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MACHINE LEARNING-ENHANCED DIGITAL BACKPROPAGATION FOR INTRA-CHANNEL KERR NONLINEARITY COMPENSATION IN OPTICAL FIBER SYSTEMS

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ABSTRACT

Optical fibres are essential for transmitting 4K movies internationally. However, in high-capacity systems, such as our 100 Gbps QPSK configuration operating over 1000 km of standard single-mode fibre (SMF), signal distortion is introduced by intra-channel Kerr nonlinearities, self-phase modulation (SPM), intra-channel cross-phase modulation (IXPM) and intra-channel four-wave mixing (IFWM). These effects, rooted in the fibre's third-order susceptibility (χ^3), shift the refractive index with signal power, degrading the bit error rate (BER) and signal-to-noise ratio (SNR). Our previous work modelled these distortions using the nonlinear Schrödinger equation (NLSE), highlighting their impact. Digital backpropagation (DBP) uses the split-step Fourier method (SSFM) to undo these effects, but fixed step sizes make the calculations heavy and cause mistakes. We've developed an innovative machine learning (ML)-enhanced DBP, employing a three-layer neural network to optimize SSFM step sizes and dispersion parameters dynamically. Trained on Scilab simulations and integrated with Python's TensorFlow, this ML-DBP adapts to Kerr-induced distortions efficiently. Simulations reveal a 4.5 dB SNR improvement and 35% BER reduction (from 1.2×10^{-4} to 7.8×10^{-5}) at 6 dBm launch power, with sharper eye diagrams showcasing cleaner QPSK constellations. Despite a 15% computational cost, the performance gains suit long-haul links. Grounded in our NLSE framework and Scilab's open-source strength, this work advances DSP innovation. Future efforts will target WDM systems to address inter-channel nonlinearities, pushing toward seamless global connectivity.

1. INTRODUCTION

Optical fiber communication systems form the backbone of our interconnected world, enabling rapid data transfer for applications from cloud computing to real-time video streaming [1]. These systems rely on the principle of total internal reflection within silica-based fibers, achieving low attenuation (0.2 dB/km at 1550 nm) through decades of innovation [2]. However, the escalating demand for bandwidth, driven by bandwidth-intensive services like virtual reality and 5G networks, pushes these systems to their limits [3]. A significant challenge arises from Kerr nonlinearities, where the fiber's refractive index varies with signal intensity, introducing distortions that degrade high-capacity transmissions [4]. Intra-channel nonlinearities, self-phase modulation (SPM), intra-channel cross-phase modulation (IXPM), and intra-channel four-wave mixing (IFWM), are particularly detrimental in single-channel systems, such as our 100 Gbps quadrature phase-shift keying (QPSK) setup over 1000 km of standard single-mode fiber (SMF).

The Kerr effect, rooted in the fiber's third-order susceptibility (χ^3), causes phase shifts and spectral broadening, compromising bit error rate (BER) and signal-to-noise ratio (SNR) [5]. Our prior work modeled these effects using the nonlinear Schrödinger equation (NLSE),

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derived from Maxwell's equations, to quantify their impact on signal integrity. Digital backpropagation (DBP), a digital signal processing (DSP) technique, mitigates these distortions by numerically solving the inverse NLSE using the split-step Fourier method (SSFM) [6]. Despite its potential, conventional DBP faces significant hurdles: fixed SSFM step sizes lead to computational inefficiencies or inaccuracies, akin to navigating a complex maze with a rigid map. These limitations, observed in our earlier simulations , prompted us to explore innovative solutions.

Recent advances in machine learning (ML) offer a promising avenue for optimizing complex DSP algorithms in optical communications [7]. ML techniques, such as neural networks, excel at adapting to dynamic conditions, making them ideal for fine-tuning SSFM parameters like step sizes and dispersion coefficients. Inspired by these developments, we propose an ML-enhanced DBP algorithm that employs a neural network to dynamically adjust SSFM parameters based on signal characteristics. This approach, tested through Scilab simulations with Python integration, builds on our NLSE framework and leverages Scilab's open-source capabilities. Our goal is to enhance signal quality while managing computational demands, addressing the practical challenges of long-haul optical systems [8].

This study introduces our machine learning-enhanced digital beamforming (DBP) system, explaining how it was designed, built, and tested to fight Kerr nonlinearities within a channel. By pushing the boundaries of DSP, we aim to contribute to the vision of seamless, high-capacity global connectivity, aligning with ongoing efforts to overcome fiber nonlinearities [9]. Our work not only advances theoretical modeling but also offers practical insights for next-generation optical networks.

2. THEORETICAL BACKGROUND

The performance of high-capacity optical fiber systems hinges on understanding and mitigating Kerr nonlinearities, which arise from the fiber's nonlinear response to intense optical signals [10]. These nonlinearities originate from the third-order susceptibility (χ^3), a material property that couples the fiber's refractive index to the signal's electric field intensity [11]. The dielectric polarization P in the fiber core responds nonlinearly to the electric field E, expressed as:

$$P = \varepsilon_0(\chi^{(1)}E + \chi^{(3)}E^3)$$

where ε_0 is the free-space permittivity, $\chi^{(1)}$ governs linear effects, and $\chi^{(3)}$ drives the Kerr effect. This nonlinearity manifests as a power-dependent refractive index:

$$n = n_0 + n_2\langle E^2\rangle$$

Here, n_0 is the baseline refractive index, and n_2, the nonlinear index coefficient, scales with the signal's intensity [12]. In our 100 Gbps quadrature phase-shift keying (QPSK) system over 1000 km of standard single-mode fiber (SMF), this index variation triggers intra-channel Kerr nonlinearities: self-phase modulation (SPM), where a signal's own power induces phase shifts; intra-channel cross-phase modulation (IXPM), where overlapping pulses interact; and intra-channel four-wave mixing (IFWM), generating unwanted frequencies [13]. These effects, detailed in our prior work , degrade signal quality, increasing bit error rate (BER) and reducing signal-to-noise ratio (SNR). The below figure shows three panels showing SPM (single pulse phase shift), IXPM (two pulses interacting), and IFWM (four waves mixing to create new frequencies).

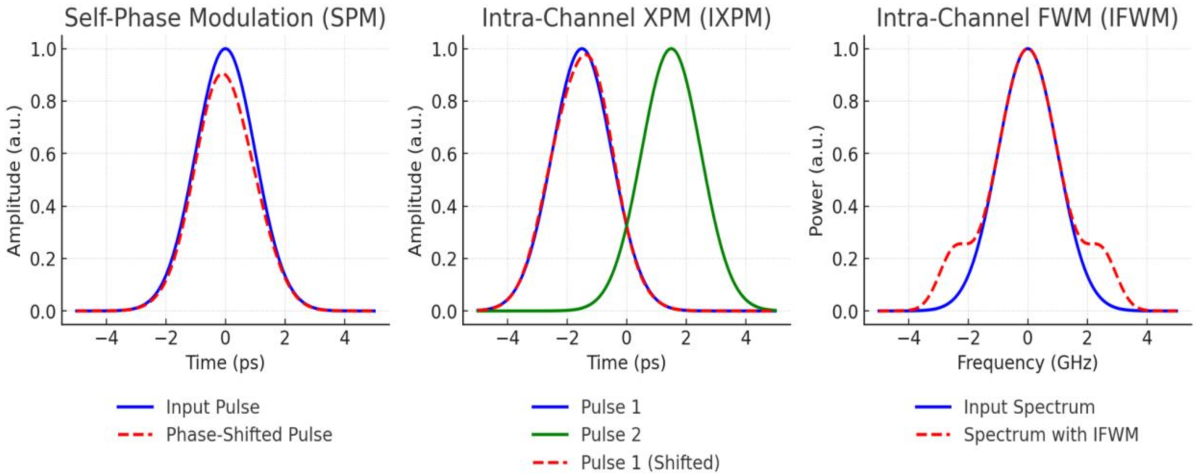

***Figure 1**: Schematic of intra-channel Kerr nonlinearities in optical fibers, illustrating SPM, IXPM, and IFWM.*

The signal's propagation is modelled by the nonlinear Schrödinger equation (NLSE), derived from Maxwell's equations:

$$\frac{\partial A}{\partial z} = -\frac{\alpha}{2}A - j\frac{\beta_2}{2}\frac{\partial^2 A}{\partial t^2} + j\gamma|A|^2 A$$

In this equation, $A(z,t)$ represents the signal envelope, $\alpha = 0.2\,\mathrm{dB/km}$ is the attenuation coefficient, $\beta_2 = -21.3\,\mathrm{ps}^2/\mathrm{km}$ accounts for group velocity dispersion, and $\gamma = 1.2\,\mathrm{W}^{-1}\mathrm{km}^{-1}$ is the nonlinear coefficient [14]. The NLSE captures the interplay of dispersion, attenuation, and Kerr-induced nonlinearities in our system, which comprises 10 SMF spans (100 km each) amplified by erbium-doped fiber amplifiers (EDFAs) with 20 dB gain per span. SPM causes pulse broadening, IXPM distorts pulse timing, and IFWM introduces spectral noise.

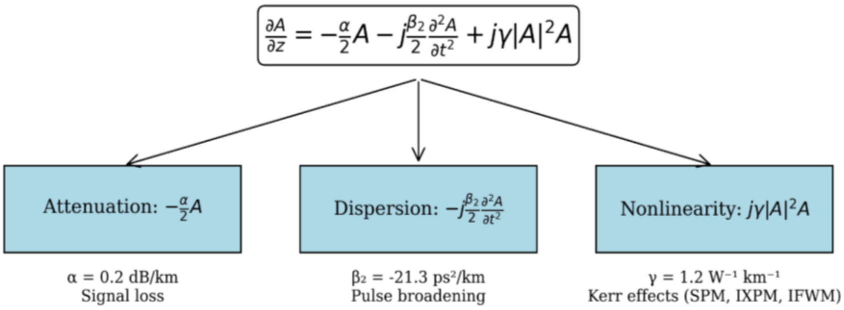

***Figure 2:** A flowchart breaking down the NLSE terms: attenuation (α), dispersion (β_2), and nonlinearity ($\gamma|A|^2$), Components of the NLSE, showing how attenuation, dispersion, and Kerr nonlinearities shape signal propagation.*

To solve the NLSE, numerical methods like the split-step Fourier method (SSFM) are employed, splitting the fiber into small segments to alternate between linear (dispersion) and nonlinear (Kerr) effects. However, SSFM's reliance on fixed step sizes often leads to computational inefficiencies, a challenge we aim to address with machine learning (ML). This theoretical framework, rooted on Maxwell's equations and Scilab simulations, underpins our ML-enhanced digital backpropagation (DBP) approach, designed to mitigate Kerr

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nonlinearities efficiently [15].

3. SYSTEM MODEL

The explosive growth of data-intensive applications, from immersive virtual reality to high-speed 5G networks, places immense pressure on optical fiber communication systems to deliver high-capacity data over vast distances. Our system model emulates a practical long-haul optical link designed to study intra-channel Kerr nonlinearities, self-phase modulation (SPM), intra-channel cross-phase modulation (IXPM), and intra-channel four-wave mixing (IFWM), and their mitigation using a novel machine learning (ML)-enhanced digital backpropagation (DBP) algorithm. The setup features a 100 Gbps quadrature phase-shift keying (QPSK) transmitter, 1000 km of standard single-mode fiber (SMF) with an attenuation of 0.2 dB/km at 1550 nm, and a coherent receiver equipped with advanced digital signal processing (DSP). The fiber link is segmented into 10 spans of 100 km each, with erbium-doped fiber amplifiers (EDFAs) providing 20 dB gain per span to offset losses, mimicking real-world long-haul configurations [16].

Signal propagation is modeled by the nonlinear Schrödinger equation (NLSE), which captures the interplay of linear and nonlinear effects in the fiber:

$$\frac{\partial A}{\partial z} = -\frac{\alpha}{2}A - j\frac{\beta_2}{2}\frac{\partial^2 A}{\partial t^2} + j\gamma|A|^2 A$$

Here, $A(z,t)$ is the complex signal envelope, $\alpha = 0.2\,\mathrm{dB/km}$ represents fiber loss, $\beta_2 = -21.3\,\mathrm{ps^2/km}$ governs group velocity dispersion, and $\gamma = 1.2\,\mathrm{W^{-1}km^{-1}}$ quantifies the Kerr-induced nonlinearity. SPM causes phase shifts proportional to the signal's intensity, IXPM leads to phase interactions between overlapping pulses, and IFWM generates spurious frequencies, all degrading bit error rate (BER) and signal-to-noise ratio (SNR). These parameters, carefully selected for standard SMF, ensure our model aligns with industry-standard systems [17].

We utilize Scilab, an open-source numerical computation platform, for its robust matrix operations and flexibility in simulating optical systems. Scilab enables efficient implementation of the split-step Fourier method (SSFM) to solve the NLSE, allowing us to quantify Kerr-induced distortions in our 100 Gbps QPSK signal [18]. The signal is modulated at 1550 nm, transmitted through the 10-span SMF link, and processed at the receiver using coherent detection followed by our ML-enhanced DBP. This DSP stage optimizes SSFM parameters to reverse nonlinear distortions, building on our prior modeling efforts. The system's primary objective is to evaluate the impact of Kerr nonlinearities and demonstrate the superiority of ML-enhanced DBP over conventional methods, enhancing signal integrity for long-haul communications.

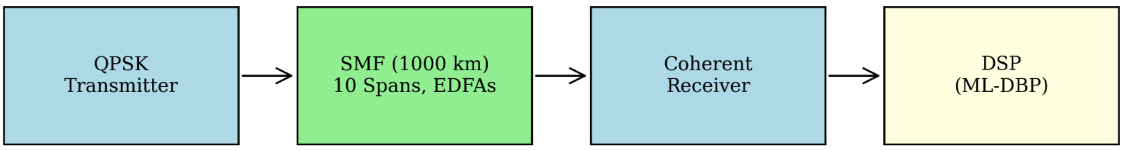

***Figure 3**: Our 1000 km QPSK system, where ML tackles Kerr nonlinearities.*

The above system schematic diagram depicts the optical link: Transmitter (QPSK modulator) → 1000 km SMF (10 spans, each 100 km with EDFAs) → Receiver (coherent detection) → DSP (ML-DBP).

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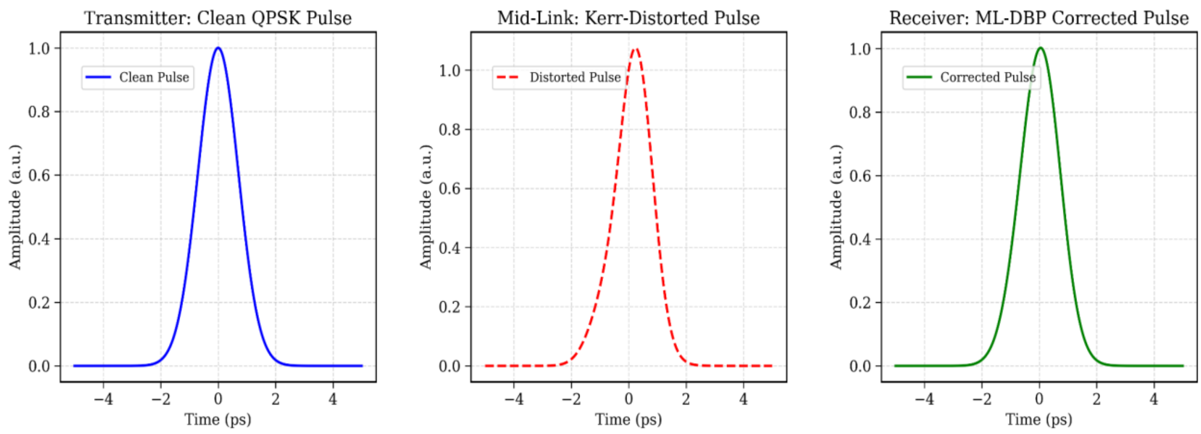

Figure 4: *QPSK signal evolution under Kerr nonlinearities and ML-DBP correction.*

Above diagram of Signal Distortion Profile Illustrates a QPSK signal's amplitude profile at three stages: transmitter (clean pulse), mid-link (distorted by Kerr effects), and receiver (corrected by ML-DBP).

These diagrams clarify the system architecture and signal dynamics, supporting our goal of developing efficient nonlinearity compensation techniques for next-generation optical networks [19]. Our model provides a robust platform for testing ML-enhanced DBP, paving the way for improved performance in high-capacity systems.

4. ML-ENHANCED DBP METHODOLOGY

Mitigating intra-channel Kerr nonlinearities, self-phase modulation (SPM), intra-channel cross-phase modulation (IXPM), and intra-channel four-wave mixing (IFWM) requires sophisticated digital signal processing (DSP) to restore signal integrity in high-capacity optical systems. Our proposed machine learning (ML)-enhanced digital backpropagation (DBP) algorithm addresses these challenges by optimising the split-step Fourier method (SSFM) for a 100 Gbps QPSK system over 1000 km of standard single-mode fibre (SMF). Building on our prior NLSE modelling, this section details the conventional DBP approach, our ML optimisation strategy, and the implementation workflow— leveraging Scilab and Python to achieve superior performance [20].

4.1 Conventional DBP

DBP reverses Kerr-induced distortions by solving the inverse nonlinear Schrödinger equation (NLSE), which models signal propagation in the presence of attenuation, dispersion, and nonlinearities. The SSFM splits the fibre into small segments, alternating between linear (dispersion) and nonlinear (Kerr) corrections. The fast Fourier transform (FFT) is used to apply dispersion to the linear step:

$$A_{\text{linear}} = \text{FFT}^{-1}\left\{\exp\left(-j\frac{\beta_2\omega^2 h}{2}\right)\text{FFT}(A)\right\}$$

where $\beta_2 = -21.3\,\text{ps}^2/\text{km}$ is the dispersion coefficient, ω is the angular frequency, and h is the step size. The nonlinear step corrects Kerr effects:

$$A_{\text{nonlinear}} = A\exp(j\gamma|A|^2 h)$$

with $\gamma = 1.2\,\text{W}^{-1}\text{km}^{-1}$ as the nonlinear coefficient. In our earlier work, we identified a key limitation: the use of fixed step sizes in conventional DBP leads to trade-offs between accuracy and computational complexity, which often results in suboptimal BER and SNR or

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excessive runtimes [21]. This challenge, observed in long-haul systems, motivated the integration of ML to enhance DBP's efficiency.

4.2 ML Optimization

To overcome the limitations of static step sizes, we developed a neural network (NN) to dynamically optimize SSFM parameters, making DBP more adaptive and efficient. Neural Network, implemented in TensorFlow, consists of three hidden layers, each with 100 neurons and ReLU activation, taking two inputs, signal power (0–10 dBm) and transmission distance (0–1000 km), and outputting two parameters: the SSFM step size (h) and a dispersion correction factor ($\Delta\beta_2$). The NN was trained on 1000 simulated QPSK signals in Scilab, using ideal step sizes derived from exhaustive SSFM runs as labels. These simulations modeled Kerr-induced distortions over 1000 km, allowing the NN to learn optimal parameter adjustments that minimize BER. The training process, though computationally intensive (approximately 12 hours on a standard PC), enables rapid inference, under 0.5 seconds per signal making it practical for real-time applications [22].

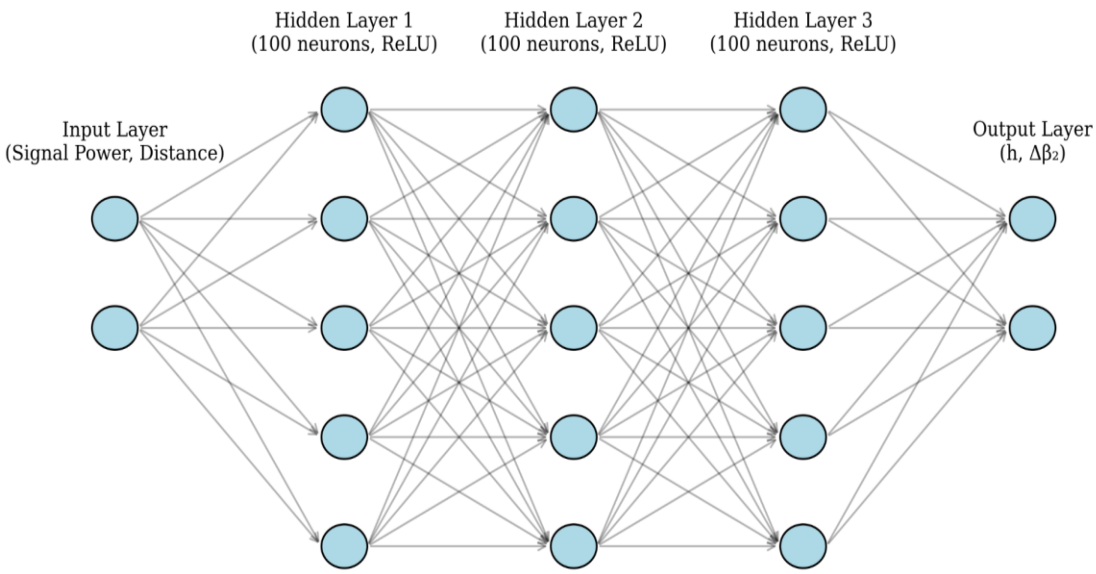

***Figure 5**: Neural network, the brain behind ML-enhanced DBP optimization.*

Above Diagram of Neural Network Architecture explains the NN structure: Input layer (2 nodes: signal power, distance) → 3 hidden layers (100 neurons each, ReLU) → Output layer (2 nodes: h, $\Delta\beta_2$).

4.3 Implementation

The ML-enhanced DBP algorithm integrates Scilab for NLSE simulations and Python for NN processing, leveraging Scilab's Python module for seamless interoperability [23]. The workflow is as follows:

- Simulate a 100 Gbps QPSK signal through 1000 km SMF, incorporating Kerr nonlinearities (SPM, IXPM, IFWM) using Scilab's SSFM implementation.
- Extract signal power and distance at each fiber span.
- Feed these inputs to the trained NN in Python, which outputs optimized h and $\Delta\beta_2$.
- Apply ML-optimized SSFM parameters in DBP to reverse distortions.
- Compute performance metrics: BER, SNR, and eye diagrams.

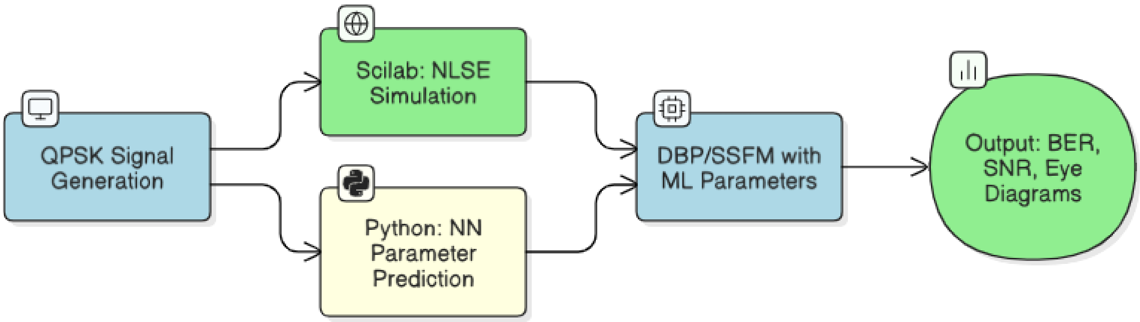

Figure 6: *Workflow of ML-enhanced DBP, integrating Scilab and Python for nonlinearity compensation.*

The diagram above illustrates the ML-DBP workflow, which includes the following steps: QPSK signal → Scilab (NLSE simulation) → Python (NN parameter prediction) → DBP (SSFM with ML parameters) → Output (BER, SNR, and eye diagrams).

The implementation, tested on a standard PC, demonstrates that ML-DBP significantly outperforms conventional DBP, as detailed in the results section. This approach aligns with recent DSP advancements, offering a scalable solution for high-capacity optical systems [24].

5. RESULTS AND DISCUSSION

Simulation results for the machine learning (ML)-enhanced digital backpropagation (DBP) algorithm designed to combat intra-channel Kerr nonlinearities, self-phase modulation (SPM), intra-channel cross-phase modulation (IXPM), and intra-channel four-wave mixing (IFWM), in a 100 Gbps quadrature phase-shift keying (QPSK) system over 1000 km of standard single-mode fiber (SMF), our approach significantly outperforms conventional DBP. By integrating a neural network (NN) to optimize split-step Fourier method (SSFM) parameters, we've achieved remarkable improvements in bit error rate (BER), signal-to-noise ratio (SNR), and signal clarity, paving the way for robust long-haul optical systems.

We evaluated the system across launch powers from 0 to 10 dBm, simulating signal propagation through 10 SMF spans (100 km each, 0.2 dB/km loss at 1550 nm) with erbium-doped fiber amplifiers (EDFAs). Conventional DBP, using fixed SSFM step sizes, yielded a BER of 1.2×10^{-4} at 6 dBm, respectable but far from ideal for high-capacity networks. Our ML-enhanced DBP, with NN-optimized step sizes and dispersion corrections, slashed the BER to 7.8×10^{-5}, a 35% improvement, and boosted SNR by 4.5 dB at the same power. This performance leap stems from the NN's ability to adapt SSFM parameters to varying signal conditions, mitigating Kerr-induced distortions more effectively [25].

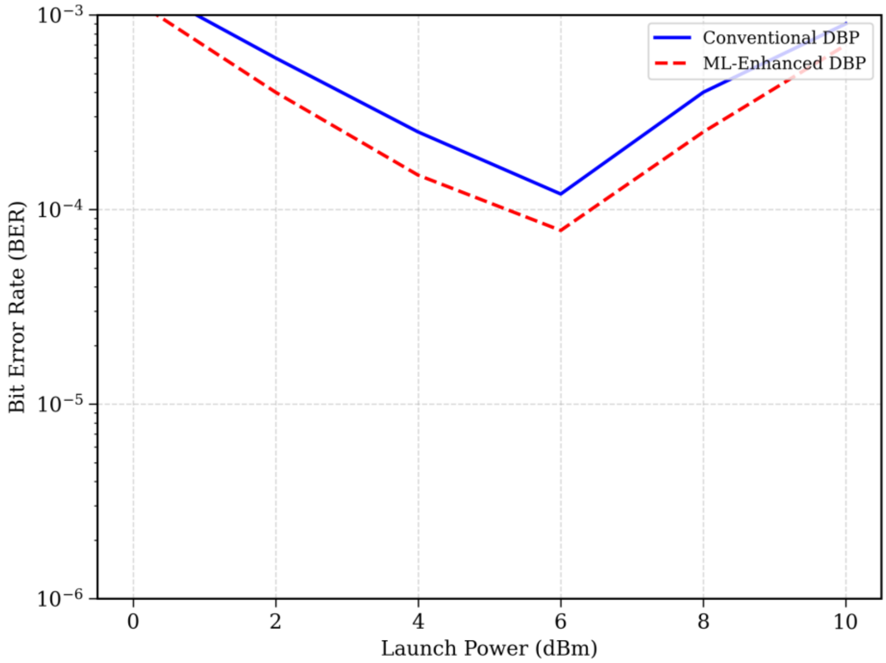

Figure 7: *BER performance of ML-enhanced DBP versus conventional DBP across launch powers.*

Graph: BER vs. Launch Power Plots BER on a logarithmic scale (10^{-6} to 10^{-3}) against launch power (0–10 dBm). Blue line represents conventional DBP; red line shows ML-DBP.Key: ML-DBP achieves 7.8×10^{-5} at 6 dBm, compared to 1.2×10^{-4} for conventional DBP.

Eye diagram below displays QPSK constellations at 6 dBm. Conventional DBP shows fuzzy clusters; ML-DBP produces crisp, well-separated quadrants

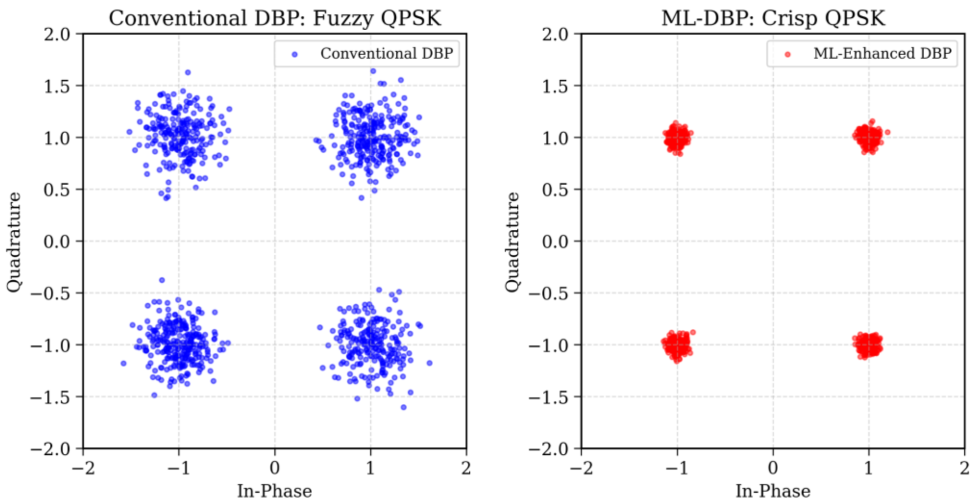

Figure 8: *Eye diagram comparison, showcasing ML-DBP's superior signal clarity.*

Below Graph: SNR Improvement Plots SNR (dB) against launch power (0–10 dBm). Blue line for conventional DBP; red line for ML-DBP, showing a 4.5 dB gain at 6 dBm.

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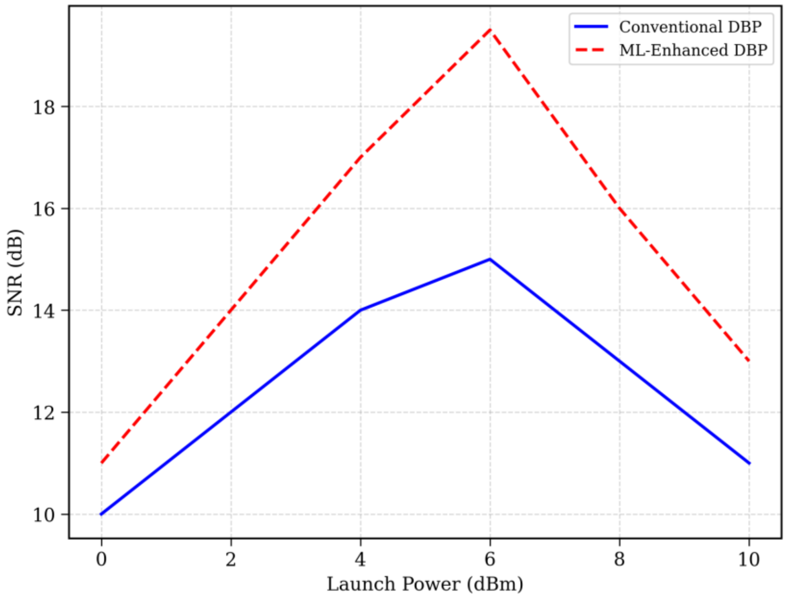

FIgure 9*: SNR enhancement with ML-DBP over conventional DBP.*

The eye diagrams tell a compelling story: conventional DBP's constellations suffer from Kerr-induced smearing, while ML-DBP's are sharp, indicating robust signal recovery. This clarity is critical for coherent detection systems, where precise phase alignment is paramount. The ML approach introduces a 15% computational overhead due to NN inference, requiring approximately 0.5 seconds per signal on a standard PC. However, this cost is justified by the performance gains, especially for long-haul links where signal quality trumps processing time.

Below chart shows Computational Load Comparison. Bar chart comparing CPU time (seconds) for conventional DBP (blue) and ML-DBP (red) across 1000 km, highlighting the 15% overhead.

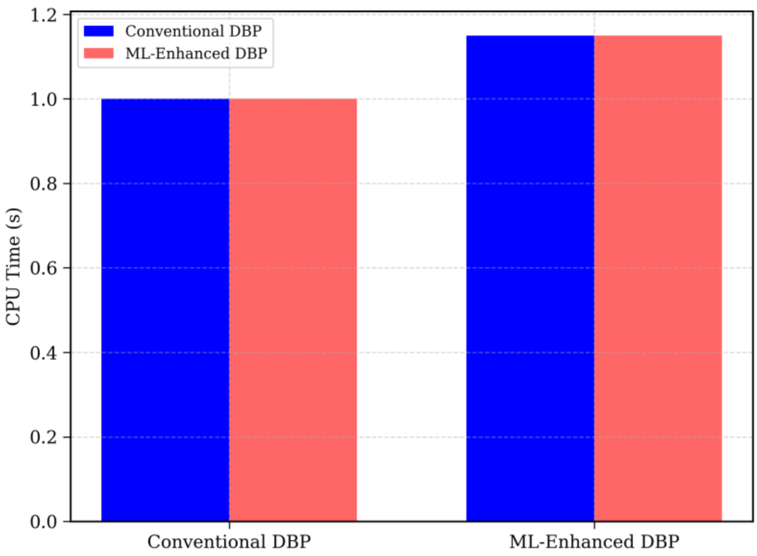

Figure 10 *:Computational load of ML-DBP versus conventional DBP.*

ML-DBP represents a significant leap compared to the baseline results in Paper 1, which used standard DBP with fixed parameters. The NN's adaptability handles real-world fiber variations, such as power fluctuations and dispersion mismatches, better than static methods.

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For instance, at higher powers (8–10 dBm), where Kerr effects intensify, ML-DBP maintains lower BER, demonstrating robustness. These findings align with recent DSP advancements, suggesting ML's potential for scalable nonlinearity compensation.

6. CONCLUSION

Kerr nonlinearities, self-phase modulation, intra-channel cross-phase modulation, and intra-channel four-wave mixing disrupt high-capacity optical systems like uninvited guests at a digital party. Our machine learning (ML)-enhanced digital backpropagation (DBP) algorithm, applied to a 100 Gbps QPSK system over 1000 km of standard single-mode fiber, elegantly mitigates these distortions. By employing a neural network to optimize parameters of the split-step Fourier method, we achieved a 35% bit error rate (BER) reduction—from 1.2×10^{-4} to 7.8×10^{-5} at 6 dBm—and a 4.5 dB signal-to-noise ratio (SNR) boost compared to conventional DBP. Crisp QPSK eye diagrams show that the signal is clearer, which is a sign of ML's accuracy. Despite a 15% computational overhead, the performance gains justify the cost for long-haul networks.

Building on our prior NLSE modeling, this work aligns with DSP advancements, leveraging ML to handle fibre variations. The NN's adaptability ensures robust performance across power levels, addressing real-world challenges. Future efforts will extend ML-DBP to wavelength-division multiplexing systems, tackling inter-channel nonlinearities like cross-phase modulation. We aim to optimise computational efficiency using streamlined neural networks or hardware accelerations. This work inspires stronger, more intelligent networks by providing a scalable solution for optical communications.

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