Degradation Detection and Severity Estimation by Exploiting an Optical Time and Frequency Digital Twin

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Abstract: We exploit the intrinsic advantages of a time and frequency domain digital twin to detect degradations and to estimate their severity. Noticeable performance shown for filter failures confirms the usefulness of this approach. © 2023 The Authors

1. Introduction

Solutions for optical network failure management have been extensively investigated in the latest years (see, e.g., [1]-[3]) as they aim at avoiding the severe consequences that an unexpected service breakdown caused by a *hard-failure* can signify for a network operator. Failure management needs to cover: *i*) the *detection* of degradations (i.e., *soft-failures*) that do not currently affect the service, before they become hard failures; *ii*) *severity estimation*, i.e., if they will become hard-failures, when this would happen. Estimating the severity of soft-failure is a useful tool to plan maintenance; *iii*) *identification* of the root cause, i.e., what type of device/element is causing the observed degradation; and *iv*) *localization* of device/element in the network.

Solutions for failure management proposed in the literature are based on specific algorithms that analyze different aspects of the signal. For instance, the authors in [1] analyzed the evolution of bit error rate (BER) in the transponders, whereas the authors in [2] dealt with filter failures by analyzing the spectrum using optical spectrum analyzers (OSA) installed in the intermediate reconfigurable optical add/drop multiplexers (ROADM). The authors in [3] provided algorithms based on the analysis of optical signal-to-noise ratio (OSNR). The authors in [4] provided a digital twin (DT) framework based on deep neural networks (DNN) to model the propagation of optical signals through a lightpath, from the transmitter to the receiver. In our previous work in [5], we extended the work in [4] and created a DT that model the propagation of optical signals in both time and frequency domains. In this paper, we take advantage of developed models and functions to compare the received signals (X_r) and the expected ones generated by the DT (X_e) in the time and frequency domains; we call that function $diff(X_r, X_e)$. We propose methods that detect degradations by analyzing the evolution of $diff(\cdot)$ in the time and frequency domains and estimate their severity by analyzing the evolution of time domain features.

2. Time-Frequency Analysis for Failure Management and Use Cases

Fig. 1 shows an illustrative scenario of a lightpath connecting two remote locations and includes two transponder nodes TPA and TPB, *n* ROADMs and *n*-1 optical links with erbium-doped fiber amplifier (EDFA) and single mode fibers (SMF). We assume that every ROADM consists of two wavelength selective switches (WSS) and EDFAs (except the last one). Every optical node is controlled by a local node agent that configures the underlying optical devices and collates telemetry data from them, as well as from OSAs in the case of the ROADMs.

On top of the architecture, a software-defined networking (SDN) controller connects to the node agents and to an optical layer DT modeling the data plane. The DT includes (or it has access to): *i*) a telemetry database (DB), where data collected from the data plane is stored. Such data includes spectral measurements collected from the OSAs in the ROADMs that the lightpath traverses, as well as optical constellations from the coherent receiver in TP B; *ii*) a model DB that includes DNN models for the optical time domain [4] and analytical models that represent filter transfer functions for the frequency domain. With such models, optical propagation through the lightpath can be modeled end-to-end in both time and frequency; *iii*) a sandbox domain, that is used to compose the models for the lightpath; and *iv*) a set of algorithms that analyze the features of the signals received and stored in the telemetry DB and compare to those generated by the models in both time and frequency. In this paper, we focus on algorithms for degradation detection and severity estimation.

Two main failure conditions are analyzed: *i*) one single filter-related failure localized in a WSS of an intermediate ROADM; here, two causes of failure are considered: filter shift (FS) and filter tightening (FT). FS or FT failures appear at some point in time and its magnitude increases over time; and *ii*) the transmitter operates at a sub-optimal launching power and FS failure appears. Note that such non-ideal network conditions might make the detection of the degradation and the estimation of its severity more difficult.

3. Detection and Severity Estimation

Algorithm I presents the pseudocode of degradation detection at the frequency domain, which is executed in the DT every time that new spectrum S_r sample is received in the telemetry DB from the last OSA in the lightpath.

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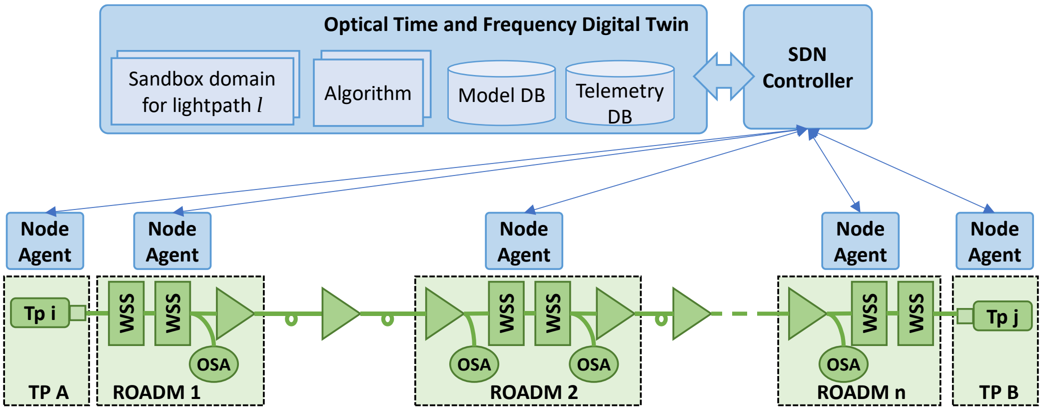

Fig. 1. Overview of the envisioned network scenario.

A similar algorithm is executed every time that new constellation C_r is available. The algorithm receives: *i*) the models for the lightpath *ml* that include those for time and frequency domains that were trained in the sandbox domain and stored in the model DB; *ii*) historical DB *hl* with observations for time and frequency and computed diff(·) values; *iii*) a list *O* with the operational parameters used for fitting models; and *iv*) the current time *t*. The expected spectrum S_e is generated using the model for the lightpath (line 1 in Algorithm I) and used to compare with the received samples (line 2). The $\text{diff}_s(\cdot)$ function computes the Euclidean norm of the residual vector computed by subtracting S_r from S_e [2]. For the time domain, the $\text{diff}_c(\cdot)$ function computes the Euclidean distance between the features extracted from C_r and C_e [4]. The results are stored in the historical database (line 3). Next, a linear regression model for the evolution of *diff* is trained with a fitting window of length *T* based on historical data in *hl* and tested over the last measurements for a period Δlr (lines 4-6). The relative root-mean squared error (rRMSE) between the predicted evolution and the observed one is computed and stored (lines 7-8). A threshold is set by applying a margin *k* over the rRMSE moving average in a time window Δlr. This threshold is exploited to detect unexpected behaviors of the analyzed time series. Whenever the threshold is exceeded, a positive detection is returned (lines 9-11).

Algorithm I. Degradation detection at frequency domain

```
INPUT: ml, hl, O, t                 OUTPUT: degradation
 1: Se ← ml.generateS()
 2: diffS ← diffs(hl.get("Sr", t), Se)
 3: hl.append("diffS", diffS, t)
 4: diff[] ← hl.get("diffS", t-O.Δlr-O.T, t-O.Δlr)
 5: lrmodel ← lr_fit(diff[])
 6: Ylr← lrmodel(t-O.Δlr, t)
 7: Err← rRMSE(Ylr, hl.get("diffS", t-O.Δlr, t)
 8: hl.append("ErrS", Err, t)
 9: ErrS[] ← hl.get("ErrS ", t-O.Δlr, t)
10: if Err > MovAvg(Errs[]) * O.k then return true
11: return false
```

Algorithm II shows the pseudocode of the severity estimation algorithm, which is run as soon as a degradation is detected and then periodically for more accurate results. The algorithm uses the average symbol variance *AvgVar* computed from the received constellation samples C_r, to estimate when the degradation will result into a hard failure. We assume a correlation between *AvgVar* and the BER and then, we can estimate the severity of the found degradation by studying the evolution with time of the former. We claim that the severity estimation by analyzing the received signal in the time domain can be used disregarding whether the degradation is detected in the time or the frequency domains. Then, let us assume that the pre-FEC BER threshold is reached when *AvgVar* reaches some specific value, *AvgVar_th*. The algorithm receives the historical database *hl* and operational parameters *O* as input. The last received constellations are retrieved from *hl* and the observed *AvgVar* time series is obtained (lines 1-2 in Algorithm II). Time series forecasting is based on two models: polynomial regression and Holt-Winters exponential smoothing trained with a fitting window Δfr (lines 3-4). The algorithm identifies the time of service disruption when one of the forecasts exceeds *AvgVar_th* within a given time limit *Tlim* (line 5); the shortest time in which any of the forecasts exceeds *AvgVar_th* is then returned (line 6). Otherwise, no service disruption is considered (line 7).

Algorithm II. Severity Estimation

```
INPUT: hl, O                        OUTPUT: time_disrupt
 1: Cr[] ← hl.get("Cr", t-O.Δfr, t)
 2: AvgVar[] ← featureExtraction["AvgVar"](Cr[])
 3: pr_mod ← pr_fit(AvgVar[])
 4: hwes_mod ← hwes_fit(AvgVar[])
 5: if pr_mod(t+O.Tlim)> AvgVar_th OR
          hwes_mod(t+O.Tlim)> AvgVar_th then
 6:     return first_t(pr_mod, hwes_mod, AvgVar_th)
 7: return ∞
```

4. Results

A simulator of a digital coherent system implemented in MATLAB was employed to reproduce the optical layer. The considered scenario consisted of a lightpath passing through 8 ROADMs and a total fiber length of 1120 km. Each link consisted of 80-km SMFs spans characterized by fiber loss 0.21 dB/km, dispersion 16.8 ps/nm/km and nonlinear coefficient 1.3 $W^{-1}km^{-1}$. A WDM signal with three DP-16QAM@64GBd channels and 75GHz channels spacing was transmitted over the SMF at the optimal launching power of -1 dBm obtained through power sweeping. The pulse propagation was simulated through a split-step-Fourier method (SSFM) with step of 1 km including effects such as group velocity dispersion (GVD), higher order dispersion, polarization dependent fiber

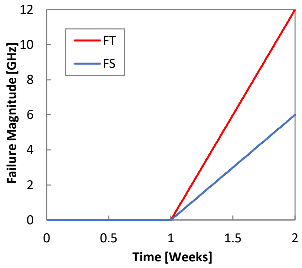

Fig. 2. FS and FT failure magnitude

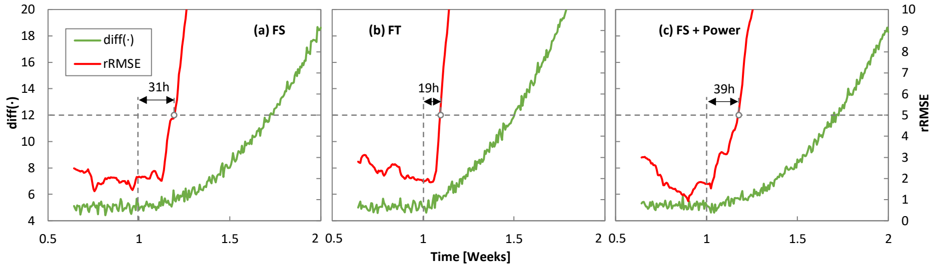

Fig. 3. Failure detection using diff(·) for the three failure scenarios.

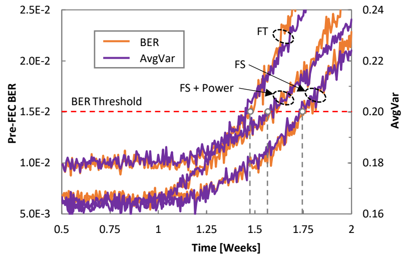

Fig. 4. BER vs AvgVar correlation for FS and FT.

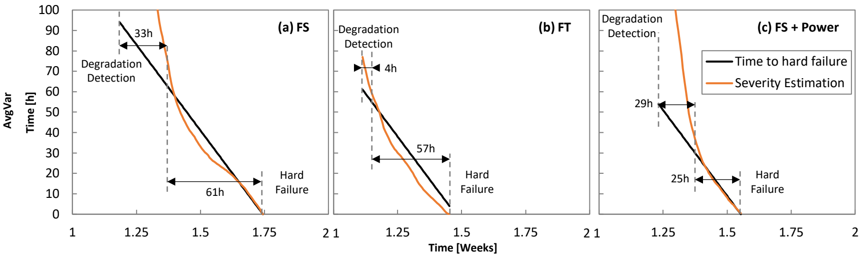

Fig. 5. Accuracy of severity estimation. Relative (a) and absolute error (b)

loss, arbitrary fiber birefringence, and self-phase modulation (SPM). The cascade filtering penalties are considered employing measured transfer functions from a 1x9 WSS filter with 75 GHz. Finally, the EDFAs with gain and noise figure of 4.5 dB are considered. At the receiver side, a 4 samples/symbol DAC rate was assumed to reconstruct the signal.

In the simulations, 2^{17}-long bit sequences were generated. For time analysis, constellation points were modeled as bivariate Gaussian distributions and 5 features were extracted: the mean and variance of the real and imaginary components, and the symmetric covariance. Finally, *AvgVar* was computed by averaging the real and imaginary variance for all the constellation points. For the frequency analysis, 8 features were extracted from the optical spectrum at -6 dB and -3dB: the bandwidth, the two edges and the central channel frequencies.

Fig. 2 shows the evolution of the failure magnitude for FS and FT in a WSS in an intermediate ROADM. Those failures start after the first week with a small frequency shift or bandwidth tightening, which slightly degrades the optical signal. The magnitude increases linearly during the second week, when the degradation becomes a hard failure. One observation per hour was performed (337 in total). Fig. 3 shows the accuracy achieved by the proposed detection method (Algorithm I) for the three failure scenarios considered, i.e., FS (a), FT (b), and FS + sub-optimal power (c). Degradation detection was performed with the following parameters O: T=84h (half a week), Δlr = 24h (1 day), Δfr = 96h (4 days) and k=2. All the three failures were detected in short times, just a few hours after the failure actually started. Interestingly, the presence of a previous degradation coming from sub-optimal launching power (Fig. 3c) only delays FS detection for a few hours with respect to FS and optimal power (Fig. 3a), which shows the feasibility of these methods to operate under realistic scenarios.

Fig. 4 shows a strong correlation between BER and the *AvgVar* feature for the studied values and considered failure scenarios. We observe that *AvgVar*~0.2 indicates that pre-FEC BER equals the threshold (1.5×10^{-2}). This result validates the feasibility of using *AvgVar_th* = 1.94×10^{-1} to estimate the severity of the failure in Algorithm II. With that threshold, Fig. 5 shows the actual and forecasted time to hard failure for the three use cases, as well as time when the estimation error goes below 8h. In all three cases, severity estimation progressively converges to the actual time to the failure. Note that severity estimation works well under single and multiple failures, since it is based on the analysis of the evolution of the *AvgVar* metric, which is closely related to the actual BER. These results also entail that the failure magnitude can, indeed, be related to the achievable severity estimation accuracy. With such estimation, maintenance can be scheduled with enough time before the degradation becomes a hard failure.

5. Conclusions

To summarize, algorithms that take advantage of a digital twin to perform failure detection in the frequency and time domains and severity estimation in the time domain have been validated. Three failures have been investigated confirming the feasibility of the algorithms.

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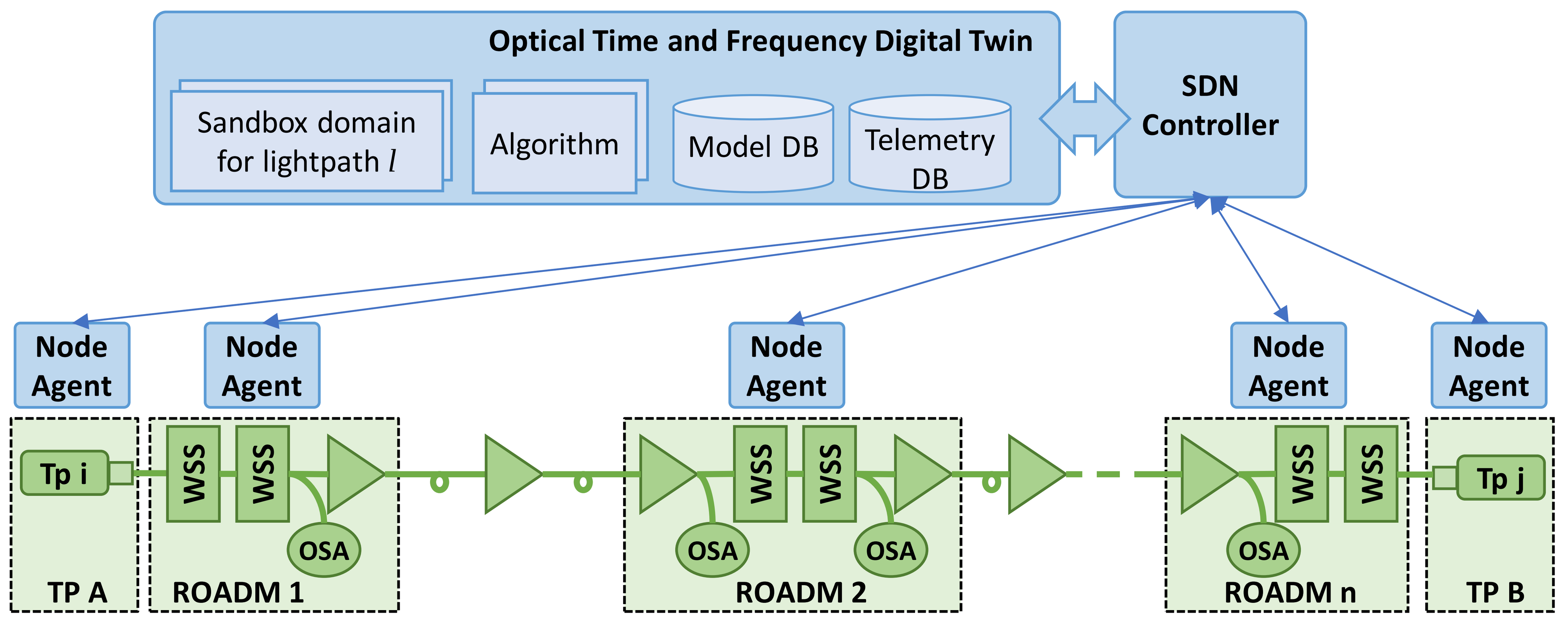
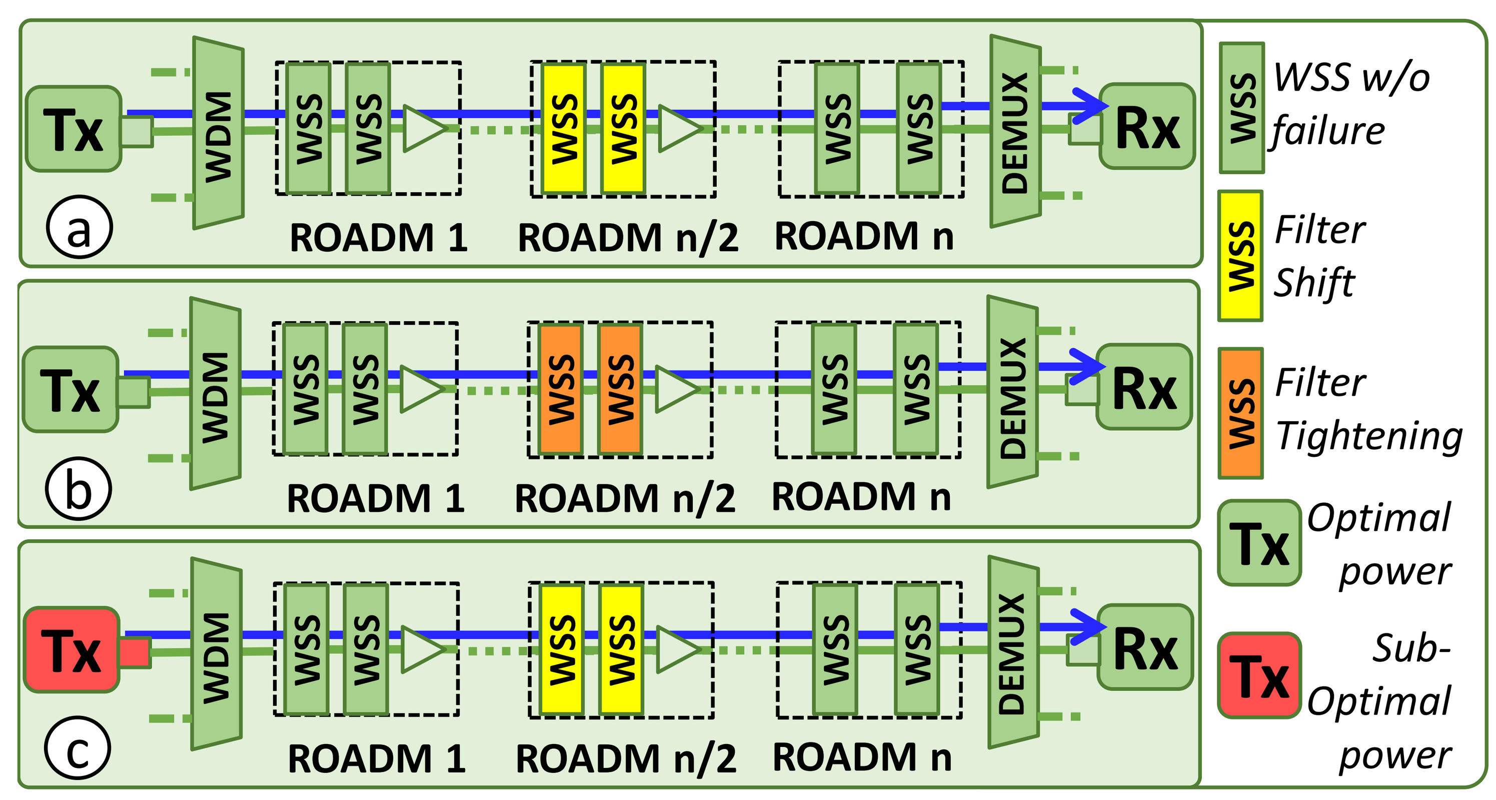
Abstract: We exploit the intrinsic advantages of a time and frequency domain digital twin to detect degradations and to estimate their severity. Noticeable performance shown for filter failures confirms the usefulness of this approach.

Optical Time and Frequency Digital Twin



Use Cases



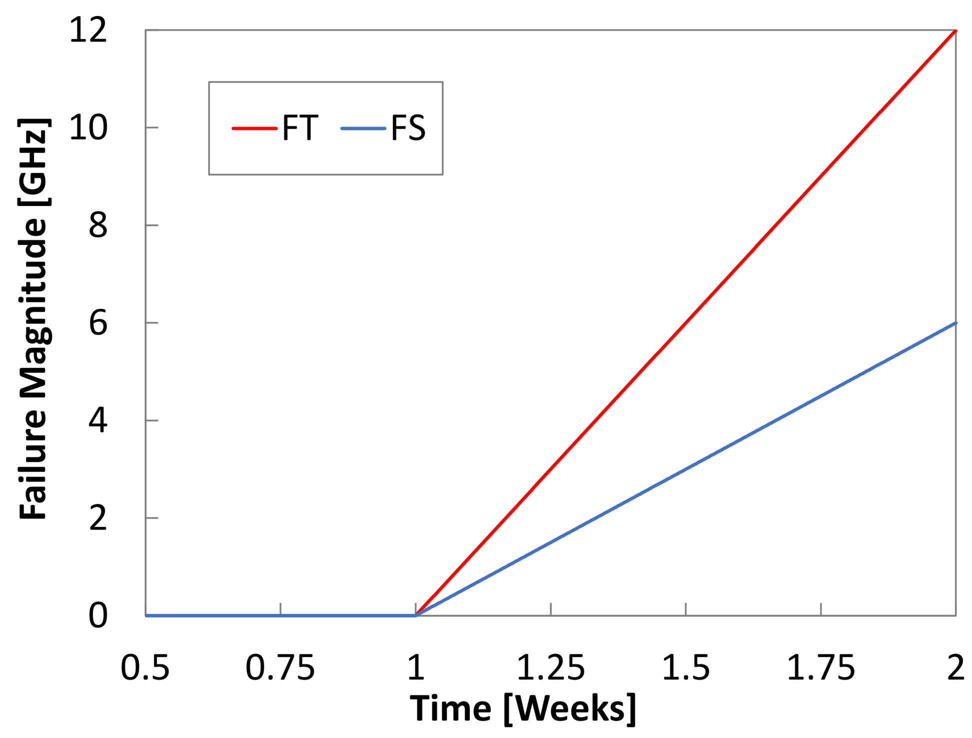
Simulation environment

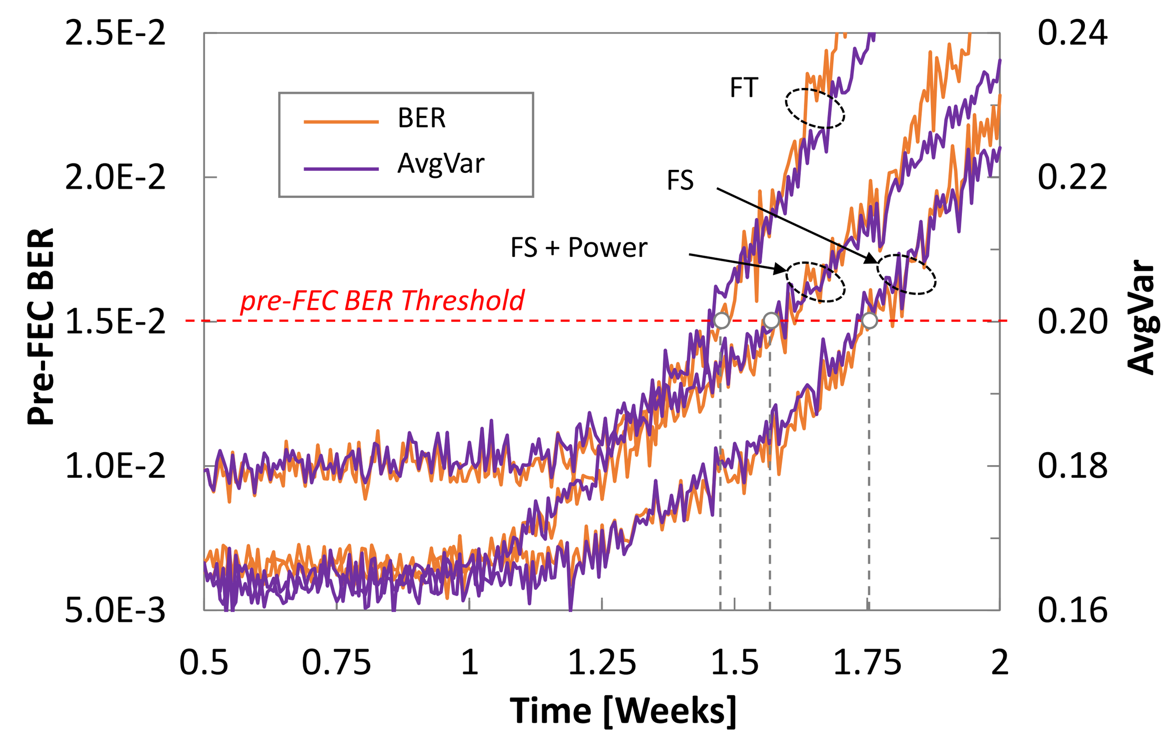
Transmission of 2^{17} PRBS over 3 channels modulated with DP-16QAM at 64GBd with 75GHz spacing and shaped by a root-raised cosine filter with a 0.06 roll-off factor.

The considered lightpath consists in 6 links each composed by 2 spans of SSMF 80km long (α=0.21 dB/km, γ=1.3 $(W\ km)^{-1}$, D=16.8ps/nm/km).

The simulations are based on the SSFM with step size 1000 m.

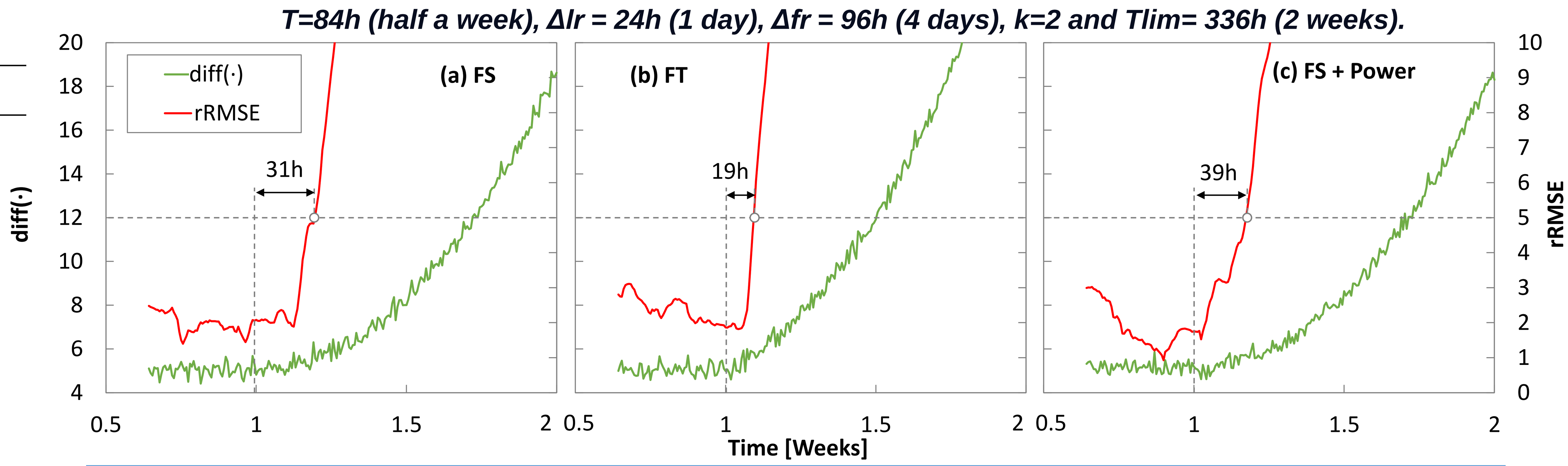
337 observations were performed over 2 weeks (1 per hour).





Failure Detection

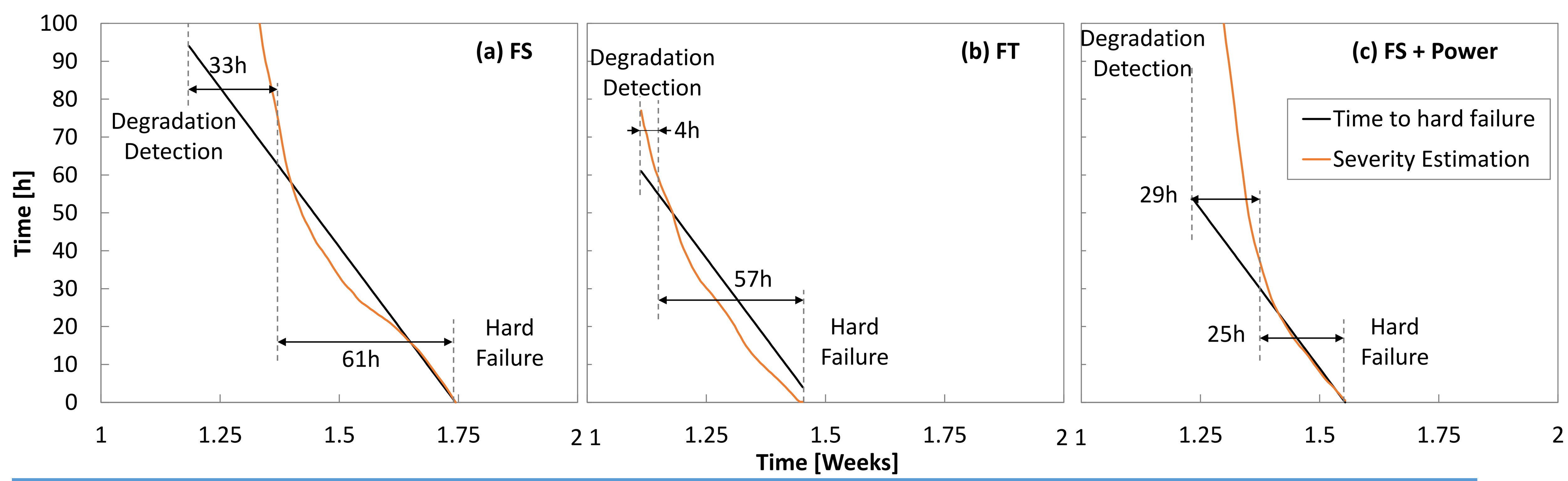
```
INPUT: ml, hl, O, t        OUTPUT: degradation
S_e ← ml.generateS()
diffS ← diff_s(hl.get("Sr", t), S_e)
hl.append("diffS", diffS, t)
diff[] ← hl.get("diffS", t-O.Δlr-O.T, t-O.Δlr)
lrmodel ← lr_fit(diff[])
Ylr← lrmodel(t-O.Δlr, t)
Err← rRMSE(Ylr, hl.get("diffS", t-O.Δlr, t)
hl.append("ErrS", Err, t)
ErrS[] ← hl.get("ErrS ", t-O.Δlr, t)
if Err > MovAvg(Errs[]) * O.k then return true
return false
```



All the three failures were detected just a few hours after the degradation started

Severity Estimation

```
INPUT: hl, O     OUTPUT: time_disrupt
Cr[] ← hl.get("Cr", t-O.Δfr, t)
AvgVar[] ← featureExtraction["AvgVar"](Cr[])
pr_mod ← pr_fit(AvgVar[])
hwes_mod ← hwes_fit(AvgVar[])
if pr_mod(t+O.Tlim)> AvgVar_th OR
     hwes_mod(t+O.Tlim)> AvgVar_th then
  return first_t(pr_mod, hwes_mod, AvgVar_th)
return ∞
```



Shortly after the detection, accurate severity is estimated with an error below 8h

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