SEP is obtained as:

$\bar{P}_a(\bar{\kappa}) = E\kappa[P_a(\kappa)] = \int_0^{\infty} P_a(\kappa)\psi(\kappa)d\kappa$ **(8)**

The above expectation is numerically evaluated using Monte-Carlo simulation as:

$\bar{P}_a(\bar{\kappa}) \approx (1/N) \sum_{i=1}^{N} P_a(\kappa_i) \quad \kappa_i = \bar{\kappa}|h_i|^2$ **(9)**

where h_i represents ith fading channel realization, $|h_i|^2$ denotes the corresponding fading power gain and $N = O(10^6)$. The SEP expression obtained upon evaluating Eq. 9 is used as a benchmark to test the accuracy of predicted SEP using the AG-BiLSTM framework over the given SNR range.

5. Results and Discussion

This section portrays the description of the dataset used in this study, as well as illustrates the results obtained over the suggested technique towards SEP computation.

5.1. Dataset Description

The suggested AG-BiLSTM model is trained and evaluated on a synthetic labeled dataset created using analytical SEP expressions for M-QAM modulation under Rayleigh fading. While 6G THz channels exhibit more complex propagation characteristics, Rayleigh fading remains a fundamental statistical model capturing small-scale variations and is suitable for generating baseline learning patterns. With 0.25 dB increments, SNR values for modulation orders M = 4, 16, 64 are adjusted from 0 dB to 30 dB. The average SEP for each SNR-modulation pair is obtained by generating 10,000 Rayleigh fading realizations and adding Gaussian noise to simulate errors. In order to ensure strong model generalization, the dataset comprising of 100,000 samples, is split into 70% training, 15% validation, and 15% testing sets. The Table 1 provides a description of the parameters used for SEP estimation.

Table 1: Training Parameters of AG-BiLSTM framework

Category	Parameter	Value
Input Features	Instantaneous SNR sequence length	8
	Modulation order	$\log_2 M$
Model Architecture	Network type	Attention-Guided BiLSTM
	Number of BiLSTM layers	2
	BiLSTM units (Layer 1)	128
	BiLSTM units (Layer 2)	64
	Attention mechanism	Temporal
	Dense layer units	32
	Output layer	1 neuron (log-SEP)
Training Setup	Loss function	MSE
	Optimizer	Adam
	Learning rate	5×10^{-4}
	Batch size	128
	Early stopping patience	25 epochs
Dataset Configuration	Modulation schemes	4-QAM, 16-QAM, 64-QAM
	SNR range	0–30 dB
	SNR increments	0.25 dB
	Channel model	Rayleigh fading
Evaluation Metrics	Error metrics	MAE, R^2

5.2. Experimental Results

The plot shown in Fig. 2 illustrates how the distribution of instantaneous SNR changes with Rayleigh fading. It demonstrates that even though the average SNR is kept constant, fluctuations due to small-scale fading can be extreme. The large variation illustrated represents the challenges in signal propagation at higher frequencies and clearly demonstrates the limitations of deterministic models for SEP evaluation. The log-scale histogram of SEP depicted in Fig. 3 illustrates that the SEP distribution is heavily weighted toward low error probability with the occurrence of a few high error events. This behavior of SEP distributions across SNR values indicates an opportunity to utilize attention-guided deep learning models that can model these nonlinear yet important error probabilities over traditional approximation methods.

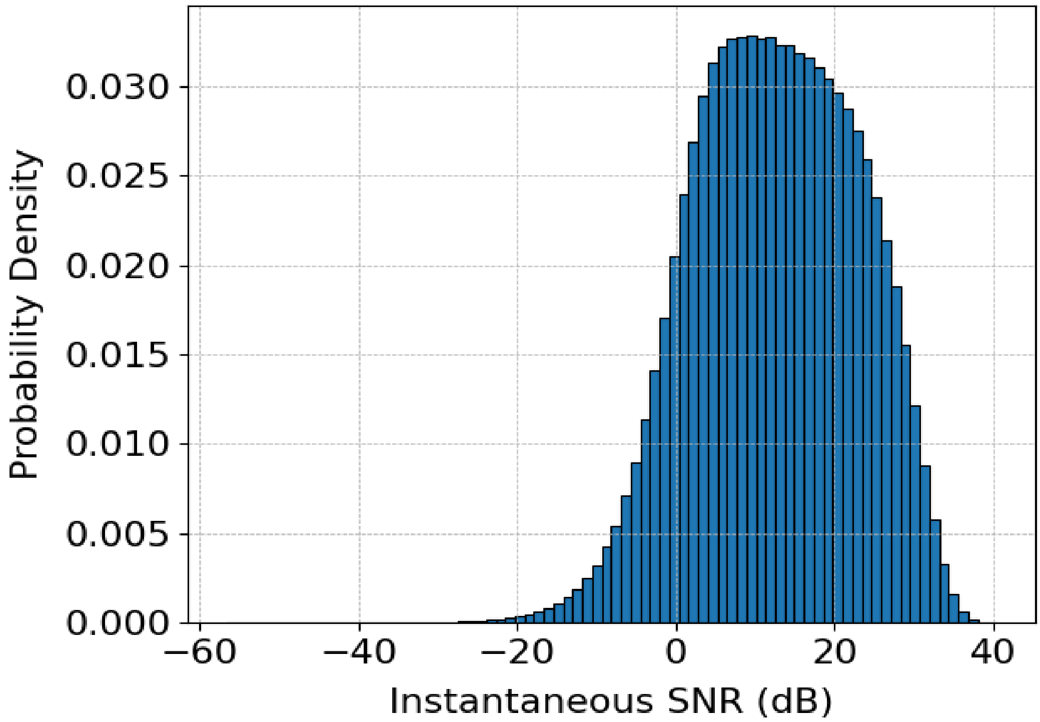

Fig. 2: Plot demonstrating the histogram of instantaneous SNR under Rayleigh fading environment.

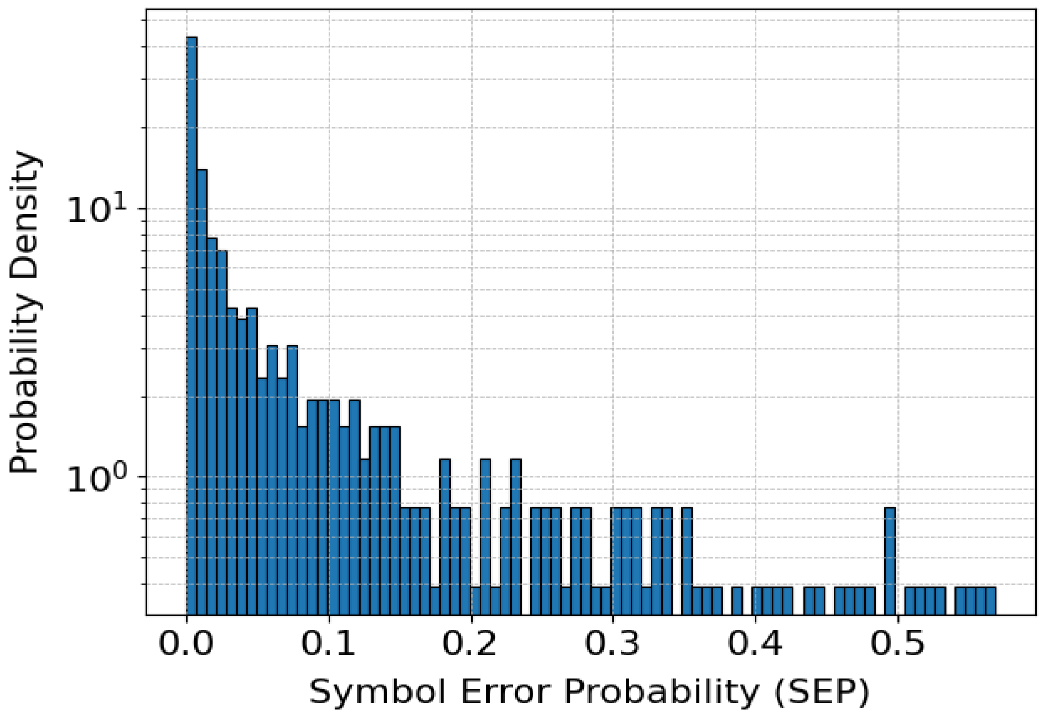

Fig. 3: Plot demonstrating the histogram of SEP values under Rayleigh fading environment.

The SEP vs. average SNR curve, as illustrated in Fig. 4, over Rayleigh fading compares the AG-BiLSTM predictions to the traditional technique obtained using Monte-Carlo method. The close agreement between the two sets of curves over the entire SNR range is characterized by a small MAE of 1.25×10^{-3}, indicating that this model can well capture the SEP behavior over fading channels.

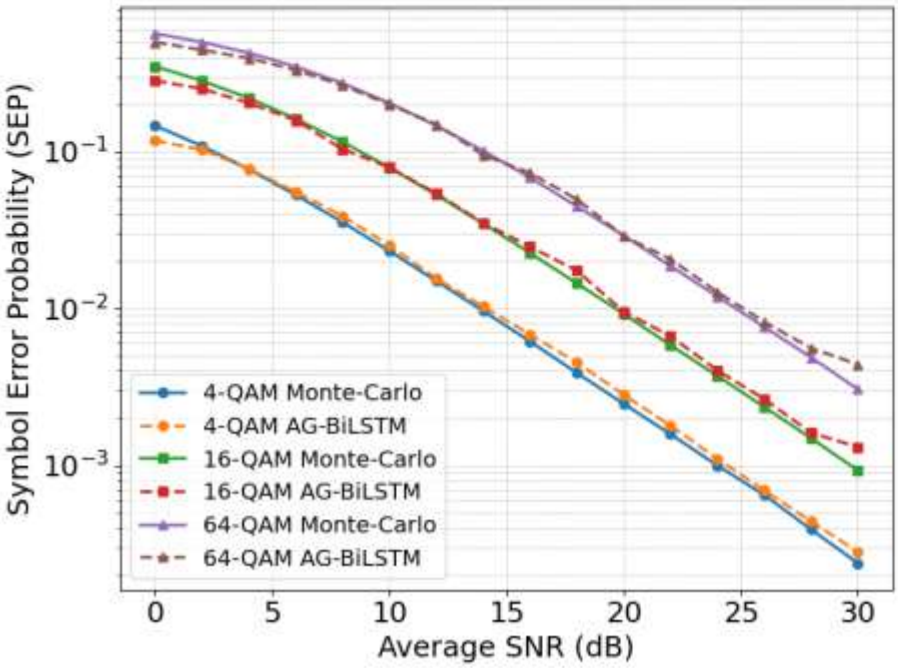

Fig. 4: Plot demonstrating SEP performance comparison under Rayleigh fading.

Fig. 5 represents the scatter plot for predicted vs. simulation values, which clearly shows that the estimated values are strongly correlated with the actual values, since they are aligned on the y = x line and have a very high Coefficient of Determination (R^2) value of 0.9707, illustrating that the regression model has been accurately fitted to the data.

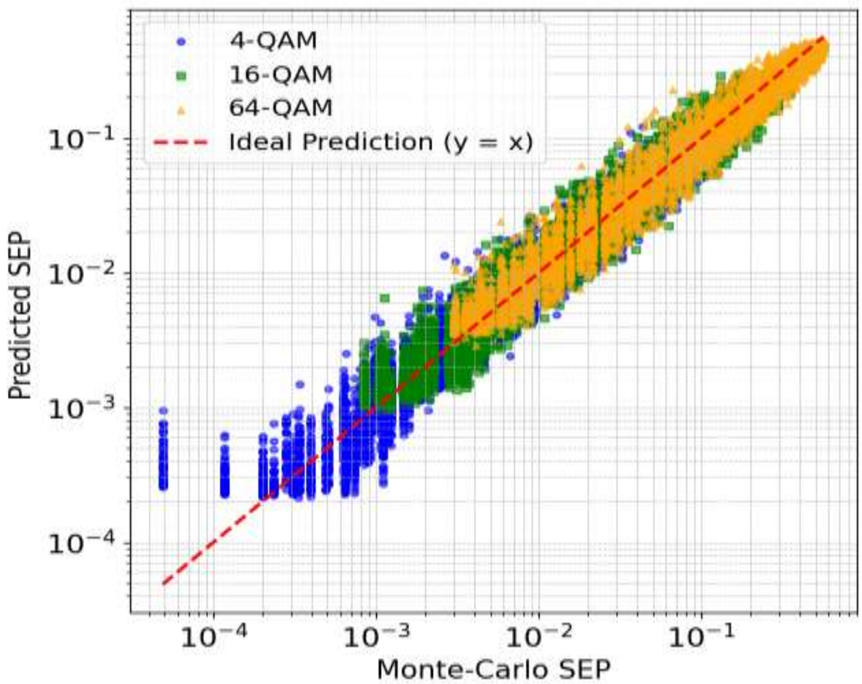

Fig. 5: Scatter plot of predicted vs analytical SEP (Monte-Carlo scheme).

6. Conclusion

This research presented an AG-BiLSTM framework for estimating SEP over Rayleigh fading channels. The model was trained using analytical datasets to effectively capture the non-linear relationships between average SNR, modulation order, and the SEP averaged over fading states. The results demonstrate close agreement between AG-BiLSTM predicted values and Monte-Carlo methods for several square QAM modulation schemes. Furthermore, the proposed methodology achieves lower MAE and higher R^2 values. Overall, the AG-BiLSTM framework represents a simpler and more reliable approach for computing SEP compared to traditional estimation methods that require intensive numerical integration, enabling real-time system performance evaluation in future-generation wireless communication systems.

Conflict of Interest

The authors declare no known conflict of interest.

Data Availability

The datasets generated are available from the corresponding author on reasonable request

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