# Uncertainty Aware Real-Time Performance Monitoring for Elastic Optical Networks

Petros Ramantanis[1], Camille Delezoide[1], Patricia Layec[1] and Sébastien Bigo[1]
[1] Nokia Bell Labs, 7 route de Villejust, Nozay, France, petros.ramantanis@nokia-bell-labs.com

**Abstract** *We propose a quality of transmission metric which unifies different performance-related metrics into one. Our metric presents advantages such as the reduction of stored and transmitted data, low controlled uncertainty and high monitoring speed, while it is compatible with an extended range of performance regimes.*

## Introduction

Today optical networks are designed with a high level of margins to guarantee robust transmission of predefined capacities for 10 to 20 years. At a time where system vendors are asked to increase capacity while lowering costs, leveraging margins is attractive. To do so, coherent receivers allow closed-loop capacity upgrade based on quality of transmission (QoT) monitoring[1]. Besides, since margins are a mere reflection of uncertainties[2], QoT monitoring can also be used to reduce uncertainty of the physical system parameters[3], to trigger alarms related to network health issues[4] etc. As in any real-time scheme, the overall performance fundamentally depends on the speed and accuracy of the QoT estimation, hence the motivation to optimize both.

Many performance metrics are used to assess the QoT before forward error correction (FEC): pre-FEC bit error ratio (BER), $Q^2$ factor, error vector magnitude (EVM)[5], generalized signal to noise ratio (GSNR)[6], OSNR, etc. These metrics generally derive from three measurement methods. First, the optical signal to noise ratio (OSNR) is typically measured before the receiver with an optical spectrum analyser. This technique inherited from the 10G era is deprecated now due to its poor accuracy for transparently routed coherent wavelength division multiplexed channels. Second, the pre-FEC BER is reported in coherent receivers e.g. via the parity check violation rate provided by the FEC decoder. Third, the GSNR is measured directly from the received noisy samples, right-before FEC.

In this paper we first revisit the theoretical accuracy of both BER and EVM measurements and we discuss how they are influenced by the number of samples used, i.e. the monitoring period. Then we propose a new metric which leverages both measurements to simultaneously optimize both speed and accuracy of the QoT estimation. Finally, we provide numerical simulation results to support the achieved benefits of our metric and discuss on the challenges left to be addressed.

## Theoretical accuracies of QoT monitoring for AWGN channels

We first focus on the error count method currently used to evaluate the pre-FEC BER and $Q^2$ in coherent transponders. Since the monitored BER may fluctuate in time, the system performance is best described by the expected value of the BER, namely the bit error probability (BEP).

The relative uncertainty of each BER measurement is approximately given[7] by the inverse square root of the expected number of counted erroneous bits $N_e$, i.e.

$$\varepsilon = \sigma_{BER}/BEP = E[N_e]^{-\frac{1}{2}} = (N_b BEP)^{-\frac{1}{2}} \qquad (1)$$

with the expected value of BER given by $E[BER] = BEP = E[N_e]/N_b$. $N_b$ is the number of bits used for the BER estimation with $N_b = N_s \cdot k$, where $N_s$ is the number of received complex samples used in the BER assessment and $k$ is the average number of bits per symbol. Then the number of complex samples is linked with the monitoring period $T_m$ by the relation

$$N_s = N_p \cdot R_s \cdot T_m \qquad (2)$$

where $R_s$ is the symbolrate and $N_p$ is the number of polarizations used in the calculation (i.e. $N_p = 2$ for PDM formats). Combining eqs. (1) and (2), the BER uncertainty can be defined as

$$\delta BER = n \cdot \sigma_{BER} = n\sqrt{BEP/(kN_pR_sT_m)} \qquad (3)$$

where the coverage factor $n$ is a multiplier of the standard deviation $\sigma_{BER}$ to obtain an expanded uncertainty. As it is evident from eqs. (2) and (3), for a system with arbitrary BEP, the relative error can be reduced by increasing $N_s$, i.e. by increasing $T_m$. However, due to the quadratic dependence of eq. (3), $T_m$ needs to be increased by 4 to reduce the error by 2.

For arbitrary modulation, the BEP can be approximately given as a function of the “nominal GSNR”, denoted $GSNR_n$, through the relation[8, 9]

$$BEP = (1/b) \cdot erfc\left[\sqrt{GSNR_n/(2c)}\right] \qquad (4)$$

where $b$ and $c$ are modulation dependent parameters, e.g. for QPSK $(b, c) = (2, 1)$ and for 16QAM $(b, c) = (8/3, 5)$. The parameter $GSNR_n$ is defined for any channel with a given BEP, but it is equal to the theoretical SNR only if the channel is truly impacted by additive white

978-0-7381-4679-9/21/$31.00 ©2021 IEEE

Gaussian noise (AWGN). Inverting eq. (4), an estimation of $GSNR_n$ in dB can be obtained from a BER value by

$$GSNR_{BER}[dB] = g\left[2\,\mathrm{erfc}^{-1}(b \cdot BER)^2\right] + g(c) \quad (5)$$

where $g(x) = 10\,log_{10}(x)$. As a first order approximation, the uncertainty of a quantity $y = f(x)$ can be expressed as a function of the error $\delta x$, through the relation

$$\delta y \approx |\partial f(x)/\partial x|\delta x \quad (6)$$

Combining eqs. (3), (5) and (6) and assuming $BEP \approx BER$ (i.e. the average BER is equal to the current BER sample) we can estimate the $GSNR_{BER}$ error, denoted $\delta SNR_{BER}$, as

$$\delta GSNR_{BER}[dB] \approx \frac{ne^{\frac{GSNR_n}{2c}}\sqrt{\mathrm{erfc}\left(\sqrt{\frac{GSNR_n}{2c}}\right)}}{\frac{\ln 10}{20}\sqrt{\frac{GSNR_n bkN_s}{2\pi c}}} \quad (7)$$

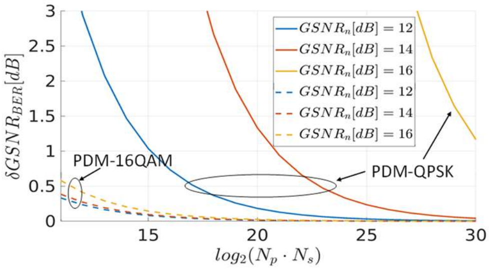


**Fig. 1:** $GSNR_{BER}$ uncertainty for PDM-QPSK and PDM-16QAM vs. the number of symbols $N_s$ for arbitrary values of $GSNR_n$

In Fig. 1 we illustrate the uncertainty of eq. (7) as a function of the number of samples $N_s$, for PDM-QPSK and PDM-16QAM, $n = 3$ and different $GSNR_n$ values. For $GSNR_n = 12dB$ PDM-QPSK operates well above and PDM-16QAM slightly below typical FEC limit. In this case we note that, for instance, $N_s = 2 \times 16384$ yields uncertainty of about 1 dB, while $2 \times 65536$ complex samples are required to achieve 0.5dB. On the other hand, since PDM-16QAM yields more errors, we reach uncertainties of 0.08dB and 0.04dB. Equivalently, obtaining low $\delta GSNR_{BER}$ for high $GSNR_n$ is a challenge for real-time BER monitoring. For instance, with PDM-QPSK and $GSNR_n = 16dB$, getting $\delta GSNR_{BER} = 0.01dB$ requires at least four minutes, while $\delta GSNR_{BER} = 0.001dB$ comes at the price of several hours of monitoring. Such monitoring periods may be incompatible with real-time applications or high-frequency events.

To overcome the abovementioned issue, statistics of the received signal constellation can be calculated and used to extrapolate the BER, in the high $GSNR_n$ regime, independently of the number of counted errors. For instance, the GSNR can be assessed through the EVM as

$$GSNR_{EVM} \approx EVM^{-2} \quad (8)$$

Nevertheless, EVM is biased for low $GSNR_n$, with this bias given for square MQAM formats by[5]

$$\begin{aligned} GSNR_{bias}^{-1} &= GSNR_{EVM}^{-1} - GSNR_n^{-1} \\ &\approx -\frac{4\sqrt{6}\sum_{k=1}^{\sqrt{M}-1}\gamma_k e^{-\frac{3\beta_k^2 GSNR_n}{2(M-1)}}}{\sqrt{\pi(M-1)GSNR_n}} \\ &+\frac{12}{M-1}\sum_{k=1}^{\sqrt{M}-1}\gamma_k\beta_k \mathrm{erfc}\left(\sqrt{\frac{3\beta_k^2 GSNR_n}{2(M-1)}}\right) \end{aligned} \quad (9)$$

where $\gamma_k = 1 - k/\sqrt{M}$ and $\beta_k = 2k - 1$. For high $GSNR_n$ the bias vanishes and $GSNR_{EVM}$ is equal to the noise total variance. The assessment of a complex noise variance $V$ though, through a finite number of samples $N_s$ has a standard deviation $\delta V$, which using eq. (6) verifies the expression[10]

$$\delta V[dB] = (10/ln10)(N_s - 1)^{-1/2} \quad (10)$$

Finally, combining eqs. (9) and (10) we propose to estimate the error of the EVM measurement as

$$\delta GSNR_{EVM}[dB] = \sqrt{[-g(1 + GSNR_n/GSNR_{bias})]^2 + \delta V[dB]^2} \quad (11)$$

## Proposed metric and numerical simulations

In Fig. 2 we illustrate the predictions of eqs. (7), (10) and (11) for QPSK modulation as a function of $GSNR_n$, for a system corrupted by AWGN, using $N_s = 65536$ received complex samples. The simulated quadratic errors $\delta \widehat{GSNR}_{BER}$ and $\delta \widehat{GSNR}_{EVM}$ are also plotted for ten noise seeds. We verify that, for the low $GSNR_n$ regime, the error of the BER assessment remains low and the error of the EVM assessment exponentially increases, while the opposite happens in the high $GSNR_n$ regime, with the BER error increasing exponentially and the EVM error saturating to $\delta V$ of eq. (10). $\delta GSNR_{BER}$ and $\delta GSNR_{EVM}$ are equal for $GSNR_n = GSNR_{th}$, where the parameter $GSNR_{th}$ can be computed given the modulation and the number of samples used for monitoring.

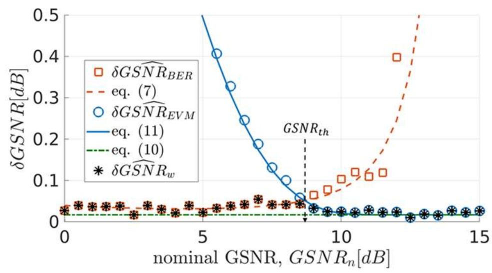


**Fig. 2:** $GSNR$ uncertainty for QPSK modulation when EVM or BER are used. Markers denote the quadratic error for a simulation with $N_s = 65536$ symbols.

We also note that, while increasing the number of samples for high $GSNR_n$ will improve the accuracy of $GSNR_{BER}$ at the cost of a longer monitoring period, the $GSNR_{EVM}$ measurement is already accurate in this regime, without the need of collecting more samples. We now define a new metric allowing to optimize both accuracy and

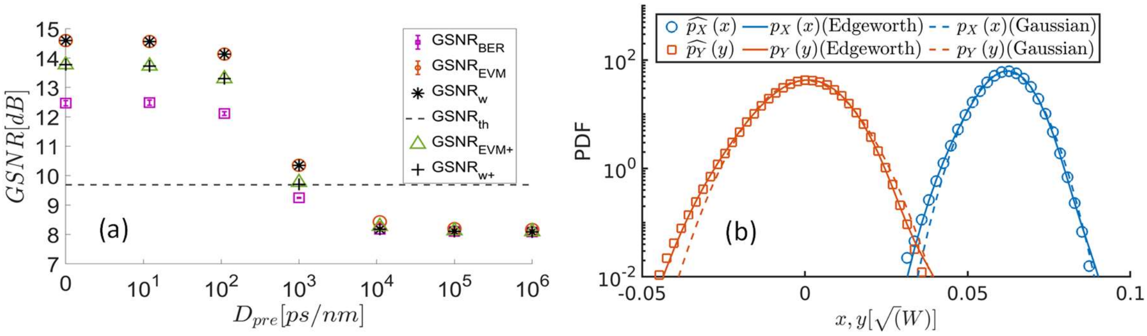


**Fig. 3:** (a)Nonlinear channel GSNR assessed through $GSNR_{BER}$, $GSNR_{EVM}$, $GSNR_w$, $GSNR_{EVM+}$ and $GSNR_{w+}$ (b) marginal PDFs for the in-phase and quadrature NL noise components for P=9dBm. Markers denote simulation, solid lines denote 2nd order Edgeworth series and dashed lines denote the Gaussian PDF.

speed when assessing the QoT, as the weighted sum of the two assessments, i.e.

$$GSNR_w \equiv aGSNR_{BER} + (1-a)GSNR_{EVM} \quad (12)$$

where $a$ is a coefficient. A direct way to set $a$ is to assume $GSNR_n \approx GSNR_{BER}$ and then use

$$a = \begin{cases} 0, GSNR_{BER} > GSNR_{th} \\ 1, GSNR_{BER} < GSNR_{th} \end{cases} \quad (13)$$

or otherwise, a smooth function can be used for the transition between the two regimes. The simulation result for $\delta GSNR_w$ is also plotted in Fig. 2, showing that $GSNR_w$ inherits the best from both QoT readings, while its accuracy is upper-bounded for all $GSNR_n$ regimes by the value

$$\delta GSNR_w = \delta GSNR_{BER}(GSNR_{th}) \quad (14)$$

## Limitations and future challenges

The considerations of the previous sections concerning EVM are rigorously valid only for an AWGN channel. This is approximately the case of systems in the scope of the Gaussian noise (GN) model[11, 12], where nonlinear distortion is treated as AWGN. While this is undoubtedly the most frequent case, QoT may also be monitored for links outside the validity domain of the GN model. To illustrate the limitations of our approach we therefore focus on one extreme case of system impacted by nonlinear distortion with non-AWGN statistics. For this, we simulate propagation over one large effective area fiber (LEAF) span, with a variable input dispersion pre-distortion[13, 14] denoted $D_{pre}$, PDM-QPSK format, symbol-rate $R = 32Gbaud$, 13 channels, spacing of 50GHz and 0.01 root-raised cosine pulse shape. Traffic was emulated by pseudorandom sequences of $N_s = 2^{20}$ symbols and input power per channel was set to 9dBm. Amplifiers were considered flat gain repeaters and the receiver was ideal with matched filtering, ideal dispersion compensation and data-aided phase recovery. In Fig. 3(a) we plot $GSNR_{BER}$, $GSNR_{EVM}$ and $GSNR_w$ as a function of $D_{pre}$, using the received samples of both polarization tributaries. We show with dashed line the threshold $GSNR_{th}$ and the associated error-bars of each GSNR assessment from eqs. (7), (11) and (14). We stress that $N_s = 2 \times 10^{20}$ samples yields $\delta GSNR_{BER} < 0.07dB$ and therefore $GSNR_{BER}$ is fairly accurate for any $D_{pre}$. We note that for high $D_{pre}$, $GSNR_w$ coincides with $GSNR_{BER}$, correctly accounting for the error-bar of $GSNR_{EVM}$. However, for low $D_{pre}$ we observe a mismatch of about 2dB between $GSNR_{BER}$ and $GSNR_{EVM}$ which is not covered by the error-bars and $GSNR_w$ is (erroneously) set to $GSNR_{EVM}$. In such cases, the EVM reading could be discarded, but using only the BER reading over a long monitoring period, could potentially hinder accuracy-sensitive real-time applications. Otherwise, ~2dBs of extra margin is needed.

The above-mentioned issue can be attributed to the non-AWGN nature of NL noise, suggesting that EVM is not a sufficient statistic to describe its probability density function (PDF). In Fig. 3(b) we plot with markers the simulated PDFs for the in-phase and quadrature components of the NL noise for $D_{pre} = 0ps/nm$. Gaussian PDFs are denoted with dashed lines and solid lines denote a 2nd order Edgeworth series (ES)[15], involving high order statistics like skewness and kurtosis, which can be calculated from the received signal together with EVM. Integrating ES we assess the BEP which is then converted into GSNR by eq. (5), denoted $GSNR_{EVM+}$ and assessed in Fig. 3(a) for the simulated signals. Replacing $GSNR_{EVM}$ with $GSNR_{EVM+}$ in eq. (12), we get the quantity $GSNR_{w+}$, also plotted in Fig. 3(a), which reduces the difference from $GSNR_{BER}$ by ~0.8dB and therefore the corresponding extra margin.

## Conclusions

We introduce a new metric for performance monitoring, leveraging the readings of both error counting and statistics of the received noisy signal. The new metric has a low accuracy for the whole performance range of systems impacted by AWGN and presents advantages for real-time applications. We finally confront the new criterion to an extreme case of nonlinear noise and we briefly discuss the remaining challenges and possible solutions for non-AWGN channels.

## References


[1] C. Delezoide, P. Ramantanis, and P. Layec, “Leveraging Field Data For The Joint Optimization of Capacity and Availability in Low-Margin Optical Networks,” *Journal of Lightwave Technology*, pp. 1–1, 2020.

[2] P. Ramantanis, C. Delezoide, P. Layec, and S. Bigo, “Revisiting the calculation of performance margins in monitoring-enabled optical networks,” *Journal of Optical Communications and Networking*, vol. 11, no. 10, pp. C67–C75, 2019.

[3] E. Seve, J. Pesic, Y. Pointurier, and Y. Pointurier, “Associating machine-learning and analytical models for quality of transmission estimation: combining the best of both worlds,” *Journal of Optical Communications and Networking*, vol. 13, no. 6, pp. C21–C30, Jun. 2021.

[4] S. Shahkarami, F. Musumeci, F. Cugini, and M. Tornatore, “Machine-Learning-Based Soft-Failure Detection and Identification in Optical Networks,” in *2018 Optical Fiber Communications Conference and Exposition (OFC)*, Mar. 2018, pp. 1–3.

[5] R. Schmogrow, B. Nebendahl, M. Winter, A. Josten, D. Hillerkuss, S. Koenig, J. Meyer, M. Dreschmann, M. Huebner, C. Koos, J. Becker, W. Freude, and J. Leuthold, “Error Vector Magnitude as a Performance Measure for Advanced Modulation Formats,” *IEEE Photonics Technology Letters*, vol. 24, no. 1, pp. 61–63, 2012.

[6] V. Kamalov, M. Cantono, V. Vusirikala, L. Jovanovski, M. Salsi, A. Pilipetskii, D. Kovsh, M. Bolshtyansky, G. Mohs, E. R. Hartling, S. Grubb, T. Stuch, H. Fevrier, E. Mateo, Y. Inada, T. Inoue, P. Pecci, V. Letellier, O. Courtois, O. Ait-Sab, O. Gautheron, and P. Mehta, “The subsea fiber as a shannon channel,” in *in Suboptic 2019*, 2019.

[7] A. Bononi, L. Rusch, A. Ghazisaeidi, F. Vacondio, and N. Rossi, “A Fresh Look at Multicanonical Monte Carlo from a Telecom Perspective,” in *Global Telecommunications Conference, 2009. GLOBECOM 2009. IEEE*, 2009, pp. 1 –8.

[8] J. Proakis, *Digital Communications*. McGraw-Hill Science/Engineering/Math, 8 2000, 4.

[9] K. Cho and D. Yoon, “On the general BER expression of one- and two-dimensional amplitude modulations,” vol. 50, no. 7, pp. 1074–1080, 2002.

[10] G. Casella and R. L. Berger, *Statistical inference*, 2nd ed. Cengage Learning, 2002.

[11] P. Poggiolini, “The GN model of non-linear propagation in uncompensated coherent optical systems,” *J. Lightwave Technol.*, vol. 30, no. 24, pp. 3857–3879, Dec 2012.

[12] F. Vacondio, O. Rival, C. Simonneau, E. Grellier, A. Bononi, L. Lorcy, J.-C. Antona, and S. Bigo, “On nonlinear distortions of highly dispersive optical coherent systems,” *Optics Express*, vol. 20, no. 2, pp. 1022–1032, 1 2012.

[13] E. Seve, P. Ramantanis, J.-C. Antona, E. Grellier, O. Rival, F. Vacondio, and S. Bigo, “Semi-analytical model for the performance estimation of 100Gb/s PDM-QPSK optical transmission systems without inline dispersion compensation and mixed fiber types,” in *Optical Communication (ECOC 2013), 39th European Conference and Exhibition on*, 2013, pp. 1–3.

[14] P. Jennevé, P. Ramantanis, F. Boitier, N. Dubreuil, and S. Bigo, “Experimental investigation of the validity domain of the Gaussian noise model over dispersion managed systems,” in *Optical Fiber Communication Conference*. Optical Society of America, 2016, p. W3I.3.

[15] C. S. Withers and S. Nadarajah, “The dual multivariate Charlier and Edgeworth expansions,” *Statistics & Probability Letters*, vol. 87, pp. 76–85, Apr. 2014.