Mitigation of Nonlinear Effects using Machine Learning in Coherent Optical Access Networks

Mitigación de Efectos No Lineales usando Aprendizaje Automático en Redes Ópticas de Acceso

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Abstract

Introduction— The use of coherent detection jointly with high-level modulation formats such as 16 and 64-QAM seems to be a convenient strategy to increment capacity of future optical access networks. However, coherent detection requires high complexity digital signal processing to mitigate different impairments.

Objective— Mitigate signal distortions using non-symmetrical demodulation techniques based on Machine Learning (ML) algorithms.

Methodology— First, a single channel Nyquist m-QAM system at 28 and 32 Gbps was simulated in VPIDesignSuite software. Then, different signals modulated at 16 and 64-QAM were generated with different laser linewidth, transmission distances and launch powers. Two ML algorithms were implemented to carry out the demodulation of the generated signals. The performance of the algorithms was evaluated using the Bit Error Rate (BER) in terms of different system parameters as laser linewidth, transmission distance, launch power and modulation format.

Results— The use of ML allowed gains up to 2 dB in terms of optical signal-to-noise ratio at a BER value of for 16-QAM and 1.5 dB for 64-QAM. Also, the use of ML showed that it is possible to use a lower cost laser (100 kHz linewidth vs 25 kHz) with a better BER performance than using conventional demodulation.

Conclusions— We showed that the use of both algorithms could mitigate nonlinear effects and could reduce computational complexity for future optical access networks.

Keywords— Coherent communications; digital signal processing; machine learning; optical access networks; quadrature amplitude modulation

Resumen

Introducción— Una de las estrategias más convenientes para el incremento de las capacidades en las redes ópticas de acceso, es el uso de la detección coherente junto con formatos de modulación de alto nivel tales como 16 y 64-QAM. Sin embargo, la detección coherente es una tecnología que requiere de un complejo procesamiento digital de señales para la mitigación de diferentes fenómenos. Objetivo: Minimizar efectos distorsivos de las señales ópticas usando demodulación no simétrica basada en algoritmos de Aprendizaje Automático.

Metodología— Se simuló un sistema Nyquist m-QAM a 28 y 32 Gbps en el software especializado VPIDesignSuite. Luego, se generaron diferentes señales moduladas a 16 y 64-QAM a diferentes anchos de línea de láser, longitudes de transmisión y potencias. Se implementaron dos algoritmos de aprendizaje automático para realizar demodulación de las señales generadas. Finalmente, el desempeño de la demodulación se midió en términos de la Tasa de Error de Bit (BER, del inglés Bit Error Rate), en función de varios parámetros del sistema tales como longitud de fibra, potencia de salida, ancho espectral del láser y formato de modulación.

Resultados— A un valor de BER de , el uso de los algoritmos permitió ganancias de hasta 2 dB en términos de relación señal a ruido óptica para 16-QAM y de 1.5 dB para 64-QAM. Además, la demodulación basada en estos algoritmos permitió una transmisión de hasta 50 km usando un láser con un ancho espectral de 100 kHz logrando un BER menor que usando un láser de 25 kHz sin implementar las técnicas de demodulación propuestas.

Conclusiones— Se demostró que las dos técnicas pueden ser aplicadas para minimizar efectos no lineales, y a su vez, permitiría una reducción de complejidad computacional en futuras redes de acceso ópticas.

Palabras clave— Aprendizaje de Máquina; comunicaciones coherentes; modulación de amplitud en cuadratura; procesamiento digital de señales; redes ópticas de acceso

I. Introduction

In the last decades, data traffic has shown an exponential growth due to new broadband services and high number of devices connected to same network. It forces to carry out an upgrading of current deployed networks [1]-[2]. Moreover, considering the Internet of Thing (IOT) era and the develop of fifth generation (5G) networks, it is expected that in coming years the enhanced mobile broadband bandwidth would reach 20 Gbps [3]. On one hand, the long-haul networks based on coherent receivers with QPSK modulation format will not fulfill the demanded capacities, thence, advanced modulation formats such as 16-QAM and 64-QAM are proposed to increase the network capacity [4]. On the other hand, in optical access networks have been proposed the used of coherent receivers to also increase the capacity, but the high cost of this technology would be a limitation if a good trade-off (between capacity and cost) is not reached. Nevertheless, the use of m-QAM modulation formats in access networks would further increase the network capacity taking advantage that Optical Signal-to-Noise Ratio (OSNR) penalty in short distances is not a significant issue, although in these networks low complex equalization techniques for mitigation of signal distortions aiming to low cost solutions would be required [5]. Thus, mitigation of nonlinear impairments using nonlinear equalization (i.e. Backpropagation algorithm) would not be a viable solution due to the high computational complexity [6]-[7]. Machine Learning (ML) techniques have been recently explored for monitoring and signal impairments mitigation [8]-[10]. For example, Artificial Neural Networks (ANN) is one of the most explored algorithms for mitigation of nonlinear effects [10]-[13], though, its computational complexity is comparable to an nonlinear equalizer. Support Vector Machine (SVM) is another algorithm that has been applied to nonlinear effects mitigation [14], [15], presenting launch power gains and phase noise mitigation. Nevertheless, these recently approaches have been focused on long-haul networks where transmission distances exceed 100 km of optical fiber. Thus, the use of ML techniques should be extended to optical access networks to relax the hardware requirements. Most of the ML techniques are applied to In-Phase and Quadrature (IQ) signal components in post-slicing process which perfectly fit in the proposal of including m-QAM modulation formats in optical access networks. The IQ components can be analyzed in a constellation diagram, for better comprehension of the received symbols' threshold. Besides, unlike the well-known Additive White Gaussian Noise (AWGN) that affect the signal distorting the symbols position creating circular shapes seen in the constellation diagram [4] (Figs. 1a; Fig. 1c), nonlinear distortions due to laser phase noise and due to high launch power, increases the symbol distortion resulting in non-circular shapes [11]-[13]. These distortions increase the Bit-Error-Rate (BER) because the assignation of symbols in traditional demodulation is based on hard-decision metric that basically creates a symmetric grid seen in a constellation diagram. Moreover, nonlinear phase noise occurs, mainly, because of the lack of monochromatic sources, which introduce instantaneous frequency shift, and therefore phase changes in the optical carrier [18]. Hence, the optical carrier frequency is time-varying and the resultant broadened spectrum is well-known as laser linewidth. On the other hand, high launch power required to maintain high OSNR for high-level modulation formats, stimulates nonlinear effects of the optical fiber due to the changes of its refraction index. This phenomenon is called Kerr effect [19] and it also leads to undesirable symbols position as shown in Fig. 1b and Fig. 1d.

Therefore, in this paper, we propose two non-symmetrical digital demodulation methods based on, first, an unsupervised algorithm called k-Means and second, a supervised algorithm called k-Nearest Neighbors (KNN) enabling mitigation of nonlinear effects in optical access networks. The implementation of the respective algorithms is carried out in R2020b Matlab® as well as the results obtaining. The performance is evaluated in terms of BER in a Nyquist m-QAM system modeled in VPIDesignSuite v10.1 software for different transmission distance.

The remainder of this paper is organized as follows: in Section 2 details of the simulation setup are given, in Section 3, a brief explanation of the ML techniques, implemented for non-symmetrical digital demodulation is presented; results and discussion are exposed in Section 4; finally, conclusion and future work is shown in Section 5.
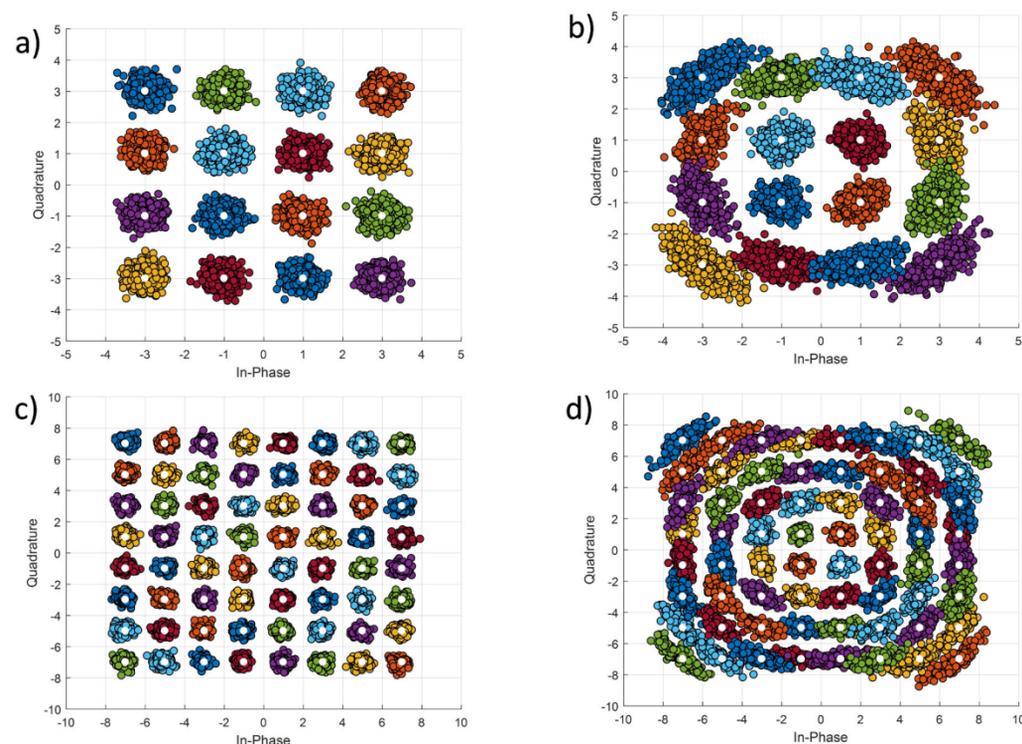
Fig. 1. a) 16-QAM constellation affected with Gaussian Noise. b) 16-QAM constellation affected with Nonlinear Noise. c) 64-QAM constellation affected with Gaussian Noise. d) 64-QAM constellation affected with Nonlinear Noise.
Source: Authors.

II. SIMULATION SETUP

The simulation setup is a Nyquist coherent single-channel optical system at 28 and 32 Gbps which would be a typical link in future optical access networks. The system is modeled in VPIDesignSuite and Fig. 2 shows the setup scheme. A Pseudo Random Binary Sequence (PRBS) with length of 65536 bits is generated to be mapped in (16 or 64)-QAM modulation formats using a dual drive Mach-Zehnder Modulator (DD-MZM) with a continuous wave laser. With the aim to obtain different levels of phase noise, laser linewidths of 1 kHz, 25 kHz and 100 kHz are used. Launch powers of 0 dBm and 9 dBm are guaranteed by an ideal amplifier at the output of the optical transmitter, to stimulate nonlinear effects in the last case. Optical signals are transmitted through single mode fiber (SMF) with distances up to 90 km in one span. Optical noise is injected to yield and OSNR values from 10 to 25 dB. The optical coherent receiver includes a laser with the same configuration as the one used at the transmitter side. DSP module includes chromatic dispersion compensation, clock recovery and linear LMS (Least Mean Square) equalizer using a training sequence of only 500 symbols. Finally, the two different ML algorithms were applied over the equalized signals which are frames of 16.384 symbols. Each symbol contains its respective I and Q component.
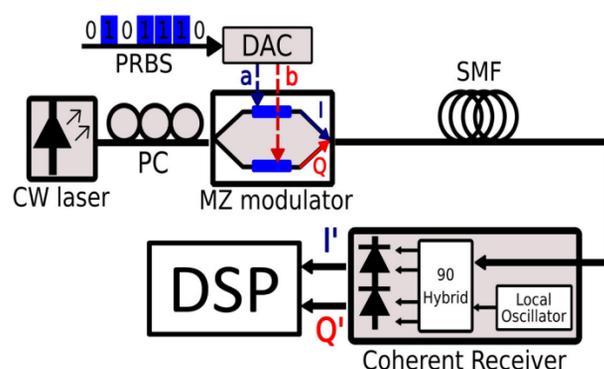

Fig. 2. Single-channel Optical System simulated in VPI and MATLAB.
Source: Authors.

III. Demodulation Based on Machine Learning

We chose two low-logical complexity algorithms because future optical access networks would require low-cost solutions in all aspects.

A. *k-Nearest Neighbors (KNN)*

The K-Nearest Neighbors algorithm is a supervised machine learning technique that identifies different classes of data based on a previous training stage [16]. The algorithm classifies data identifying the k nearest neighbors (training data) to a specific analyzed data point (in digital demodulation, it is a received symbol) based on Euclidean distance. For m-QAM modulations formats, each symbol has one I (In-Phase) and Q (Quadrature) component, these IQ values are the features of the data used in the ML process. Hence, the class is the modulation symbol (0 to 15). According to the classes of the k nearest neighbors (which are part of the training data), the most common class among them is assigned to the received symbol under evaluation. k is usually an odd number (avoiding draws). Fig. 3 shows an illustrative scheme showing the choice of the nearest neighbors, following the classification according to the commonest class in a 16-QAM constellation diagram.

The distances calculated follows (1).

$$d(X_q \ X_i) \quad \sqrt{\left(I(X_r) - I(X_t)\right)^2 \quad \left(Q(X_r) - Q(X_t)\right)^2} \qquad (1)$$

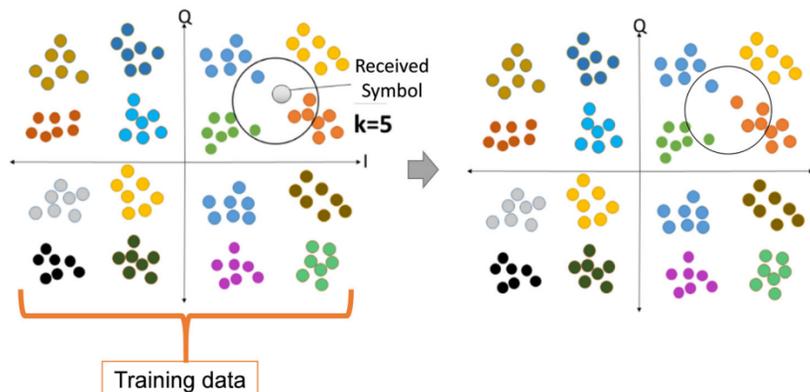Where X_q is the received symbol and X_t is an arbitrary training symbol.

Fig. 3. KNN functionality in a 16-QAM scenario.
Source: Authors.

A parametrization is needed due to not all *k* values are useful to perform the demodulation in the whole dataset. Hence, the choice of the best *k* and training length in terms of BER is carried out demodulating frames received symbols in each scenario under evaluation. For example, for a transmission distance of 50 km and laser linewidth of 25 kHz, Fig. 4a and Fig. 4b shows BER vs Training Length for different *k* values in a 16-QAM scenario with 6 dBm and 9 dBm launch power, respectively, whereas Fig. 4c and Fig. 4d shows same cases for 64-QAM. It is seen that *k* = 3 has a good trade-off in BER for all scenarios. Furthermore, a training length of 400 symbols is a good trade-off to achieve a low BER value.

B. *k-Means*

K-Means algorithm is an unsupervised machine learning technique that groups the data in 'clusters' due to its similarities [17]. For demodulation, initial cluster positions are given by the m-QAM ideal constellation points. Hence, the clusters are the demodulation symbol (as the class in KNN algorithm). Classification starts by choosing the closest cluster for each received symbol, and then, clusters centroid position is updated regarding to the total symbols classified into each cluster. Algorithm iterates until centroids do not change their positions

[18]. Fig. 5 shows the k-Means algorithm functionality in a QPSK constellation diagram. Besides, the k-Means algorithm is generalized by the minimization of (2) where k is the number of clusters.
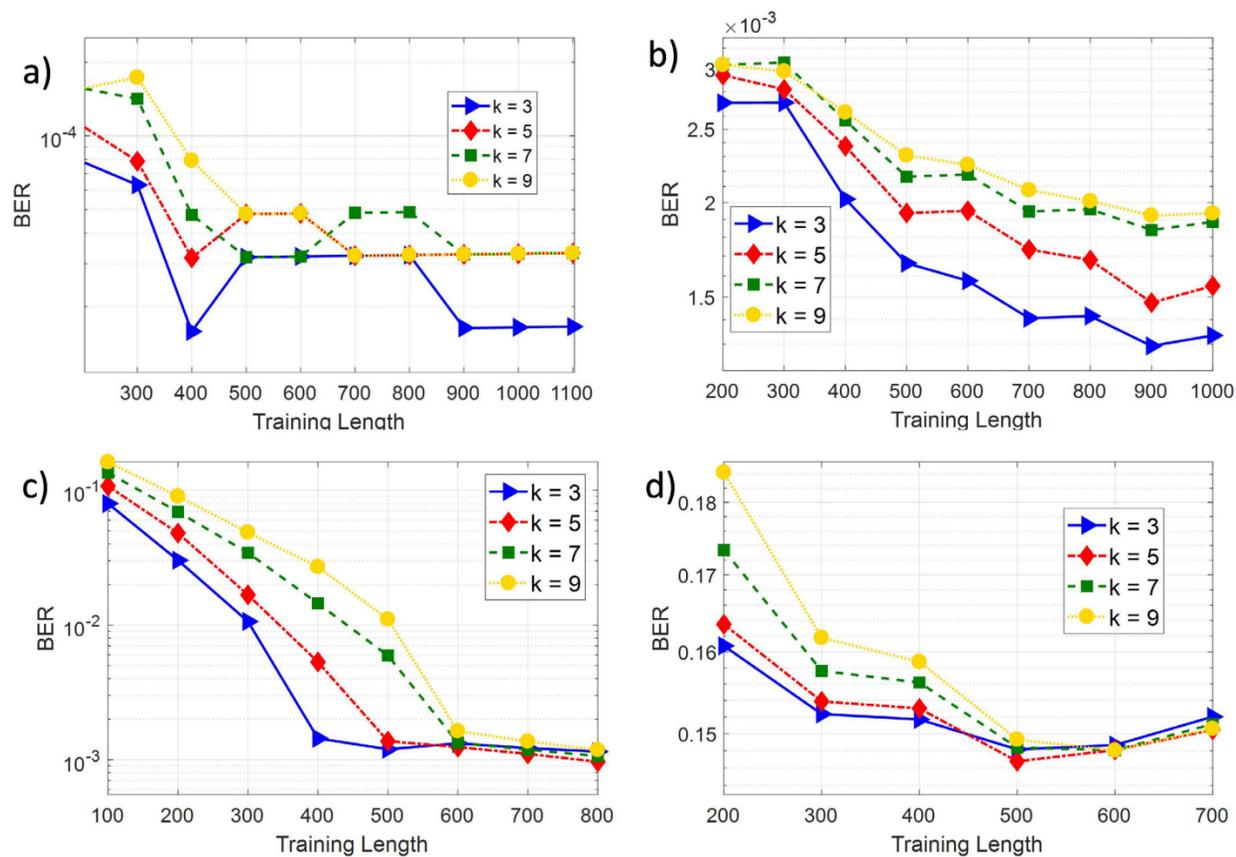

Fig. 4. BER vs Train Length for different k values in scenarios of a) 16-QAM and 6 dBm launch power, b) 16-QAM and 9 dBm, c) 64-QAM and 6 dBm, d) 64-QAM and 9 dBm.
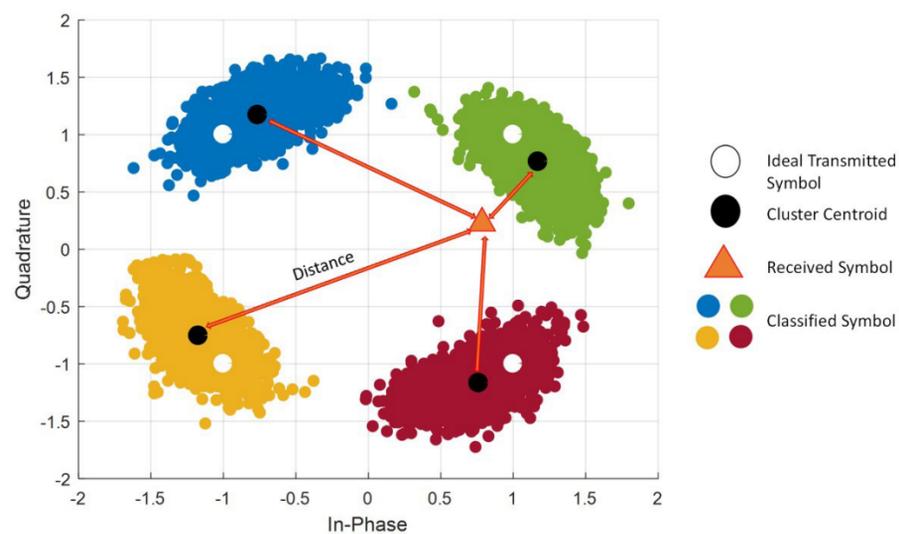Source: Authors.

Fig. 5. k-Means algorithm applied to a QPSK constellation diagram.
Source: Authors.

$$J = \sum_{j=1}^{k} \sum_{i=1}^{n} \left\| x_i^{(j)} - c_j \right\|^2 \tag{2}$$

Then, the centroids position is updated by the mean estimation of the classified data (3).

$$c_j = \left(\frac{1}{n} \right) \sum_{i=1}^{n} x_i^{(j)} \tag{3}$$

IV. Results and Discussion

A. *16-QAM*

First, the proposed techniques are evaluated for different launch power: 0 dBm, 3 dBm, 6 dBm and 9 dBm in a scenario with 25 kHz laser linewidth, 50 km transmission distance at 32 Gbps. Results are shown in Fig. 6. Gains achieved by using k-Means increase when the launch power is higher. For example, at 3 dBm launch power (Fig. 6b), the OSNR gain is ~0.5 dB at a BER value of 1×10^{-2}, meanwhile for 9 dBm (Fig. 6d) the gain is ~1.6 dB.
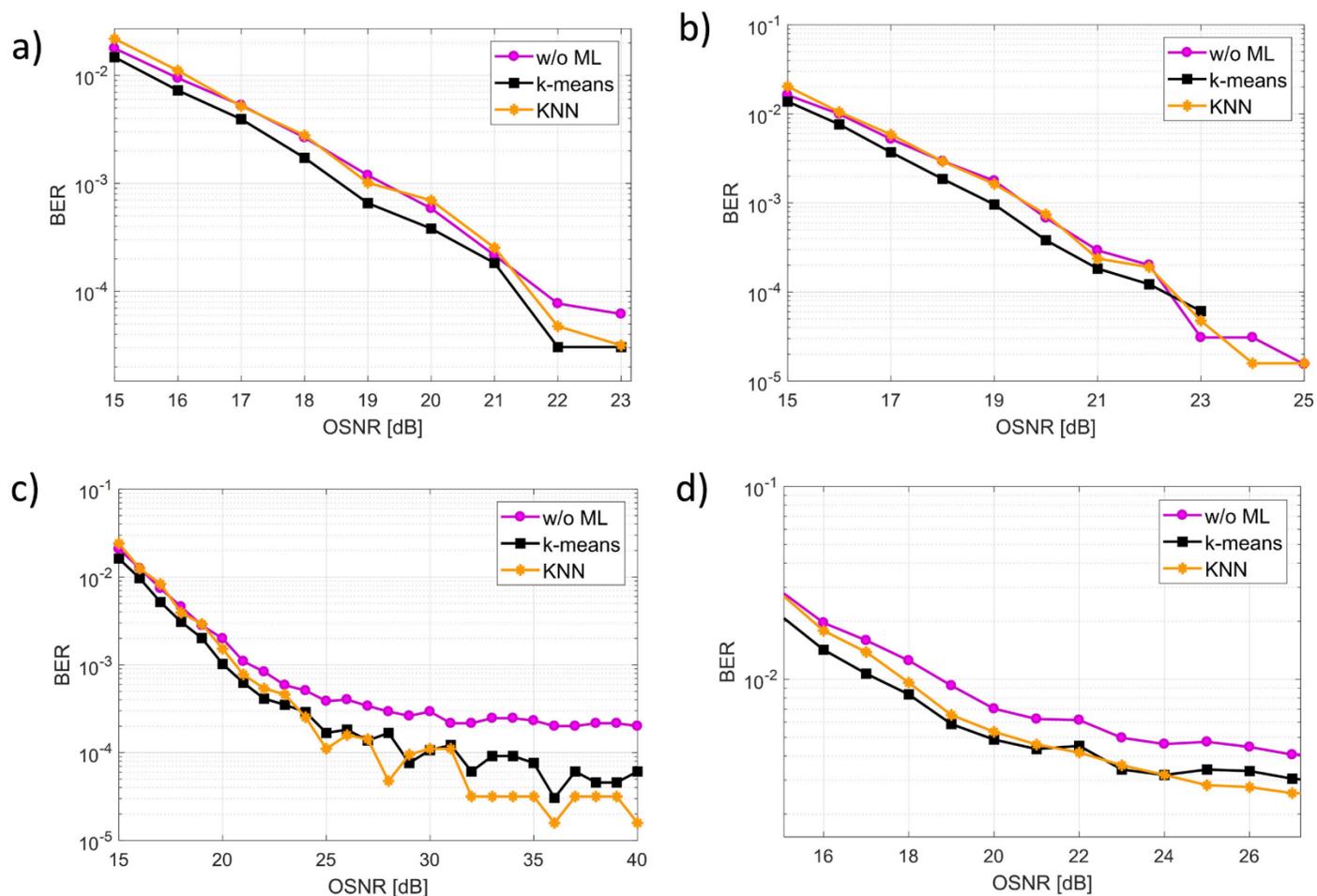

Fig. 6. 16-QAM BER vs OSNR for scenario of 25 kHz laser linewidth, 32 Gbps data rate and 50 km of transmission distance for a) 0 dBm launch power, b) 3 dBm, c) 6 dBm, d) 9dBm
Source: Authors.

Furthermore, similar behavior is seen by using the KNN-based demodulation. Improvement in terms of BER is higher regarding to the launch power increment. For example, at 0 dBm launch power, KNN did not show BER improvement due to nonlinear distortions are not stimulated, in contradiction to 9 dBm, where gains are similar as the achieved ones by using k-Means. Hence, we evidence that both techniques can mitigate nonlinear impairments due to high launch power.

Besides, results based on variation of laser linewidth and transmission distance at data rate of 32 Gbps for two different OSNR values are shown in Fig. 7. Fig. 7a shows BER vs Transmission distance for an OSNR of 16 dB. It can be seen how the ML techniques improve the BER performance when transmission distance is higher. Moreover, the BER achieved by using k-Means with a laser linewidth of 100 kHz is similar to the BER reached by conventional demodulation with a laser linewidth of 25 kHz. Meanwhile, for an OSNR of 19 dB (Fig. 7b), this behavior is even better by using the k-Means demodulation compared to the conventional demodulation. Furthermore, the gain in terms of BER is higher when laser linewidth is 100 kHz by using the ML-based demodulation.
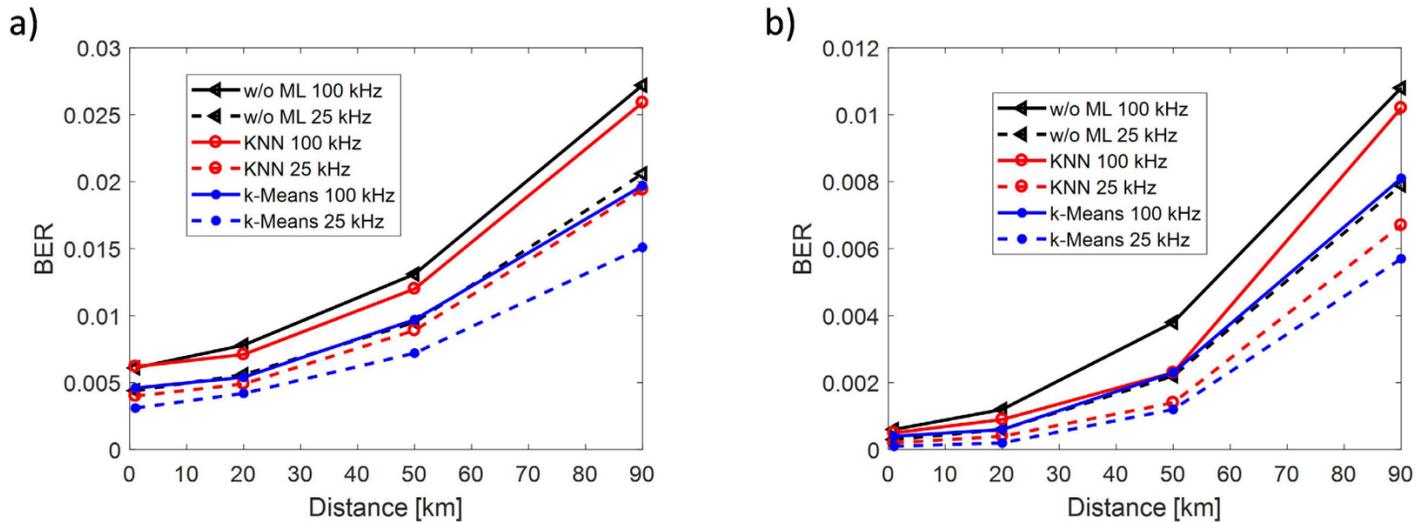
Fig. 7. 16-QAM BER vs Distance demodulation with variation of laser linewidth at a
data rate of 32 Gbps for OSNR of a) 16 dB, b) 19 dB.
Source: Authors.

In addition, ML techniques are evaluated for different bit rates with laser linewidth of 100 kHz. BER vs transmission distance is shown in Fig. 8. It is evidenced that at 50 km transmission distance, BER performance by using the ML techniques at 32 Gbps is better than at 28 Gbps using conventional demodulation. Thus, we demonstrated that it is possible to increase the network capacity only adding ML modules in the coherent receiver. Besides, BER performance using k-Means in a 90 km transmission distance at 32 Gbps is almost the same as conventional demodulation at 28 Gbps for both OSNR value, 16 dB and 19 dB. This confirms that it is possible to increase the network capacity maintaining BER requirements. On the other hand, by using KNN there is not significant BER improvement at 16 dB for any of the data rates, but, when OSNR is 19 dB a gain of ~0.001 in terms of BER is achieved at 28 Gbps.
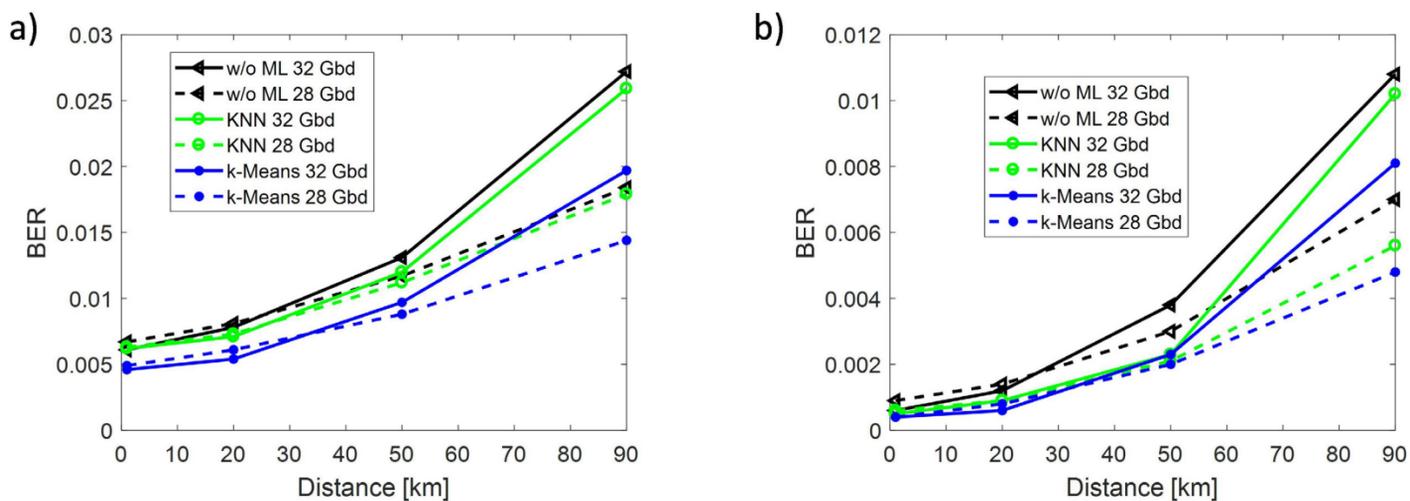

Fig. 8. 16-QAM BER vs Distance demodulation with variation of data rate with laser
linewidth of 100 kHz for OSNR of a) 16 dB, b) 19 dB.
Source: Authors.

B. *64-QAM*

First, evaluation of the proposed demodulation techniques for different launch powers are shown in Fig. 9, in a scenario of 25 kHz laser linewidth and 50 km transmission distance. Gains in terms of OSNR are only distinguishable at launch power of 0 dBm (Fig. 9a), where at a BER value of 3×10^{-3}, using the KNN algorithm, a gain of 2.5 dB is achieved, on the other hand, by using k-Means ~4 dB is reached. Besides, at 6 dBm launch power (Fig. 9c), conventional demodulation reached a BER of 1.9×10^{-2}, meanwhile by using KNN and k-Means BER of 1.3×10^{-2} and 0.8×10^{-2} were achieved, respectively.

Furthermore, at 9 dBm launch power, data transmission was not recovered. Thence, analysis for different laser linewidth and transmission distance for two OSNR values is shown in Fig. 10 at data rate of 28 Gpbs. For cases at 50 km transmission distance, the non-symmetrical demodulation using the *k*-Means always showed a BER improvement compared to conventional demodulation, with gains around ~0.03 at 25 kHz laser linewidth for 16 of OSNR. Moreover, KNN did not show BER gain at 50 km transmission distance and 25 kHz laser linewidth. This is because high distorted symbols may create confusion in neighbors' class choosing.
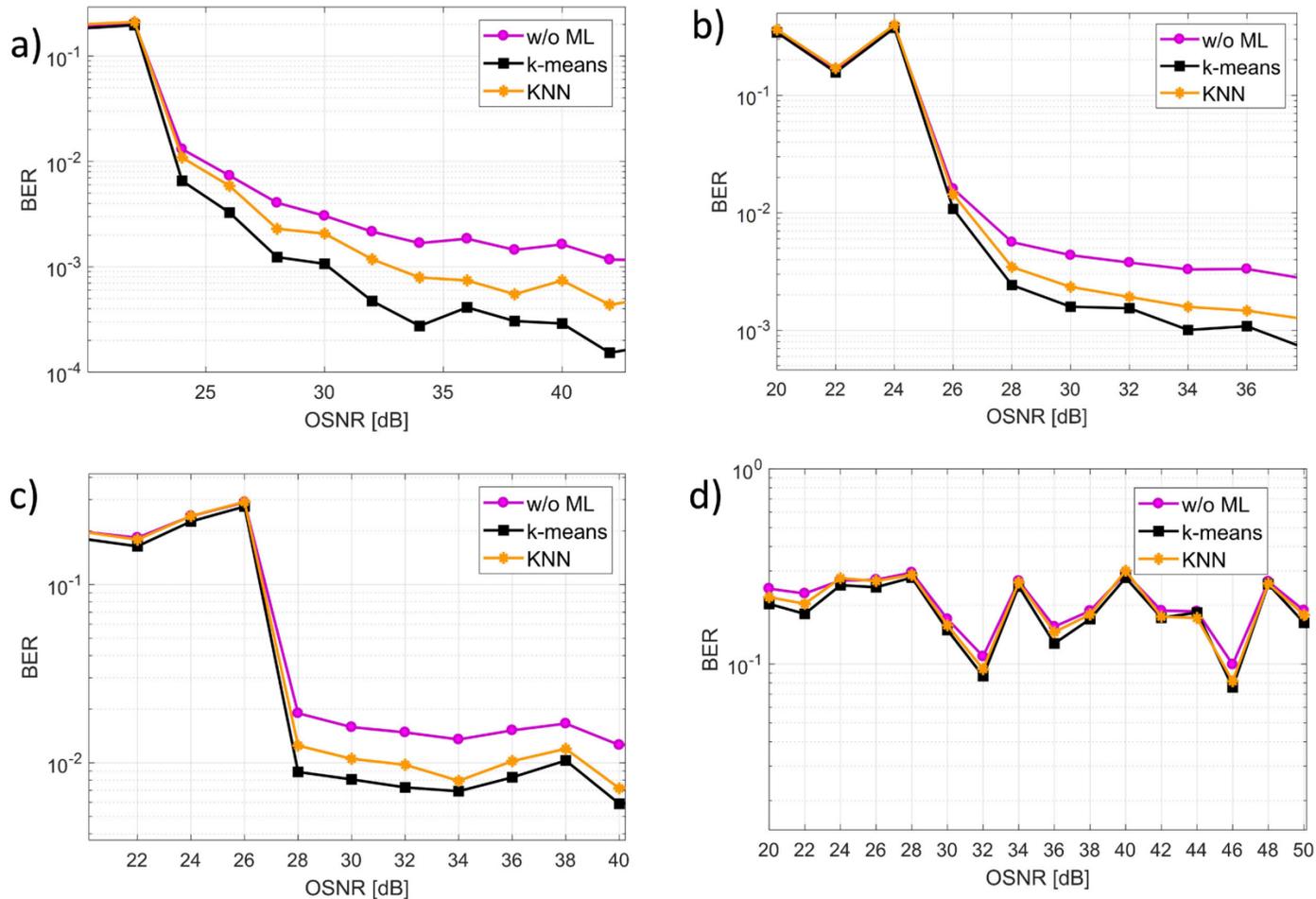

Fig. 9. 64-QAM BER vs OSNR for scenario of 25 kHz laser linewidth, 32 Gbps data rate and 50 km of transmission distance for a) 0 dBm launch power, b) 3 dBm, c) 6 dBm, d) 9dBm.
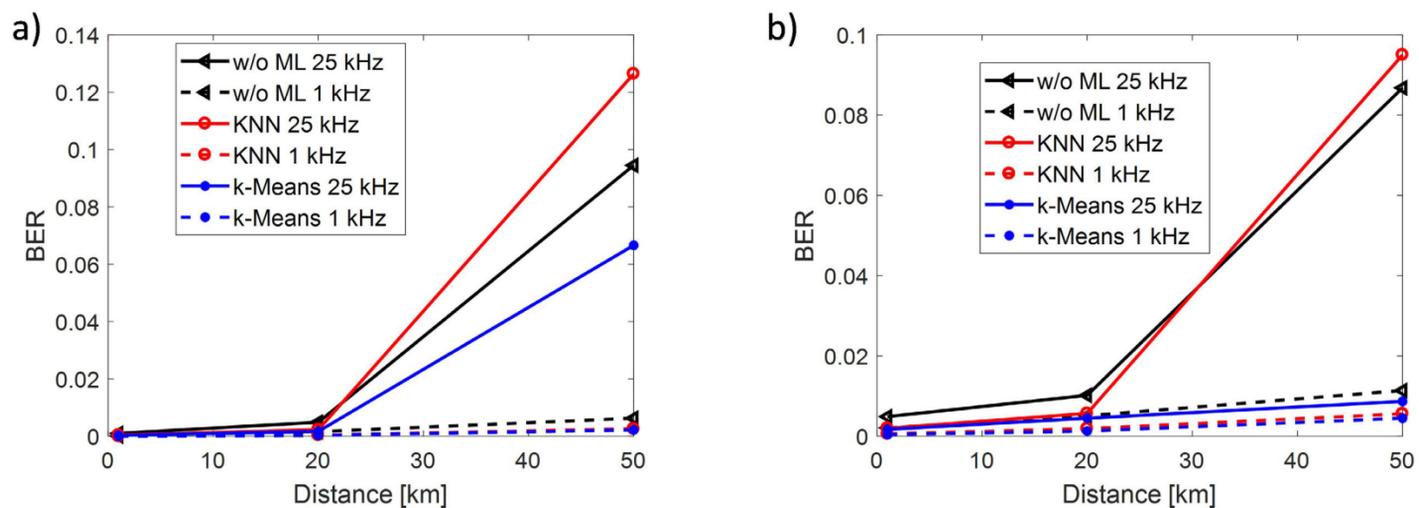Source: Authors.

Fig. 10. 64-QAM BER vs Distance demodulation with variation of laser linewidth at a data rate of 28 Gbps for OSNR of a) 26 dB, b) 32 dB.
Source: Authors.

V. Conclusions

The k-Nearest Neighbors and k-Means algorithms were implemented to perform non-symmetrical demodulation for 16-QAM and 64-QAM modulation formats in DSP-based coherent receivers of optical access networks. By using these ML techniques, mitigation of non-linear effects due to high launch power and mitigation of phase noise due to the laser linewidth were demonstrated. Results showed that for 16-QAM, demodulation based on k-Means and KNN can reduce the BER at 50 km transmission distance and 25 kHz laser linewidth for launch powers higher than 6 dBm, with gains up to 2 dB. Furthermore, the worst performance using ML-based demodulation is equal to the conventional demodulation, thus, the use of the ML algorithms would enable time-varying distortions in different nonlinear scenarios. Besides, the use of k-means or KNN in 16-QAM demodulation for all transmission distances evaluated, showed that it is possible to use a lower cost laser (100 kHz linewidth vs 25 kHz) with a better BER performance than using conventional demodulation. This is important because the deployment of new generation optical networks would require low-cost solutions in transmission as well as in reception and these techniques are transparent for the signal impairments, thus, could be implemented in any optical fiber-based communications system. Finally, the use of k-Means requires low computational processing when modulation format is defined, nevertheless, the use of KNN and any other supervised ML techniques would require a computational complexity study for implementation in optical access networks. Thence, evaluation of computational complexity for supervised algorithm is an opened opportunity for future work.

Acknowledgments

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