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Maxwell-Boltzmann PMF Design Using Machine Learning for Reconfigurable Optical Fiber Networks

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Abstract: A neural network is used to predict the optimal Maxwell-Boltzmann probabilistic constellation shaping for a nonlinear channel with inline dispersion-compensation. The network uses only system parameters available at the transmitter and thus requires no feedback. © 2021 The Authors

1. Introduction

Standard spectrally efficient optical communication systems can be improved by constellation shaping, which tailors the modulation format to the noise characteristics of the channel [1]. However, for dispersion-managed communication systems nonlinear propagation characteristics render conventional closed-form channel models insufficient and thus adaptive constellation design would require time-consuming online optimization [2]. This is disadvantageous for reconfigurable networks, where rerouting can change the end-to-end channel characteristics and thus make online optimization cause downtime.

In this paper, we demonstrate that neural networks using system parameters as input are effective at designing channel-optimized constellation shapes from the Maxwell-Boltzmann (MB) family for dispersion-managed systems. The used input parameters are all available to the transmitter and require no auxiliary feedback. The obtained probability mass functions (PMFs) achieve rates closely matching numerically optimized PMFs within a margin of 0.02 b/symbol across arbitrary distances and link configurations from 200 to 2000 km.

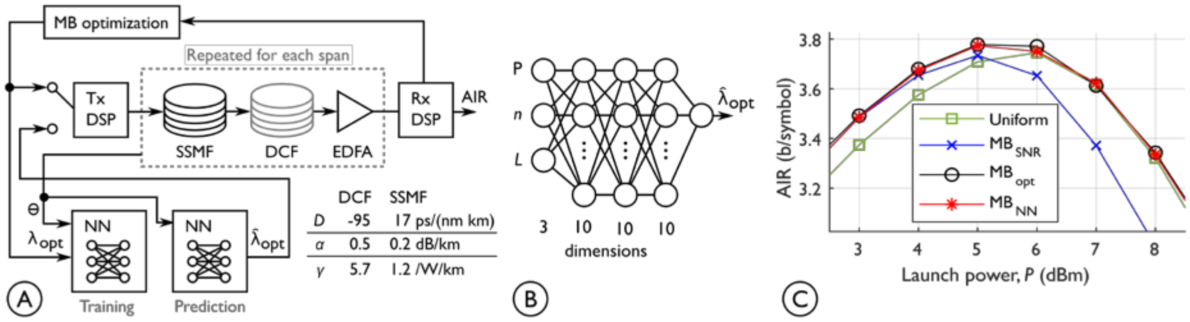

Fig. 1: (A) Simulation and training setup. Insert table shows fiber parameters. (B) Neural network for λ_{opt} prediction. (C) AIR vs. power for the four constellation types. 18 spans; 1200 km.

2. Probabilistic constellation shaping using a neural network

We will consider probabilistic constellation shaping of quadrature-amplitude modulated (QAM) symbols. A widely used choice of PMF is the MB probability distribution [3], $p(x) \propto \exp(-\lambda|x|^2)$, where x denotes the constellation symbols. For a given channel, an optimal λ_{opt} exists for the MB parameter. Under an additive, white, Gaussian noise (AWGN) channel assumption, a λ_{opt} can be chosen using a measure of the signal-to-noise ratio (SNR) [4]. For an arbitrary channel, λ_{opt} can be obtained by using expected information rate as the utility of an optimization. We seek to design a neural network, which optimizes the scalar λ_{opt} given only system parameters, which are available at the transmitter. These constraints reduce model complexity by only having scalar output and ensure fast reconfiguration by avoiding auxiliary feedback, like SNR estimates. A setup for training and model validation is shown in Fig. 1: (A) Simulation and training setup. Insert table shows fiber parameters. (B) Neural network for λ_{opt} prediction. (C) AIR vs. power for the four constellation types. 18 spans; 1200 km.(A). The system parameters, Θ, consist of launched signal power, *P*, the number of spans, *n*, and total transmission distance, *L*. The individual span lengths are not explicitly part of the input parameters, and non-uniform lengths are used in the training data in order to better resemble practical scenarios. The neural network, in Fig. 1: (A) Simulation and training setup. Insert table shows fiber parameters. (B) Neural network for λ_{opt} prediction. (C) AIR vs. power for the four constellation types. 18 spans; 1200 km.(B), is composed of three hidden layers of 10 dimensions, with tan-sigmoid activation functions and an output layer with a linear activation function. The model is trained using the Levenberg-Marquardt algorithm [5]. We note that no channel-specific modeling is used in the neural network.

The training data is generated using a split-step Fourier method (SSFM) simulation of an optical fiber channel composed of multiple spans. Each span consists of a segment of a standard single-mode fiber (SSMF) of random length <100 km, followed by a segment of dispersion-compensating fiber (DCF), length-tuned to undo dispersive effects [6]. Between each span is an Erbium-doped fiber amplifier (EDFA) with a noise figure of 3 dB. The transmitted signal is a 7-channel, dual-polarization wavelength division multiplexed symbol sequence of 10^5 64-QAM symbols per channel with probabilistic shaping, a 0.01 roll-off root-raised cosine pulse shape and a fixed symbol rate of 32 GBd. The receiver estimates the achievable information rate (AIR) using the mismatched decoding principle [7]. The AIR is used as the utility function for finding channel-optimal MB PMFs. The system parameters of the channel are varied to produce the training data for the neural network. The data set includes variations of: launch powers ranging from 0 to 12 dBm and number of spans from 4 to 20 spans. Span lengths are randomly drawn and need not be uniform, resulting in random total transmission distances between 200 km and 2000 km. The dataset is ensured to contain the boundary cases of 200 and 2000 km. The total of 400 such configurations are split into 75 % for training, 5 % for validation and 20 % for testing. Optimal MB PMFs, denoted MB_{opt}, are found for all cases using numerical search.

3. Results

In Fig. 1: (A) Simulation and training setup. Insert table shows fiber parameters. (B) Neural network for λ_{opt} prediction. (C) AIR vs. power for the four constellation types. 18 spans; 1200 km.(C), AIR vs. power is plotted for a test configuration, where the SNR-designed MB PMF, MB_{SNR}, is a suboptimal choice at and above the optimal launch power. The neural network predicted MB constellations, MB_{NN}, are able to consistently outperform or match uniform, speaking to its ability to make the trade-off between linear and nonlinear effects, without having explicit knowledge of the given scenario. Compared to MB_{opt}, MB_{NN} achieves within 0.02 b/symbol of the maximum attainable gain. To observe the rate improvement obtained from the shaping, the maximum rate for each constellation shape is compared at several test configurations in Fig. 2. The improvement is relative to the uniform, unshaped constellation and all values are taken at the respective optimum power, which varies slightly depending on the choice of constellation shape. For all distances, we note a good correspondence between MB_{NN} and MB_{opt}, with a deviation of less than 0.02 b/symbol. AWGN assumptions are insufficient to model the nonlinear effects, revealed in the lower performance of MB_{SNR} compared to MB_{opt}. This is especially pronounced as span length increases, where MB_{SNR} in several cases tend to underperform compared to uniform, unshaped constellations. However, MB_{NN} manages to adapt only based on high-level system parameters to these effects arising from both linear noise contributions and nonlinear signal interaction. For a few number of spans (4 spans), the shaping gain is overall small for the chosen 64-QAM and we note a near exact correspondence in rate improvement. For long distances, above 1600 km, the rate improvement from MB_{opt} is close to zero and thus a predictive model can not achieve a gain over uniform. The nonlinear effects penalize the MB constellations and they reduce to uniform constellations [2].

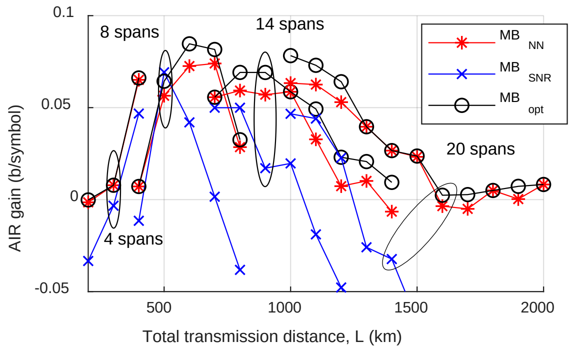

Fig. 2: Improvement in AIR at optimum power vs. transmission distance for different number of spans.

4. Conclusions

A neural network can be used to predict near-optimal choice of Maxwell-Boltzmann probabilistic constellation shapes using only system parameters as input. The obtained constellations outperform SNR-based methods, despite not relying on any auxiliary feedback. The model-predicted constellations achieve gains within 0.02 b/symbol of that of numerically optimized constellations.

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