MACHINE LEARNING IN SOA OPTICAL COMMUNICATION SYSTEMS

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The performance of cascaded optical communication systems with in line semiconductor optical amplifiers is evaluated by means of machine learning approaches based both on a regression model and an artificial neural network.

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1. Introduction

QoT predications is a fundamental topic for any network and, concerning optical transmission systems, recently several analytical models have helped in the performance evaluation of very long nonlinear fiber links. However, due to the presence of more and more elements in networks, to which an infinity of random parameters are associated, the application of the analytical models is increasingly difficult.

The rapid developments of Machine Learning (ML) technologies has attracted many researchers to explore the performance estimations and various ML-based methods have been proposed to predict QoTs in optical networks [1].

In this paper two ML techniques are proposed, a regressive approach and a simple Artificial Neural Network (ANN), to show how these innovative methods can be of great help in understanding the performance evaluation of systems affected by different nonlinear degradations as in the case of in-line Semiconductor Optical Amplifiers (SOA) links. We take up the analysis done in past [2] where specific models were introduced to evaluate the signal evolution inside SOAs.

2. Short overview about ML approaches

Optical network performance evaluation needs the knowledge of specific laws, often unknown, which link many parameters together, and it is now recognized that a great help can be given by the use of techniques typical of the big data to extract (or learn) the relevant information from raw data; in fact ML approaches are giving important results also in this field.

To better introduce the ML methods let us suppose to have a group of QoT indicators represented by the vector Z that depends on group a of Y variables representing the link data, according to unknown lows; ML purpose is to find a model $Z=f(Y, \varepsilon)$, where ε is a list of parameters that have to be achieved by means of a training phase [1] that best fit the relationship between Z and Y. In some cases a process can be described by means of simple functions and therefore the ML approach can be traced back to the estimate of a limited group of parameters with regressive methods. However this approximation cannot be used often and therefore other ML approaches are required and ANN is the one that allows us to achieve an excellent relationship between Z and Y.

In the case of optical amplified systems the Q factor is often related to the input average power with the typical expression $Q^{-2}=(K+az^2P^3+bz^2P^5)/P$ [3], where P is the input power, z the link length and K, a, b depend on the link characteristics.

3. Link model and ML appraoch

All the details of the SOA link under investigation are reported in [2]. We adopt a SOA gain time evolution according to eq. (4) of [2]. The simulations were carried out with 8192 bits and we evaluate the Q factor both with the hard decision (without considering the bit pattern), and by taking into account the bit patters (the belonging of a bit to one of 16 bit patterns is decided after the sampling detection of the signal). The regressive ML approach is based on the search for the values K, a, b that best fit the relationship between the Q factor obtained by simulations and P. The simple ANN approach is based on an input of the 7 link and transmitter parameters (L_{amp}, GVD, fiber loss, α_H, P_{sat}, τ_c, P), only one hidden layer [1] with 7 neurons, and a sigmoidal activation function, while as output we consider the Q factor and time jitter. The training phase could be considered as complete after 30 Epochs. This method can be extended to other investigation concerning for example the pulse shape and bit rate. The ML approaches also allow us to investigate about the separate nonlinear contributions to the system performance.

4. Results

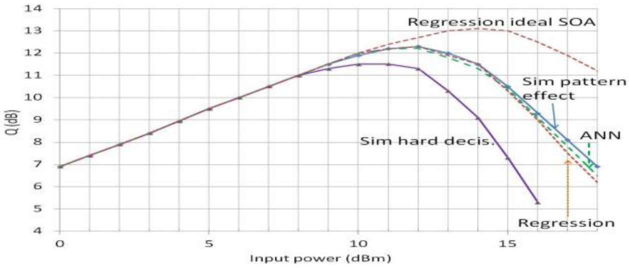

Fig. 1: Q factor from simulation and from ML

As example in fig. 1 the results concerning the Q factor evaluation are reported for a case of fig. 5 of [2] with the following parameters: 10 Gb/s NRZ IM-DD system with an amplifier spacing of 50 km, loss 0.4 dB/km and a GVD of -1 ps^2/km and for SOA α_H=5 (Henry constant), saturation power of 30 mW, τ_c=200 ps (carrier life time), n_{sp}=5. The importance of the Q evaluation taking into account the pattern effects has to be underlined especially when the amplifier gain is not time constant. Both the ML approaches produce reliable results. In the same figure also the case of ideal SOA amplification (constant gain) is reported.

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