Advances in Modeling and Mitigation of Nonlinear Effects in Uncompensated Coherent Optical Transmission Systems

G. Bosco(1), A. Carena(1), M. Ranjbar Zefreh (1), P. Poggiolini(1), F. Forghieri(2)

(1) DET, Politecnico di Torino, C.so Duca degli Abruzzi 24, Torino, Italy, gabriella.bosco@polito.it
(2) Cisco Photonics Italy srl, via Santa Maria Molgora 48/C, 20871 Vimercate (MB), Italy

Abstract *Recent results on analytical modeling of non-linear interference due to signal propagation in multi-span optical systems are reviewed, including high-symbol rate and ultra-wideband scenarios. Latest advances in nonlinearity mitigation, based on the use of machine learning techniques and non-linearity tolerant modulation formats, are also discussed.*

Introduction

The nonlinear interference (NLI) noise generated by the nonlinear interaction between different WDM channels is a major limiting factor to the capacity of long-haul coherent optical systems. As transmission power is increased, the nonlinear Kerr effect degrades the system performance, preventing operation at the transmission rates that would be achieved in a linear system[1], as shown in Fig. 1.

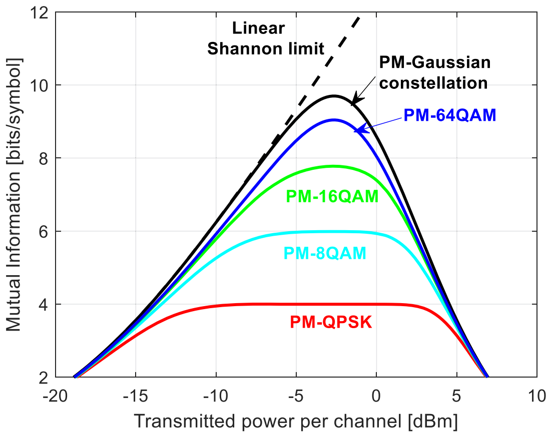

Fig. 1: Mutual information vs. transmitted power per channel over 20 spans of SSMF (span length = 85 km), assuming the transmission of different modulation formats occupying the entire C-band [1]. The black dashed line is the conventional Shannon limit in additive white-Gaussian noise.

This performance limitation motivated the development of several nonlinear compensation techniques, as well as of analytical models for signal propagation in an optical fiber. These models, which have become widespread in recent years, are useful tools for both the performance prediction of coherent optical systems and the design of efficient NLI mitigation algorithms.

In this paper, we briefly review the most commonly used methods and the recent advancements in modeling and mitigation of nonlinear effects in uncompensated coherent optical transmission systems.

Modeling of Non-Linear Interference

The majority of the models that predict the performance degradation in optical fiber communications due to Kerr nonlinearity solve the nonlinear Schrödinger equation analytically using a first-order perturbation approach[2]. Among them, those based on the “GN-model” approach[1] have become quite popular, thanks to a good balance between accuracy, complexity and ease of use. Their simplicity, with respect to other models, derives from the assumption that, in highly dispersive channels such as uncompensated long-haul coherent systems, each WDM signal can be treated as Gaussian noise.

However, it has been pointed out that the dispersed signal is only first-order Gaussian, whereas multiple samples of the signal do not have a jointly Gaussian distribution[3]. The fact that the GN model neglects this aspect leads to several limitations, among which the inability to resolve the format-dependent NLI generation.

Removing the Gaussian assumption requires taking into account not only the 2nd moment of the launched signal, but also higher order moments. In this way, the models of nonlinear propagation become more complex in terms of computational effort, but the accuracy is increased. In particular, a detailed modelling of all the NLI components is obtained, including short-correlated quasi-circular noise and long-correlated nonlinear phase noise (NLPN) and polarization noise[3,4].

The enhanced-GN model (or EGN model[4]) is a complete and accurate model in the frequency domain, computationally very complex. A reduced version exists, which is quite accurate and 1/3 as complex, but complexity is still high[2]. In addition, in its current form it does not permit to separate out nonlinear phase and polarization rotation noises (PPRN) from circular NLI, though it does permit to approximately factor out NLPN. In fact, it has been shown that, if all the long-

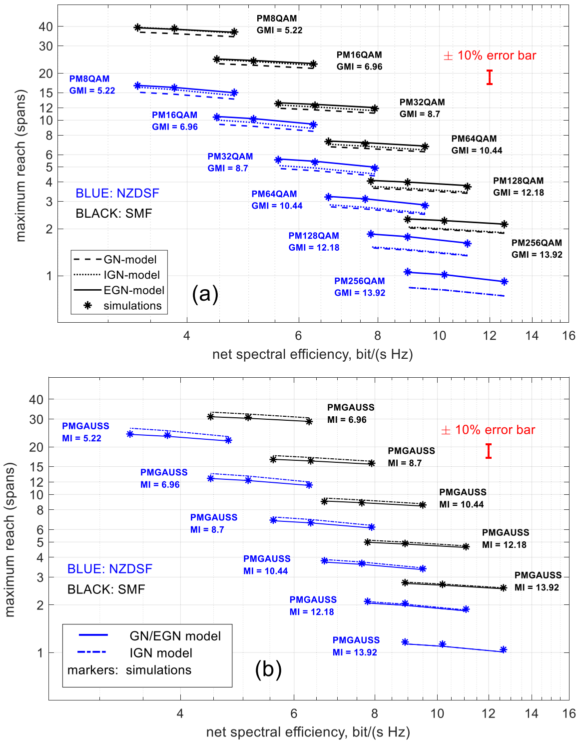

Fig. 2: System maximum reach in number of spans vs. net spectral efficiency. (a) QAM constellations. (b): Gaussian constellations. Asterisks: simulation results. Lines: predictions using the GN, EGN and incoherent GN-model. System data: span length 100km, EDFA noise figure 6dB, rate R_s=64GBaud, 15 channels. Channel spacings Δf 76.2, 87.5 and 100 GHz. For each format the target GMI (for PM-QAM) or MI (for PM-Gaussian) is shown.

correlated phase noise is ideally taken out, then any PM-QAM system is well described by the EGN model calculated as if PM-QPSK was transmitted [5,6]. A simplified, yet less accurate, form of the GN model (the IGN model[1]) can be obtained assuming an incoherent combination of the NLI components generated in each span during propagation, i.e. assuming that that NLI adds up in power at the end of the link.

The time-domain models described in[7,8] are very similar to the EGN model in terms of accuracy and complexity when predicting NLI variance. In addition, they are also able to predict PPRN and temporal correlations. They describe nonlinear interference as an inter-symbol interference (ISI), and predict the contribution of the various ISI terms, which can be used to examine and evaluate the performance of various ISI cancellation techniques.

Spatially-resolved models[9,10] are an alternative description of the EGN model, which predict temporal correlations of the optical nonlinear interference and focus on nonlinear spatial interactions along the link, such as nonlinear signal–noise interaction. Their complexity grows with the system length.

Lately, strong industry innovative trends have developed towards a quick-paced uptake of Gaussian-shaped constellations and a swift increase in symbol rates, with rates up to 128 Gbaud and beyond foreseen in the short-medium term. The EGN model appears to be extremely reliable, across all the explored parameter space, as shown in[6,11]. It handles all formats, QAM and Gaussian constellations, spacing values and symbol rates from 8 to 512 Gbaud, within a very small error bracket vs. simulations, as shown in Fig. 2. Remarkably, for Gaussian-shaped constellations, the EGN model coincides with the much computationally simpler GN model.

The GN model has been recently extended to take into account the impact of inter-channel stimulated Raman scattering (ISRS) on the optical Kerr nonlinearity[12,13], enabling an accurate modeling of nonlinear propagation in wideband optical systems that occupy the entire C+L band (approximately 10 THz) or beyond.

In order to reduce the computational complexity of NLI models and make them *real-time*, Closed-Form Model (CFM) approximations of the GN/EGN models have been proposed[14,15] capable of assessing whole links in fractions of a second. These models were originally derived from a closed-form incoherent GN model approximation proposed in[1], which was then extended to take into account the frequency-dependence of both loss and dispersion, and the impact of ISRS[15,17]. They were also augmented with various correction terms to improve their accuracy and bring it to EGN-model level[15,16], also using machine-learning techniques[15].

As an example, Fig.3 shows the high degree of accuracy reached by some of these CFMs, vs. the EGN model. In particular, the green

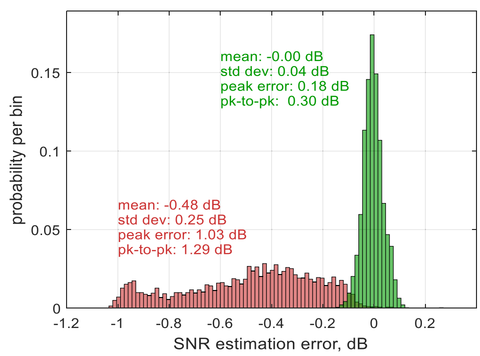

Fig. 3: Histograms of the SNR estimation error between a real-time CFM and the EGN model, tested over 2800 randomized C-band WDM systems, of which 2050 are fully-loaded and 750 are partially loaded. The systems had highly diversified channel formats, symbol rates, spacings, fibers, as well as other parameters[15]. Red histogram: CFM1 from[15]. Green histogram: CFM4 from[15] with ML enhancement and analytical “coherence term”.

histogram is related to the so-called CFM4 which uses a simple machine-learning based correction term[15]. When tested over 2800 full C-band systems the error is very small. The most current versions of these CFMs[15-17] are capable of delivering near-EGN-model accuracy over C+L band systems, with ISRS taken into account[17].

NLI Mitigation Techniques

The NLI analytical models are useful tools to obtain an accurate prediction of the ultimate performance achievable by the various mitigation techniques[1,18]. However, the actual performance gain will also depend on several implementation issues that cannot be easily included in the analytical estimations, such as the sub-optimum performance of low-complexity compensation algorithms[19] or the higher impact of NLPN in digital multi-subcarrier systems[20], which would prevent a full exploitation of the NLI mitigation benefits and need to be addressed separately.

Several techniques have been proposed to reduce the power of the NLI noise[18,21]. The effectiveness of nonlinearity mitigation depends on the nature of the NLI, which can be divided into two main classes: *in-band interference,* which includes the NLI generated within the electronic bandwidth of the transceiver, and *out-of-band interference*, which includes the NLI generated by the interaction with WDM channels that are note accessible to transmitter and receiver. An ideal NLI mitigation technique should effectively compensate the nonlinearity using the lowest computational effort possible.

Digital backpropagation (DBP) is among the best solutions, in terms of accuracy, to remove fiber nonlinearity[22]. It is based on a numerical approximation of the nonlinear Schrödinger equation (NLSE) solution using the split step Fourier method (SSFM). The performance of DBP improves with the number of steps per span used in the SSFM. In order to achieve good performance, multiple steps per span are necessary, which come at the cost of additional complexity for the extra digital circuits needed to implement of the Fourier transforms. The filtered DBP (FDBP) [23] is an approach that can be used to reduce the number of steps per span. It is based on the application of an additional filtering operation to the intensity signal at each nonlinear step in order to limit the over-compensation of the non-linearity. An alternative approach to mitigate in-band fiber nonlinearities, with a similar complexity as standard DBP, is based on the use of Volterra series transfer functions[24]. However, Volterra series approaches suffer from a severe performance penalty when the computational complexity is reduced[25].

Out-of-band NLI generated solely by out-of-band channels is typically treated as non-removable noise, while out-of-band NLI that involves the channel under test can be modelled as time-varying ISI and can be partially mitigated using several techniques (such as MAP or ML decoding)[26]. Mitigation of the impact of NLI can be also obtained using different approaches that optimize one or more transmission parameters, among which: symbol-rate optimization (SRO)[27], dispersion pre-compensation[28] and constellation or pulse shaping[29].

Very recently, several NLI mitigation methods based on machine-learning (ML) approaches have been proposed[30]. By learning the characteristics of nonlinear impairments from the collected data at the receiver, ML techniques have great potential to compensate for stochastic nonlinearity-induced signal distortions.

When applied in nonlinearity compensation, ML techniques are similar to digital compensation methods that equalizes the nonlinear effects at Rx side based on received symbols. Two major approaches are followed: the first treats the received symbols as ordinary data samples and develop a ML model for symbol detection without considering system parameters, while the second integrates fiber parameters into ML modeling, thus using more comprehensive knowledge of optical fibers and transmission systems [31].

Based on the observation that DBP has a similar mathematical structure as a neural network (NN), deep learning based DBP techniques have been recently proposed [32-34], which use ML-based approaches to optimize the steps of the DBP compensation algorithm, thus reducing the overall complexity.

Conclusions

The field of the investigation of the modeling of nonlinear fiber effects has been extremely active over the last decade. The obtained results and developed practical tools have been extensively used by the community, both in transmission and in optical networking sectors. The next few years will certainly see further progress in nonlinearity mitigation, also because the DSP computational power is still significantly increasing, so that sophisticated techniques that seemed to be unrealistically complex not long ago, are gradually becoming viable. This might enable a further substantial increase in the performance of optical transmission systems and networks.

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