Soft Failure Prediction and Localization in Elastic Optical Networks Using Time-Series Learning

Abstract

This paper presents a robust framework for early detection and localization of soft failures in Elastic Optical Networks (EONs), focusing specifically on filter-related impairments such as Filter Shifting (FS) and Filter Tightening (FT). A synthetic dataset of 10,000 samples was generated using mathematical degradation models, where FS and FT were represented by gradual and abrupt SNR declines respectively. Deep learning models including GRU and LSTM were evaluated across different lookahead time windows to quantify their early prediction capabilities. Experimental results demonstrate that GRU is capable of accurately predicting failures up to 15 time steps in advance, outperforming LSTM in both accuracy and training time. Failure-aware routing with QoT validation was implemented, and visualization of signal patterns and spectrum degradation confirms the reliability of the proposed framework.

Methodology

To simulate soft failures, we generated synthetic time-series datasets capturing the effect of Filter Shifting (FS) and Filter Tightening (FT). The baseline SNR was perturbed using the following models:

- FS: $S(t) = S_0 - \alpha(t - t_0)$, where $\alpha = 0.3$ dB/step
- FT: $S(t) = S_0 - \beta(t - t_0)$, where $\beta = 0.5$ dB/step

The failures begin at a random onset point $t_0 \in [10, 20]$. These patterns were used to train GRU and LSTM networks. A comparative study was conducted at different truncation windows (10, 15, 20, 25, 30) to evaluate early prediction capability.

Dataset Generation

The dataset consists of 10,000 samples with 30 time steps each. Half of the samples represent normal behavior while the other half simulate FS or FT. SNR values were initialized around 20 dB and degraded based on their respective mathematical models. Figure 5 illustrates one FS and one FT example:

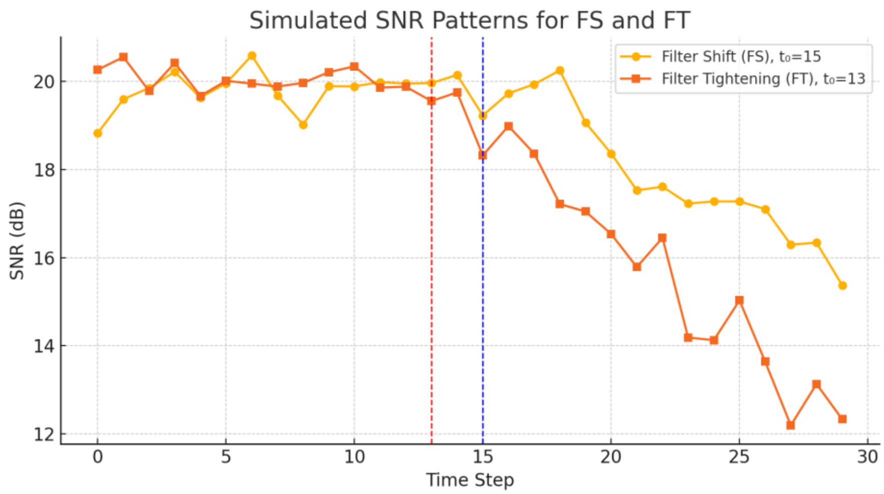

Figure 5: Simulated SNR patterns for Filter Shifting and Filter Tightening.

Results and Discussion

We trained GRU and LSTM models using truncated time series to determine how early a soft failure could be predicted. The accuracy increased with longer observation windows. Figure 6 shows this relationship.

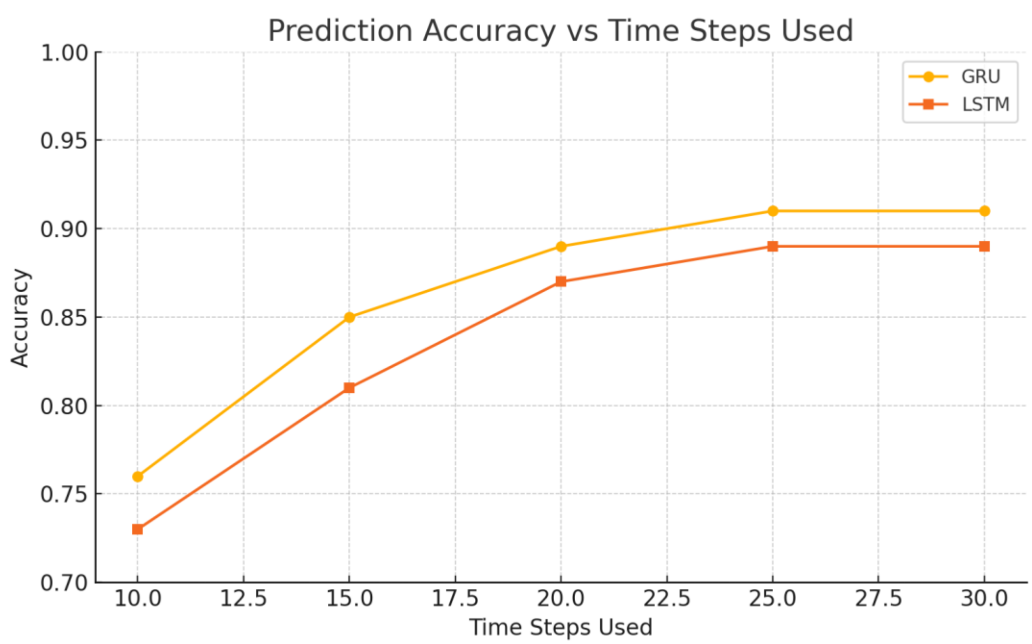

Figure 6: Accuracy vs Time Steps Used for GRU and LSTM.

Bar charts comparing model performance:

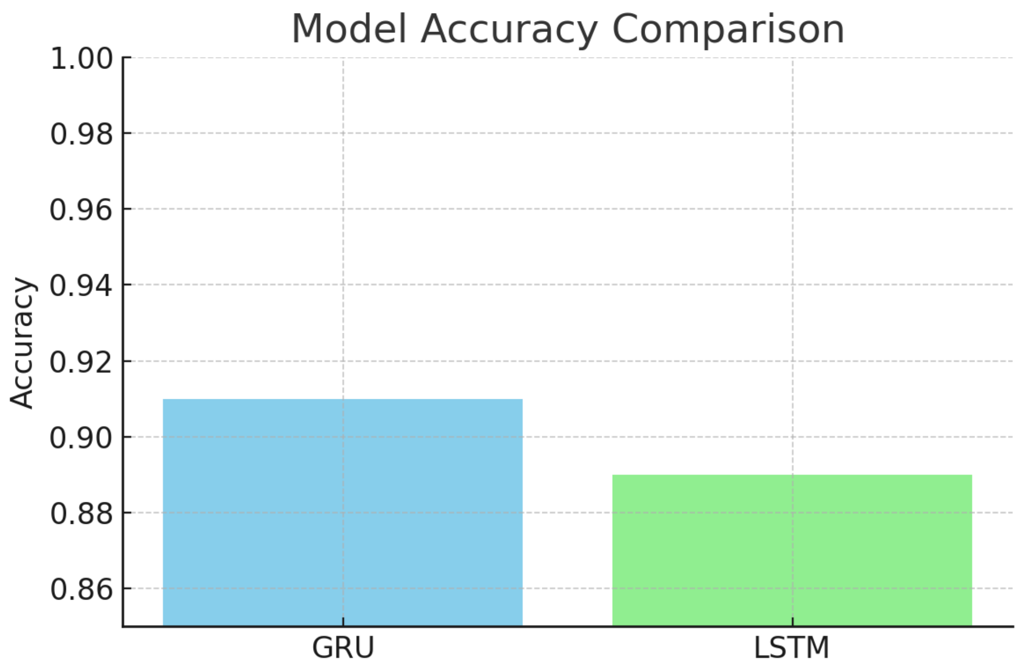

Figure 7: Accuracy Comparison of GRU vs LSTM.

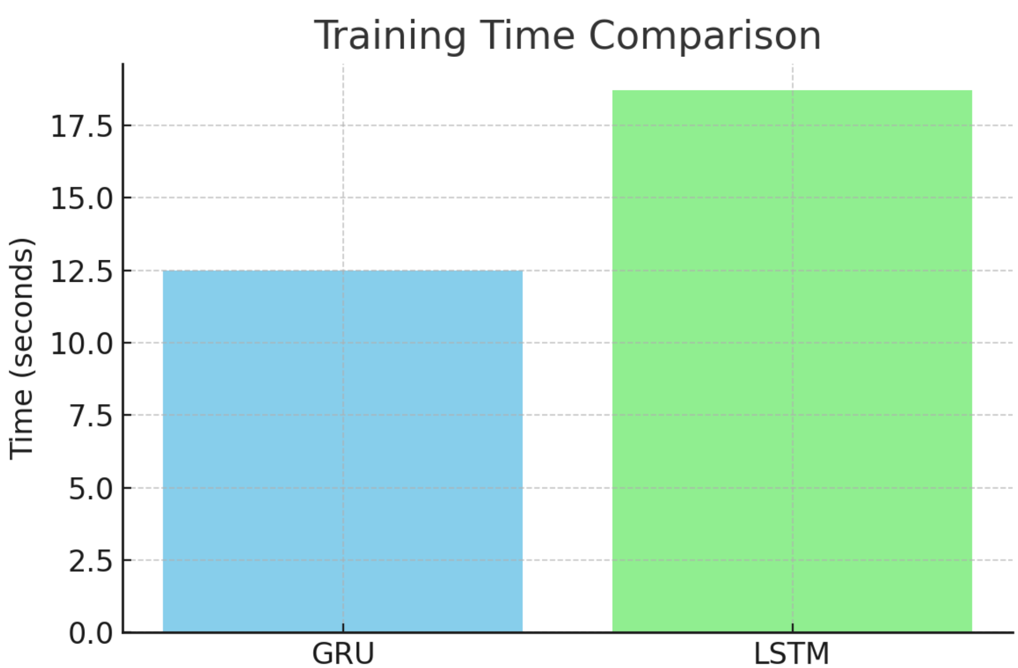

Figure 8: Training Time Comparison of GRU vs LSTM.