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***Abstract*— Optical amplifiers play a critical role in the optimization of communication systems striving to achieve maximum throughput. Here, we review recent efforts in amplifier modeling – from physics-based to black-box modeling – for amplifier inverse design to full system optimization.**

Keywords—optical amplifiers, NN models, optimization

I. INTRODUCTION

Wideband optical amplification has been a key enabler for optical communication systems opening up to the era of wavelength-division multiplexed (WDM) communication. An amplifier's performance in terms of gain and noise properties over frequency is critical in defining the performance of a communication system. The recent interest in opening up new communication bands (L-band, S-band, E-band, etc.) [1-3] further boosted the interest in accurate and easily tractable amplifier models. The research focus has been dedicated to both *direct* and *inverse* models. Direct models map the amplifier tunable properties (e.g. pumping characteristics) – inputs to the model – into its spectral gain and noise response – outputs of the model. Inverse models, instead provide the amplifier settings – output of the model – required to achieve a target amplifier spectral response – input to the model. Whereas direct models can be realized both through physics-based and black-box modeling, inverse modeling normally requires a black-box approach.

In this short review, we aim at providing a brief insight into the most common black-box modeling approach based on neural networks that have been reported for different amplifier technologies. The recent efforts on the topic are summarized and links between the works are discussed. Finally, the need for amplifier modeling is put in perspective focusing on the use of models for full system optimization.

II. NEURAL NETWORK MODELS

The physics behind the most common amplifier technologies such as erbium-doped fiber amplifiers (EDFAs) or Raman amplifiers is well understood. However, when it comes to modeling physical devices, physically accurate models may be either difficult to fit to physical devices due to hard-to-measure physical parameters [4] or computationally involved to solve [5]. This inherently impairs the ability to optimize efficiently the operation of optical amplifiers.

In the context of flexible networks, a fast reconfiguration of optical amplifiers is desirable [1,2]. Therefore, machine learning (ML) models based on neural networks (NN) have been proposed. These models can be implemented very efficiently, providing sub-ms inference time, and, perhaps more importantly, are inherently differentiable. Fig 1 shows an example of the direct (a) and inverse (b) models proposed in [6] for a Raman amplifier. In the direct model, the function relating the Raman pump wavelength and powers (inputs) to the spectral gain (output) is learned by the NN either from numerical data [6] or directly from experimental measurements [7]. More evolved NN-based modeling has been also proposed to take into account the input channel load to the amplifier [8], or the prediction of the amplifier noise figure [9]. Ultra-wideband operation for Raman amplifiers can be achieved by increasing the number of pumps, which inherently makes the amplifier optimization more complex, further justifying the need for computationally efficient models. NN-based modeling for 100-nm [10] and 150-nm operation have been reported [7]. Finally, inverse modeling of Raman amplifiers can be extended to focus on the amplifier response over both frequency and distance. This has been proposed [11] and experimentally validated [12], to provide additional flexibility in the optimization of distributed Raman amplification over transmission links, e.g. for applications such as nonlinearity compensation techniques [13].

Similar NN-based modeling approaches have been applied to EDFA amplifiers [14-16], semiconductor optical amplifiers [17], more exotic Bismuth-doped fiber amplifiers [18], and hybrid EDFA-Raman amplifiers [19,20].

An advantage of such NN-based black-box models is indeed their ability to be trained directly from experimental data. However, due to the inherent nonlinear fitting ability of a NN, a model overfitted to a single physical device would not be of great interest. The ability of black-box models to generalize to multiple physical devices has been investigated for EDFAs [13] as well as Raman amplifiers [21], showing promising prospects for moving beyond a unit-specific model. In the latter work, generalization to amplifiers relying on different fiber types has been achieved by proposing the use of a NN model pre-trained on synthetic data generated through a loosely fit numerical model, followed by a quick re-training stage (following the paradigm of transfer learning) using experimental measurements [14]. A similar approach was discussed in [22].

Finally, such black-box models can be used together with well-established amplifier optimization approaches, such as genetic algorithm [23,24], by relying on the inverse models to provide an accurate initial condition for the online optimizer,

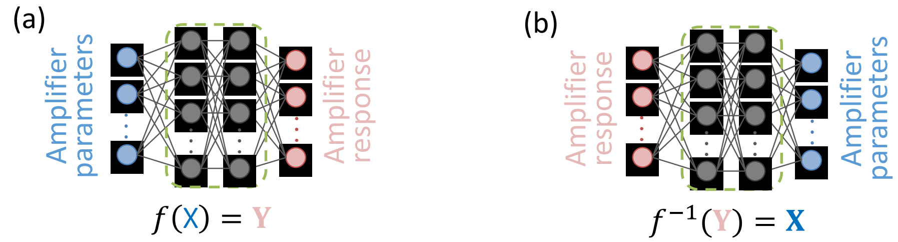

Figure 1 NN models for a fiber amplifier: (a) direct and (b) inverse model.

thus significantly increasing its convergence speed [25].

III. Full System Optimization

Whereas the modeling of a single amplifier stage may be of interest for specific applications, in the context of an optical communication system, it is desirable to optimize the full system for the best throughput or spectral efficiency. System optimization on a live system is challenging, but possible with approximate solutions [26]. Alternatively, offline optimization can be applied. It consists of either a full physical model [27], a combination of black-box models and physical models [28], or a full digital twin of the target system [29]. For off-line optimizations, NN-based models are particularly interesting as they are inherently differentiable, allowing for standard and efficient gradient-based optimization routines to be applied.

It should however be noted that NN-based models become relevant only when the physical models are not inherently differentiable or inaccurate. In the context of Raman-amplified links, the only part of the nonlinear Schrödinger equation – a highly accurate model – being inherently not differentiable is the Raman gain coefficient. Replacing such a component with a fitted differentiable model [27,30] is sufficient to allow for gradient-based optimization over the physically accurate model.

IV. Conclusions

We have reviewed the recent work on NN-based amplifier modeling and placed it into context from the perspective of optical communication system optimization.

Acknowledgment

This work was supported by the ERC-CoG FRECOM project (grant no. 771878), the Villum Young Investigator OPTIC-AI project (grant no. 29334), DNRF SPOC, DNRF123, and Ministero dell'Università e della Ricerca (PRIN 2017, project FIRST).

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