Experimental demonstration of a cognitive quality of transmission estimator for optical communication systems

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Abstract: The impact of physical layer impairments in optical network design and operation has received significant attention in the last years, thereby requiring estimation techniques to predict the quality of transmission (QoT) of optical connections before being established. In this paper, we report on the experimental demonstration of a case-based reasoning (CBR) technique to predict whether optical channels fulfill QoT requirements, thus supporting impairment-aware networking. The validation of the cognitive QoT estimator is performed in a WDM 80 Gb/s PDM-QPSK testbed, and we demonstrate that even with a very small and not optimized underlying knowledge base, it achieves between 79% and 98.7% successful classifications based on the error vector magnitude (EVM) parameter, and approximately 100% when the classification is based on the optical signal to noise ratio (OSNR).

OCIS codes: (060.4250) Networks; (060.4510) Optical communications.

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1. Introduction

Next generation optical networks will be of a highly heterogeneous nature, as they will support mixed bit-rates, mixed modulation formats and even a flexible grid for spectrum allocation. That arising scenario brings new challenges in terms of transmission robustness, optical monitoring and mechanisms for control and management. One of those challenges is the need for new estimation techniques to predict the quality of transmission (QoT) of optical connections before being established in the network, thus supporting impairment-aware networking [1].

A number of solutions have been proposed to assess the QoT of optical connections. In [2], a real-time QoT estimator, the Q-Tool, has been presented. The tool receives a network topology and a set of lightpaths based on 10 Gb/s on-off keying (OOK), and then computes their associated Q-factors, which are indicators of the QoT, as they are directly related to the bit error rate (BER). Although the tool is extremely useful to check *a priori* whether the computed lightpaths will comply with QoT requirements when they are established on the network, its high computing time (from 1 to 1000 seconds, depending on the scenario) is a significant issue [3]. In [4], a Gaussian noise (GN) model which is able to estimate accurately the optical signal to noise ratio (OSNR) of the optical channels in uncompensated coherent transmission systems has been proposed. However, it does not yet address network scenarios (where channels coming from different locations are multiplexed in an optical fiber at optical cross-connects), and it is not valid for dispersion-compensated systems.

On the other hand, we have recently proposed a different approach for assessing the QoT. It consists in taking advantage of previous experiences which are stored on a knowledge base, i.e., it relies on cognition. Thus, in [5] we proposed a novel cognitive QoT estimator which is able to predict whether a new lightpath to be established in an optical network will comply with QoT requirements (and if it will not have a significant impact on the currently established ones). This estimator employs case-based reasoning (CBR) techniques [6]. CBR is an artificial intelligence mechanism which solves a new problem by looking for the most similar problems (or cases) faced in the past, and by reusing that knowledge, either directly or after some adaptation, to provide a solution. In this way, by exploiting previous experiences, which are stored on a knowledge base (KB), the QoT estimator is able to provide fast and correct decisions on whether a lightpath fulfills QoT requirements or not, before being established, without having to rely on complex methods. Using the proposed estimator, we have demonstrated, by means of simulation, that lightpaths in a 10 Gb/s OOK 14-node wavelength-routed optical network (the Deutsche Telekom network) are correctly classified into high or low QoT categories in more than 99% of cases, with a very low computing time: three orders of magnitude lower than that required by the Q-Tool in that scenario [5]. These results were extended and improved by incorporating learning and forgetting capabilities to optimize the underlying KB on which the cognitive estimator relies [7]. As demonstrated there, the use of those techniques slightly increases the rate of successful classifications and, more importantly, it significantly reduces the size of the KB, which in turn leads to additional computing time reductions. Thus, when operating with the optimized KB, the computing time is around four orders of magnitude faster when compared with a non-cognitive approach, the Q-Tool.

In this paper, we push forward our previous work by experimentally demonstrating that cognition can be successfully employed to predict the QoT of optical channels, and also by showing that it can be employed for other modulation formats than OOK. At this stage, rather than implementing a whole network, a wavelength division multiplexed (WDM), homogeneous point-to-point optical transmission system has been built, consisting of 5 80 Gb/s polarization division multiplexed (PDM) quadrature phase-shift keying (QPSK), with a

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number of adjustable parameters such as the optical launch power, the fiber link length and the number of co-propagating channels, in order to support different lightpath and system configurations.

2. Experimental testbed

Figure 1 shows the WDM experimental setup for the quality of transmission experiment of PDM-QPSK at 80 Gbit/s through 480 km of a dispersion-compensated fiber link. At the transmitter side, 5 laser sources spaced 50 GHz apart are combined using a 50 GHz arrayed waveguide grating (AWG), 4 of them distributed feedback lasers (3 MHz linewidth) and an external cavity laser (ECL) with 100 kHz linewidth placed in the central channel. 20 Gbit/s electrical signals are generated using a 5 Gbit/s pulse pattern generator (PPG) with PRBS 2^{15}-1 and a 4:1 electrical interleaver (IL). The electrical signals are used to drive a double-nested Mach-Zehnder modulator fed by the 5 optical sources. Polarization division multiplexing (Polmux) is emulated by multiplexing the signal with its delayed copy in the orthogonal polarization. Afterwards the odd and even channels are decorrelated using a 50 GHz optical interleaver and a 3 dB optical coupler, by introducing an optical delay of 23 ps between odd and even channels. After that, an erbium-doped fiber amplifier (EDFA) is used to amplify the signal to the desired launch power.

Fiber transmission is realized over a maximum of 6 fiber spans of 80 km standard single mode fiber (SSMF) and matched dispersion compensating fiber (DCF), for a total maximum distance of 480 km. After each fiber span, the optical signal is amplified in a double-stage EDFA with the DCF placed between the two stages. The gain of the amplification stage is adjusted to compensate for each span and DCF losses. In some scenarios 4 dB extra span losses are added at the end of each fiber span to achieve 22 dB of losses per span, thus emulating changes on the link losses due to fiber aging, new splices, etc. At the receiver side, a preamplified coherent detection scheme is used. It consists of a 0.3 nm optical filter for channel selection, a pre-amp EDFA, a 2 nm optical filter to remove amplified spontaneous emission excess noise and a polarization-diversity coherent receiver with integrated balanced photodiodes. An ECL with 100 kHz linewidth is employed as local oscillator (LO). A digital sampling oscilloscope (DSO) with 40 GS/s of sampling rate and 13 GHz bandwidth is used to digitize the photodiodes outputs. The acquired data is processed offline with a digital signal processing-based (DSP-based) receiver that includes a digital filter, constant modulus algorithm (CMA), carrier phase recovery and root mean squared (RMS) error vector magnitude (EVM) calculation.

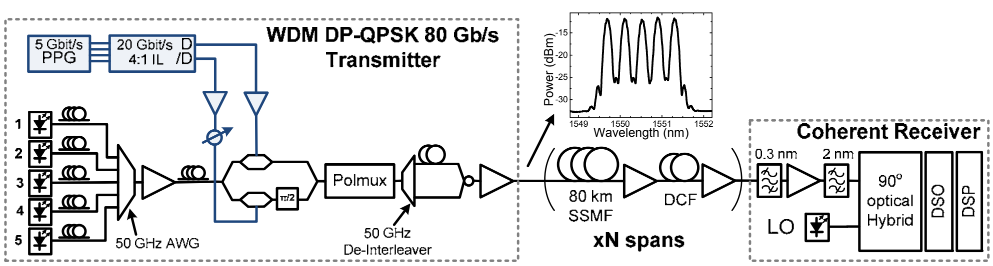

Fig. 1. Experimental testbed.

In order to emulate different lightpaths and system configurations in an optical network, the experimental setup allows for the modification of some parameters:

- number of simultaneously active channels in the link (from 2 to 5),
- launch power per channel (from −4 to 4 dBm in steps of 2 dB),
- number of spans (3 or 6, thus testing lightpath lengths of 240 and 480 km),

• average losses per span (18 or 22 dB).

Different scenarios have been configured, and the EVM of each of the active channels in each configuration has been experimentally measured, which is an indicator of the QoT of each channel. Apart from the EVM, the OSNR has also been measured. An example of the type of experimental measurements which were used to populate the KB of the cognitive QoT estimator (as it will be later described) is shown in Table 1. The set corresponds to the variation of the launch power per channel when the 5 channels are propagating through 6 fiber spans. The measured channel is the third one, placed in the middle. It can be observed that, in this example experiment, whereas the OSNR increases with the launch power, the EVM follows a different trend, and there is an optimal launch power, 0 dBm, where the EVM reaches a minimum. Therefore, the classification of a lightpath into one or another QoT category depends on the parameter used to make the decision.

Table 1. Example of experimental measurements used to populate the KB. Only one of the QoT parameters (OSNR or EVM) is included in the KB.

Channel measured	Channels (on = 1)					P_{in}/ch (dBm)	# of spans	Span loss (dB)	OSNR dB/0.1 nm	EVM (%)
	1	2	3	4	5					
3	1	1	1	1	1	–4	6	18	23.5	21.4
3	1	1	1	1	1	–2	6	18	25.4	19.6
3	1	1	1	1	1	0	6	18	27.3	19.2
3	1	1	1	1	1	2	6	18	29.1	21.1
3	1	1	1	1	1	4	6	18	30.8	24.9

3. A cognitive QoT estimator based on CBR

We have developed a cognitive QoT estimator, based on CBR, for the testbed described above. The estimator is able to classify a lightpath into a high or low QoT category, depending on the predicted value of its quality of transmission parameter, which can be either the EVM or the OSNR. The KB of the cognitive estimator is composed by a number of cases, each consisting of a description of the lightpath and its associated experimentally measured QoT value (EVM or OSNR). The description of the lightpath contains the channel wavelength, the value of launch power, the losses per span and the number of spans (i.e., the lightpath length), the set of active wavelength channels (i.e., the active lightpaths) in the link, the total input power to the link, and the total power carried by the adjacent channels of the lightpath considered, as well as that carried by those located 2, 3 and 4 channel slots apart from it. The measured QoT value in the experimental testbed for each lightpath and each configuration is also stored in the KB. It is important to remark that only one QoT parameter (EVM or OSNR) is used by the cognitive system and thus included in the KB, whereas the other is not considered at all.

Let us assume that the QoT of a new lightpath must be assessed. The cognitive QoT estimator works as follows. First of all, it retrieves the most similar lightpath from the KB to the one to be analyzed. In order to assess the similarity when comparing the new lightpath with those contained in the KB, the weighted Euclidean distance is calculated [8] according to Eq. (1),

$$Similarity\ (x,y) = -\sqrt{\sum_{a=1}^{n} W_a^{\,2} \cdot (x_a - y_a)^2} \qquad (1)$$

where a represents each attribute of the lightpaths x and y, W_a is the weight associated to that attribute, and n is the set of attributes. Thus, higher values (i.e., closer to zero values) of Eq. (1) mean higher similarity of the cases. The set of weights used is previously determined by means of a linear regression calculated on the KB.

The QoT parameter of the new lightpath is assumed to be the same one than that of the retrieved case, and that value is used to decide whether the lightpath fulfills the QoT

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requirements or not. For that purpose, the QoT parameter is compared with a threshold. If the QoT parameter is the EVM, and the value obtained is lower than the threshold, the lightpath is classified into the high QoT category; otherwise it is classified into the low QoT category. If the QoT parameter is the OSNR, the classification is done the other way round. If the OSNR is higher than the threshold, the lightpath is classified into the high QoT category, and otherwise into the low QoT class.

4. Performance results of the cognitive QoT estimator

In order to evaluate the performance of the cognitive QoT estimator, we have set the testbed with different configurations and measured the EVM and the OSNR of the different channels. In that way, a total of 153 cases have been experimentally compiled, with EVM values ranging from 14.4% to 24.9%, and OSNR values from 20.5 to 33.4 dB. Then, we have used the 10-fold cross validation technique, a standard technique to analyze the success rate of machine learning algorithms [9]. The available data (the set of 153 cases) is randomly permuted and then divided into 10 parts. 9 parts are used to compose the KB (and then the weights, W_a, to be used in the similarity computation are calculated by means of a linear regression), and the remaining part is used to test the cognitive estimator (i.e., the cases of that part are classified by the estimator and the ratio of successful classifications is calculated). The procedure is repeated 10 times (each time using a different portion for the test set, and the remaining parts to build the KB), and the results are averaged.

First, we have focused on classifying the lightpaths according to the EVM value. As previously mentioned, the OSNR values are not considered and hence not included in the KBs. Figure 2(a) represents the percentage of successful classifications provided by the cognitive QoT estimator when setting different values of the EVM as the threshold to differentiate between high and low QoT categories. The results are compared with a majority class classification. Let S_h be the success ratio obtained if all the lightpaths are classified into the high QoT class, and S_l be the success ratio obtained if all the lightpaths are classified into the low QoT category. Then, the majority class classification provides $max(S_h, S_l)$. In other words, the results are compared with the percentage of cases belonging to the most likely class. The cognitive QoT estimator improves the ratio of successful classifications between 5.8 (for an EVM threshold of 23%) and 29.0 (for an EVM threshold of 18.5%) percentage points when compared with the majority class classification. Moreover, the successful classifications are higher than 79% in all cases, and even higher than 90% except when the EVM threshold is set between 18 and 20.5%. The success ratio is lower than that obtained previously [5,7], but it should be noted that the scenario is different and, more importantly, that in this case the size of the KB is very small (nine-tenths of 153, i.e., 135 cases) and has not been optimized.

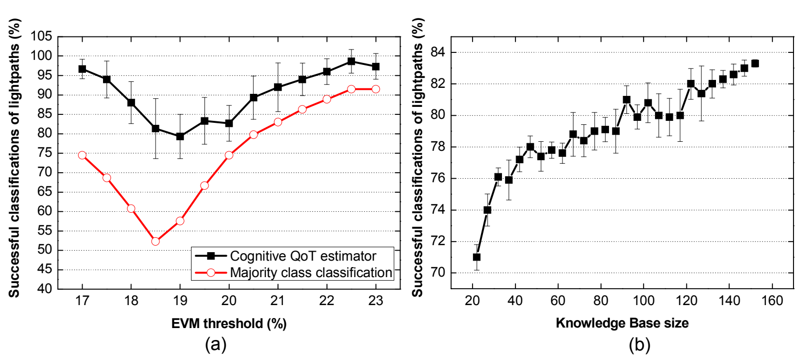

Fig. 2. (a) Percentage of successful classifications of lightpaths into high/low QoT categories according to an EVM threshold. (b) Impact of the size of the knowledge base on the percentage of successful classifications for the case of 19.5% EVM threshold.

Secondly, to further analyze the impact of the size of the KB, we have studied the performance of the cognitive QoT estimator for different KB sizes, from 22 to 152 cases, when considering an EVM threshold of 19.5%. In this occasion, a leave-*n*-out cross validation technique has been used, setting *n* to different values in order to get the desired size of the KB. As shown in Fig. 2(b), the success ratio of the classifications increases with the KB size.

Finally, we have repeated the former analysis using the OSNR as the QoT parameter that determines the category of a lightpath, proving that the cognitive QoT estimation technique is generic enough to be used with other performance parameters. The EVM values have not been considered, and thus have not been included in the KBs. Figure 3(a) represents the percentage of successful classifications provided by the cognitive QoT estimator when setting different values of the OSNR as the threshold to differentiate between high and low QoT categories. The results are again compared with a majority class classification. The cognitive estimator performs a nearly perfect classification (~100% success ratio) independently of the OSNR threshold. Figure 3(b) shows the performance of the cognitive QoT estimator as a function of the size of the KB (for an OSNR threshold of 26 dB), which improves more steadily than when the EVM is used as QoT parameter.

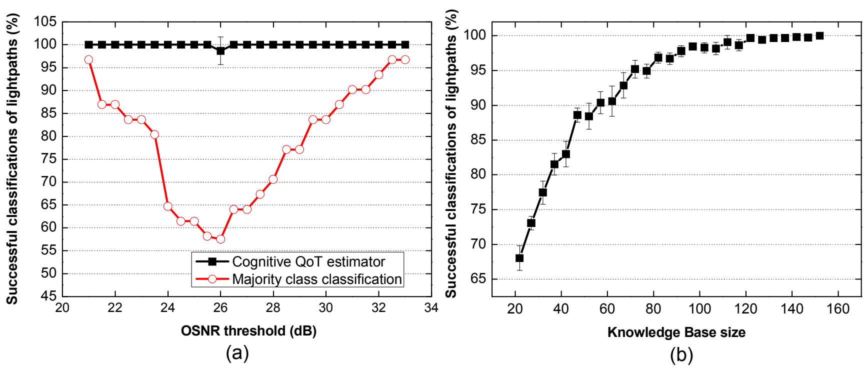

Fig. 3. (a). Percentage of successful classifications of lightpaths into high/low QoT categories according to an OSNR threshold. (b) Impact of the size of the knowledge base on the percentage of successful classifications for the case of 26 dB OSNR threshold.

5. Conclusions

We have experimentally demonstrated the use of a case-based reasoning technique to assess whether lightpaths comply with QoT requirements or not in a WDM 80 Gb/s PDM-QPSK dispersion-compensated testbed. Even with a small and not optimized KB of only 153 cases, it achieves between 79% and 98.7% successful classifications of lightpaths into high or low QoT classes according to predicted EVM values, and approximately 100% when the OSNR is used instead. These results complement previous work where we show, by means of simulation studies, the excellent performance of the cognitive QoT estimator in a 10 Gb/s OOK dispersion-compensated wavelength-routed optical network, not only in terms of successful classifications (based on the Q-factor), but also in terms of computing time, as it is around four orders of magnitude than an existing non-cognitive approach. Therefore, this shows that the case-based reasoning technique is generic enough for being used for QoT assessment in diverse networking scenarios, with different modulation formats and/or QoT parameters, hence showing its potential for application in cognitive optical networking.

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