Monitoring and Diagnostics of Power Anomalies in Transparent Optical Networks

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Abstract: Challenges in monitoring optically-transparent networks are highlighted for dynamically-controlled Raman amplification systems. We use models of amplifier physics together with statistical estimation to automatically discriminate between measurement errors, anomalous losses, and pump failures.

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OCIS codes: 060.1155, 060.2320.

1. Challenges in Monitoring Transparent Networks with Self-Compensating Control

Current and next-generation all-optical networks have greatly reduced or eliminated optical-electrical-optical (OEO) conversion units within the network backbone. The reduction of required OEO conversions increases transparency and lowers capital expense by minimizing or eliminating costly analog-to-digital and digital-to-analog conversion everywhere except at the network edges. One consequence of this architectural change is that traditional network management tools can no longer rely on the OEO conversion units to perform anomaly detection and correction in the network backbone [1]. Motivated by these challenges, our work focuses on the development of a new generation of diagnostic tools capable of monitoring and diagnosing the health of an optically-transparent network.

Transparent networks are designed with highly-automated control that can adapt to and compensate for deviations from ideal operating conditions. However, this self-correcting behavior can also mask errors and anomalies, which may remain hidden until the system is placed into a state where it is no longer able to self correct and substantial transmission penalties are incurred. Because of the potential for faults to remain hidden, the true health of the network may not be fully revealed by simple comparisons of observable system states (e.g., signal powers) to target values that are specified by, for instance, engineering rules. Instead, detailed understanding of the internal states of the hardware devices and software settings may be required to ensure adequate characterization of network health.

Raman amplification offers significant benefits for increasing network transparency [2]. The increase in transparency is due to improved noise characteristics (associated with distributed amplification within the fiber span) and the ability to provide gain flattening (ripple control) through the use of multiple Raman amplifier pumps. However, the use of the fiber plant as the amplification medium also means that it is no longer possible to rely on built-in, self-probing facilities to perform internal consistency checks of the amplifier performance. This is in contrast to systems with localized amplifiers, e.g. EDFA-based devices. Therefore, to effectively assess the health of a distributed amplification system, measurements of signal and pump powers at different physical locations must be jointly collected and analyzed.

Joint analysis of spatially non-local measurements can also provide better understanding of the propagation of potentially anomalous events. As mentioned, this can be especially useful when networks become more transparent, where greater reach, enhanced switching, and increased automation may result in anomalous effects which propagate far before being detected and corrected. As an example, consider the case of an amplifier with a hardware or software anomaly that results in undesirable noise amplification in an unused portion of the signal spectrum. If uncorrected, this can result in preferential amplification of the noise relative to the signals at each subsequent downstream amplifier node, and may eventually lead to a loss of signal several nodes away from the original fault.

In the remainder of this paper we describe a novel, model-based approach for anomaly detection and monitoring within Raman amplified systems. The proposed methodology assesses if the signal gain across a fiber span is consistent with the amplification level of the pumps being input to the span. Our approach combines models of the Raman gain physics with statistical estimation, and results in a method that allows precise statements to be made regarding the state of the network, including detection of anomalous conditions. The method focuses on detecting network behavior that is inconsistent with Raman physics, and hence may capture more complex anomalies not readily recognized by an engineering-rule-based approach.

2. Physics-Based Models for Anomaly Detection

We discuss two physics-based models: *i*) the **R-Beta model**, which approximates the span behavior as comprising two dominant physical effects, namely fiber attenuation and pump-signal Raman amplification; and *ii*) the **detailed physical model**, which includes, in addition, signal-signal Raman amplification, spontaneous Raman amplification (noise), Rayleigh back-scattering, connector loss effects, and direct correlation with launch pump powers.

2.1. The R-Beta Model

The following equation approximates the evolution of the channel power $p(z,\lambda_i)$ at channel wavelength λ_i as a function of distance z along the fiber in a Raman-amplified fiber span

$$\frac{dp(z,\lambda_i)}{dz} \approx -\alpha(\lambda_i)p(z,\lambda_i) + \sum_{j=1}^{N_{pumps}} R(\lambda_i,\lambda_j)p(z,\lambda_i)p(z,\lambda_j). \tag{1}$$

In (1), $p(z,\lambda_j)$ denotes the pump power at pump wavelength λ_j, $\alpha(\lambda_i)$ is the fiber attenuation coefficient at wavelength λ_i, $R(\lambda_i,\lambda_j)$ is the Raman gain coefficient between the pump at wavelength λ_j and the signal at wavelength λ_i, and N_{pumps} is the number of pumps. The relationship in (1) can be alternatively expressed by dividing by $p(z,\lambda_i)$ and integrating both sides from $z=0$ to L, the fiber length, resulting in the following equation

$$\ln p(L,\lambda_i) - \ln p(0,\lambda_i) + \alpha(\lambda_i)L \;\approx\; \sum_{j=1}^{N_{pumps}} R(\lambda_i,\lambda_j)\beta_j, \tag{2}$$

where $\beta_j = \int_0^L p(z,\lambda_j)dz$ represents the pump power integrated over the length of the fiber span. Denote the left hand side of (2), the attenuation-adjusted gain for channel i, by $\delta_i \equiv \ln p(L,\lambda_i) - \ln p(0,\lambda_i) + \alpha(\lambda_i)L$, and let $\Delta = [\delta_1,...,\delta_k]^T$ contain k adjusted gains. Further, with R a $k \times N_{pumps}$ matrix with elements $R_{ij} \equiv R(\lambda_i,\lambda_j)$, we can express (2) as

$$\Delta \;\approx\; R\beta. \tag{3}$$

Linear regression techniques can be used to fit a set of observed signal gains Y to (3), i.e. we write

$$Y \;=\; R\beta + \varepsilon. \tag{4}$$

Here, the quantity ε measures the gain across the Raman-amplified span that is not captured by the R-beta model in (3). The magnitude of this term, $\|\varepsilon\|$ is a measure of how well the actual measured data is described by the R-Beta amplification model, independent of particular pump levels. The residual includes measurement noise, physical effects left out by the R-Beta approximation, and the effects of any potential anomalies (see Figure 1a).

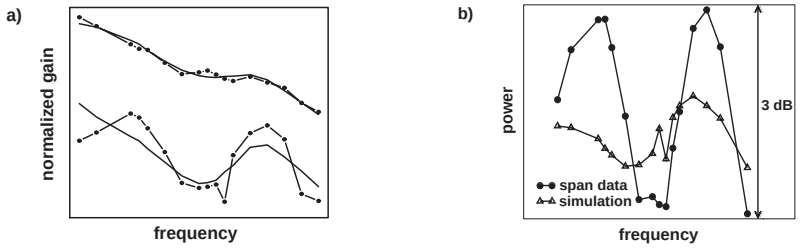


Fig. 1. **a)** Observed Y (equation (4), dotted lines) and predictions from regression model (solid lines) for two spans on a DWDM link. A large residual vector $\|\varepsilon\|$ in the second span (the lower lines) is indicative of a gain profile that is inconsistent with Raman amplification, and thus triggers an alarm. **b)** Observed signal powers (filled circles) and calibrated simulations (hollow triangles). The discrepancies in spectral shape and ripple magnitude are indicative of anomalous behavior.

Computational experiments comparing the R-Beta model with simulations from the detailed physical model (described in Section 2.2) show that (3) captures the essential physics of Raman-amplified spans extremely well. Measurement noises are expected to be small, and, thus, large values for the error norm $\|\varepsilon\|$ are indicative of anomalous behavior present on the Raman-amplified span.

2.2. *The Detailed Physical Model*

A more comprehensive model for Raman-amplification modifies the R-Beta model given in (2) to include terms that account for signal-signal Raman pumping, noise generation and Rayleigh back-scattering in the Raman span as well as important effects such as connector and splice losses. For brevity of presentation, we represent this more comprehensive model via the following equation

$$y^s(L) = f(y^s(0), P^f(0), P^b(L), \alpha(\nu), \gamma(\nu), g(\nu,\zeta)), \Delta^S, \Delta^R), \tag{5}$$

which expresses the received signal powers $y^s(L)$ as a function $f(\cdot)$ of: the launch signal powers $y^s(0)$, the launch powers of the co- and counter-propagating Raman pumps $P^f(0)$ and $P^b(L)$, the fiber attenuation coefficient $\alpha(\nu)$ at frequency ν, Rayleigh back-scattering coefficient $\gamma(\nu)$, Raman gain coefficient $g(\nu,\zeta)$ for a pair of frequencies ν and ζ, and the connector and splice losses Δ^S and Δ^R at the launch ($z = 0$) and receive locations ($z = L$). The reader is referred to [3] for further details.

The key physical parameters controlling the Raman span behavior are the attenuation coefficient $\alpha(\nu)$, the Raman gain coefficient $g(\nu,\zeta)$, the fiber length L, and the connector losses Δ^S, Δ^R. Values for L, $\alpha(\nu)$ and total connector loss $(\Delta^S + \Delta^R)$ can be estimated from OTDR (Optical Time Domain Reflectometry) and total span loss measurements, while nominal values for the Raman gain coefficient $g(\nu,\zeta)$ are typically used.

Given values of the key parameters, simulations from the detailed physical model can be employed to produce anomaly alarms in two ways. First, observed values for the launched signal $y^s(0)$ and pump powers, i.e. $P^f(0)$ and $P^b(L)$, are used to predict the received signal powers $y^s(L)$. The simulation-based prediction for $y^s(L)$ is then compared to measured values of the signal powers at $z = L$ (see Figure 1b). Second, based on some distributional assumptions, a maximum-likelihood procedure is used to estimate the connector losses, i.e. Δ^S and Δ^R, and the estimates are then compared to the nominal or provisioned values. Discrepancies observed in either of the two simulation-based approaches indicate anomalies, and may be used to trigger alarms. In particular, many anomalous conditions are associated with estimated values of the connector losses that are significantly outside of nominal ranges.

3. Joint Usage of Physics Models and Engineering Rules for Diagnostics

We have outlined two model-based procedures for detection of anomalous network behavior. The R-Beta model accounts for pump-signal amplification by modeling the Raman pumps via the path-total power β, and can be used to detect gain deviations, here represented by ε, that are not explained by Raman physics. Examples of such deviations are those due to power measurement errors, misfibering, monitor failures, and calibration errors. The approximate model has low computational cost and is an attractive choice for real-time anomaly detection.

The detailed physical model represents a comprehensive description of the important physical phenomena occurring on a Raman span, allowing the direct prediction of output signal powers given input signal and pump powers. Through simulation, this model gives a method for detecting anomalous connector losses and pump failures. With both models, the expected behavior of the alarms under various failure scenarios can be established using large-scale simulations.

The proposed model-based alarms can be used in combination with traditional rule-based approaches to provide a diagnostic tool for optically transparent networks that use dynamically-controlled Raman amplifiers. Such a tool allows for rapid detection and root cause analysis of network faults, and for proactive detection of anomalous behavior before errors affect transmission quality. As optical networks progress to more transparency and greater complexity, i.e., with mesh architectures and the use of a larger hierarchy of different equipment and components, the need for more sophisticated diagnostic tools will become more important. We have described a step towards meeting this need.

Acknowledgments We gratefully acknowledge the support of Steve Eichblatt and Sydney Taegar in data collection and processing, and the advice of John Hanson, Thomas Kissell, Narasimhan Raghavan, William Thompson, Lee Vallone, and Daniel Kilper on practical diagnostic issues.

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