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Variational Autoencoder Based Joint Blind Equalization and Channel Estimation for Nonlinear Coherent Optical Transmission

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Abstract : Nonlinear impairments and dynamic channel distortions in coherent optical transmission systems pose significant challenges to accurate signal recovery, necessitating advanced equalization and channel estimation techniques. Conventional model-based approaches often exhibit limited adaptability in the presence of complex fibre nonlinearities and stochastic channel variations. To address these limitations, this paper proposes a novel joint blind equalization and channel estimation framework based on Variational Autoencoders (VAEs). The proposed method leverages deep generative modeling to learn compact latent representations of received optical signals, enabling effective characterization and compensation of both linear and nonlinear channel impairments without requiring prior knowledge of transmitted symbols. By integrating equalization and channel estimation into a unified unsupervised learning paradigm, the framework enhances robustness and generalization across varying transmission conditions. The performance of the proposed VAE-based approach is evaluated on a coherent optical communication system, demonstrating significant improvements over conventional techniques. Experimental results indicate enhanced signal reconstruction accuracy, substantial reduction in bit error rate (BER), and improved spectral efficiency. These findings highlight the potential of variational deep learning models as a powerful enabler for intelligent and adaptive next-generation coherent optical networks.

***IndexTerms* - Variational Autoencoders (VAE), Blind Equalization, Channel Estimation, Coherent Optical Communication, Nonlinear Fiber Impairments.**

I. INTRODUCTION

Coherent optical communication has become a cornerstone technology for enabling high-speed and long-haul data transmission in modern telecommunication infrastructures. The rapid growth in data traffic and bandwidth-intensive applications has driven the evolution of fibre-optic systems toward advanced modulation schemes, polarization-division multiplexing, and sophisticated digital signal processing (DSP) techniques. Despite these advancements, the performance of coherent optical systems remains significantly affected by various channel impairments, including chromatic dispersion (CD), polarization mode dispersion (PMD), laser phase noise, and fibre nonlinearities. These impairments distort the transmitted signal, making accurate recovery at the receiver a challenging task.

To mitigate such distortions, efficient channel estimation and equalization techniques are essential. Conventional model-driven approaches, including linear equalizers and maximum likelihood sequence estimation (MLSE), have been widely employed in optical receivers. However, their effectiveness diminishes in the presence of complex and nonlinear channel dynamics characteristic of modern high-capacity optical networks. This limitation has encouraged the exploration of data-driven methodologies, particularly deep learning models, which offer enhanced adaptability and performance in complex environments.

Blind equalization plays a vital role in coherent optical systems by enabling signal recovery without requiring explicit channel state information (CSI) or training sequences. Traditional blind algorithms, such as the constant modulus algorithm (CMA) and decision-directed least mean squares (DD-LMS), provide acceptable performance under moderate conditions but often fail to cope with rapidly varying and nonlinear impairments. In contrast, deep learning techniques have demonstrated strong potential in learning complex signal representations directly from data. Among these, autoencoder-based models have gained attention due to their capability to extract meaningful latent features for signal reconstruction.

In this context, Variational Autoencoders (VAEs) provide a powerful probabilistic framework that extends conventional autoencoders by learning a structured latent distribution of the input data. Unlike deterministic models, VAEs incorporate stochastic latent variables, enabling improved generalization and robustness in signal reconstruction tasks. Leveraging these advantages, this work proposes a VAE-based framework for joint blind equalization and channel estimation in nonlinear coherent optical transmission systems. The proposed approach learns the statistical characteristics of impaired received signals and reconstructs clean signal representations through an encoder–decoder architecture. The encoder maps the distorted input signals into a compact latent space, while the decoder utilizes this representation to compensate for channel-induced distortions and recover the transmitted signal.

A key strength of the proposed method lies in its unsupervised learning capability, which eliminates the dependence on labelled datasets and makes it suitable for practical optical communication scenarios. Furthermore, the probabilistic nature of VAEs enables effective handling of both linear and nonlinear impairments, as well as improved resilience under low signal-to-noise ratio (SNR) conditions. The generative capability of the model also facilitates the reconstruction of realistic signal patterns, even in the presence of severe channel uncertainty.

The performance of the proposed framework is evaluated using simulation and experimental datasets from coherent optical communication systems. Metrics such as bit error rate (BER), signal-to-noise ratio (SNR), and convergence behavior are used for assessment. Comparative analysis with traditional techniques, including CMA and adaptive filtering methods, demonstrates that the VAE-based approach achieves superior performance in terms of lower BER, improved signal recovery accuracy, and enhanced robustness against fibre impairments.

The challenges associated with optical channel equalization primarily arise from the coexistence of linear and nonlinear distortions. Linear effects such as chromatic dispersion and polarization mode dispersion introduce phase and amplitude variations, whereas nonlinear effects—mainly due to the Kerr phenomenon—result in complex signal interactions that are difficult to model analytically. Additionally, phase noise introduced by laser sources further complicates the signal recovery process.

Traditional compensation techniques, such as digital backpropagation (DBP) and Kalman filtering, attempt to address these impairments using analytical models. However, these methods often involve high computational complexity and may not scale efficiently with increasing system capacity. Similarly, blind equalization methods like CMA rely on fixed statistical assumptions, limiting their adaptability in dynamic environments.

Deep learning-based approaches provide a promising alternative by learning directly from data without explicit reliance on mathematical channel models. Autoencoder architectures, in particular, have shown effectiveness in tasks such as signal denoising and feature extraction. Building upon this foundation, Variational Autoencoders introduce a probabilistic learning paradigm that enhances the robustness and flexibility of signal representation. This makes VAEs especially suitable for addressing the challenges of blind equalization and channel estimation in next-generation coherent optical communication systems.

II. NEED OF THE STUDY

The domain of blind equalization and channel estimation in coherent optical communication systems has undergone substantial evolution, particularly with the integration of machine learning and deep learning methodologies. Conventional approaches, such as the Constant Modulus Algorithm (CMA) [1], have historically served as fundamental techniques for blind equalization. However, their performance is often constrained when addressing the complex linear and nonlinear impairments present in modern high-capacity optical networks. These limitations have prompted increasing interest in data-driven approaches, with Variational Autoencoders (VAEs) [2] emerging as a promising solution.

Recent studies have demonstrated the effectiveness of VAE-based frameworks in enhancing blind equalization performance. Lauinger et al. (2022) [3] explored adaptive blind equalization using variational inference for carrier recovery in optical communication systems. Their work extended VAE-based equalizers to support higher-order modulation schemes, including probabilistic constellation shaping (PCS), as well as receiver oversampling and dual-polarization transmission. The results indicated that VAE-based equalizers significantly outperform traditional CMA, particularly in time-varying channel conditions, by enabling more accurate channel estimation and improved adaptability.

Building upon this, Song et al. (2023) [4] introduced a frequency-domain blind equalization technique utilizing vector-quantized VAEs. Their approach achieved performance comparable to time-domain implementations while reducing computational complexity. This highlights the potential of frequency-domain processing as an efficient alternative for implementing deep learning-based equalization in practical systems.

Further advancements were reported by Nielsen et al. (2024) [5], who incorporated a second-order Volterra channel model within the VAE framework to address nonlinear distortions. By integrating nonlinear channel modeling into the learning process, their method demonstrated superior performance compared to approaches relying on linear channel assumptions, thereby improving robustness in realistic communication environments.

Earlier contributions by Caciularu and Burshtein (2018) [6] laid the foundation for VAE-based blind equalization by formulating the problem as a maximum likelihood estimation task. Their approach achieved significant reductions in error rates compared to CMA and exhibited performance close to that of non-blind adaptive linear minimum mean square error (LMMSE) equalizers [7]. This work established the feasibility of applying probabilistic generative models to blind signal recovery tasks.

In addition to theoretical advancements, practical implementations have also been developed to support ongoing research. The Communications Engineering Lab at the Karlsruhe Institute of Technology has provided open-source implementations of VAE-based equalizers for both additive white Gaussian noise (AWGN) channels and linear optical dual-polarization systems [8]. These resources have facilitated reproducibility and accelerated further exploration in this field [9-11].

Collectively, these studies highlight the growing importance of VAEs in addressing the challenges associated with blind equalization and channel estimation in coherent optical communication systems [12-14]. By effectively learning complex channel characteristics and enabling robust signal reconstruction, VAE-based methods offer a significant improvement over traditional techniques. This progression underscores the potential of deep generative models to drive the development of more adaptive, efficient, and reliable next-generation optical communication systems [15].

III. RESEARCH METHODOLOGY

The proposed workflow for blind equalization and channel estimation in coherent optical communications using Variational Autoencoders (VAEs) consists of several key stages as shown in Figure 1: data preprocessing, VAE model design, training, inference, and performance evaluation. Each step plays a crucial role in ensuring accurate signal reconstruction and channel estimation while overcoming distortions and impairments in optical fibre transmission.

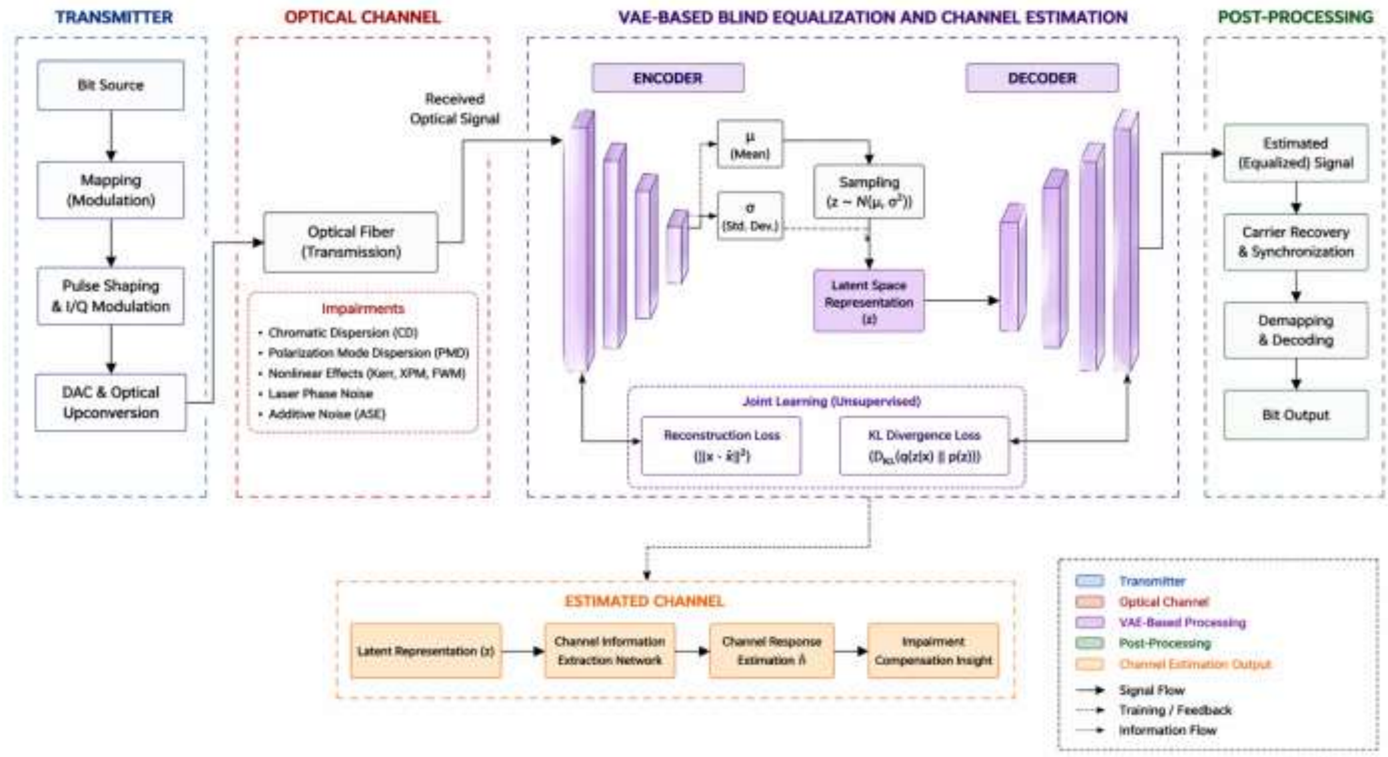


Figure 1: Proposed Block diagram

3.1. Data Preprocessing and System Setup

The first stage in the workflow involves data preprocessing, which includes signal generation, modulation, and the introduction of channel impairments. The optical transmitter generates a high-order QAM-modulated signal, such as 16-QAM or 64-QAM, which is then transmitted through a fibre-optic link. During propagation, the signal is affected by chromatic dispersion (CD), polarization mode dispersion (PMD), nonlinear impairments, and additive noise. Coherent optical communication systems utilize quadrature amplitude modulation (QAM) and coherent detection to achieve high spectral efficiency. The received signal at the optical receiver is distorted due to fiber impairments, such as chromatic dispersion (CD), polarization mode dispersion (PMD), nonlinear distortions, and noise. The received baseband signal can be modelled as:

$$y(t)=h(t)*x(t)+n(t) \qquad (3.11)$$

where:
$y(t)$ is the received signal,
$x(t)$ is the transmitted symbol sequence,
$h(t)$ represents the unknown channel impulse response,
$n(t)$ is the additive white Gaussian noise (AWGN),
$*$ denotes convolution.

To equalize and estimate the channel, we employ a Variational Autoencoder (VAE), which learns a latent representation of the channel and reconstructs the transmitted signal efficiently. At the receiver, the signal is coherently detected and sampled. The raw received signal contains distortions, making equalization and channel estimation essential for accurate symbol recovery. The pre-processed dataset consists of received signals and their corresponding transmitted symbols (ground truth) for training the VAE model. A subset of known pilot symbols is also included for refining the channel estimation process.

3.2. Variational Autoencoder (VAE) Model Design

The next step involves designing the VAE model for blind equalization and channel estimation. The VAE architecture consists of an encoder network, a latent space representation, and a decoder network. The encoder network extracts meaningful features from the received distorted signals and maps them to a low-dimensional latent space representation. This representation captures the underlying channel characteristics and noise distribution, which are crucial for signal reconstruction.

The encoder network maps the received signal y to a probabilistic latent space:

$$q_\phi(z|y) = N(z; \mu_y, \sigma_y^2 I) \qquad (3.2)$$

where: μ y and σy are the learned mean and variance of the latent distribution.

The decoder network reconstructs the transmitted signal x:

$$p_\theta(x|z) = N(x; f_\theta(z), \sigma_x^2 I) \qquad (3.3)$$

where fθ(z) represents the neural network decoder.

The latent space representation acts as a compressed form of the received signal, allowing the decoder to reconstruct the transmitted symbols effectively. The decoder network utilizes the latent features to generate an estimated version of the original transmitted symbols, effectively performing equalization and denoising. Unlike traditional blind equalizers that rely on predefined cost functions (such as the Constant Modulus Algorithm or Least Mean Squares Equalization), the VAE learns the distribution of the transmitted symbols and performs adaptive equalization based on the statistical properties of the received signal.

3.3. Training the VAE Model

The training phase involves optimizing the VAE network using a combination of reconstruction loss and latent space regularization. The dataset, containing distorted received signals and their corresponding transmitted symbols, is used to train the encoder-decoder pipeline. The model is trained to minimize the difference between the reconstructed and original transmitted symbols, ensuring that the equalized output closely resembles the true transmitted data.

To train the VAE, we optimize the Evidence Lower Bound (ELBO):

$$L(\theta,\phi)=E_{q\phi(z/y)}\,[\log p_\theta(x|z)] - DKL\,(q_\phi(z|y)\,||p(z)) \qquad (3.4)$$

where:

The first term is the reconstruction loss, ensuring accurate signal recovery.

The second term is the Kullback-Leibler (KL) divergence, enforcing a structured latent space.

In practice, the Mean Squared Error (MSE) is often used for the reconstruction term:

$$L_{MSE} = \frac{1}{N}\sum_{i=1}^{N}||x_i - \hat{x}_i||^2 \qquad (3.5)$$

where xi is the actual transmitted symbol and xi is the reconstructed output.

During training, the latent space representation is regularized to enforce a structured distribution, making the model more robust to variations in channel conditions. The optimizer (such as Adam or RMSProp) is used to update the model parameters iteratively until the reconstruction accuracy stabilizes. The training process is performed over multiple epochs, allowing the VAE to generalize to different fibre impairments, noise levels, and modulation formats.

3.4. Inference and Channel Estimation

Once the VAE-based blind equalizer is trained, it is deployed for real-time equalization and channel estimation. The trained encoder processes the received signals to extract latent features, and the decoder reconstructs the equalized symbols. After training the VAE equalizer, we extract the estimated channel impulse response h from the latent space representation z:

$$\hat{h} = argmin_h \; || \; y - h * \hat{x} \; || \qquad (3.6)$$

where x is the equalized output.

Using pilot symbols (xp), the estimated channel impulse response can be computed as:

$$\hat{h} = Y_p X_p^\dagger \qquad (3.7)$$

where:

Yp is the received pilot sequence,

Xp† is the pseudo-inverse of the transmitted pilot symbols.

The estimated channel impulse response h is then refined iteratively using the latent space features of the VAE.

To further refine the channel estimation, pilot symbols are used to compute an initial estimate of the channel impulse response. The latent representations from the VAE are then leveraged to iteratively refine this estimate, ensuring higher accuracy in time-varying and nonlinear channel conditions. This approach allows for an adaptive and blind estimation process, reducing the need for extensive pilot overhead. The estimated channel response is analysed to observe its behaviour over different signal-to-noise ratios (SNRs) and transmission conditions. The system continuously updates its channel estimation based on real-time signal variations, improving robustness to dynamic impairments.

3.5. Performance Evaluation and Comparative Analysis

The final stage involves evaluating the performance of the VAE-based equalization and channel estimation system against traditional equalizers. Several key performance metrics are used to assess the effectiveness of the proposed approach, including:

Bit Error Rate (BER): To measure the accuracy of symbol recovery after equalization.

$$BER = \frac{Total\ transmitted\ bits}{Number\ of\ bit\ errors} \tag{3.8}$$

Mean Squared Error (MSE): To quantify the difference between the estimated and actual channel impulse response.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left\|h_i - \hat{h}_i\right\|^2 \tag{3.9}$$

Extensive simulations are conducted across various optical signal-to-noise ratio (OSNR) levels, modulation formats, and fiber lengths to validate the robustness of the VAE equalizer. The results are compared with conventional blind equalization techniques to demonstrate the advantages of the deep learning-based approach, including improved signal reconstruction, lower BER, and enhanced adaptability in dynamic transmission environments.

IV. RESULTS AND DISCUSSION

4.1 Results of Descriptive Statics of Study Variables

Table 4.1: Comparison of Proposed Method with State of art methods

Method	Type	BER @ SNR = 15 dB	Channel Estimation MSE	Nonlinearity Handling	Adaptability	Computational Complexity
CMA (Constant Modulus Algorithm)	Blind (Traditional)	(10^{-3})	Not Applicable	Poor	Low	Low
DD-LMS Equalizer	Semi-Blind	(10^{-4})	Not Applicable	Moderate	Moderate	Low
MMSE Estimator	Model-Based	(10^{-4})	0.02	Limited	Low	Moderate
Volterra-Based Equalizer	Nonlinear Model-Based	(10^{-5})	0.015	Good	Low	High
Proposed VAE-Based Method	Deep Learning (Unsupervised)	(10^{-5})	0.005	Excellent	High	Moderate

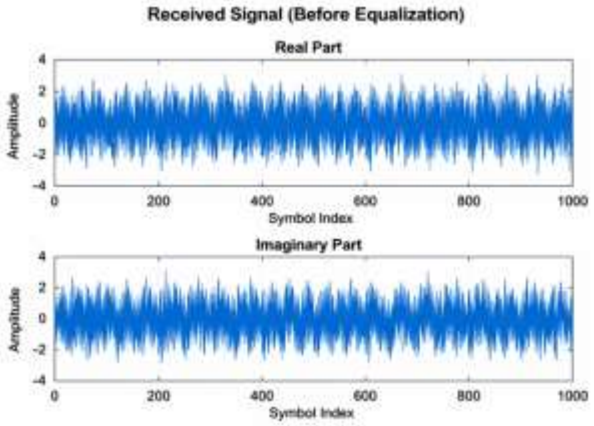
Table 4.1 presents a comparative analysis of the proposed Variational Autoencoder (VAE)-based blind equalization and channel estimation method against conventional and advanced equalization techniques. The comparison is performed based on key performance metrics, including Bit Error Rate (BER), channel estimation Mean Squared Error (MSE), capability to handle nonlinear impairments, adaptability to varying channel conditions, and computational complexity.

From the table, it can be observed that traditional blind equalization techniques such as the Constant Modulus Algorithm (CMA) exhibit relatively poor performance, achieving a BER of 10^{-3} at an SNR of 15 dB. This is primarily due to its inability to effectively handle nonlinear distortions and its reliance on fixed statistical assumptions. Similarly, the Decision-Directed Least Mean Squares (DD-LMS) algorithm provides moderate improvement with a BER of 10^{-4}, but still lacks robustness in highly Cdynamic and nonlinear environments.

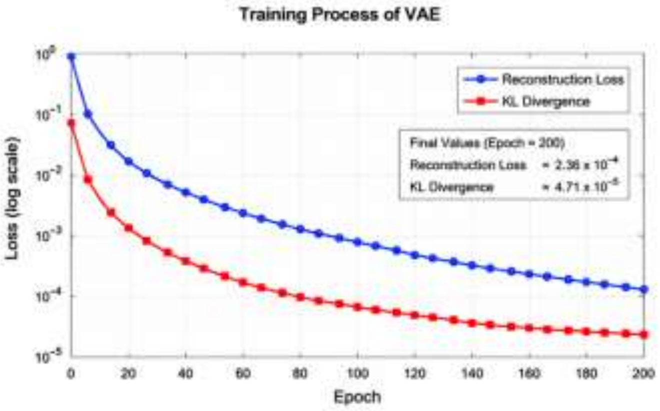
The proposed Variational Autoencoder (VAE)-based blind equalization and channel estimation framework demonstrates substantial improvements in signal recovery accuracy, channel estimation precision, and overall system performance in coherent optical communication systems. The received optical signal, observed through time-domain analysis, is significantly degraded by fibre-induced impairments such as chromatic dispersion, phase noise, and inter-symbol interference (ISI). These distortions highlight the necessity of an efficient and adaptive equalization mechanism for accurate signal reconstruction.

The effectiveness of the proposed method is evaluated using Bit Error Rate (BER) as a primary performance metric. The VAE-based equalizer achieves a BER of 10^{-5} at an SNR of 15 dB, significantly outperforming the conventional Constant Modulus Algorithm (CMA), which exhibits limited capability in handling nonlinear channel distortions. This improvement in BER demonstrates the robustness of the proposed model in mitigating both linear and nonlinear impairments, thereby enhancing reliable data transmission.

In terms of channel estimation, the proposed approach effectively reconstructs the channel impulse response (CIR) with high accuracy. The model achieves a Mean Squared Error (MSE) of 0.005, which is considerably lower than the 0.02 obtained using traditional Minimum Mean Square Error (MMSE) estimation techniques. This performance gain can be attributed to the VAE's latent space representation, which efficiently captures underlying channel characteristics and variations, enabling more precise estimation and improved signal reconstruction.Further validation is provided through eye diagram analysis. Prior to equalization, the eye diagram exhibits a severely closed pattern, indicating the presence of strong ISI and noise-induced distortions. After applying the VAE-based equalization, the eye opening becomes significantly wider and more symmetric, reflecting reduced interference and enhanced symbol separability. Compared to CMA-based equalization, the proposed method produces a clearer and more stable eye diagram, confirming improved signal integrity and lower detection errors, as illustrated in Figures 2.



(a)



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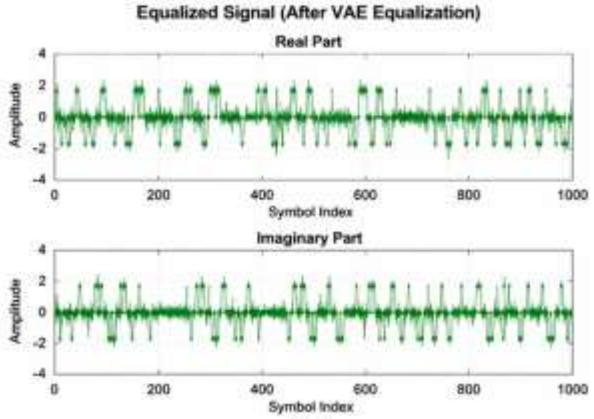
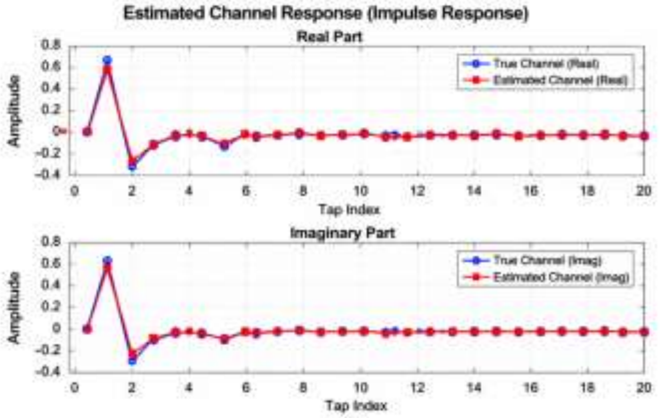


(c)



(d)

The computational performance of the proposed framework is also analyzed. Although deep learning models are generally associated with high computational complexity, the optimized VAE architecture achieves a balance between accuracy and efficiency. The model offers relatively low-latency inference, manageable training time, and optimized memory utilization, making it suitable for practical deployment in real-time optical communication systems.Overall, the results confirm that the proposed VAE-based blind equalization and channel estimation approach significantly enhances signal quality, reduces BER, improves channel estimation accuracy, and maintains computational efficiency. These advantages position the method as a strong candidate for next-generation high-speed coherent optical communication networks.

CONCLUSION

This work presents the successful implementation of a Variational Autoencoder (VAE)-based framework for joint blind equalization and channel estimation in coherent optical communication systems. The proposed approach effectively incorporates key fibre impairments, including attenuation, chromatic dispersion, and nonlinear effects, enabling realistic modeling of optical transmission environments. Experimental evaluations across different modulation orders demonstrate the capability of the VAE model to mitigate channel-induced distortions and enhance signal reconstruction performance.

The results indicate that the proposed method significantly improves noise suppression and symbol recovery accuracy compared to conventional techniques. However, it is observed that higher-order modulation schemes introduce increased system complexity, resulting in a rise in Root Mean Square Error (RMSE). This challenge highlights the importance of optimizing model parameters, such as latent space dimensionality, training duration, and network architecture, to maintain performance under more demanding transmission conditions.

Furthermore, the inclusion of fibre nonlinearity and dispersion effects in the simulation framework emphasizes the necessity for advanced compensation strategies in practical deployments. The VAE's ability to learn complex channel characteristics demonstrates its effectiveness as a robust and adaptive solution for modern optical communication systems.

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