Optimization Method for Unrepeatered Optical System Employing Probabilistic Shaping

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***Abstract*—We evaluate the design of an unrepeatered optical system based on the simultaneous optimization of its transmission, reception, and amplification parameters by a neural network algorithm (NNA), aiming at maximizing the achieved mutual information (MI). After transmission system design, the probabilistic shaping (PS) method applying the Maxwell-Boltzmann (MB) and supergaussian (SG) distributions is also optimized by an NNA considering MI as the objective function. Non-uniform constellations achieved transmission rates slightly higher than the uniform case. The minor gains observed for the MB and SG distributions suggest that their implementation may not be advantageous in the investigated case study.**

***Keywords*—Unrepeatered optical system, probabilistic shaping, system optimization.**

I. Introduction

WITH the advent of technologies that enable the development of next-generation (5G/6G) mobile networks, data streaming, and augmented reality, there is an exponential increase in the demand for data transmission capacity of communication systems. In this context, optical networks are a key technology to meet the current demand for telecommunications infrastructure. Specifically, unrepeatered optical systems, which do not have active elements along the link, are an important alternative to provide high-capacity connectivity in areas of difficult access or submarine applications [1, 2].

In the design of such systems, a maximum propagation power threshold is typically imposed for the transmitted channels to prevent them from being degraded by Kerr-related nonlinear effects arising from the propagation of high optical power through the optical fiber [3–5]. This technique is commonly used due to the complexity, cost, and energy consumption associated with digital signal processing (DSP) algorithms for nonlinear compensation. However, this solution is suboptimal, since only the power propagation profile and noise insertion are evaluated, neglecting other inherent propagation effects of a modulated channel through an optical link. Additionally, non-uniform constellations using probabilistic shaping (PS) have been widely used as an alternative to increasing the data transmission capacity of communication systems [6, 7]. However, despite being well consolidated in the literature, this technique has still been little explored concerning unrepeatered optical systems.

This work presents the design of an unrepeatered optical system based on the optimization of its transmission, amplification, and reception parameters by an optimization algorithm with a heuristic inspired by neural networks (Neural Network Algorithm – NNA) [8]. The proposed optimization procedure maximizes the mutual information (MI) without considering a priori maximum propagation power limit for the transmitted channel, aiming to achieve the best compromise between linear and non-linear degradation for the evaluated scenario. Furthermore, we conduct performance analysis using PS with various probability distributions, where the NNA algorithm is used to optimize the parameters of each distribution. In this sense, this paper is organized as follows: Section II describes the NNA algorithm's optimization methodology; Section III presents the method for designing an unrepeatered optical system using NNA; Section IV discusses the methodology used to optimize the probabilistic shaping scheme; Section V presents the results obtained considering different probability distributions; and Section VI concludes the paper.

II. Neural Network Algorithm

The Neural Network Algorithm aims to find an optimal solution to either maximize or minimize a given function, which may correspond to a performance metric [8]. The algorithm is inspired by the functioning of neurons in biological nervous systems, which leads to its implementation based on the architecture of artificial neural networks (ANNs). Figure 1 provides a flowchart detailing the operation of the NNA. First, a vector of random variables, X, is generated, representing the variables to be optimized. Additionally, a vector of weight values, W, is generated, playing the same role as weights in ANN, that is, minimizing the error between the network's predicted output and the correct output. Then, the vectors X and W are updated for the next iteration.

To mitigate the risk of converging to local minima or maxima, the algorithm employs two functions, operator bias and transfer function, which enhance the exploration of the solution search space. The first function is analogous to the mutation stage in genetic algorithms [9], acting as a noise that changes the values of X and W, allowing for broader exploration of potential optimal solutions and preventing premature convergence. The transfer function modifies new

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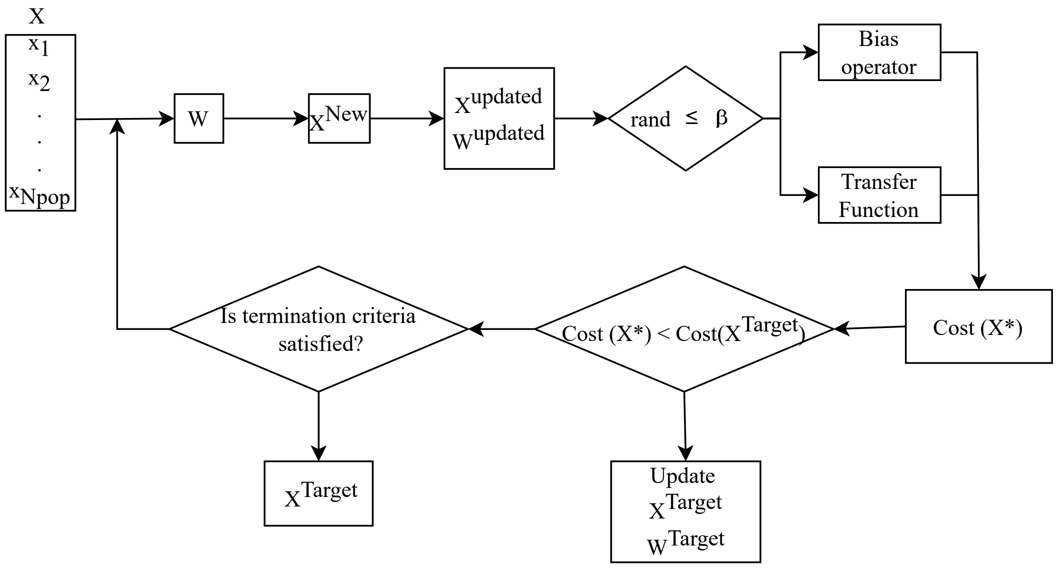


Fig. 1. Flowchart describing the NNA.

standard solutions, gradually bringing them closer to the target solutions found, as defined in Eq. 1:

$$TF(X_i(t+1)) = X_i(t+1) + \tag{1a}$$
$$2 \times rand \times (X^{Target}(t) - X_i(t+1)), \tag{1b}$$
$$i = 1, 2, ..., N_{pop}. \tag{1c}$$

where $Xi(t+1)$ is the X values of the next iteration after the step of update, $X^{Target}(t)$ is the optimal values of the vector X for maximizing or minimizing the cost function, finally N_{pop} is the size of the population of standard solutions.

After the Bias Operator or Transfer Function, the cost function is applied in the resulting X, and then compared with X^{Target}. If the result of the cost function applied in X is lower than the cost function applied in X^{Target}, X^{Target} is updated with the X value. Otherwise, X^{Target} stays the same. Subsequently, the termination criteria is verified, and the optimized X is returned. In this work, the cost function is the MI of the optical transmission, and the termination criterion is the maximum number of iterations. This optimization algorithm was selected due to its demonstrated ability to locate global optimal points and its convergence velocity efficiency.

III. Unrepeatered Optical System Design

Figure 2 summarizes the main building blocks of an unrepeatered optical transmission system. The transmitter (Tx) accomplishes electro-optical conversion. The receiver (Rx) includes electro-optical front-ends and the digital signal processing (DSP) chain to compensate for deleterious effects arising during transmission. To increase the optical link maximum reach, the amplification architecture comprises distributed Raman amplification (DRA) and remote optical pump amplification (ROPA) stages, both with remote pump units (RPUs) for forward and backward pumping schemes.

The proposed design method is implemented using an optical simulator developed in-house coded in Python, transmitting a single 1550-nm channel with quadrature amplitude modulation in 64 levels (64QAM) with 32-GBd symbol rate through a 300-km optical link. On the transmitter side, a DSP-Tx stack is employed to create the modulated optical signal through the generation of pseudo-random symbols and applying root raised cosine pulse shaping with a 0.1 roll-off factor. Subsequently, the digital-to-analog converter (DAC) converts the digital sequence into an analog waveform that modulates the optical carrier in both polarizations. The optical signal propagates through a first span composed of low-loss single-mode fiber (0.18-dB/km attenuation, 16-ps/nm/km chromatic dispersion, and 1.35-km^{-1}W^{-1} nonlinear parameter at 1550 nm) emulated with the split-step Fourier (SSF) method, where the signal is amplified by a forward-pumped DRA-Tx followed by a ROPA-Tx. The signal subsequently propagates through an intermediate link before being amplified again, this time by backward-pumped ROPA-Rx and DRA-Rx amplifiers. Finally, the signal reaches the receiver (Rx), where it is initially detected by the electro-optical front-end comprised by a $90°$ hybrid and a local oscillator, followed by balanced photodetectors, resulting in an electrical signal. This signal is converted to the digital domain by an analog-to-digital converter (ADC) and processed by the DSP-Rx. The implemented DSP chain is composed of orthonormalization, chromatic dispersion compensation, decision-directed least mean square (DD-LMS) for dynamic equalization, carrier recovery with unsupervised blind phase search (BPS), and 4^{th}-power carrier phase and frequency recovery stages. Finally, the mutual information (MI) is calculated and employed as the objective function for the NNA to optimize the system parameters. The transmitter, receiver, and amplification parameters to be optimized, as well as their search ranges, are presented in Table I. In the proposed optimization procedure, the algorithm employs 15 variables, a

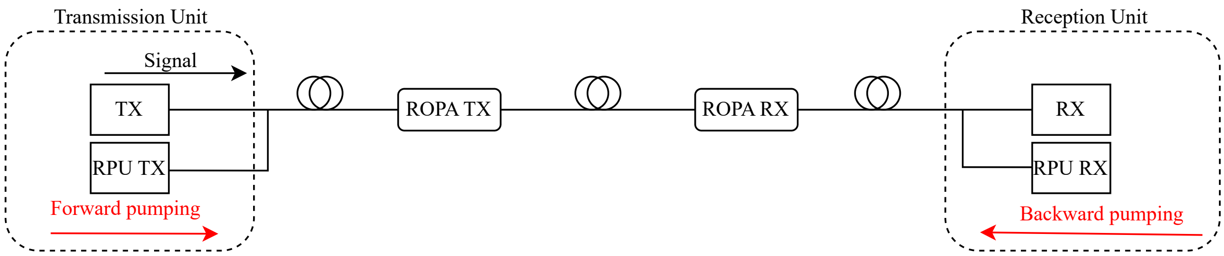


Fig. 2. Diagram architecture of an unrepeatered optical system.

population of 45, and a maximum of 10 iterations. The power profile of the resulting system is presented in Fig. 3, showing a maximum propagation power of the signal equal to 4.95 dBm at the transmitter-side ROPA output. As a result, the optimized unrepeatered system achieved a MI equal to 5.57 bit/symbol, an optical signal-to-noise ratio (OSNR) in the receiver equal to 25.39 dB, and a bit error rate (BER) before forward error correction (FEC) equal to 2×10^{-2}.

IV. Probabilistic Shaping

Additionally, a probabilistic shaping encoder was integrated into the DSP-Tx stack to produce a symbol sequence conforming to the desired probability distribution to be evaluated. This encoder was implemented by constant composition distribution matching (CCDM) [10]. In this work, we consider the Supergaussian (SG) distribution [11], expressed by Eq. 2:

$$Pr(A_k) = \frac{1}{\sum_{A_i} e^{-\lambda |A_i|^N}} e^{-\lambda |A_k|^N}, k \geq 0 \qquad (2)$$

where A_k is the symbol amplitude, and λ and N are constants factors. Likewise, the Maxwell-Boltzmann (MB) [12] distribution, which is a specific case of the Supergaussian with $N = 2$, was also evaluated. Although the MB distribution is known to be optimal for an additive white Gaussian noise channel, the Supergaussian distribution is included in the analysis to eventually cope with nonlinearities. The parameters of both distributions (*i.e.*, λ for MB distribution, and λ and N for SG distribution) are also optimized by the NNA aiming at maximizing the MI.

TABLE I
Optimal unrepeatered optical link parameters obtained by NNA.

Component	**Parameter**	**Interval**	**Optimal value**
Signal	Launched Power	-5 – 5 dBm	-3.54 dBm
	Channel wavelength	1550 – 1560 nm	1550 nm
Transmitter	1^{st} DRA pump power	50 – 150 mW	63.89 mW
	2^{nd} DRA pump power	50 – 150 mW	75.63 mW
	ROPA pump power	50 – 150 mW	135.26 mW
	ROPA position	50 – 100 km	65 km
	Erbium-doped fiber length	10 – 20 m	11 m
Receiver	1^{st} DRA pump power	100 – 300 mW	173.62 mW
	2^{nd} DRA pump power	100 – 300 mW	114 mW
	ROPA pump power	100 – 300 mW	250.12 mW
	ROPA position	50 – 150 km	55 km
	Erbium-doped fiber length	10 – 20 m	14 m
Amplification	1^{st} DRA pump wavelength	1420 – 1460 nm	1455 nm
	2^{nd} DRA pump wavelength	1420 – 1460 nm	1460 nm
	ROPA pump wavelength	1475 – 1490 nm	1480 nm

V. Results

Initially, for the MB optimization, the NNA parameters were one variable (λ) and a population equal to 5, given that we considered five times the number of variables to be optimized. A maximum number of iterations equal to 10, and maximum and minimum values of λ equal to 0.1 and 0. Resulting in an optimal λ of 0.00985165, corresponding to a MI of 5.615 bit/symbol. Equivalently, the NNA parameters to optimize the SG distribution were two variables (λ and N), a population and a maximum value of iterations equal to 10, maximum and minimum values of λ equal to 0.1 and 0, respectively, and maximum and minimum values for N equal to 3.5 and 2.0, respectively. Resulting in optimized values of λ equal to 0.005229749 and N equal to 3.5 for an MI of 5.61. The maximum number of iterations was determined based on the trade-off between execution time and cost function convergence. Figures 4 and 5 present the cost function (MI) curve as a function of the NNA algorithm's iteration for the MB and SG distributions, respectively. Given the results shown, it is observed that a maximum of 10 iterations was sufficient for the cost function of both distributions to converge.

Upon completion of the optimization process, Fig. 6 depicts the resulting 64QAM constellation symbols in a three-dimensional space, with phase and quadrature components represented on the X and Y axes and the a-priori symbol probability represented on the Z. Specifically, Fig. 6(a-c) depict the uniform, MB and SG distributions, respectively. The final MI results obtained after optimization are summarized in Table II. Using the uniform distribution, the resulting MI is equal to 5.57 bit/symbol. The optimization of the MB distribution results in an optimal λ of 0.0098, corresponding to an MI of 5.61 bit/symbol. The SG optimization procedure results in an optimal λ of 0.0052 and an N of 3.5, yielding an MI of 5.61 bit/symbol.

The results indicate that both the MB and SG distributions yield small but measurable gains compared with the uniform distribution. However, an eventual increase in complexity associated with the implementation of probabilistic shaping, and the well-known impact of PS in the chain of DSP

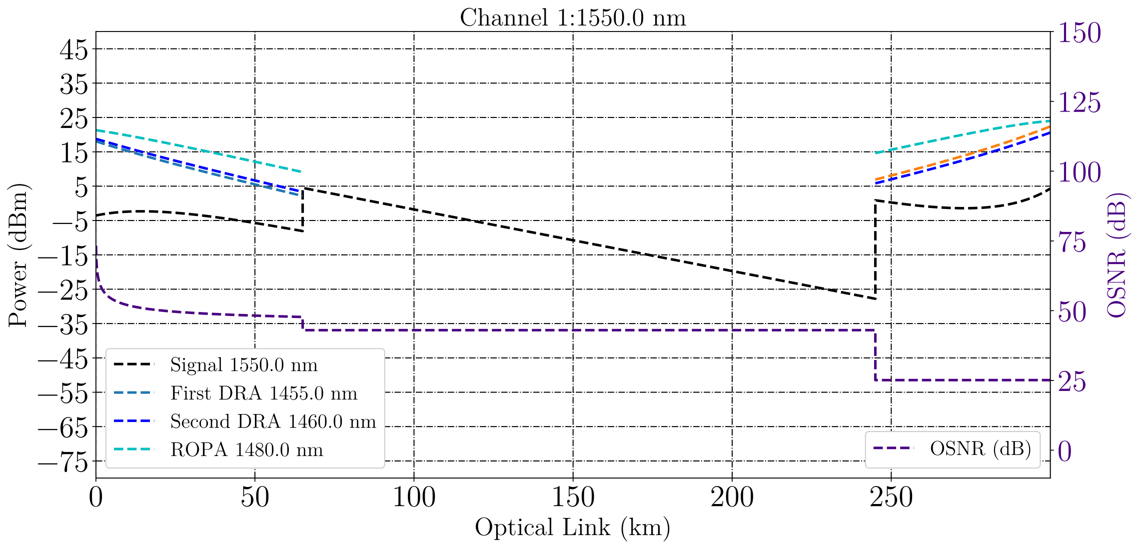


Fig. 3. Power profile of the unrepeatered system with the parameters resulting from NNA optimization.

algorithms, may not justify its implementation in the evaluated scenario. The equivalent results obtained by the MB and SG distributions suggest a Gaussian-like profile for the noise, where little gain is attained by considering the additional degree of freedom of the SG distribution. This implies that, for the unrepeatered system here considered, besides the non-definition of a maximum propagation power threshold as a design rule, the NNA resulted in a link with minimal impact of nonlinear degradation effects, being primarily limited by the insertion of amplified spontaneous emission (ASE) noise at each amplification stage.

VI. Conclusions

A method for designing unrepeatered optical links based on the optimization of systemic parameters using a neural network algorithm (NNA) was evaluated. In addition, a system performance analysis was conducted using probabilistic shaping with both Maxwell-Boltzmann and Supergaussian distributions. In this scenario, PS yielded minimal gains compared to the uniform distribution for both MB and SG distributions. These findings suggest that the complexity of PS may outweigh its benefits. The equivalent performance achieved by both MB and SG distributions suggests that the channel may resemble a Gaussian profile. In this

TABLE II
Mutual Information and the Transmission Rate Gain for the Probability Distributions Considered in the Unrepeatered Optical System Optimized.

Average Mutual Information per Polarization		
Uniform (bit/symbol)	**Maxwell-Boltzmann (bit/symbol)**	**Supergaussian (bit/symbol)**
5.57	5.62 (+1.80%)	5.61 (+1.44%)

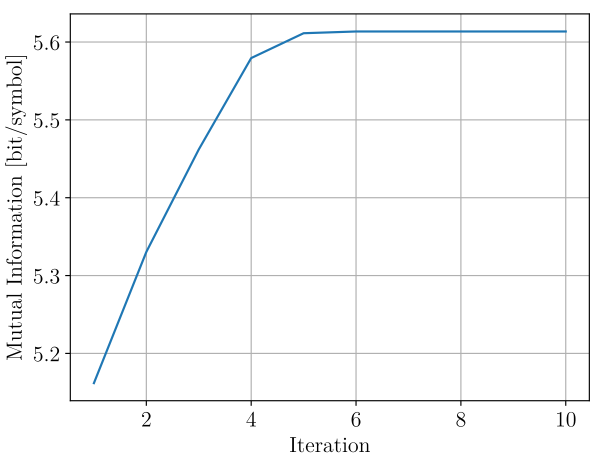


Fig. 4. Cost function (MI) as a function of NNA's iteration for cost function convergence analysis for MB distribution.

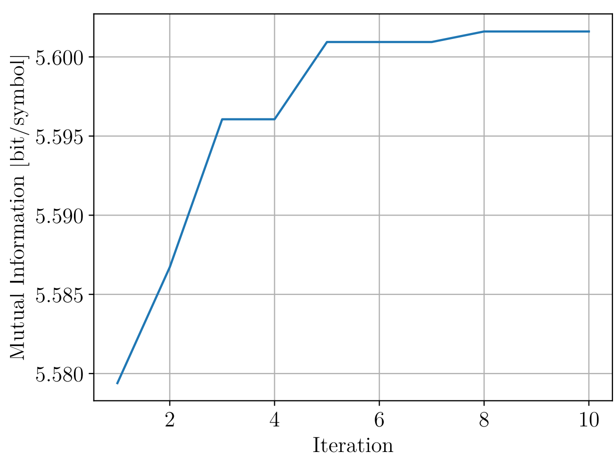
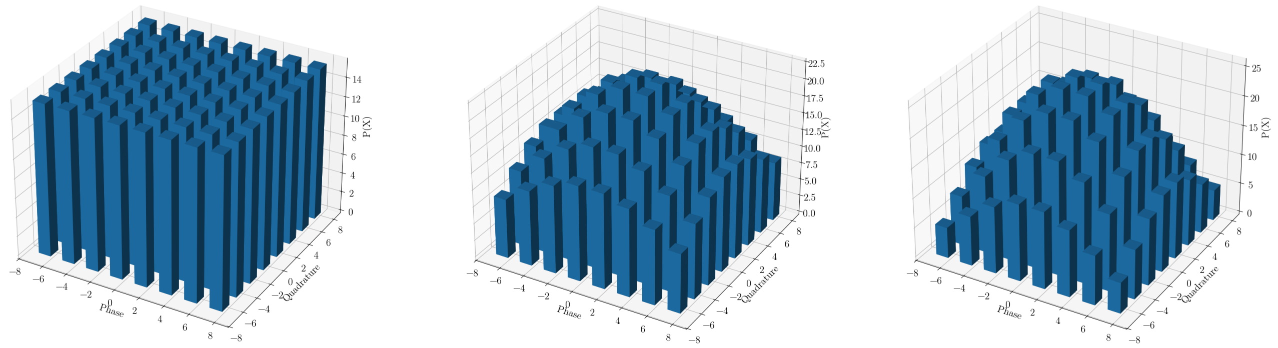


Fig. 5. Cost function (MI) as a function of NNA's iteration for cost function convergence analysis for SG distribution.



a) Constellation with uniform distribution

b) Constellation with Maxwell-Boltzmann distribution

c) Constellation with Supergaussian distribution

Fig. 6. Constellations employing probabilistic shaping with different distributions.

context, further studies may explore the application of PS in conjunction with higher-order modulation formats or in scenarios characterized by more severe nonlinear impairments, where its benefits are likely to be more substantial.

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