Improvement of Correlation-Based Longitudinal Power Monitoring in 88 km Spans Using Machine Learning

Mohammad Asif Ibna Mustafa, Olaf Schulz, Magnus Fischer, Annika Dochhan, and Stephan Pachnicke
Chair of Communications
Kiel University
Kaiserstr. 2, 24143 Kiel, Germany
asif.mustafa@tf.uni-kiel.de

***Abstract*— We propose an ML-based longitudinal power monitoring approach that extends the anomaly loss detection range in 88 km multi-span optical fiber links by up to 45 km, compared to the conventional subtraction method. The approach integrates correlation-based power profile estimation with an unsupervised Variational Autoencoder and leverages transfer learning to adapt models trained on simulation data to experimental measurements. Experimental validation on a 40 GBd coherent transmission system demonstrates significantly increased performance, achieving 100% anomaly detection accuracy and 91.1% accuracy for normal profiles.**

***Index Terms*— Longitudinal Power Monitoring, Power Profile Estimation, Machine Learning, Transfer Learning, Variational Autoencoder, Anomaly Detection**

I. Introduction

The monitoring of optical links is important to ensure robust operations of fiber-optic networks. As measuring of cumulative parameters is not sufficient for a fast detection and mitigation of (soft) network failures, the concept of longitudinal power profile estimation (PPE) has gained a lot of interest over the last years [1]. Using the fiber nonlinearity, the optical power over the whole link can be resolved in space by utilizing the received signal only. This is achieved by comparing the measured signal with a digitally propagated one using correlation, minimum-mean-square or linear-least-square approaches [2,3].

Most existing work focuses on systems with high baud rates (> 90 GBd) and/or fiber spans of ~50 km in length, which limits their use in existing systems [4]. Many optical transmission systems still operate at baud rates of 64 GBd and below, and the commonly used spans are in the range of ~80 km. Detecting a power loss in such systems is challenging because the accuracy/resolution of the power profiles is highly dependent on the baud rate [2]. Several anomaly detection techniques have been proposed, including the subtraction method, subtraction with differentiation, and wavelet-based denoising [5]. Among these methods, the subtraction method has shown particularly strong performance in low-baud-rate scenarios. However, its performance degrades in longer fiber spans, where fiber nonlinearity diminishes toward the end of the link. As a result, the difference between normal and anomalous profiles becomes increasingly subtle, and measurement fluctuations make these differences hard to see, making threshold selection difficult. Consequently, the subtraction method becomes unreliable for consistent loss detection under such conditions [5].

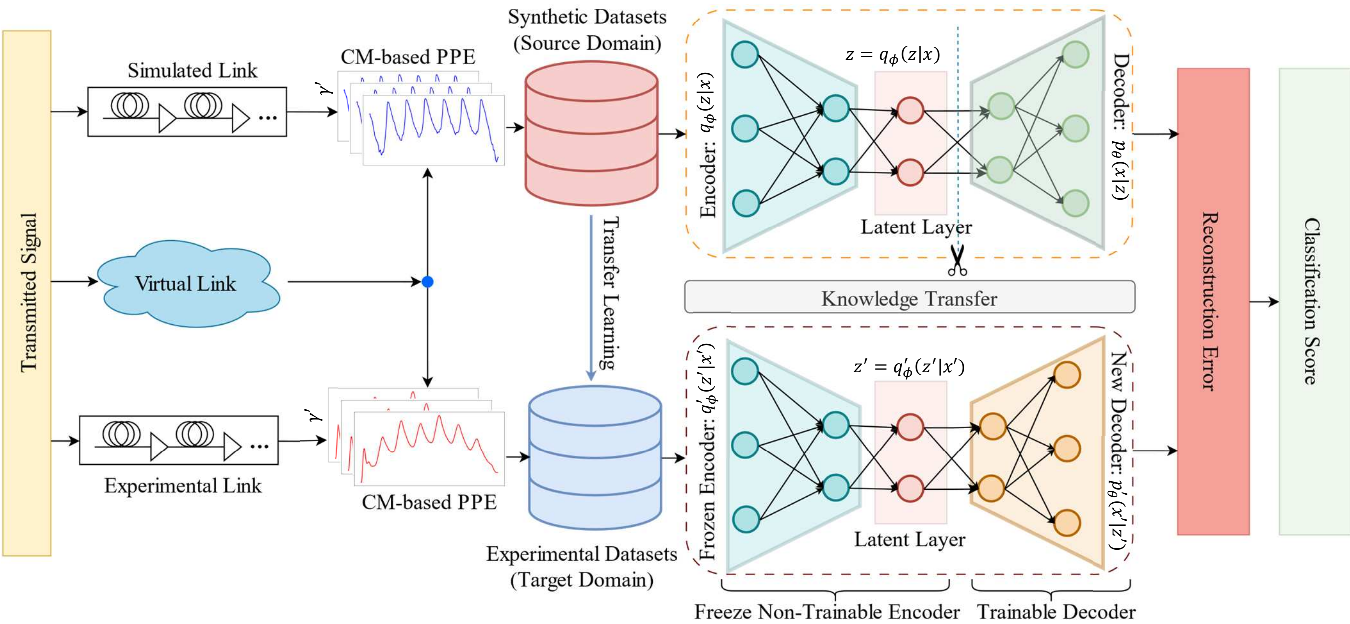

Fig. 1. Block diagram of the ML-based longitudinal power monitoring concept.

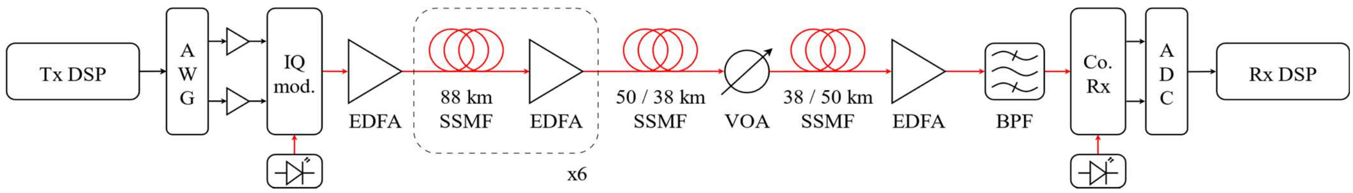

Fig. 2. Block diagram of the experimental setup.

We will address this problem with the help of machine learning (ML). Since it is much more difficult to collect training data in field trials than through simulations, this application appears to be an excellent candidate for transfer learning, in which a model is first trained with simulation data and then adapted using limited experimental data. In addition, unsupervised learning is chosen so that the model can be trained using only reference data, as it is not realistic to obtain training data with additional losses at arbitrary locations from a system that is in operation

In this paper, we will present, to the best of our knowledge, for the first time an ML-based longitudinal power monitoring (LPM) concept, capable of increasing the possible loss detection range in a simulative 64 GBd system with 88 km spans by up to 45 km compared to the subtraction method. The pretrained model is then adapted to a 40 GBd experimental setup for verification using transfer learning.

II. ML-BASED LONGITUDINAL POWER MONITORING CONCEPT

Computed power profiles γ' using the correlation method (CM) form the basis for our new concept. The CM can be formulated as $\gamma' = \Re[\boldsymbol{G}^H A_1[L]]$, where $A_1[L]$ is the nonlinear part of the received signal and the Hermitian transformed $\boldsymbol{G} = [A_0^{ref}, \dots, A_k^{ref}, \dots, A_L^{ref}]$ is the reference signal (virtual link) for each step k, calculated using the first-order regular perturbation model [2]. While this method has low complexity, it suffers from limitations in terms of accuracy compared to the true power profile of the investigated link, making it less robust for practical monitoring scenarios. To overcome this issue, an unsupervised ML method is employed to improve the performance. It learns the underlying structure of normal data and detect anomalies based on deviations from this learned representation. This enables reliable anomaly detection even in the absence of labeled fault data compared to supervised learning, where large volumes of labeled data are required, which are often scarce, specially for rare anomaly events.

In this work, a Variational Autoencoder (VAE) is employed as the core model, combining autoencoding with variational inference to learn a compact latent representation of PPE traces [6]. This unsupervised architecture captures the distribution of normal power profiles and facilitates anomaly detection through reconstruction error analysis. The encoder $q_\phi(z|x)$ approximates the posterior $p_\theta(z|x)$ and produces latent variables via the reparameterization $z = \mu + \sigma \odot \epsilon$, where $\epsilon \sim \mathcal{N}(0, I)$. The decoder reconstructs the input $\hat{x}$, optimized by minimizing

$$\mathcal{L}_{VAE} = \mathbb{E}_{q_\phi(z|x)}\left[||x - \hat{x}||_2^2\right] + \beta D_{KL}\left(q_\phi(z|x)\right) || \mathcal{N}(0, I),$$

where β balances the trade-off between reconstruction accuracy and distribution regularization.

The overall framework, illustrated in Fig. 1, consists of two stages: (i) training on synthetic PPE data to learn normal system behavior, and (ii) adapting the model to experimental data using transfer learning. In the first stage, synthetic PPE traces are generated using simulations of a 64 GBd signal transmitted over a 7×88 km standard single-mode fiber (SSMF) link. The launch power is set to 5 dBm and the EDFA noise figures (NF) to 5 dB. Fiber propagation was modeled using the Split-Step Fourier Method (SSFM) with a 50 m step size and parameters $\alpha = 0.2\ \frac{\text{dB}}{\text{km}}$, $\beta_2 = -21.7\ \frac{\text{ps}^2}{\text{km}}$, and $\gamma = 1.3\ \frac{1}{\text{W km}}$.

Then the VAE is trained on 1,000 synthetic reference PPE traces, using an 80:20 split for training and validation, to learn a compact representation of the power evolution along the link. Model hyperparameters are optimized using the *Optuna* framework for 100 trials to ensure optimal reconstruction accuracy and generalization [7]. The model processes 617-dimensional input vectors (1 km spatial resolution) and reconstructs outputs of the same size. It employs a fully connected encoder-decoder architecture that encodes 2 encoder layers [325, 169] into a 41-dimensional latent space using ReLU activation for 300 epochs. Training is performed with the Adam optimizer and early stopping of 30 to prevent overfitting. Anomalies are detected based on the reconstruction error, using a percentile threshold (τ = 94$^{\text{th}}$) derived from normal traces, which achieved the best F1-score and clear separation of normal and anomalous PPE traces, demonstrating strong generalization across the link.

III. VALIDATION OF THE PROPOSED FRAMEWORK ON EXPERIMENTAL DATA

To validate the proposed method the model is adapted from simulation to experiment using a heterogeneous feature-extractor transfer learning (TL) scheme (Fig. 1). In this approach, the pretrained encoder and latent layers are frozen to preserve simulation-learned representations, while a newly initialized decoder is trained on experimental PPE data. This strategy effectively mitigates domain shifts between the source (simulation) and target (experiment) domains, which arise from variations in transmission baud rate, EDFA gain tilt, launch power differences, and other non-ideal system effects.

The experimental setup, shown in Fig. 2, employs a 40 GBd 16-QAM transmitter using raised cosine pulses (roll-off = 0.1), an 88 GSa/s arbitrary waveform generator (AWG), an IQ modulator, and a 100 kHz linewidth laser at 1550 nm. The optical signal, launched at 6 dBm, traverses a recirculating loop consisting of two 88 km SSMF spans and EDFAs (NF = 5 dB) repeated three times, totaling 528 km transmission. A final 88 km span incorporates a variable optical attenuator (VOA) to generate anomalies (3 dB loss) at 38 km or 50 km.

After coherent detection using a 100 kHz linewidth local oscillator and an 80 GSa/s sampling oscilloscope, standard receiver-side digital signal processing (Rx DSP) was applied, including chromatic dispersion (CD) compensation, timing

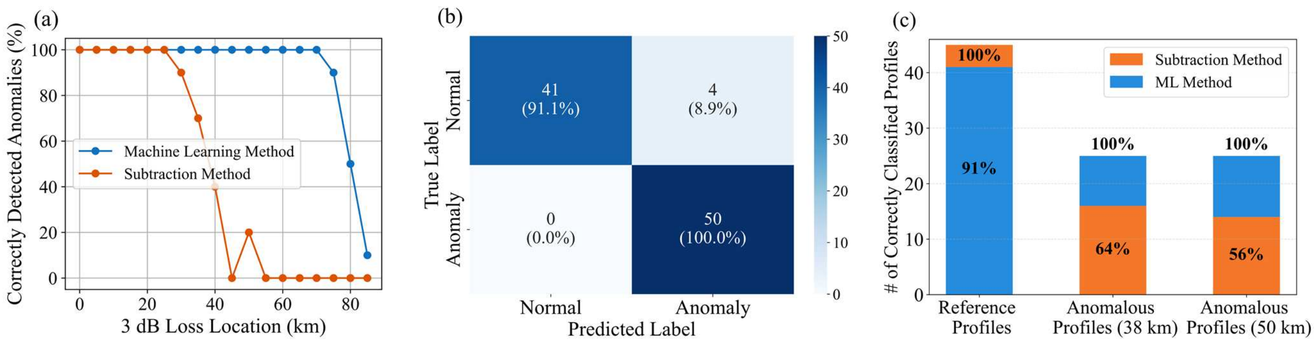

Fig. 3. (a) Correctly detected anomalies of occurring 3 dB fiber losses in the last span for two different methods. (b) Confusion matrix of the experimental PPE traces. (c) Comparison of correctly classified profiles between our ML method and the subtraction method.

synchronization, carrier frequency offset compensation, and carrier phase recovery. After CD reload, 29,000 PPE traces were computed from measurements without additional loss using the VOA and averaged 200 times to improve the signal-to-noise ratio, yielding a final dataset of 145 reference (normal) PPE traces. Of these, 100 traces were used for training and validation with an 80:20 ratio, and the remaining 45 traces were reserved for testing. In addition, 50 anomalous traces (25 for each attenuation position) were generated and used for evaluation.

The transfer-learned VAE retained the frozen encoder and 41-dimensional latent space of the pretrained model while introducing a new decoder optimized using the *Optuna* framework for 50 trials. Training was performed for 200 epochs with early stopping of 10 to prevent overfitting. The same percentile-based decision rule as in the simulation stage was applied, using the $\tau = 94^{\text{th}}$ percentile reconstruction-error threshold to distinguish normal from anomalous PPE profiles.

IV. Results and Discussion

As the possible loss insertion points in our lab setup are limited, Fig. 3(a) first simulatively compares the performance of the proposed ML-based anomaly detection method with the traditional subtraction-based approach across different anomaly locations along the last fiber span, where the cumulative ASE noise is at the highest point. A 3 dB attenuation was inserted at every 5 km from 0 to 88 km (528 to 616 km in total link length). The x-axis represents the anomaly position in km, while the y-axis denotes the number of correctly detected anomalous PPE profiles out of ten injected lossy cases. It can be seen that the ML-based model can reliably detect anomalies up to 75 km within the span, whereas the subtraction-based method maintains good performance only up to approximately 30 km. Beyond this point, the detection accuracy deteriorates rapidly, as noise accumulation and limitations in accuracy and spatial resolution significantly reduce the distinguishability between normal and anomalous power profiles.

Figure 3(b) presents the confusion matrix of the transfer-learned VAE model evaluated on experimental PPE traces. The model demonstrates excellent generalization performance after domain adaptation from simulation to experiment, accurately identifying all anomalous traces introduced at one of the two positions (38 km or 50 km) of the 7th span. Specifically, 100% of anomalous profiles were correctly detected, while 91.1% of normal profiles were accurately classified. Only 8.9% of the normal traces were falsely labeled as anomalous, indicating a favorable balance between sensitivity and false-alarm rate. Figure 3(c) shows a direct comparison of our ML-based approach with the traditionally used subtraction method. The threshold for the subtraction method was set to the maximum difference of the reference profiles, therefore all reference curves were classified correctly, in contrast to our ML-based method. The performance of the classification of the profiles with induced losses on the other hand gets significantly worse, only 64% of the traces with the loss position at 38 km and 56% of the traces with the loss position at 50 km were classified correctly in contrast to our accuracy of 100% using the ML-based method. The proposed approach can be extended to other impairments (e.g., gain tilt, PDL). The predictions of the machine learning model are quite fast supporting near real-time operation, while PPE computation remains the main computational bottleneck.

V. Conclusions

We presented for the first time an ML-based framework that enhances longitudinal PPE based on the correlation method for low baud rates (40 GBd) optical transmission systems. The proposed approach substantially improves LPM performance by extending the detectable loss range from approximately 30 km to 75 km within an 88 km fiber span, clearly outperforming the conventional subtraction-based method. By integrating unsupervised learning and transfer learning, the model effectively adapts from simulated data to experimental measurements. Experimental validation confirms 100% anomaly detection accuracy and 91.1% classification accuracy for normal profiles, demonstrating the robustness and practical applicability of the proposed method for real-world optical network monitoring.

Acknowledgment

This work has been funded by the German Federal Ministry of Research, Technology and Space in the project SUSTAINET-Advance #16KIS2278.

References

[1] T. Tanimura et al., "Fiber-Longitudinal Anomaly Position Identification Over Multi-Span Transmission Link," JLT, 2020.

[2] T. Sasai et al., "Performance Limit of Fiber-Longitudinal Power Profile Estimation Methods," JLT, 2023.

[3] T. Sasai et al., "Linear Least Squares Estimation of Fiber-Longitudinal Optical Power Profile," JLT, 2024.

[4] T. Sasai et al., "Recent Advances in Digital Longitudinal Monitoring and Tomography," in Proc. OECC/PSC, 2025.

[5] M. Sena et al., "DSP-Based Link Tomography for Amplifier Gain Estimation and Anomaly Detection," JLT, 2022.

[6] T. Iqbal et al., "Reconstruction Probability-Based Anomaly Detection Using VAEs," Int. J. Comput. Appl., 2022.

[7] T. Akiba et al., "Optuna: A Next-Generation Hyperparameter Optimization Framework," in Proc. KDD, 2019.