Investigation of Neural Equalization-Enhanced Phase Noise Mitigation

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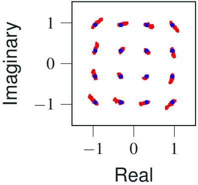
Outline

Agenda

1. Motivation
2. Mitigation Techniques
3. Summary

Equalization-Enhanced Phase Noise (EEPN)

- EEPN is a critical impairment in optical communication systems.
- Arises from the interplay between laser phase noise and electronic dispersion compensation.
- Degrades the signal quality, resulting in increased bit error rates (BER).



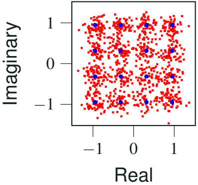


Figure: EEPN Effect

Phase Noise Model

- Simulates phase noise as a Wiener process, commonly referred to as a random walk.
- Incorporates cumulative randomness to simulate the drifting nature of phase noise over time.

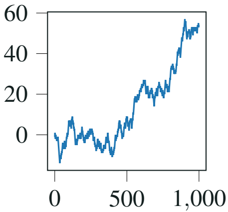


Figure: Random Walk

Conventional Mitigation Techniques

Mitigating EEPN requires advanced techniques due to its nonlinear and time-varying nature.

- Phase noise estimation and compensation methods, such as phase-locked loops (PLLs), can partially mitigate EEPN.
- Methods limited by the complexity of EEPN and may fail under severe conditions.

Block Diagram of Setup

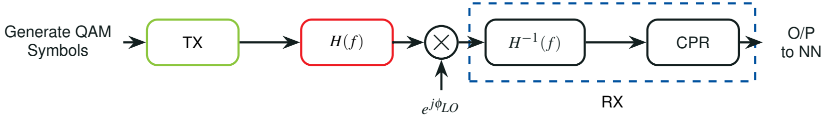


Figure: Flowchart of Setup

Machine Learning Mitigation Techniques

Neural networks can address the effects of EEPN.

- Can learn the nonlinear relationships between the Tx and Rx signals.
- Convolutional Neural Networks (CNNs) can model spatial relationships in the signal.

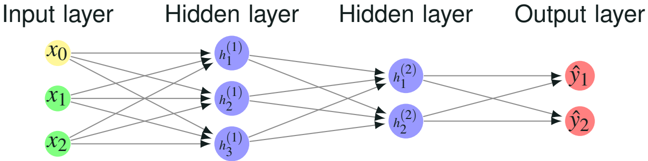


Figure: Basic Neural Network

Neural Network Architecture

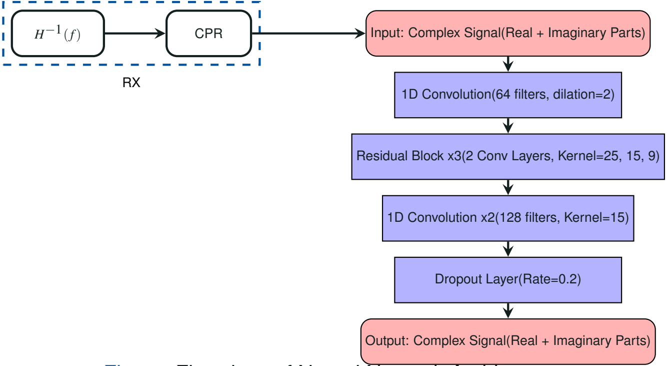


Figure: Flowchart of Neural Network Architecture

Loss Functions in Neural Networks

Loss functions quantify the difference between predicted outputs and actual targets.
The objective during training is to minimize the loss function and improve model performance.

- Regression tasks: predict continuous values, measure the difference between predicted and true values.
  eg. Mean Squared Error (MSE), Mean Absolute Error (MAE).
- Classification tasks: predict a category or class label, measure the difference between predicted class probabilities and true class labels.
  eg. Cross-Entropy Loss (Log Loss).

Mean Squared Error (MSE)

Mean Squared Error (MSE) is a loss function used in neural networks, especially for regression tasks.

- The equation for MSE is

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{1}$$

MSE Results

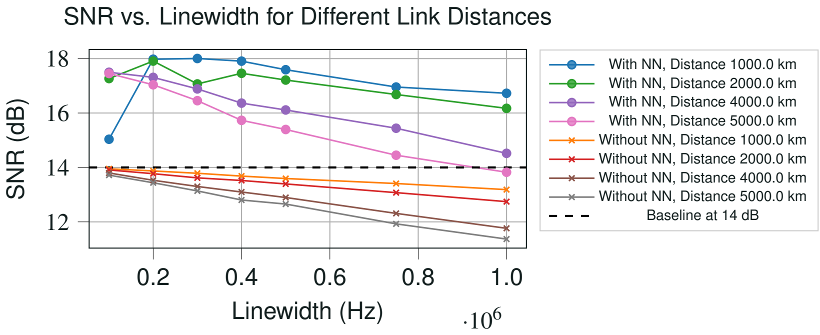


Figure: SNR vs Linewidth for Different Link Distances

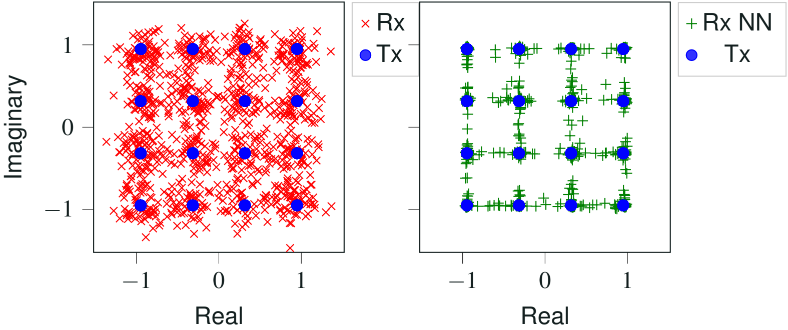


Figure: Scatter Plot for Tx vs Rx with and without NN for linewidth 750KHz and link distance 2000km

Jail Window

- MSE can lead to a phenomenon known as the jail window.
- A form of overfitting where the model's predictions become overly rigid and locked into a small region of the output space.
- ”Jail Window” is a constrained, narrow range of outputs the model produces despite having a larger potential output range.

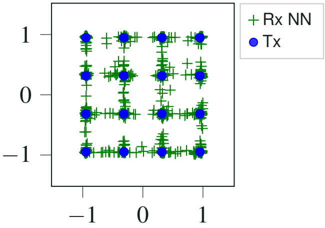


Figure: Jail Window Effect

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Mitigation Techniques for Jail-Window Effect

Entropy Regularized Mean Squared Error (MSE-X) [1]

- Extension of traditional MSE.
- Incorporates entropy regularization where additional uncertainty or noise is present.
- Helps maintain a more flexible and generalized approach where models may lock into overly confident, narrow predictions (leading to the ”jail window” effect).

[1]F. Diedolo, G. Böcherer, M. Schädler, and S. Calabró, ”Nonlinear Equalization for Optical Communications Based on Entropy-Regularized Mean Square Error,” in European Conference on Optical Communication (ECOC) 2022, J. Leuthold, C. Harder, B. Offrein, and H. Limberger, eds., Technical Digest Series (Optica Publishing Group, 2022), paper We2C.2.

MSE-X Equation

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}|x-y|^2 \tag{2}$$

$$Q_Y = \frac{1}{\sqrt{2\pi\cdot\text{MSE}}}\exp\left(-\frac{|x-y|^2}{2\cdot\text{MSE}}\right) \tag{3}$$

$$\text{entropy\_reg} = -\frac{1}{n}\sum_{i=1}^{n}\log\left(Q_Y\right) \tag{4}$$

$$\text{MSE-X} = \text{MSE} - 2\cdot(\text{MSE}\cdot\text{entropy\_reg}) \tag{5}$$

MSE-X Results

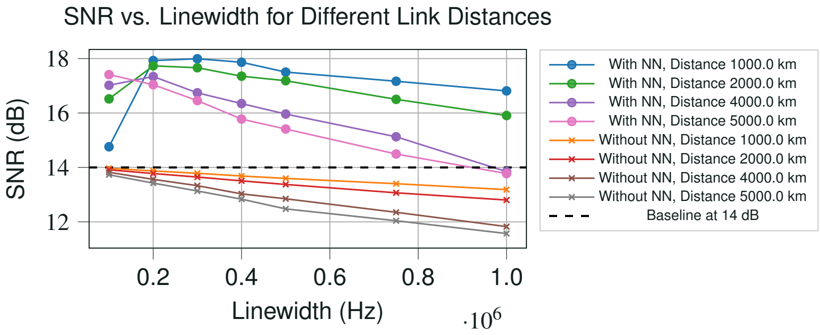

Figure: SNR vs Linewidth for Different Link Distances

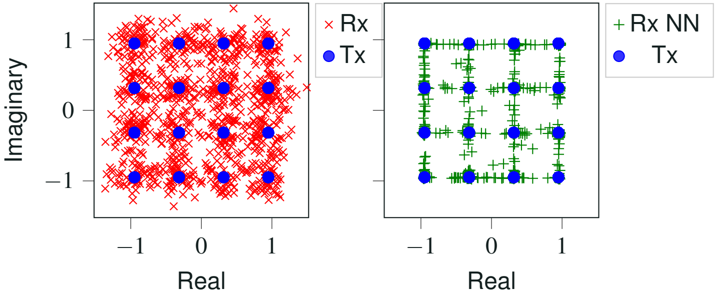

Figure: Scatter Plot for Tx vs Rx with and without NN for linewidth 750KHz and link distance 2000km

Achievable Information Rate (AIR)

- Measure of maximum mutual information that can be transmitted over a noisy communication channel.
- Instead of solely focusing on minimizing the loss, the objective is to also maximize mutual information (MI).
- In terms of PDFs for continuous distributions, MI can be calculated as,

$$(X;Y) = \frac{1}{n}\sum_{i=1}^{n}(\log P(X,Y) - \log P(Y)) \tag{6}$$

where, $\log P(X,Y)$ is log joint density, and
$\log P(Y)$ is log marginal density

$$AIR = \frac{I(X;Y)}{\log(2)} \tag{7}$$

Use of AIR for Early Stopping

- Halt training when model reaches a point where it can no longer increase the AIR significantly.
- Prevent model from continuing to overfit.

$$\text{Best Loss AIR} = \max(\text{AIR}_{\text{train}}, \text{Best Loss AIR}) \tag{8}$$

AIR with Early Stopping Results

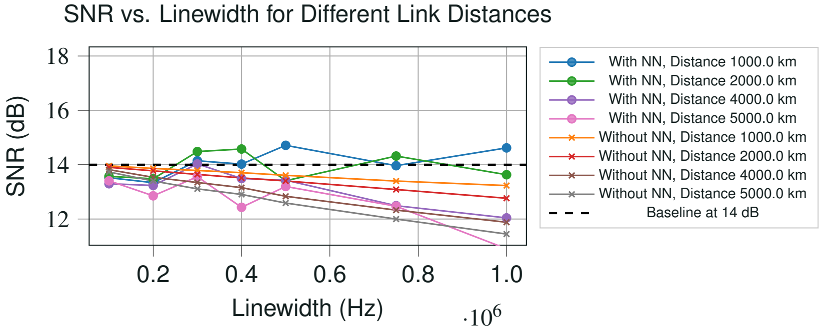

Figure: SNR vs Linewidth for Different Link Distances

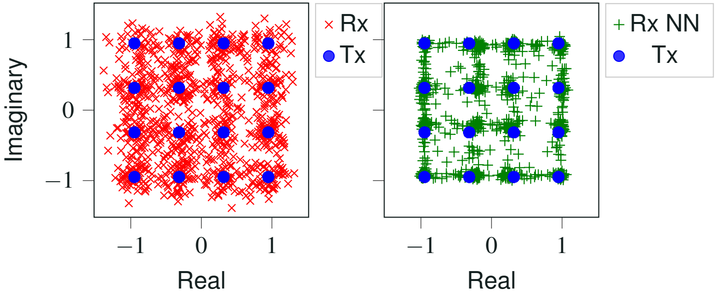

Figure: Scatter Plot for Tx vs Rx with and without NN for linewidth 750KHz and link distance 2000km

AIR vs. Epoch for Different Linewidth and Link Distances

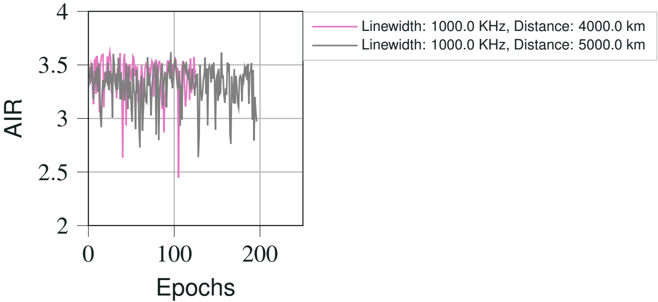

Figure: AIR with Early Stopping

AIR with Entropy Regularisation

- Combining AIR maximization with entropy regularization can further help mitigate the jail window.
- Entropy regularization can help maintain uncertainty in model predictions.

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Conclusion

While the integration of neural networks for EEPN mitigation shows promising results, further research is required to:

- enhance model robustness,
- address jail window challenge, and
- explore real-time deployment scenarios.

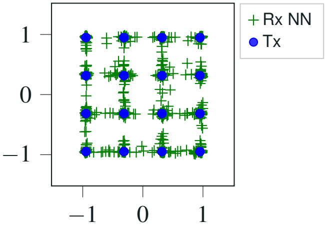

Figure: Jail Window Effect

Thank you for your attention!