Master's Dissertation

Evaluating the impact of EDFA response modeling in the optical network QoT estimation

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supervised by
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Computing Institute
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FEDERAL UNIVERSITY OF ALAGOAS
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EVALUATING THE IMPACT OF EDFA RESPONSE MODELING IN THE OPTICAL NETWORK QOT ESTIMATION

Master's Dissertation submitted to the Computing Institute of the Federal University of Alagoas in partial fulfillment of the requirements for the degree of Master of Science in Informatics.

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Dedication

I dedicate this work to my mother Gilvanete and my brother Alyson, for always believing in me and for making me believe too.

Allan Amaro Bezerra da Silva

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I thank my family for understanding my commitment to this research and for always being by my side during these little more than 2 years of postgraduate studies, for them all the effort was worth it. I thank my girlfriend Samira for her patience and understanding during all the canceled commitments and difficult moments of absence, supporting me and being a point of tranquility in the midst of a lot of turbulence. I thank my friends for celebrating my achievements and never letting me get discouraged. Finally, I thank my supervisor Prof. Dr. Erick de Andrade Barboza, for all the support, clarity, kindness and organization, making this journey much smoother.

July 01, 2024, União dos Palmares - AL *Allan Amaro Bezerra da Silva*

There'd better be a mirrorball for me.

Alex Turner

Abstract

Estimating the quality of transmission (QoT) in optical networks is a key metric for planning, managing, and optimizing networks. QoT estimation depends on good modeling of the internal components of the optical link to accurately simulate transmission and consequent signal degradation. The amplifier is a source of noise and signal distortion; therefore, amplifier modeling plays a crucial role in the estimation of QoT. We present an evaluation of the impact of different amplifier models on the estimation of QoT in four single-link scenarios and two optical network topologies. We based our simulation on GNPy, a QoT estimator widely used to simulate and optimize the design of optical networks. Our main contributions are: (1) a new version of the GNPy in which the amplifier can be modeled using a power mask; (2) a benchmark considering GNPy's advanced amplifier model (Advanced Model) and the estimator based on a numerical simulator that uses power masks with real-world amplifier data (Power Mask Model); and (3) an analysis of the impacts in the network QoT for each amplifier model. The results show that, considering single link scenarios, the Power Mask Model achieved better approximations to the OptiSystem simulator used as a benchmark, presenting a good advantage over the Advanced Model. In the network scenarios, the results show that the Advanced Model tends to deliver more optimistic and flat estimates even in cases of high tilt, whereas the Power Mask Model is more sensitive to transmission noise in these cases, estimating lower GSNR and transmission rates, including several cases of connection blocking. The findings of this study may be useful to optical network researchers and operators who want to have more flexible network management and optimization through simulations and software-controlled networks.

Keywords*: *Telecommunications*; *Optical Networks*; *Simulation*; *Optical Amplifier*; *Power mask.

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List of Abbreviations

AM Advanced Model.

ASE Amplified Spontaneous Emission.

BER Bit Error Rate.

BP Blocking Probability.

DGT Dynamic Gain Tilt.

EDFA Erbium-Doped Fiber Amplifier.

EGN Extended Gaussian Noise.

GGN Generalized Gaussian Noise.

GNPy Gaussian Noise simulation in Python.

GSNR Generalized Signal-to-Noise Ratio.

IGN Incoherent Gaussian Noise.

LSTM Long Short-Term Memory.

MBT Multi-band Transmission.

MLP Multilayer Perceptron.

NF Noise Figure.

NLI Non-Linear Interference.

OS OptiSystem.

OSNR Optical Signal-to-Noise Ratio.

PMM Power Mask Model.

QoT Quality of Transmission.

SAMBA Semi-Analytical Model for Brisk Assessment.

SIMTON Simulator for Transparent Optical Networks.

SNR Signal-to-Noise Ratio.

SRS Stimulated Raman Scattering.

SVM Support Vector Machine.

WDM Wavelength Division Multiplexing.

WSON Wavelength Switched Optical Networks.

Contents

Chapter 1

Introduction

Optical networks are made up of various components and equipment that ensure that the information is transmitted to its final destination at the right signal levels for the receiver. Among these equipment are EDFAs (*Erbium-Doped Fiber Amplifier*), which are essential for the correct operation of the network, as they allow transmission over long distances by recovering the attenuated signal along the path. This attenuation is caused by other equipment present in the optical network, such as couplers and multiplexers, in addition to being the result of intrinsic characteristics of the optical fiber.

Although EDFA applies a gain to the optical signal capable of compensating for losses along the path, there is also a depreciation in the quality of the transmitted signal. The gain of the amplifier is not linear and is not exactly the same at each wavelength, as there is a dependence between gain and wavelength. Small variations in the gain between the channels in an EDFA can cause significant variations in the power difference between the channels at the output of the cascade of amplifiers. Therefore, a correct representation of the EDFA response is essential to obtain accurate results when estimating the quality of transmission (QoT) and to avoid simulation results that are far from reality [Seve et al., 2018].

GNPy (Gaussian Noise simulation in Python) is a QoT estimator in wavelength division multiplexed optical networks, commonly used in several works in the literature to simulate and optimize optical networks considering capacity and performance metrics.

As examples of the use of GNPy in recent works in the literature, it is possible to mention the study of signal amplification and transport phenomena through modeling and optimization of the operation of optical amplifiers, as demonstrated in works [de Moura et al., 2023], [Yankov et al., 2023], and [Soltani et al., 2022]. Regarding the QoT estimator provided by the application, it is possible to point out the works published in [Sadeghi et al., 2022] and [D'Amico et al., 2022], where the estimator is used as a performance metric in studies on optimization of optical fibers and signal transmission in multi-band scenarios, respectively. It is also used in [Souza et al., 2023] as a reference to analyze the performance of different QoT estimation methods, and in [Zhang et al., 2023] as a data generator to build an estimator used in optical network lightpaths.

However, the most sophisticated amplifier output model estimator available in GNPy considers that the noise figure can be modeled through one polynomial equation. GNPy uses a third degree polynomial to represent the spectrum of the amplifier's noise figure and the Dynamic Gain Tilt (DGT) method to represent the spectrum of the amplifier's gain. The DGT is a curve that represents the amplifier's gain at any point in its operating range when an amplifier is of the Advanced Model type in GNPy. With this modeling, the amplifier response is the same, even if its input power or gain changes.

On the other hand, the concept of power mask considers a characterization of the amplifier in which its response is different according to its operating point. The amplifier power mask is a set of data in which all of the amplifier's operational information is considered, being presented as a table that contains the gain and noise figure spectrum for a set of operating points. The power mask is obtained through the characterization of the amplifier in the laboratory, where an input signal is applied and the gain of the amplifier is varied to measure several parameters at different operating settings, until complete scanning of the operational region is achieved. In this characterization process, for any input power and gain value selected for the amplifier, there will be a spectrum with the response of the amplifier [Fei et al., 2015].

In [Fei et al., 2015], the authors proposed a numerical framework that uses power mask data to estimate the amplifier response. In [Lima et al., 2023], this framework was compared with the DGT method of the GNPy's Advanced Model in the same estimation task, but considering only single-link scenarios, showing significant differences.

Given this scenario, it is possible that the use of the amplifier model based on power masks can improve the task of estimating QoT in an optical network, since its source of information presents a more detailed and sensitive characterization of the amplifier in comparison to the Advanced Model, being able to present more accurate results in relation to it.

This work will present an evaluation of the impact on the QoT estimation of optical networks when different amplifier output estimators are used, considering both the more traditional estimator in the literature (GNPy's Advanced Model) and the more detailed estimator based on power masks, called here the Power Mask Model. These contributions may be valuable to researchers and engineers focused on using software estimation to manage and optimize real optical networks.

1.1 Goals

1.1.1 Main goal

Contribute to the QoT estimation of optical networks using the optical amplifier power mask technique Power Mask Model in network scenarios.

1.1.2 Specific goals

1. Create a new version of GNPy's QoT estimator in which the amplifier can be modeled using a power mask.

2. Perform a benchmark of the Advanced Model and Power Mask Model as estimators considering a numerical simulator and real-world amplifier data.

3. Produce an analysis of the impact on network QoT when different amplifier models are used.

1.2 Work structure

In Chapter 2 the theoretical foundation used as a reference in this work is presented. Chapter 3 presents recent works in the literature related to the work presented here, in addition to the relevance of this work to the study of optical networks. Chapter 4 presents the methodological steps that were performed to carry out the simulations. In Chapter 5 the results obtained are presented and discussed, in light of the objectives of this work. This work is concluded in Chapter 6, with findings, limitations, and intentions for future work.

Chapter 2

Fundamentals

2.1 Optical amplifier

Optical amplifiers are devices inserted into an optical network for the purpose of compensating for the losses that affect the optical signal during its transmission caused, for example, by the optical fiber itself. According to [Barboza, 2013], its introduction took place as a way to enable the transmission of optical signals at multiple frequencies, simultaneously, and on the same optical fiber, in a concept known as Wavelength Division Multiplexing (WDM). This allowed a substantial increase in the transmission speed of these signals, as well as favoring the use of Wavelength Switched Optical Networks (WSON), where, according to [de Andrade Barboza, 2017], the wavelengths are used to define multiple communication channels, so that the amplifier can apply a power gain to all of them simultaneously.

In the multi-channel optical transmission scenario, the first amplifier model proposed was the EDFA. According to [Barboza, 2013], EDFA has become quite popular, especially due to its simplicity and the wide availability of its components.

2.1.1 Power mask

In order to map the operating region of optical amplifiers and establish an important source of information on their practical behavior, [Moura et al., 2012] established a laboratory characterization process that defines their operating points, where all desired parameters are measured. In this process, an input signal is applied and the gain of the amplifier is varied to measure the desired parameter at different operating settings, so that for any value of input power and gain selected for the amplifier, there will be a spectrum with the response of the amplifier [Fei et al., 2015]. This process is carried out until the complete scanning of the operational region is achieved. The result of this process is called a power mask, which is a set of data in which all the amplifier's operating information is presented, consisting of a relationship between the information provided to

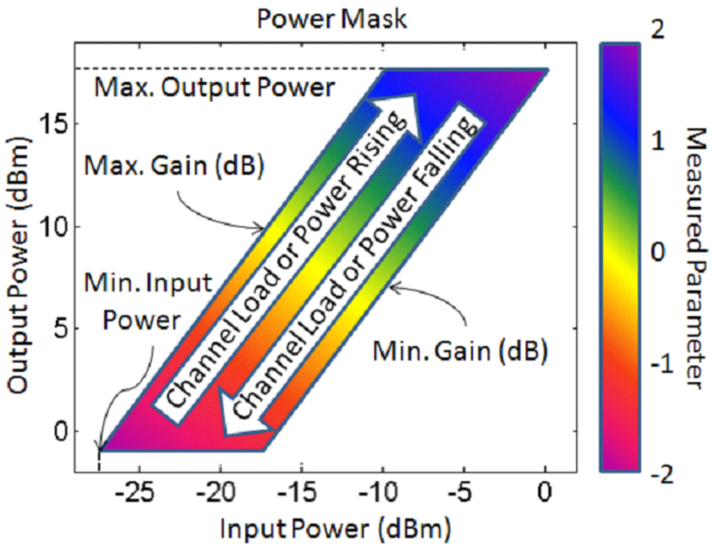


Figure 2.1: Power mask of an optical amplifier for a given parameter. (source: [Bastos-Filho et al., 2013].)

the amplifier, such as ranges of input power values, the frequency channels used and the desired gain, and the information returned by the amplifier, such as the output power per frequency channel and applied gain, the noise figure (NF) and the energy consumption of the equipment. The power mask can be displayed as a graph with a color bar on the side indicating the magnitude of the measured parameter and the input power and output power values, representing the gain, on the horizontal and vertical axes, respectively.

Figure 2.1 displays the graphical representation of a power mask of an optical amplifier, for a certain parameter returned by it, considering the range of total input power, on the horizontal axis, and the respective applied gains, which increase horizontally from right to left, between the diagonal lines. On the vertical axis, the range of total power output is displayed. Through the lines that make up the central element of the graph, the values of minimum total input power and maximum total output power, as well as maximum and minimum applied gain, are identifiable. The behavior of the measured parameter can be observed through a color scale, according to the palette shown to the right of the mask.

2.1.2 Tilt

A negative aspect of the optical signal amplification process is the insertion of noise and distortions into the shape of the signal, causing its degradation. According to [de Andrade Barboza, 2017], physical characteristics of the EDFA model generate harmful effects on optical signals, of which, according to [Xavier, 2016], it is possible to mention the Amplified Spontaneous Emission (ASE) noise, gain saturation and ASE saturation as the most significant. Such effects cause variations in the gain spectrum of the amplified signals, causing different gains in each channel and affecting the gain flatness measure,

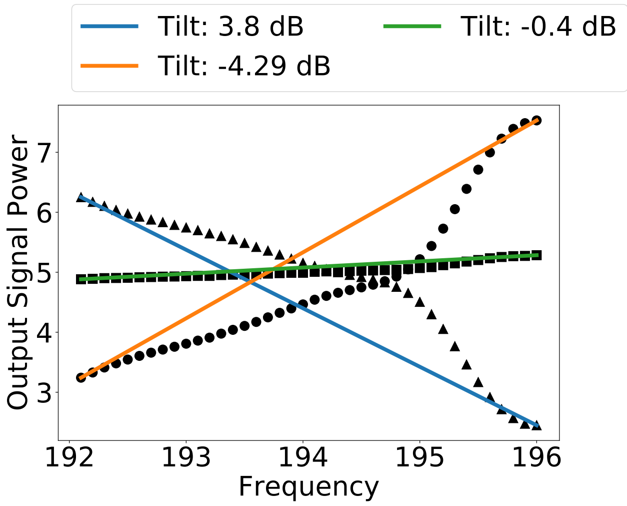


Figure 2.2: Output power spectrum of three signals with different tilt measurements. (source: [Barboza et al., 2021].)

given by the maximum gain variation between the amplified channels.

In this context, according to [de Andrade Barboza et al., 2019], one of the quality metrics of an amplifier is the tilt, used to quantify the distortion of an optical signal through the angular coefficient of the straight line that represents the linear difference existing between the powers in its frequency channels, being a characteristic of non-flat signals. In practical terms, the tilt of a signal can be defined by the difference, in dB, between the powers of its lowest and highest frequency channel.

Considering this tilt calculation method, Figure 2.2 presents an illustrative example of the output power spectrum of three signals with different tilt measurements in an amplifier, highlighting with straight lines the aspects of a positive tilt, a negative one and another close to 0 dB.

It is worth saying that the amplifier characterization process can be carried out with both flat and non-flat signals, resulting, respectively, in a flat mask or non-flat masks, with tilt measurements. Figure 2.3 shows an example of power masks resulting from the process of characterizing a commercial EDFA amplifier from input signals with and without tilt, with the ripple as measured parameter of the output signals. Signals with a tilt of -12 dB (Figure 2.3a), flat signals (Figure 2.3b) and signals with tilt of 12 dB (Figure 2.3c) were used.

2.2 QoT estimation in optical networks

In the planning phase of an optical network, it is common to define a QoT threshold for the project, so that every signal transmitted on a network route must have a quality level above this threshold. This threshold can be composed of several signal quality

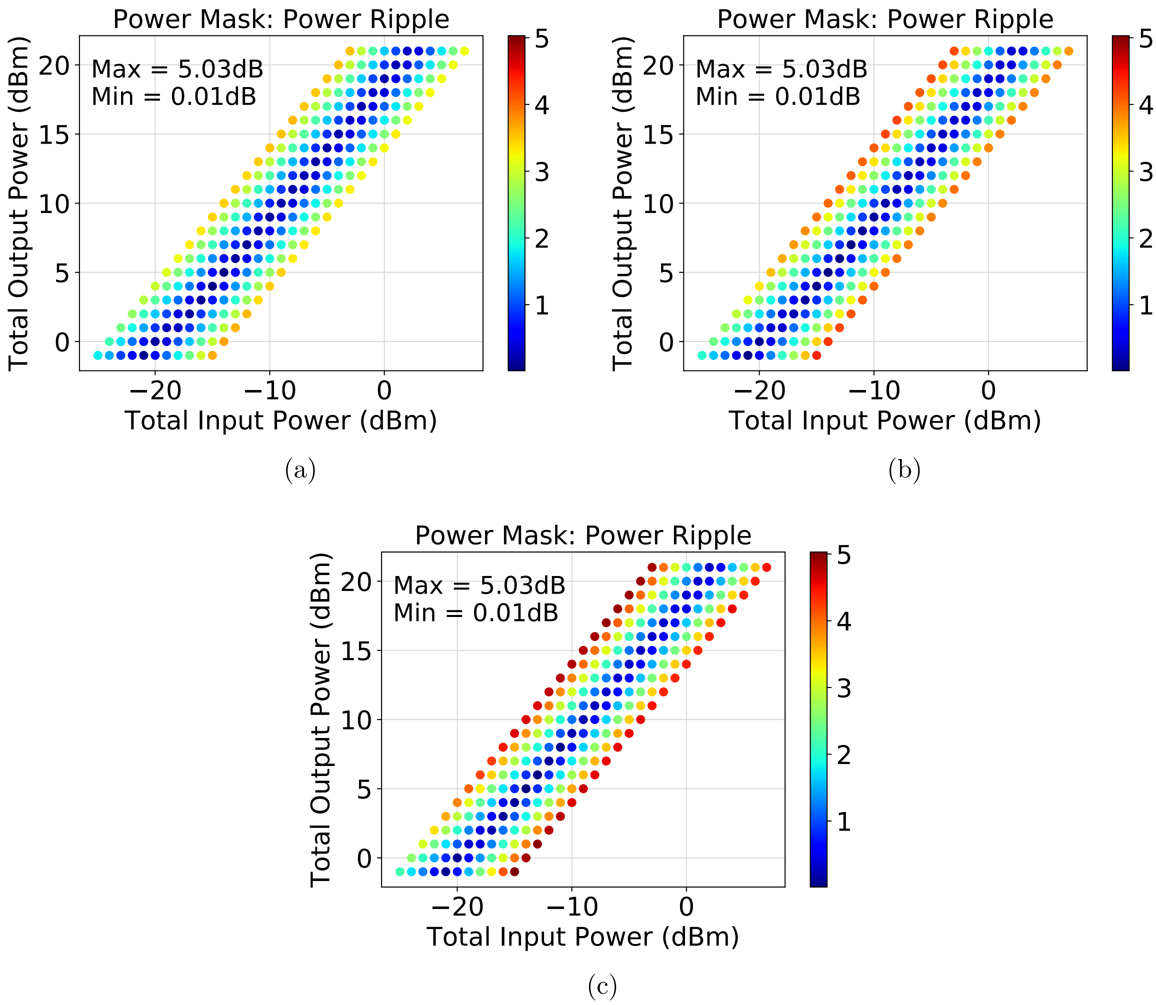


Figure 2.3: Power masks produced from the characterization of an EDFA amplifier with input signals with tilt of -12 dB (a), flat (b) and with tilt of 12 dB (c), measuring the ripple of the output signals. (source: provided by the supervisor.)

metrics, such as Signal-to-Noise Ratio (SNR) and Bit Error Rate (BER), generally calculated through analytical models due to the good balance between precision and computational cost presented by them. These models, such as the Semi-Analytical Model for Brisk Assessment (SAMBA) and the Extended Gaussian Noise (EGN), covered in [Seve et al., 2018], are used as QoT estimator tools.

In order to obtain a good representation of QoT in an optical network, the calculation of the metric addressed must work with good approximations of the noise that affects the propagation of the signal along its route, whose values are also estimated through analytical models.

2.2.1 IGN model

Proposed in [Poggiolini et al., 2014], the analytical model IGN (Incoherent Gaussian Noise) is presented as a simple variation of the Gaussian noise model, used in the calculation of non-linear effects that affect the transmission of optical signals, called Non-Linear Interference (NLI). According to [Hartling et al., 2019], unlike the calculation of linear noises such as ASE, the calculation of nonlinearities presents itself as a more complex task and dependent on simulations and approximate analytical models. In this context, according to [de Andrade Barboza, 2017], the model presents good accuracy in predicting the performance of optical systems and shorter processing time compared to more robust models.

Also in [de Andrade Barboza, 2017], the model is used as an evaluator of amplifier cascades, receiving as input parameters characteristics of the cascade and the propagated signal, such as the number of channels and the frequency spectrum used, in addition to the power of the input signal per channel, the gain and NF per channel of each amplifier in the cascade, among others. As output, the model presents the power spectral density of the NLI and different network and signal quality assessment metrics in each channel of the last amplifier in the cascade.

2.2.2 GSNR metric

One of the indicators used to quantify the degradation of an optical signal during its transmission is the Optical Signal-to-Noise Ratio (OSNR). According to [de Araújo, 2015], during its propagation between transmitter and receiver, the optical signal is affected by several sources of noise, such as ASE and non-linear effects, which can accumulate to the point of making it impossible to decode the signal in its reception. Thus, OSNR is defined as the ratio between the average power of the optical signal at the receiver P_{signal} and the average power of a given noise present at reception P_{noise}, being calculated in decibels (dB) by the equation:

$$OSNR = 10 \cdot log_{10} \frac{P_{signal}}{P_{noise}}$$

It is easy to see that the quality of the optical signal upon reception is directly proportional to the OSNR.

As pointed out in [Hartling et al., 2019], it is possible to approximate the effect of disturbances such as ASE and NLI in the form of Gaussian noise, which can then be summed. Another metric was then defined in [Pilipetskii et al., 2019], called Generalized Signal-to-Noise Ratio (GSNR), whose effectiveness in estimating QoT has already been demonstrated in [Filer et al., 2018]. It is given by the ratio between the useful power of the optical signal and the sum of the powers of all noise sources that affect it:

$$\frac{1}{GSNR} = \frac{1}{OSNR_{ASE}} + \frac{1}{OSNR_{NLI}}$$

It is important to highlight that the calculation of OSNR and, consequently, GSNR, can be done per frequency channel, and it is common to represent them by an average value.

2.3 Optical network analysis

According to [de Araújo, 2015], the analysis of optical networks can be carried out on several fronts, including a study of the cost of implementing the network, its energy consumption and its performance through QoT metrics, the latter being the criterion covered in this work.

Some indicators offer a global view of the performance of an optical network with dynamic traffic, such as the blocking probability. The blocking probability (BP) is defined in [de Araújo, 2015] as the ratio between the number of requests not established on the network $R_{blocked}$ and the total number of requests made R_{total}, so that the higher the BP, the lower the performance of the network, as fewer users will be served.

$$BP = \frac{R_{blocked}}{R_{total}}$$

The estimation of BP and other performance indicators of a network, in general, is done through discrete event simulators, capable of creating scenarios in which a large number of requests are made. At the end of the simulator operation, various aspects of the signals and the network are analyzed, such as possible blocked calls due to lack of resources available for transmission, also taking into account the various QoT metrics, such as those presented in Section 2.2. Therefore, considering a scenario in which a request is used to estimate the BP of an optical network, if the network does not have available frequency channels, or if one of the metrics analyzed in this call does not satisfy the established QoT threshold, the performance will be deemed insufficient and such request will be blocked.

2.3.1 Network simulation

Discrete event simulators use a practical approach to the problem of analyzing the performance of optical networks, which according to [de Araújo, 2015] guarantees good accuracy in their estimations, but presents a high computational cost due to the large amount of data used during the simulation.

One of the network simulators used in the literature to estimate BP is SIMTON (Simulator for Transparent Optical Networks), proposed in [Chaves et al., 2010]. It is characterized by having a good representation of the physical layer of WDM networks, taking into account the presence of amplifiers, fibers, switches, among others. In this way, the simulator is capable of reproducing a range of penalties that affect network performance, such as ASE, switch losses and residual chromatic dispersion in the fiber.

It is possible to mention other simulators present in the literature, such as OMNeT++[1], ElasticO++, proposed in [Tessinari et al., 2016], and GNPy[2], proposed in [Ferrari et al., 2020]. The first is characterized by providing model frameworks for different types of networks, such as wireless and optical networks themselves, while the others are specialized in optical networks, with GNPy being a frequent choice in recent studies in the area.

[1] `https://omnetpp.org/`
[2] `https://gnpy.app/`

Chapter 3

Related works

This chapter will present a brief description of some of the works presented in the literature regarding the estimation of QoT in optical networks and the estimation of the output of optical amplifiers, in Sections 3.1 and 3.2, respectively. Both themes are related to the present work and its relevance in relation to the cited works will be clarified in Section 3.4. A short presentation of the GNPy optical network simulator, a tool of great importance for this proposal, will be given in Section 3.3.

3.1 QoT estimation in optical networks

In [Allogba et al., 2022] a comparative study is presented between different machine learning techniques in QoT estimation and prediction problems in complex and heterogeneous optical networks. The study addresses both QoT estimation in the network planning scenario, where it is necessary to observe, for example, different configurations of optical fibers and transmission devices, as well as predicting the need for maintenance due to performance degradation in networks already deployed, where the models must take into account nonlinearities over the operating time, such as the useful life of equipment, the influence of wind, temperature, and other forms of noise. Despite the authors' difficulty in capturing real data in both scenarios, forcing them to use synthetic data in the estimation scenario, the results presented demonstrate the potential of even simpler techniques, such as SVM (Support Vector Machine), compared to the traditional neural network, achieving better performance than it in an estimation scenario with little data. The prediction scenario, on the other hand, shows a greater dependence on more robust techniques, such as LSTM (Long Short-Term Memory), which achieved good results where simpler techniques, such as MLP (Multilayer Perceptron), are disadvantaged by being more susceptible to outliers.

[Seve et al., 2018] describes a proposal to reduce optical network design margins through an optimization process based on gradient descent. Such margins are added to the design parameters used by QoT estimators to compensate for prediction uncertainties and achieve a desired quality threshold, which can lead to oversizing and wasted resources. The study proposes to capture such parameters in the field and use them to train a learning model. The objective is for the model to be able to refine these parameters, providing them to the QoT estimators and allowing a more reliable prediction by the estimator, resulting in smaller design margins. The authors tested the model with two QoT estimators from the literature, considering data from a european backbone network, and achieved significant reductions in prediction errors.

3.2 Estimation of the output signal of optical amplifiers

In [Yu et al., 2021] a modeling of the gain spectrum of EDFA amplifiers is proposed using a combination of neural networks and an analytical model of the EDFA gain dynamics based on center of mass. The experiments presented in the work took into account only one amplifier, and their results showed that the proposed combined model, in comparison to the performance of its individual components, was able to increase the accuracy in predicting the gain spectrum, in addition to decreasing the time of prediction and the amount of data needed for its training.

The proposal presented in [Yankov et al., 2020] also aims to model the EDFA gain spectrum, but in a segmented manner. The idea is to model amplifier and fiber separately, the first through a neural network that takes into account the total input and output power of the amplifier, in addition to the input power per channel, while the second uses an analytical model based on the Stimulated Raman Scattering (SRS) phenomenon, where power transfer occurs between neighboring channels in the fiber, which is considered a form of noise. The study addresses cascade scenarios of up to three amplifiers, and its results show that the strategy addressed presents itself as a flexible modeling option, in addition to being fully differentiable, allowing optimization of the output in real time.

The Spectrum-Tilt neural network model was proposed in [Barboza et al., 2021] with the objective of estimating the output power spectrum of EDFA amplifiers, according to the power spectrum of the input signal and its tilt, in addition to the desired amplification gain. The model was trained and tested with power masks generated by characterizing two EDFA amplifiers with signals occupying 40 frequency channels. In this process, different gain, tilt and input power settings were considered in the amplifiers, in order to represent a significant part of their operating space. The results demonstrate the model's high generalization power, which achieved good accuracy even in test scenarios with few training masks.

3.2.1 TIP and TIP-Tilt

TIP is an estimator proposed in [Fei et al., 2015] in the form of a numerical modeling framework based on linear interpolation of flat power mask data, where it is assumed that the gain that each frequency channel receives from the amplifier is a function of the total input power of the optical signal, regardless of the power presented in each channel. This framework is made up of a combination of 4 modules, namely:

- Module 1: *Finer Spectrum Granularity*, is responsible for extending the list of mask frequencies beyond those used in the characterization, through linear interpolation.
- Module 2: *Continuous Input Power Values*, is responsible for extending the mask's total input power values beyond those used in the characterization, in a similar way to Module 1.
- Module 3: *Unequally Powered Input Signals*, is responsible for considering each frequency channel individually when estimating the signal output power, in order to cover cases in which the input power is different between the channels.
- Module 4: *Non-Fully-Loaded Span*, is responsible for considering cases in which not all frequency channels are used by the optical signal, estimating the output power of only the loaded channels.

The execution flow of the TIP technique can be seen in Figure 3.1. It has as input, in (1), the 40 input powers of the optical signal, the set of frequencies corresponding to the 40 channels of this signal, in addition to the desired power gain, totaling 81 input values. As output, in (END), it delivers 40 values referring to the estimation of the output power spectrum in each frequency channel used.

Its operation is based on Module 3, in (2a), by the function

$$P_{out}(f_i) = P_{in}(f_i) \cdot g(f_i, P_{in}, G_{set}),$$

where $P_{in}(f_i)$ and $P_{out}(f_i)$ are, respectively, the input and output powers of the frequency channel f_i, and g is the function that returns the power gain of this channel, receiving its frequency, the total input power P_{in} of the signal (calculated by the sum of the input powers of all channels of the optical signal) and the desired gain G_{set} in the amplifier. This calculation is performed for all frequency channels of the input signal. If not all channels are loaded, the same function is performed, but by Module 4, in (2b), and only for the loaded channels.

The function g is defined in Module 2, in (3), as

$$g(f_i, \hat{P}_{in}, G_{set}) = (1 - x) \cdot s(f_i, P_{in}^{-}, G_{set}) + x \cdot s(f_i, P_{in}^{+}, G_{set}),$$

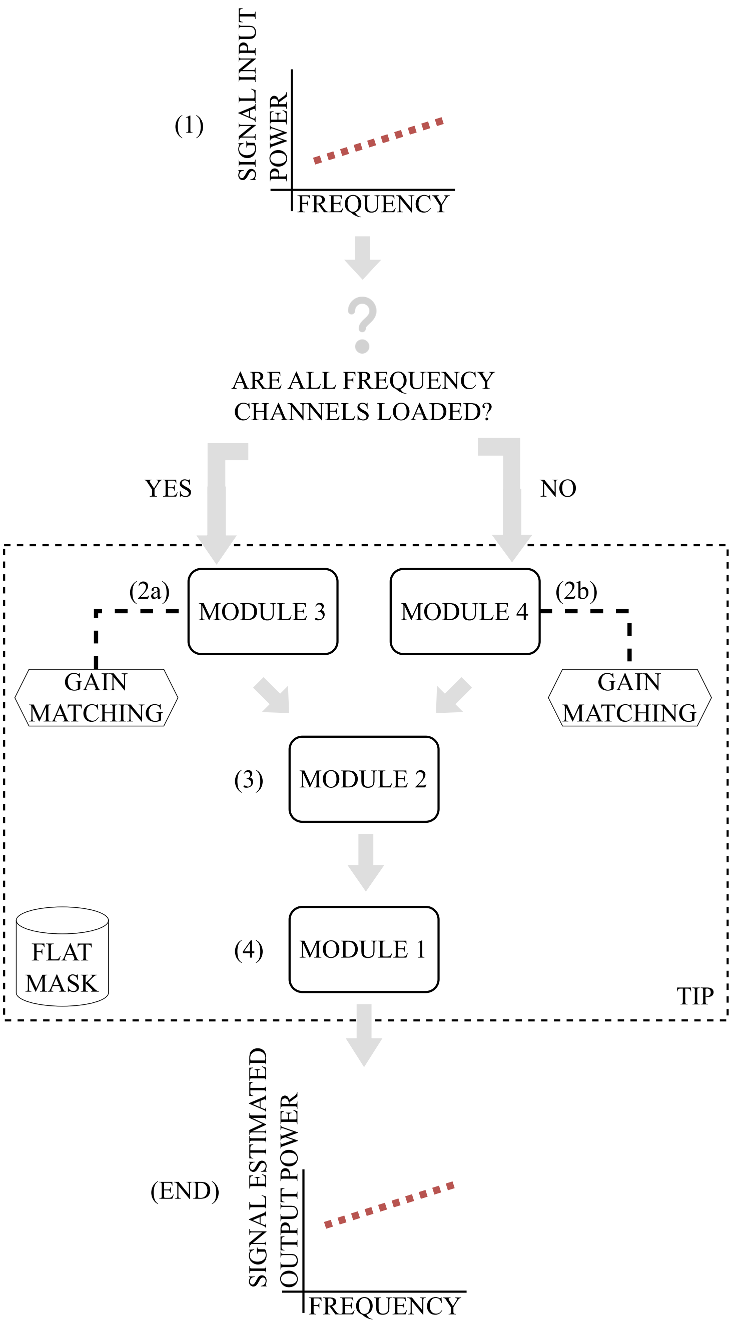


Figure 3.1: Execution flow of the TIP technique. (source: adapted from [Fei et al., 2015].)

where $\hat{P}_{in}$ is the total input power of the signal received by the g function, which may or may not exist in the characterization mask. Because of this, the s function is executed twice, once for P_{in}^{-} and another for P_{in}^{+}, with both powers present in the power mask and being $P_{in}^{-} \leq \hat{P}_{in} \leq P_{in}^{+}$. Furthermore, the s function also receives the frequency f_i of the channel whose power gain is to be estimated and the desired gain G_{set}. In order to use the concept of interpolation, a multiplication is applied to the gain returned by calls to the s function, where $x = \frac{\hat{P}_{in} - P_{in}^{-}}{P_{in}^{+} - P_{in}^{-}}$.

The function s is defined in Module 1, in (4), as

$$s(\hat{f}_k, P_{in}, G_{set}) = (1 - x) \cdot m(f_i, P_{in}, G_{set}) + x \cdot m(f_{i+1}, P_{in}, G_{set}),$$

where $\hat{f}_k$ is the channel frequency received by the function s whose gain must be estimated, which may or may not exist in the power mask. For this reason, the function m is executed for two frequencies, f_i and f_{i+1}, which are the frequencies closest to $\hat{f}_k$ present in the characterization mask. In the same way as in Module 2, the interpolation of information is done through multiplication by a factor $x = \frac{\hat{f}_k - f_i}{f_{i+1} - f_i}$.

The m function is responsible for consulting the amplifier characterization mask and returning the power gain corresponding to the frequency channels f_i and f_{i+1}, for a total input power signal P_{in} and for a desired gain G_{set} in the amplifier.

The framework also incorporates the Gain Matching function. It is responsible for correcting the power gain estimated by the g function at the end of the algorithm execution, in order to make it closer to the real gain applied to the optical signal by the amplifier. If the Gain Matching function is used, the execution of the TIP starting from Module 3 or 4 is modified to

$$\hat{P}_{out}(f_i) = P_{in}(f_i) \cdot \frac{G_{set}}{G_{tot}} \cdot g(f_i, P_{in}, G_{set}),$$

where $\hat{P}_{out}(f_i)$ is the estimated output power in the frequency channel f_i corrected by Gain Matching, given by multiplying the estimated gain and the factor formed by dividing the desired gain G_{set} by the total gain G_{tot}. The total gain is calculated by the ratio between the total output power P_{out} (calculated by the sum of the output powers of all channels of the optical signal) and the total input power P_{in} of the optical signal.

An adaptation of the TIP model, called TIP-Tilt, was proposed in [Bezerra Da Silva et al., 2021], having the same input and output parameters as the original model. The operation of TIP-Tilt depends on the construction of a power mask base consisting of signals with and without tilt (i.e. flat and non-flat masks), so that, in its process of estimating the output power spectrum, this base is consulted in search of a signal with the same characteristics as the tested input signal. Its execution flow is represented in Figure 3.2.

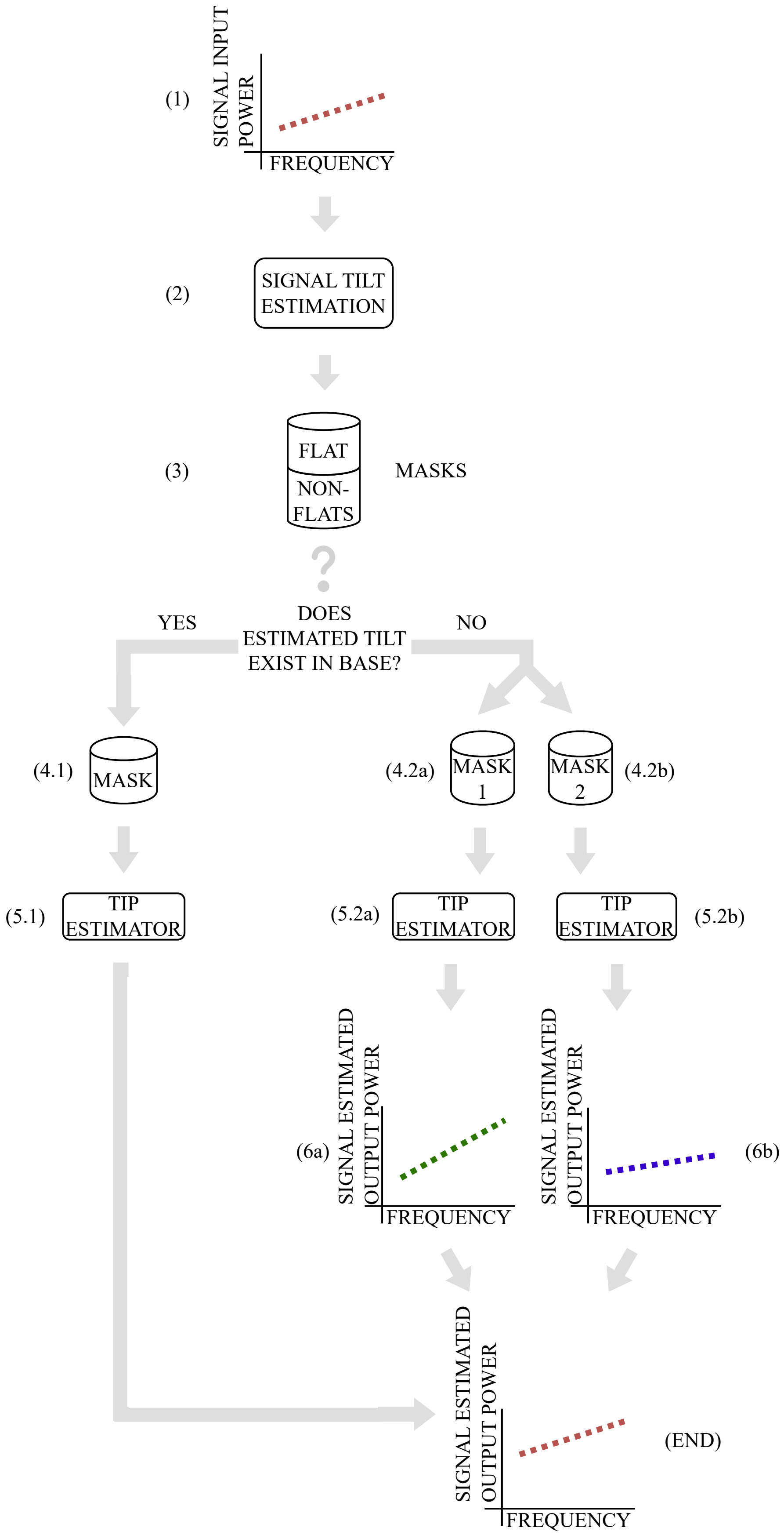


Figure 3.2: Execution flow of the TIP-Tilt technique. (source: adapted from [Bezerra Da Silva et al., 2021].)

The TIP-Tilt estimator takes into account the same 81 input attributes and 40 output attributes of the original technique at steps (1) and (END), respectively. The main difference is the input signal tilt estimation at step (2) and the addition of non-flat masks to its original query base at step (3). After the tilt estimation, there is the selection of the mask whose tilt is equivalent to the one estimated for the input signal considering the set of masks known by the technique. From this point, the algorithm can follow two paths, depending on whether or not the query base has a mask with the same tilt of the input signal. If so, this mask is selected at step (4.1) and used as a query basis in the TIP estimator at step (5.1), which returns the signal estimated output power at step (END). If not, the masks with the larger nearest and smaller nearest tilt existing in the base concerning the tilt of the input signal are selected (steps 4.2a and 4.2b). Thus, each selected mask is used as a query basis in independent calls of the TIP estimator, at steps (5.2a) and (5.2b). Each call returns the estimated output power of a signal corresponding to the estimation based on their respective mask (steps 6a and 6b). The two resulting signals are then interpolated following the same approach as the original TIP algorithm, using

$$P_{out}(f_i) = (1 - x) \cdot P_{out}(f_i)_{6a} + x \cdot P_{out}(f_i)_{6b}$$

where $P_{out}(f_i)$ is the estimated output power of the signal at step (END), given by the weighted sum of the output powers $P_{out}(f_i)_{6a}$ and $P_{out}(f_i)_{6b}$, estimated at (6a) and (6b) respectively. Such weighting is done by a factor $x = \frac{T - T^-}{T^+ - T^-}$, where T is the estimated input signal tilt at (2), with T^+ and T^- being the larger nearest and smaller nearest tilts relative to the estimated tilt, according to the masks selected at (4.2a) and (4.2b), respectively.

In the exceptional case where there is no mask with a larger nearest or smaller nearest tilt value than the estimated input signal tilt (in other words, if one of the masks that is presented at (4.2a) and (4.2b) does not exist), only the existing mask is selected, thus following the same flow represented at (4.1) and (5.1).

[Bezerra Da Silva et al., 2021] explains that the original TIP implementation used by TIP-Tilt does not use the Gain Matching function, as it negatively affected the performance of the adapted model in the tested scenarios.

3.3 GNPy

Proposed in [Ferrari et al., 2020], GNPy is an open source application, distributed in the form of a Python library. It is a QoT estimator in wavelength division multiplexed optical networks, being used, among other applications, to simulate and optimize the design of optical networks considering capacity and performance metrics, among other applications.

The modular structure used by the application, in which it is possible to declare and configure amplifiers and optical fibers, for example, allows the creation of complex optical network topologies and the simulation of the effects of signal propagation between two points on it, using as QoT metric the GSNR of each channel in the frequency spectrum.

The work presents application validation experiments, using a Microsoft structure as a test space that simulates a commercial optical network with different amplifier models and fiber lengths. The objective was to estimate both OSNR and GSNR in the most diverse transmission scenarios, considering greater and lesser distances, different modulation formats and signal power levels. The authors demonstrated good results in the proposed experiments, achieving good accuracy in estimating both metrics addressed.

In recent years, GNPy has been used in various researches. As an application of the tools made available by GNPy, the works presented in [de Moura et al., 2023], [Yankov et al., 2023] and [Soltani et al., 2022] can be cited, which address, respectively, modeling of Raman amplifiers, their optimization and application, and use in their proposals a numerical solver of equations that describe the phenomena involving the amplification and transport of signals in networks with such amplifiers. Also, GNPy has also been frequently used as the main QoT estimator. In [Sadeghi et al., 2022] the authors use GNPy as a GSNR estimator to compose a numerical analysis method for optical networks, with the aim of comparing different network designs and transmission scenarios in terms of allocation capacity and energy consumption. In [D'Amico et al., 2022], GNPy's generalized Gaussian noise (GGN) model is used as a comparative parameter for a new GGN-based estimator considering a multi-band transmission (MBT) scenario. In [Souza et al., 2023] the authors also use the numerical implementation of GGN available in GNPy as a reference to analyze the computational time and precision of different QoT estimation methods suitable for MBT systems. In [Zhang et al., 2023] GNPy is used as a simulation engine to generate a database that enables the creation of a machine learning model to estimate the GSNR of optical network lightpaths.

The wide use of GNPy demonstrates its versatility and validates its work proposal.

3.4 Relevance of the proposal considering the previous works

This work aims to verify whether modeling the optical amplifier using power masks is a good alternative to amplifier models already known in the literature, especially in the task of estimating the QoT of optical networks, where this approach has not yet been used. Since the information contained in the masks is the result of a more detailed and sensitive characterization of the amplifier compared to other models, it is possible that the power mask modeling can present more accurate results in relation to it.

In relation to the estimation of QoT in optical networks, this proposal has the advantage of using the characterization of EDFA amplifiers in power masks through the TIP-Tilt algorithm, something not covered in [Allogba et al., 2022], for example. Furthermore, unlike the proposal in [Seve et al., 2018], which considered a single network, this work intends to test more optical network scenarios, taking into account different amplifier configurations and fiber sizes.

Regarding the estimation of the output of optical amplifiers, it is worth pointing out that the techniques mentioned in Section 3.2 take into account scenarios of just one to three amplifiers, lacking tests on more complex networks, as is intended to be done in this work.

Chapter 4

Materials and Methods

This work uses the GNPy optical network implementation and optimization library (version 2.6[1]) for output power and GSNR estimation. The results presented in this work come from three steps. First, GNPy was adapted to use power masks. Then, the GNPy estimations using power mask and its traditional estimation method Advanced Model (AM) were compared with a numerical simulator to verify the accuracy of the models in a single-link scenario. Finally, the model comparison was extended to consider network scenarios already available in the GNPy library. Each step is detailed in the following sections.

4.1 GNPy Adaptation to Consider Amplifier Power Mask

The GNPy has three standard amplifier response models: variable gain, fixed gain, and AM. A new amplifier response model, called the Power Mask Model (PMM), was included. Including a new EDFA amplifier model to GNPy consists of changing the GNPy source code to use the new model to estimate the gain and noise figure spectral responses of the amplifier during the simulation.

Figure 4.1 shows the GNPy simulation flow after adaptation. The process starts in (a), with the user defining which optical network will be used, through the name of its JSON file. This file must indicate the entire network structure, containing all nodes and their links, the size of each link, the amplifier model used per link, among other information. Finally, the User will also define between which pair of nodes the simulation should take place. Once the simulation is requested, GNPy reads the simulation parameters defined in (a), in addition to the loaded equipment and network information files (b) to start the process. During simulation, at each amplification stage, GNPy checks which amplifier model the link uses. If the model is not the PMM, GNPy uses the DGT method to calcu-

[1]`https://github.com/Telecominfraproject/oopt-gnpy/releases/tag/v2.6`

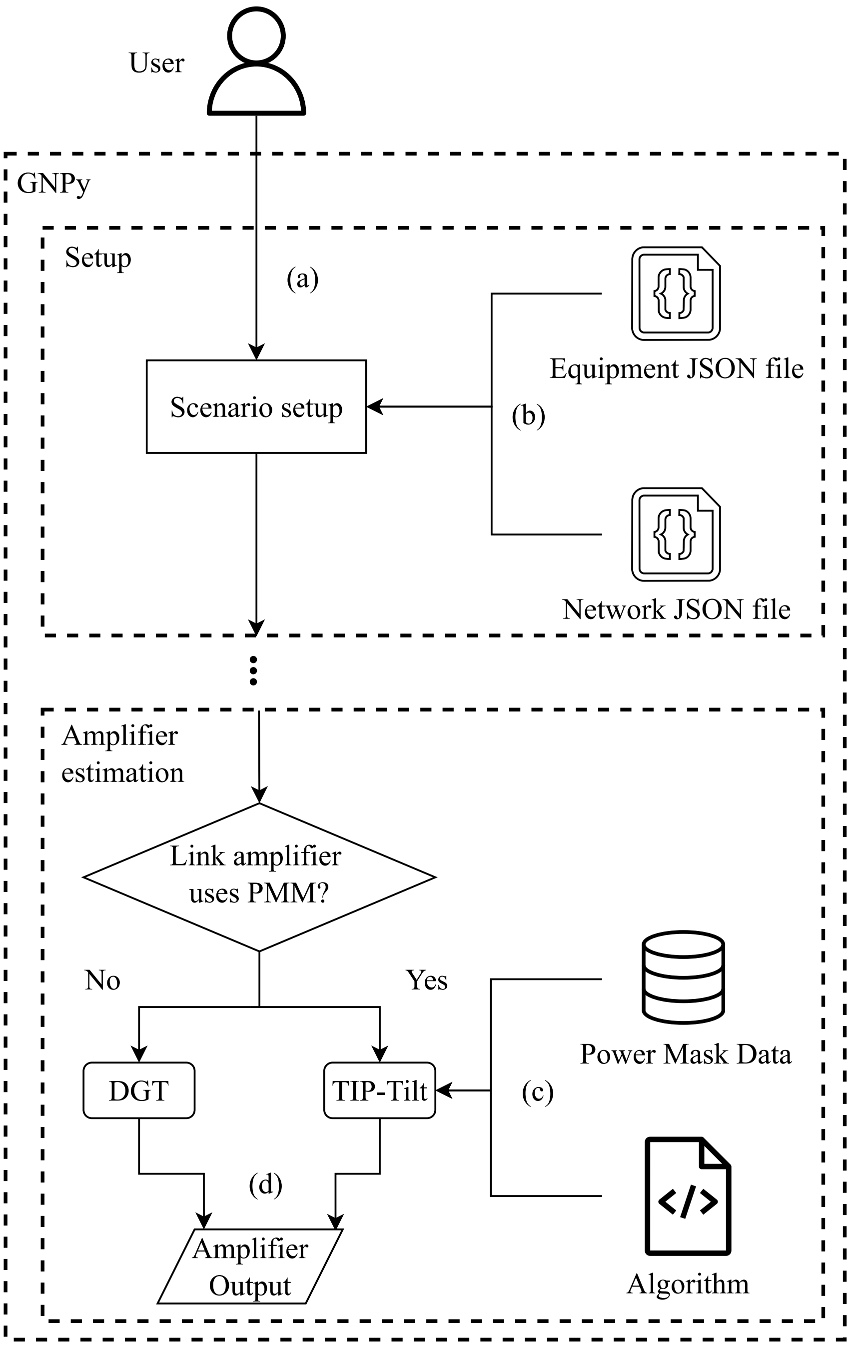
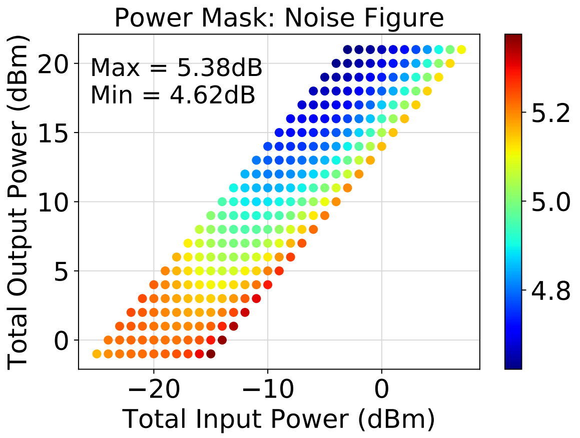
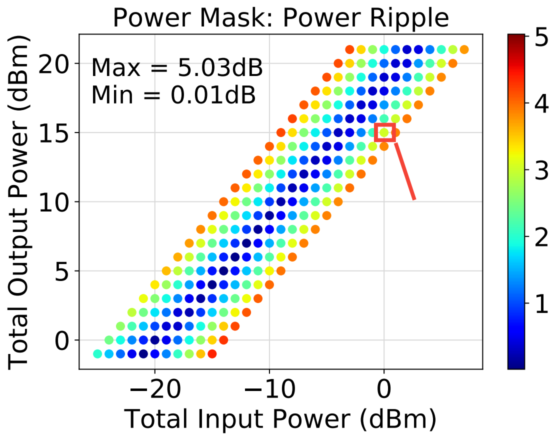


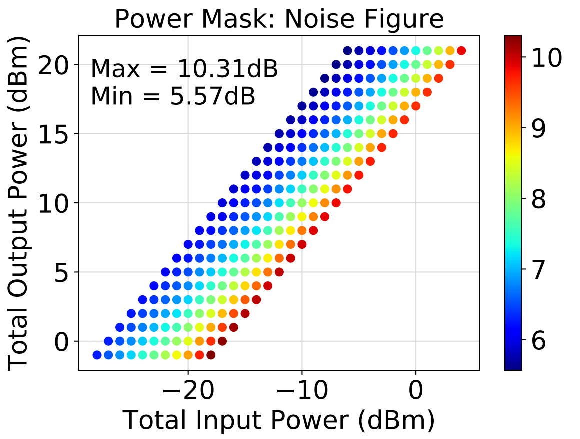
Figure 4.1: GNPy transmission simulation flow after adaptation to consider amplifier power masks.



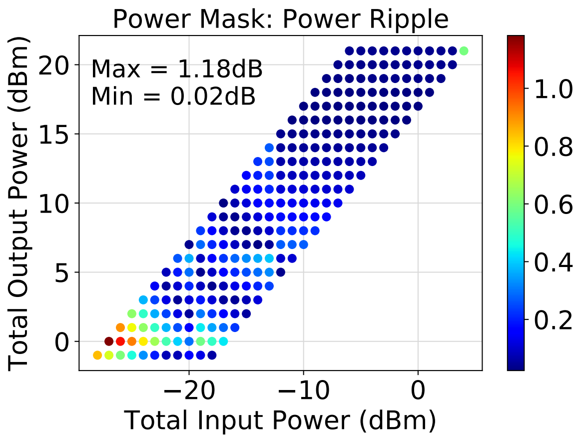
(a) EDFA 1 - Noise Figure



(b) EDFA 1 - Power Ripple



(c) EDFA 2 - Noise Figure



(d) EDFA 2 - Power Ripple

Figure 4.2: Amplifiers power masks using colors to show (a)(c) the worst noise figure and (b)(d) the worst power ripple of each operating point for the two models considered.

late the gain spectrum. Otherwise, the TIP-Tilt algorithm [Bezerra Da Silva et al., 2021] is used to predict the output power and the noise power of the transmitted signal. During its execution, TIP-Tilt reads the power mask files of the amplifier used in the network link, according to the folder directory containing the mask files configured in the JSON file of the equipment. In the last stage of the simulation (d), GNPy applies to the propagated signal the gain and noise figure profiles returned by the algorithm used. Finally, GNPy calculates the output parameters, such as the output power per channel and the GSNR.

The PMM uses the TIP-Tilt algorithm to perform an estimation of the amplifier response considering the power mask data.

Two sets of power masks that refer to two commercial grade EDFA amplifiers, called EDFA1 and EDFA2 here, have been added to GNPy. Figure 4.2 shows the power mask of the two EDFA amplifiers used in the simulations. Each point in the power masks represents the worst ripple and worst noise figure among the 40 channels used in the

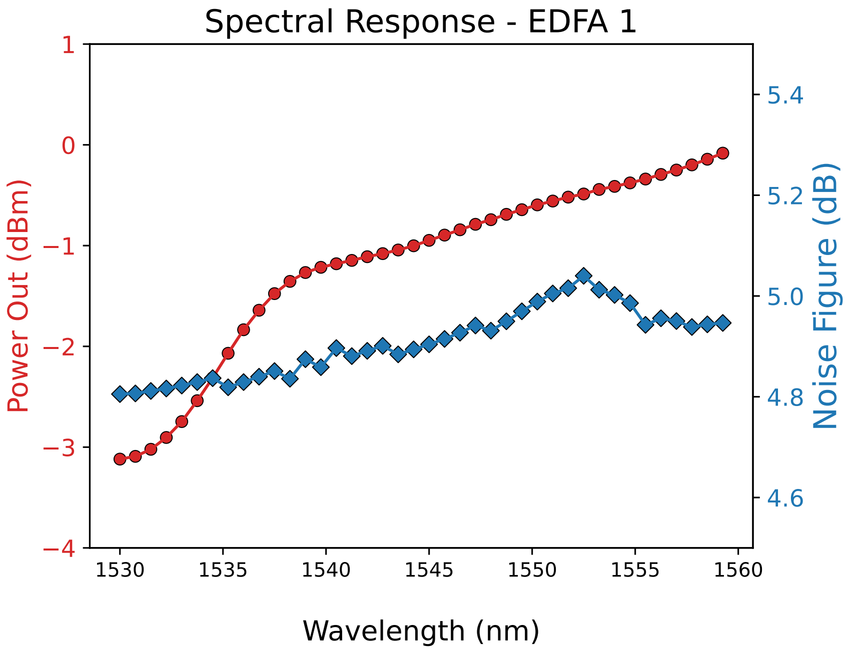


Figure 4.3: Output power and noise figure spectrum of the EDFA1 considering an input power of 0 dBm and a gain of 15 dB.

amplifier experimental characterization in laboratory, and they are indicated as the color mapping values. Ripple is defined as the difference between the channel with the highest and lowest power values. The point highlighted by a square in Figure 4.2b indicates that, for an input power of 0 dBm and a gain of 15 dB, the power ripple is approximately 3 dB; the gain and noise figure of this point can be seen in Figure 4.3. In other words, each point of the power mask corresponds to a line in the table with all the channel information, as illustrated in Figure 4.3. Thus, with the power mask, it is possible to have the complete response of the amplifier for any value of gain and input power chosen on the link.

EDFA1 amplifier has a minimum allowable gain of 14 dB and a maximum gain of 24 dB. For EDFA2, these parameters are 17 dB and 27 dB, respectively. In simulations with PMM, given that its estimation algorithm is based on power masks data from these amplifiers, all desired gain values that exceeded any of these limits were adjusted to the closest allowed value. Both EDFA models have a maximum output power equal to 21 dBm. EDFA1 has a set of power masks, each power mask was characterized with input signals with different tilts, the considered tilt range is -10 dB to 10 dB with a step of 2 dB as in [Bezerra Da Silva et al., 2021]. Regarding the power ripple, the EDFA1 power masks have a minimum and maximum value of 0.01 dB and 5.03 dB, respectively. For the noise figure, these values are 4.62 dB and 5.38 dB. The EDFA2 has only the flat mask (the tilt equals 0 dB) because its response is more flat and only the flat mask is sufficient to estimate the output with good precision in various scenarios [Bezerra Da Silva et al., 2021]. The EDFA2 mask has a minimum and maximum Power Ripple value of 0.02 dB and 1.18

dB, respectively, while for the Noise Figure, these values are 5.57 dB and 10.31 dB. In summary, EDFA1 inserts less noise and more tilt to the signal, whereas EDFA2 inserts more noise and less tilt to the signal.

GNPy's AM versions of EDFA1 and EDFA2 were also created. In this way, it is possible to run GNPy simulations with PMM and AM models using the same EDFA amplifier equipment. The AM version of the amplifiers was created by calculating the DGT curve for both amplifiers using the power mask data. The DGT curve is obtained from the gain spectrum $g1(\lambda)$ and $g2(\lambda)$ considering the same wavelength for two different levels of signal power or pumping. The relationship established by the DGT is

$$DGT(\lambda) = \frac{\Delta g\,(\lambda)}{\Delta g\,(\lambda 0)} \tag{4.1}$$

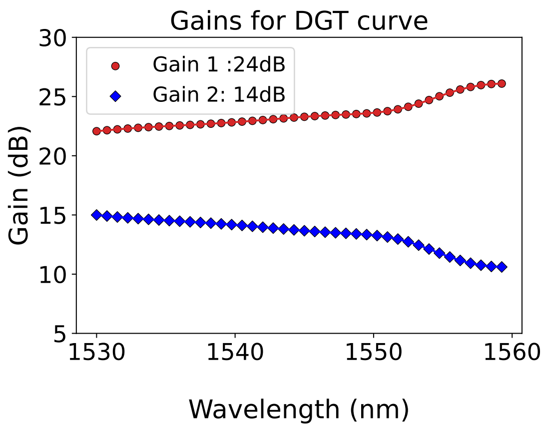
where $\Delta g = g2\,(\lambda) - g1\,(\lambda)$. Δg represents the difference in gain at the same wavelength, and $\lambda 0$ represents a reference wavelength [Di Ruro, 2000].

Figure 4.4a shows the two gain ($g1$, $g2$) spectrums used to obtain the DGT curve for EDFA1. The blue curve shows the amplifier response spectrum when configured for a gain of 24 dB (max gain), and the red curve shows the spectrum for a gain of 14 dB (min gain). Both curves consider the amplifier's response to an input power of -15 dBm. After applying Equation 4.1, the DGT curve of the amplifier used in the simulations was found. The $\lambda 0$ was the last channel (1560 nm). This wavelength was chosen so that all gain values were at least 1 dB in the DGT curves of both amplifiers. Any other wavelength chosen as a reference would result in the same DGT curve design, shifted vertically.

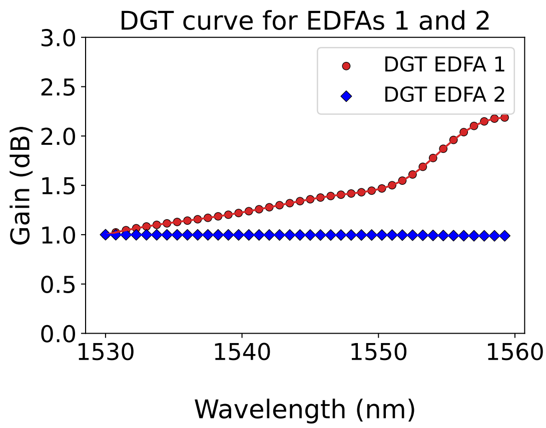
Figure 4.4b shows the resulting DGT curves of the two amplifiers. One can see that the DGTs curves show the same pattern presented in the power mask, that is, the EDFA2 response is practically flat, whereas the EDFA1 response is tilted. Therefore, it is possible to see that for some extent the AM is capable of modeling the amplifier characteristics. Drawing a parallel between the power mask and the DGT, it is possible to say that the DGT is a single curve that represents the entire operation of the amplifier, while the power mask shows a curve for each selected operating point. Due to that, modeling using the power mask is expected to represent more faithfully the amplifier's behavior in practical applications.

Listing A.1 shows the JSON file of the equipment configuration (*eqpt_config.json*) after adding the amplifier variations mentioned in this section. The version of GNPy with these modifications and with the power mask data are available on GitHub[2]. It is intended to submit a pull request to the official GNPy branch in the future.

[2]`https://github.com/Felipefnol/Projeto_RedesOpticas_GNPY/tree/allan/AmbienteVirtual/Lib/site-packages/gnpy`



(a) Selected gains of EDFA 1 considering a −15dBm input power to obtain its DGT curve.



(b) Final DGT curves of EDFA 1 and EDFA 2.

Figure 4.4: DGT curves examples.

4.2 PMM and AM benchmark

To validate the PMM estimation, four single-link scenarios were defined and simulated using GNPy and OptiSystem[3] (OS; version 13.0), one of the most accurate optical system design softwares used by the community to simulate optical links, to compare the power and OSNR per channel at the end of the link.

The single-link scenarios are described below.

1. 4 spans of 65 km, using 5 EDFA1 amplifiers with a gain of 14 dB, with an input signal of -14 dBm per channel;

2. 19 spans of 95 km, using 20 EDFA1 amplifiers with a gain of 20 dB, with an input signal of -20 dBm per channel;

3. 19 alternating spans of 65 km and 115 km, using 20 EDFA1 amplifiers with alternating gains of 14 dB and 24 dB, with an input signal of -14 dBm per channel;

4. 19 spans of 80 km, using 20 EDFA2 amplifiers with a gain of 17 dB, with an input signal of -17 dBm per channel.

Each scenario was defined to explore different amplifier operation conditions. In scenario 1, the EDFA1 is at a high-tilt operating point. It has only five amplifiers because its output has a slope above 20 dB after six amplifiers. On the other hand, the EDFA1 in scenario 2 is at a low tilt operating point, and for this reason it has more amplifiers. In scenario 3, EDFA1 alternates between operating points with positive and negative tilts, resulting in a low slope output signal. Finally, EDFA2 was used in scenario 4 to have a setting with low tilt and high noise figure.

[3]`https://optiwave.com/products/optisystem/`

This simulation considered a link to be composed of a booster amplifier and a set of spans composed of fiber and amplifier. Therefore, in an example scenario with two spans, there are three amplifiers and the link configuration is: booster amplifier, fiber, line amplifier, fiber, and pre-amplifier.

The OS simulation considered a signal with 40 x 256 Gb/s PM-16QAM modulated channel, a WSS (available within the ROADM node), a cascade of EDFAs and SMF28 fibers. The optical signal was launched without noise. Furthermore, the amplifier characteristics, such as component losses, noise levels, and doped fiber characteristics, were defined to match the values measured experimentally in the laboratory to maintain simulations as close as possible to the experimental systems. Therefore, the performance of the amplifiers, in terms of noise figure and gain tilt, are the same as shown in the characterization masks shown in Figure 4.2. In GNPy, the simulation was configured to have the same link and the same signal parameters. Listing A.2 shows an example of a single-link scenario added to GNPy, in the form of a JSON file containing the definition of each link element, including source and destination, spans, amplifiers, and their connections.

4.3 PMM and AM comparison in network scenarios

For simulations with optical networks, two GNPy network implementations were used: Sweden_OpenROADMv5, called Sweden in this work, and CORONET_CONUS_Topology, called CORONET here. The first implementation models a Swedish optical network with 15 nodes, 23 line amplifiers and 45 spans, and the second models a United States network with 75 nodes, 336 line amplifiers and 435 spans, both of which can be seen in Figures 4.5 and 4.6, respectively. A node consists of transceiver, booster amplifiers and pre-amplifiers. All spans have an average length of approximately 90 km. These networks were selected because the intention was to make a comparison considering a network with short links (Sweden) and a network with long links (CORONET).

Since GNPy simulation requires a source and destination node, to evaluate the network, a simulation was run for each possible source and destination pair. The output power and the GSNR (in 0.1 nm) per channel was captured for each simulation. These parameters were chosen from those available in GNPy to better observe the behavior of the signals estimated by each model, and their respective impact on the network's QoT. All amplifiers from the Sweden and CORONET networks were replaced by the aforementioned EDFA models, resulting in four network scenarios: Sweden EDFA1, Sweden EDFA2, CORONET EDFA1, and CORONET EDFA2. The simulation in each network consisted of transmitting a signal using 40 frequency channels between pairs of their respective nodes. The signal band width is 32 GHz, and the frequency of the channels

[4] `https://gnpy.app/`

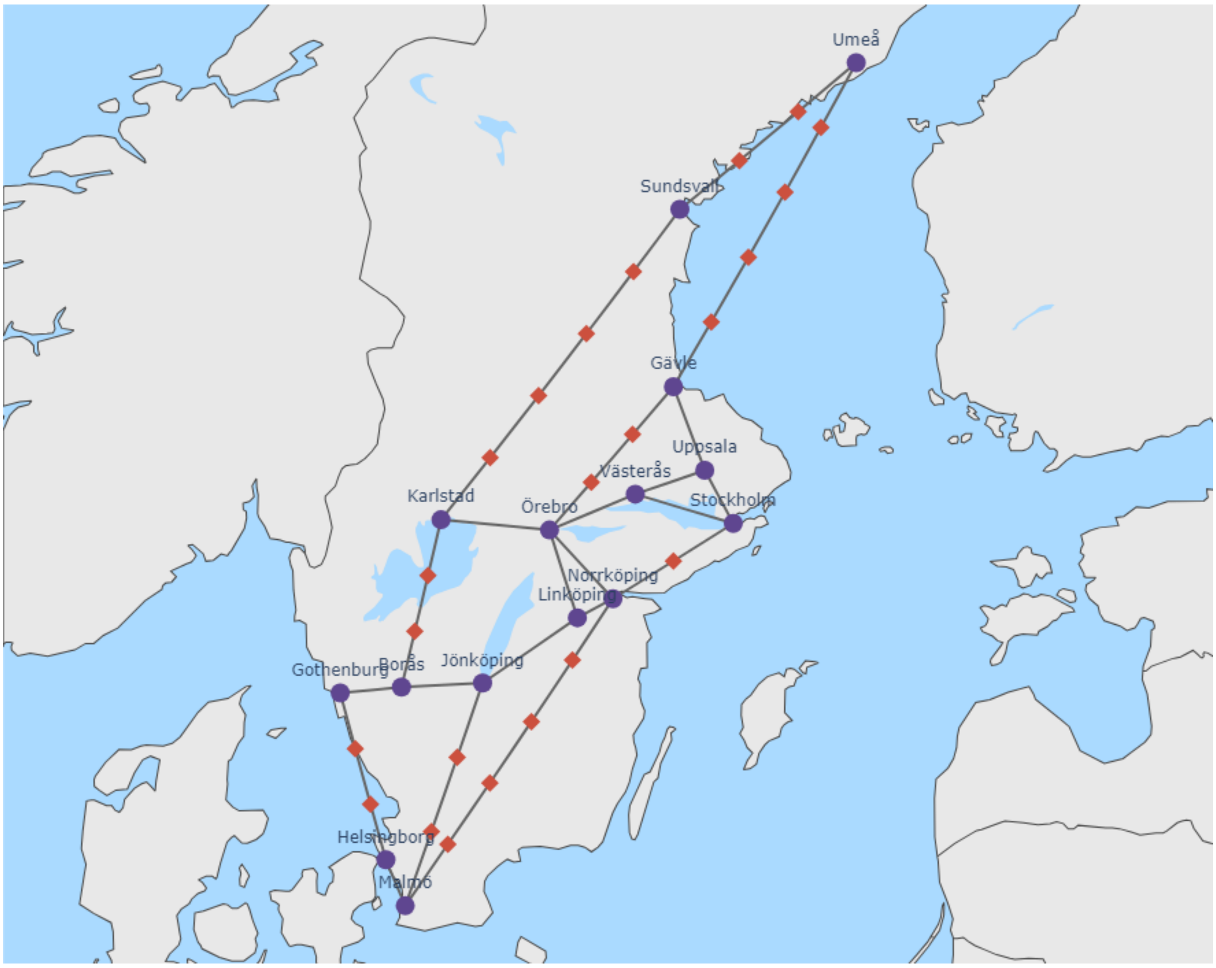


Figure 4.5: Sweden network topology, where the purple circles are nodes (transceiver, booster amplifiers and pre-amplifiers), the red diamonds are line amplifiers, and the black dashes are spans (fibers). (source: GNPy[4])

ranges from 192.1 Thz to 196.0 THz, with a step of 100GHz.

The transmission rate was calculated considering the GSNR estimated by GNPy. The relationship between GSNR and transmission rate was made according to Table 4.1 [Lima et al., 2022]. The transmission rate was calculated for each channel, with the transmission rate of the link being given by the sum of the transmission rates of all channels. A transmission block was considered on channels with a GSNR lower than 9 dB, which means that for these channels the transmission rate is zero.

Table 4.1: GSNR to Transmission Rate conversion table (source: [Lima et al., 2022])

Gb/s	Modulation Format	Minimum GSNR required (dB)
40	DP-BPSK	9
100	DP-QPSK	12.5
200	DP-QPSK	16
200	DP-16QAM	19
400	DP-64QAM	24

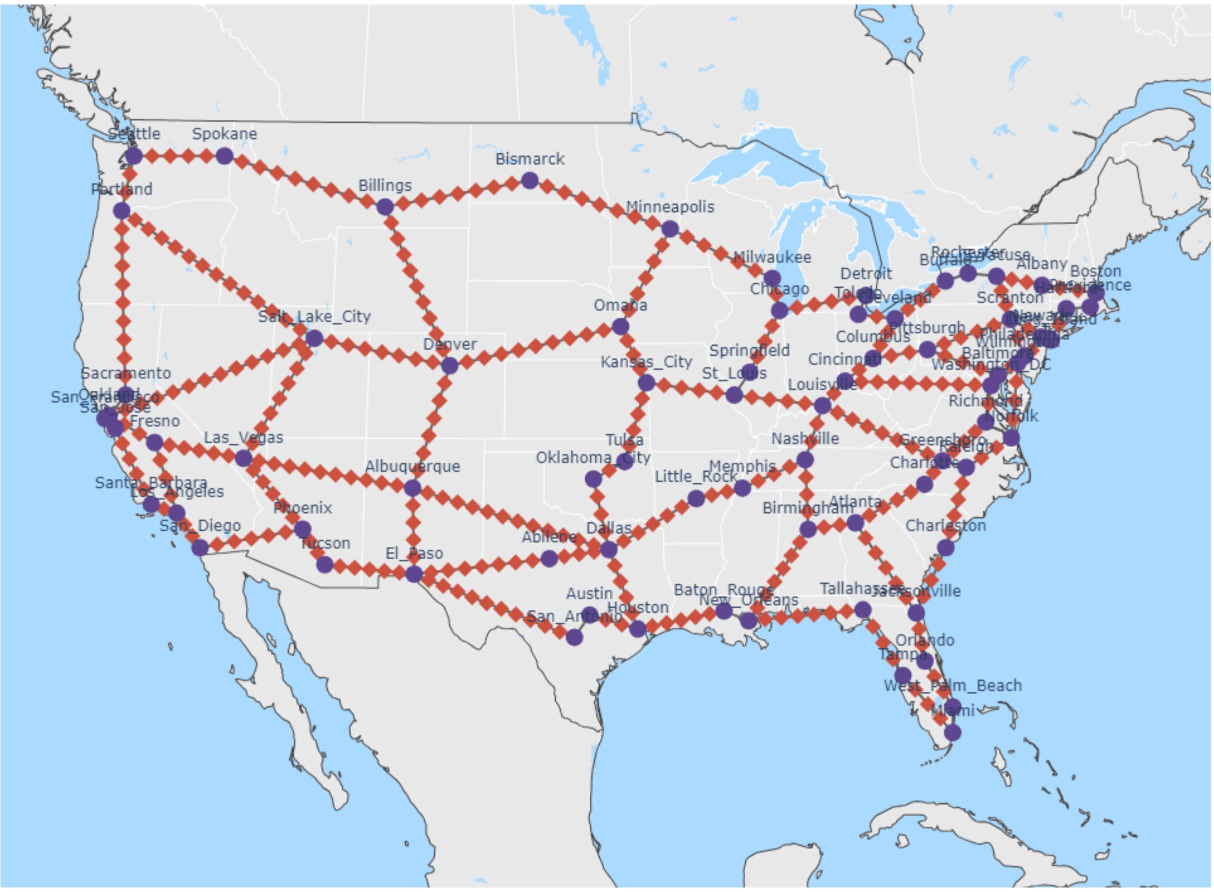


Figure 4.6: CORONET network topology, where the purple circles are nodes (transceiver, booster amplifiers and pre-amplifiers), the red diamonds are line amplifiers, and the black dashes are spans (fibers). (source: GNPy[4])

Simulations with modified versions of the two networks mentioned here were also carried out. The purpose of the modification was to evaluate the impact in QoT if all network links had the same characteristics of the link in the single-link scenario 1. As this configuration has a benchmark analysis of the PMM and AM models together with the OS simulator, replicating it in a network scenario will allow a better understanding of the behavior of the models in the original network scenarios. Three modifications were made to all the links of both networks:

- ROADM loss set to 14 dB, to guarantee an input signal with -14 dBm per channel in the first amplifier of the link;
- Gain of all amplifiers set to 14 dB;
- Distance between each node set at 70 km, to guarantee an input signal with -14 dBm per channel in all amplifier of the link (considering a flat amplifier response). This distance is different from the 65 km of single-link scenario 1 due to different loss configurations of the fiber connectors between this scenario and the networks, with

this larger fiber size being necessary in the modified network scenarios to guarantee the same loss measure.

These modifications were inspired by the work presented in [Souza et al., 2023], in which the authors consider that all the links in an Italian network are the same as the ones they used in a previous simulation of a single-link scenario, thus replicating its configuration for the larger scenario.

Chapter 5

Results

5.1 Single-link scenarios

Figures 5.1, 5.2 and 5.3 show the output power and OSNR returned by the OS and by the GNPy considering PMM and AM. The values are obtained at the end of the link. The figures consider the results in single-link scenarios 1, 2, and 3, respectively, and using only EDFA1 amplifiers.

Considering the output power and OSNR values returned by OS as a benchmark, it can be seen that PMM returned a better estimate than AM in scenarios with the same amplifier gain configuration (Figures 5.1 and 5.2). The maximum absolute errors between the output power value predicted by PMM and the simulated by OS are 0.62 dB and 0.81 dB for single-link scenarios 1 and 2, respectively. On the other hand, the maximum absolute errors between the output power value predicted by AM and the value simulated by OS, considering the same scenarios, are 17.06 dB and 13.16 dB, respectively.

Considering a more diverse scenario of amplifier gains and span lengths (Figure 5.3), PMM was also able to return better results than AM considering that its maximum absolute error is 2.85 dB and AM's is 4.61 dB.

Figure 5.4 also shows the output power and OSNR of the OS simulator, PMM and AM, considering the last amplifier in single-link scenario 4, this time using EDFA2 amplifiers. One can see that the PMM presented a good estimate of the link's OSNR in relation to the OS result. Although PMM visually appears to be unable to estimate the shape of the link's output power, possibly due to the nature of its interpolation process in conjunction with some noisy signals in the power masks, it is important to note that the graph scale is very low, so that PMM and AM have a maximum error of only 0.58 dB and 0.7 dB, respectively. Furthermore, the OSNR graph makes clear the effectiveness of PMM in estimating this scenario, presenting a good advantage over AM. Considering that the EDFA2 is an amplifier with a more diverse noise figure spectrum, and that the AM considers a more general noise figure spectrum, whereas PMM considers the characterized

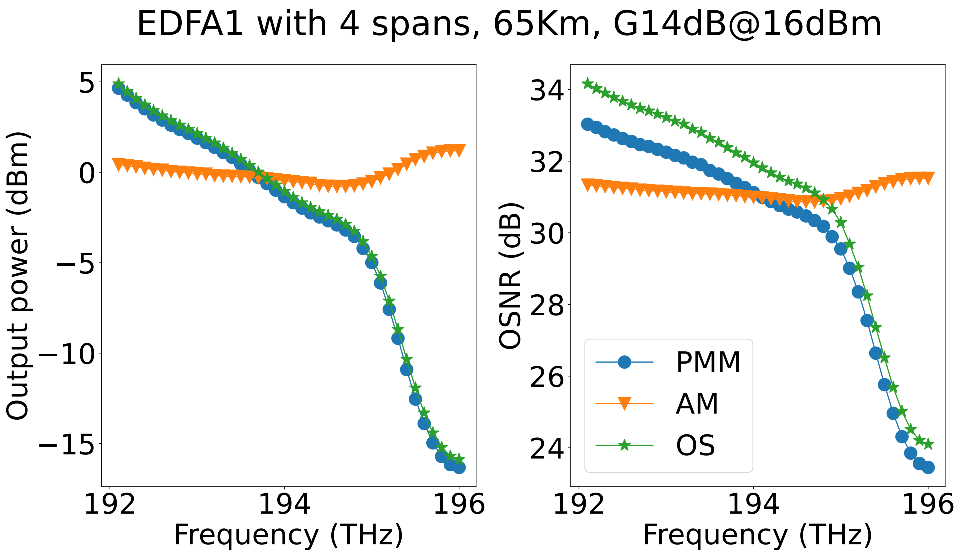


Figure 5.1: Output power and OSNR returned by the OptiSystem (OS) simulation, and estimated by the GNPy using Power Mask Model (PMM) and Advanced Model (AM), in single-link scenario 1.

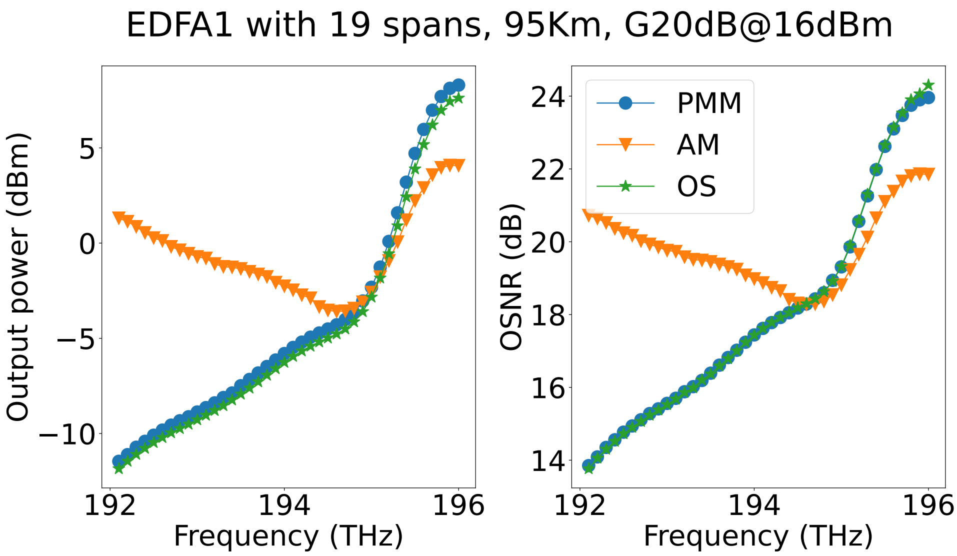


Figure 5.2: Output power and OSNR returned by the OptiSystem (OS) simulation, and estimated by the GNPy using Power Mask Model (PMM) and Advanced Model (AM), in single-link scenario 2.

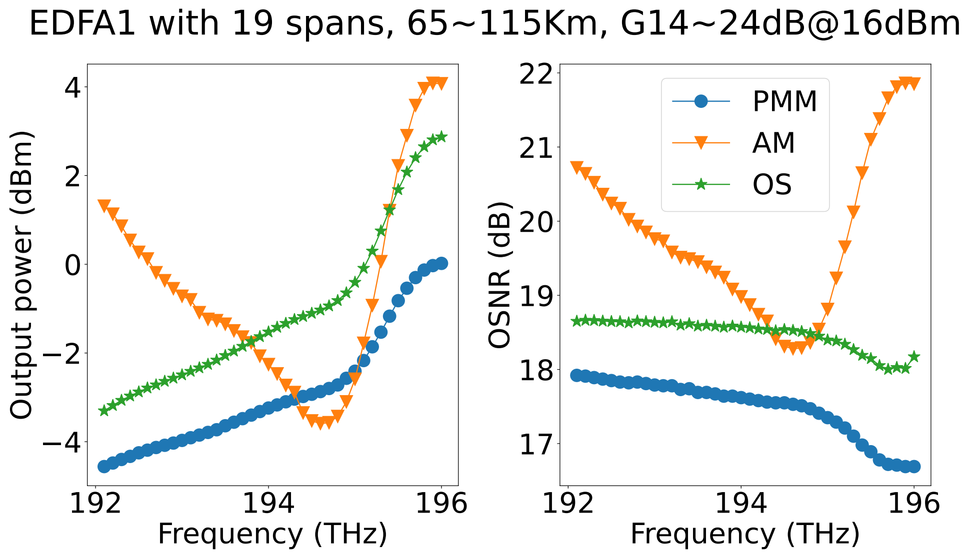


Figure 5.3: Output power and OSNR returned by the OptiSystem (OS) simulation, and estimated by the GNPy using Power Mask Model (PMM) and Advanced Model (AM), in single-link scenario 3.

NF spectrum, the difference between AM and PMM in estimating the OSNR spectrum is justifiable.

5.2 Network scenarios

Regarding the network simulations, for each link, two GNPy simulations were executed, one using PMM and the other using AM. For each optical channel, the difference between the GSNR estimated by PMM and by AM at the end of the link was calculated. These results are presented in Figures 5.5, 5.7, 5.9 and 5.11. To illustrate the impact of GSNR differences on QoT, the aggregated transmission rate of each link was calculated. These results are presented in Figures 5.6, 5.8, 5.10 and 5.12.

5.2.1 Sweden Network

Figure 5.5 shows the histogram of the difference between the GSRN estimated by PMM and AM on each link of the Sweden network using the EDFA1 and EDFA2 amplifier. The difference is calculated by subtracting the GSNR estimated using AM from the GSNR estimated using PMM. One can see that when the network is equipped with EDFA1 amplifiers the GSNR difference is between -1 dB and 1 dB in 97.9% of the cases. On the other hand, the cases in the same range drop to 64.2% when the network is equipped with EDFA2 amplifiers. Furthermore, the median of the difference distribution is 0.26 dB using EDFA1 amplifiers and 0.89 dB using EDFA2 amplifiers, the lowest difference (considering the difference modulus) is 3.44×10^{-5} dB using EDFA1 amplifiers and 3.94×10^{-4} dB

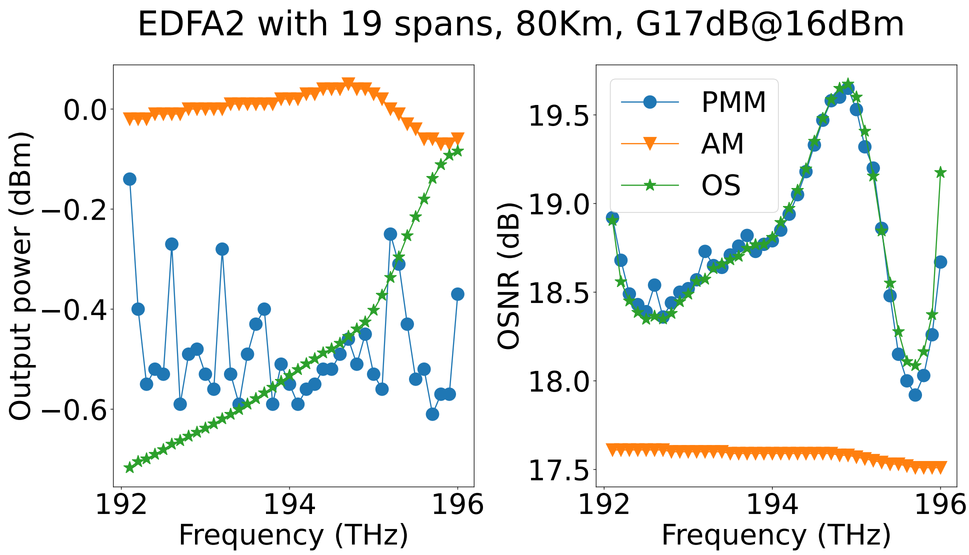


Figure 5.4: Output power and OSNR returned by the OptiSystem (OS) simulation, and estimated by the GNPy using Power Mask Model (PMM) and Advanced Model (AM), in single-link scenario 4.

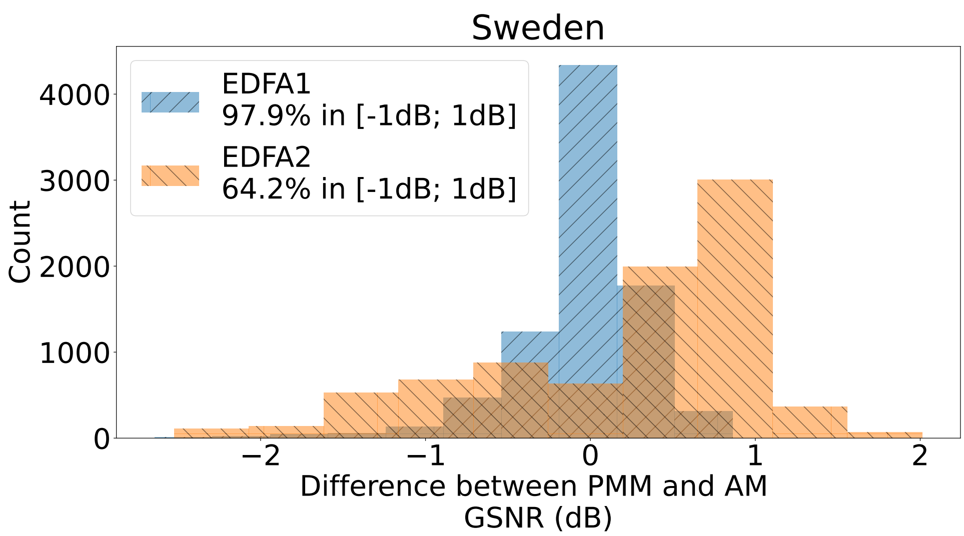


Figure 5.5: Histogram of the difference between the GSNR estimated with Power Mask Model (PMM) and Advanced Model (AM) on each link of the Sweden network, considering EDFA1 and EDFA2 amplifiers.

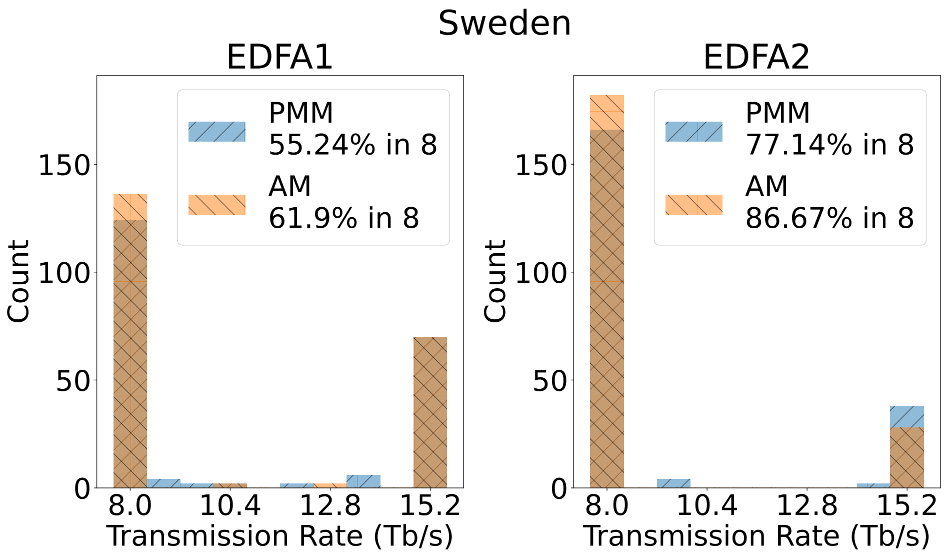


Figure 5.6: Histogram of the distribution of the aggregate transmission rate estimated with Power Mask Model (PMM) and Advanced Model (AM) across all links of the Sweden network, considering EDFA1 and EDFA2 amplifiers.

using EDFA2 amplifiers, the highest difference (considering the difference modulus) is -2.47 dB using EDFA1 amplifiers and -2.30 dB using EDFA2 amplifiers.

Figure 5.6 shows the histogram of the distribution of the aggregate transmission rate achieved by PMM and AM, considering the Sweden network with EDFA1 and EDFA2 amplifiers. One can see that most of the links (more than 50%) had an aggregate transmission rate of 8 Tb/s. For both amplifiers, the PMM estimated more links with aggregated transmission rates higher than 8 Tb/s than the AM. This means that the PMM GSNR estimation is higher than the AM in more cases, leading to higher transmission rates on some links. An interesting observation is that both PMM and AM showed generally lower transmission rates in the EDFA2 tests than in the EDFA1. This can be explained because EDFA2 has the worse noise figure than EDFA1, resulting in a lower GSNR and consequently lower transmission rates. Furthermore, for this network, none of the channels on any of the links had a GSNR lower than 9 dB.

5.2.2 CORONET Network

Figure 5.7 shows the histogram of the difference between the GSRN estimated by PMM and AM on each link of the CORONET network using the EDFA1 and EDFA2 amplifier. One can see that when the network is equipped with an EDFA1 amplifier, the GSNR difference is between -1 dB and 1 dB in 90.8% of the cases. On the other hand, the cases in the same range drop to 36.6% when the network is equipped with EDFA2 amplifiers. Furthermore, the median of the difference distribution is -5.38×10^{-3} dB using EDFA1 amplifiers and -6.66×10^{-2} dB using EDFA2 amplifiers, the lowest absolute difference is 9.00×10^{-8} dB using EDFA1 amplifiers and 8.64×10^{-6} dB using EDFA2 amplifiers,

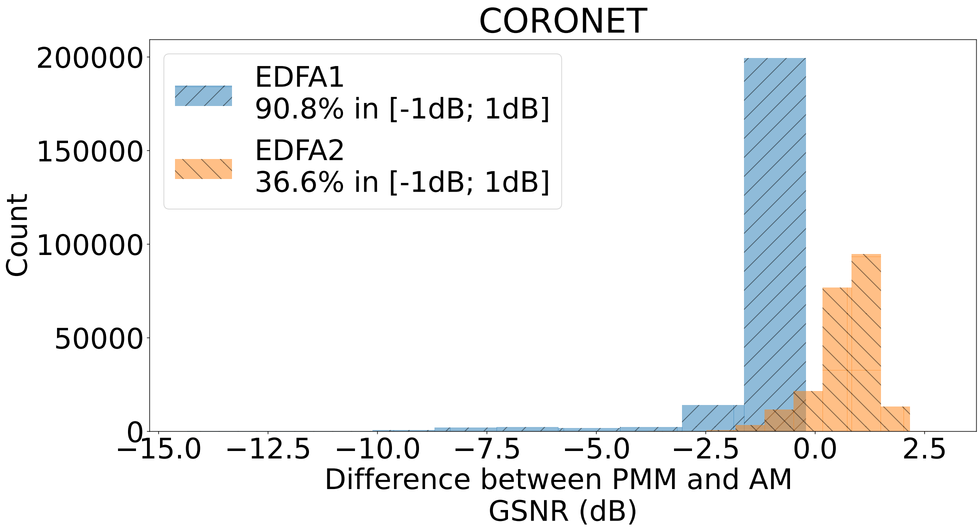


Figure 5.7: Histogram of the difference between the GSRN estimated with Power Mask Model (PMM) and Advanced Model (AM) on each link of the CORONET network, considering EDFA1 and EDFA2 amplifiers.

the highest absolute difference is −13.64 dB using EDFA1 amplifiers and −3.48 dB using EDFA2 amplifiers.

Figure 5.8 shows the histogram of the distribution of the aggregate transmission rate considering the CORONET network scenario, using PMM and AM, and EDFA1 and EDFA2 amplifiers. It can be seen that when this network is equipped with EDFA1, most links (more than 50%) had an aggregate transmission rate of 8 Tb/s for both estimation methods. However, the PMM estimates link with transmission rates below 4 Tb/s, whereas the AM lower bound is 4 Tb/s. This means that in this network with EDFA1 the PMM GSNR estimation is lower than the AM in some cases, leading to lower transmission rates in some links. On the other hand, when the network is equipped with EDFA2, it can be seen that most of the links had an aggregate transmission rate less than 4 Tb/s for both estimation methods. Since the EDFA2 is a more noisy amplifier, a scenario with only this amplifier implies in channels with lower GSNRs and, consequently, lower bit rates.

For this network, a total of 3,089 channels had a GSNR lower than 9 dB. All these channels were estimated by PMM, 3,027 in the EDFA1 scenario and 62 in the EDFA2 scenario. One can see that the PMM estimates lower GSNRs than the AM for many channels. Moreover, this difference can have consequences in the estimation of the network workload, because with AM some connections will be considered able to be established, whereas considering PMM the same connections will be blocked due to physical impairments.

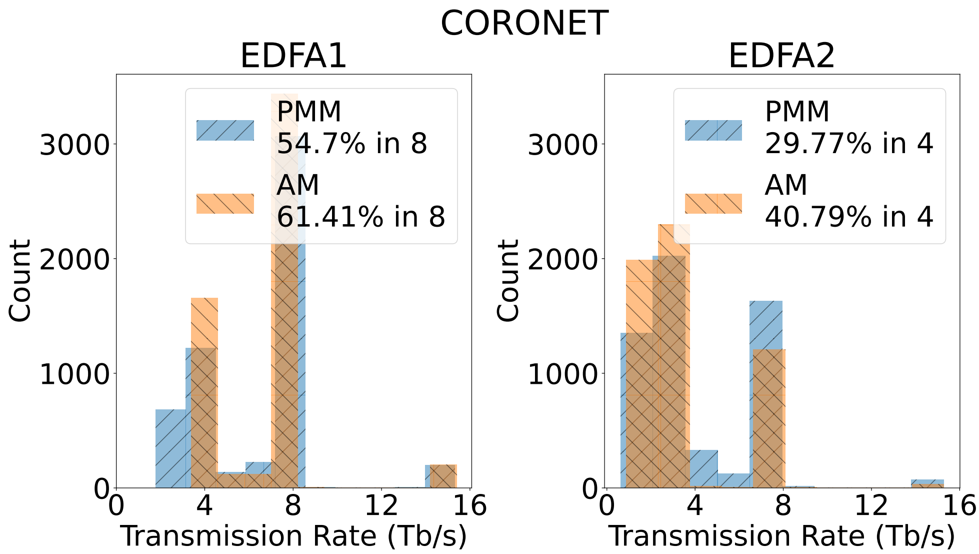


Figure 5.8: Histogram of the distribution of the aggregate transmission rate estimated with Power Mask Model (PMM) and Advanced Model (AM) across all links of the CORONET network, considering EDFA1 and EDFA2 amplifiers.

5.2.3 Discussion

Comparing the results presented for the networks, the most notable difference is the decrease in the number of cases in which the difference between PMM and AM is in the range of -1 dB and 1 dB in the CORONET network, showing that the models presented more distinct estimates than for the Sweden network, especially using EDFA2 amplifiers.

Although there is no significant difference in the distribution presented in Figures 5.5 and 5.7, the PMM model estimated 3,089 channels with GSNR less than 9 dB and the AM model estimated none with such a lower GSNR, indicating that there is a significant difference between the values that the two models estimated when the CORONET network was considered.

5.3 Modified network scenarios

The difference between PMM and AM is not significant on the Sweden network. One hypothesis is that in this network the amplifiers operate mostly in a region of the power mask in which the response of the amplifier is very similar to the simplified response of the AM (*i.e.* with low ripple). To test this hypothesis, the results presented in this section consider simulations performed with modified versions of the Sweden and CORONET networks. Such modifications were explained in detail in Section 4.3 and aim to replicate the configuration of the single-link scenario and observe the behavior of the PMM and AM GSNR estimation in these networks compared to their original versions. The objective is to verify whether the differences between PMM and AM will be greater, especially in the Sweden network, as observed in the single-link results in Section 5.1.

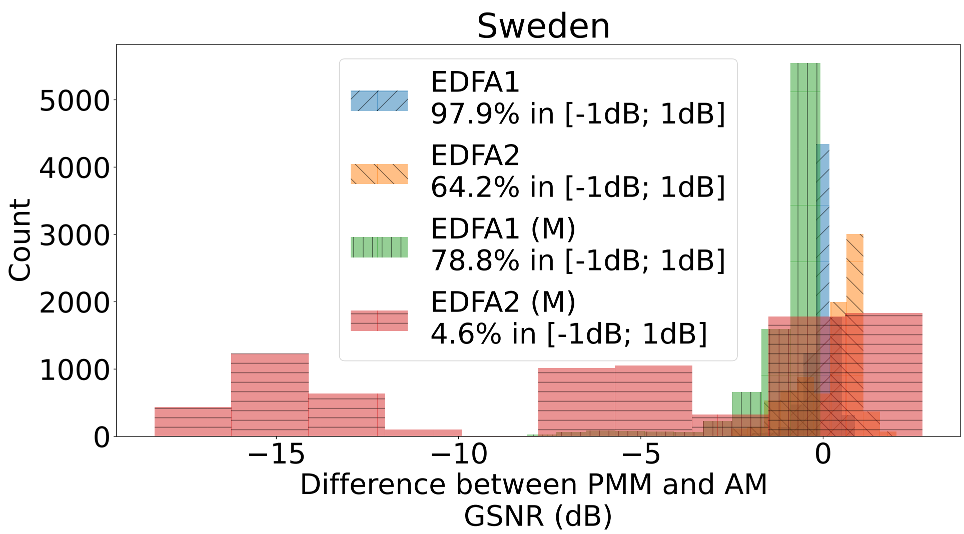


Figure 5.9: Histogram of the difference between the GSNR estimated with Power Mask Model (PMM) and Advanced Model (AM) on each link of the original and modified (M) Sweden network, considering EDFA1 and EDFA2 amplifiers.

5.3.1 Modified Sweden Network

Figure 5.9 shows the histogram of the difference between the GSNR estimated with PMM and AM on each link of the original and modified (M) Sweden network, considering the EDFA1 and EDFA2 amplifiers. One can see that when the modified network is equipped with EDFA1 amplifiers, the difference in GSNR is between -1 dB and 1 dB in 78.8% of the cases. On the other hand, the cases in the same range drop to 4.6% when the network is equipped with EDFA2 amplifiers. Furthermore, the median of the difference distribution is 0.24 dB using EDFA1 amplifiers and 3.24 dB using EDFA2 amplifiers, the lowest absolute difference is -2.69×10^{-4} dB using EDFA1 amplifiers and -1.70×10^{-3} dB using EDFA2 amplifiers, the highest absolute difference is -7.71 dB using EDFA1 amplifiers and -17.28 dB using EDFA2 amplifiers.

One can see that the difference distribution considering the modified network is wider than the same distribution considering the original network (Figure 5.9). The median of the difference distribution using EDFA1 amplifiers decreased 0.02 dB in relation to tests with the original network, whereas using EDFA2 amplifiers the difference increased by 2.35 dB after the modifications. The largest difference between the models increased 5.24 dB and 14.98 dB considering the tests with EDFA1 and EDFA2 amplifiers, respectively.

Figure 5.10 shows the histogram of the distribution of the aggregate transmission rate estimated with PMM and AM, considering the modified Sweden network with amplifiers EDFA1 and EDFA2. It can be seen that, considering the EDFA1 scenario, PMM tends to estimate transmission rates lower than AM, which means a generally lower GSNR for PMM. Similarly, at several links in the EDFA2 scenario, the PMM did not estimate sufficiently high GSNR values for transmission to occur, resulting in several cases with 0

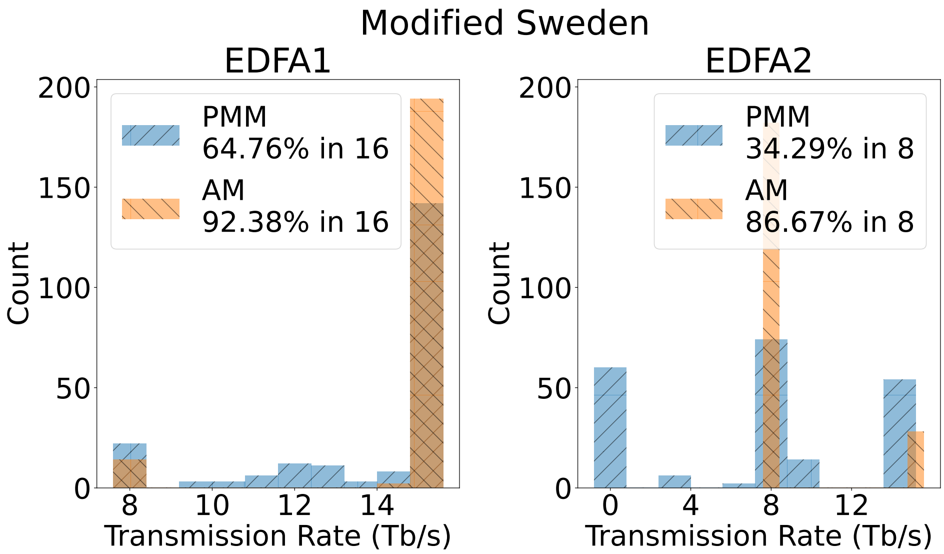


Figure 5.10: Histogram of the distribution of the aggregate transmission rate estimated with Power Mask Model (PMM) and Advanced Model (AM) across all links of the modified Sweden network, considering EDFA1 and EDFA2 amplifiers.

Tb/s. This did not happen with AM in any case; actually, the AM lower bound is 8 Tb/s in this scenario.

Table 5.1: Number of channels estimated by the PMM with GSNR less than 9 dB for both networks in its original and modified version, and for both amplifiers. The AM did not estimate channels with GSNR less than 9 dB.

	Sweden		**CORONET**	
	EDFA1	*EDFA2*	*EDFA1*	*EDFA2*
Original Version	0	0	3,027	62
Modified Version	0	2,400	102,577	190,067

A total of 2,400 channels had GSNR less than 9 dB. All these channels were estimated by PMM considering EDFA2. One can see that PMM estimates lower GSNRs than AM for many channels. It should be noted that there were no channels with GSNR less than 9 dB in the simulations with the original Sweden network, which shows the impact on QoT when the amplifiers are at a different operating point (see Table 5.1).

5.3.2 Modified CORONET Network

Figure 5.11 shows the histogram of the difference between GSNR on each link of the original and modified CORONET network scenario, using PMM and AM, with EDFA1 and EDFA2 amplifiers. The difference in GSNR ranges from -1 to 1 dB in 19.0% of the cases when the modified network is equipped with EDFA1 amplifiers. However, when equipped with EDFA2 amplifiers, the number of cases in the same range drops to 1.1%.

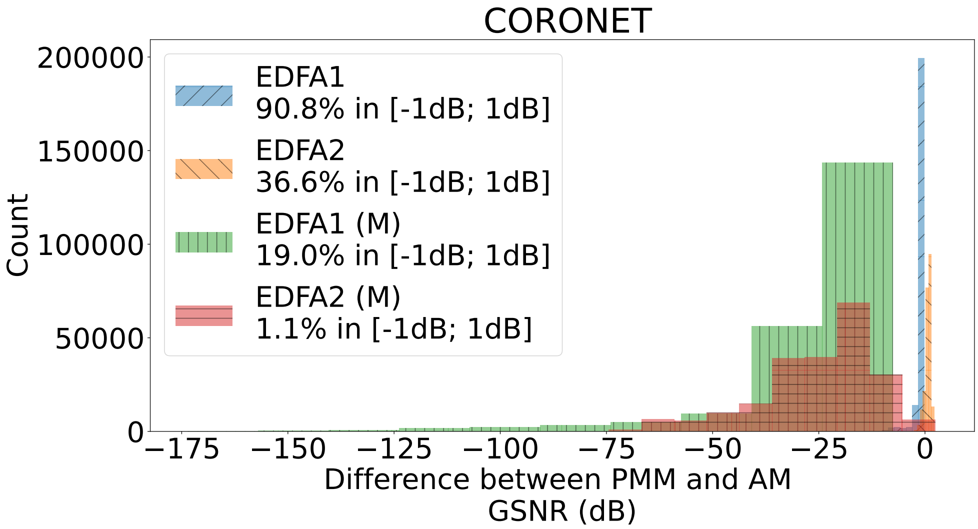


Figure 5.11: Histogram of the difference between the aggregate transmission rates estimated with Power Mask Model (PMM) and Advanced Model (AM) on each link of the original and modified (M) CORONET network, considering EDFA1 and EDFA2 amplifiers.

The median difference is 5.66×10^{-2} dB using EDFA1 amplifiers and -1.52 dB using EDFA2 amplifiers, the lowest absolute difference is 2.58×10^{-5} dB using EDFA1 amplifiers and 1.47×10^{-3} dB using EDFA2 amplifiers, the highest absolute difference is -165.28 dB using EDFA1 amplifiers and -70.57 dB using EDFA2 amplifiers.

One can see that the difference distribution considering the modified network is larger than the same distribution considering the original network (Figure 5.7).

The median of the difference distribution increased 5.12×10^{-2} dB using EDFA1 amplifiers compared to the original network simulations, while it increased by 1.45 dB using EDFA2 amplifiers. The biggest difference between the models increased by 151.64 dB and 67.09 dB considering the EDFA1 and EDFA2 amplifiers, respectively.

The histogram in Figure 5.12 shows the distribution of the aggregate transmission rate for the modified CORONET network scenario, using PMM and AM, with EDFA1 and EDFA2 amplifiers. One can see that PMM generally produced a lower GSNR estimate than AM in both amplifiers, resulting mainly in lower transmission rates. The PMM estimate shows many cases of lack of transmission, with 37.71% of the cases having 0 Tb/s in the EDFA1 scenario and 84.41% in EDFA2.

A total of 292,624 channels had a GSNR of less than 9 dB. All of these channels were estimated by PMM, with 102,577 considering EDFA1 and 190,047 considering EDFA2. The number of channels with unacceptable GSNR increased when the network was modified, as shown in Table 5.1. This demonstrates the impact on network QoT when the same amplifier is at a different operating point.

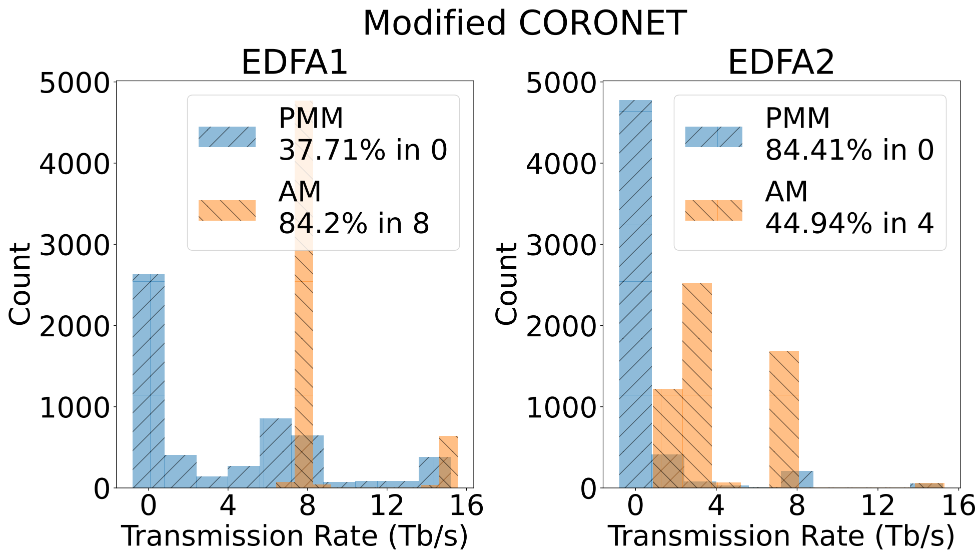


Figure 5.12: Histogram of the distribution of the aggregate transmission rate estimated with Power Mask Model (PMM) and Advanced Model (AM) across all links of the modified CORONET network, considering EDFA1 and EDFA2 amplifiers.

5.4 Discussion

One can see that there is an increase in the difference in GSNR estimation between PMM and AM with the modified networks compared to their original versions. It can be seen from the decrease in the number of cases between -1 dB and 1 dB, and the enlargement of the histogram, in both networks, which are shown in Figures 5.5 and 5.9, and in Figures 5.7 and 5.11.

The AM did not estimate that the GSNR was lower than 9 dB, while the PMM estimated thousands of cases that were small enough to be considered connection-blocking cases, as shown in Table 5.1. The results of the modified CORONET showed significant negative differences and a high number of links with a transmission rate of 0 Tb/s when using PMM (Figures 5.11 and 5.12). The occasional cases of abnormally low GSNR can again be explained by the PMM interpolation process in combination with noisy signals in the power masks. The hypothesis presented is proven in this section, indicating that in the original network scenario the amplifiers operate in a stable region of the EDFA1 and EDFA2 amplifiers with low ripple.

Table 5.2 presents the smallest and largest difference in GSNR ($PMM - AM$), their respective links, the number of ROADM nodes between the transmitter and receiver nodes, and the minimum and maximum GSNR per channel returned by PMM and AM, considering each network. One can see that the largest estimation difference in the CORONET network can be explained by the generally higher number of amplifiers in the CORONET network links compared to the Sweden network links. Moreover, in CORONET, there are long links without ROADMs in the middle, as in the case of the link between Portland and Salt Lake City, which is a link with 15 amplifiers and no intermediate ROADM. However,

Table 5.2: Smallest and largest GSNR difference ($PMM - AM$), their respective links, the number of nodes with ROADM between the transmitter and receiver nodes, and the minimum and maximum GSNR per channel returned by PMM and AM, considering each EDFA model, and each tested network.

Scenario	**Difference (dB)**	**Transmitter**	**Receiver**	**Amplifiers**	**Intermediate ROADMs**	**Min GSNR PMM (dB)**	**Max GSNR PMM (dB)**	**Min GSNR AM (dB)**	**Max GSNR AM (dB)**
Sweden	3.44×10^{-5}	Borås	Örebro	6	1	23.58	24.05	23.52	24.05
EDFA1	-2.47	Umeå	Gävle	6	0	20.67	24.17	23.07	23.85
Sweden	3.94×10^{-4}	Umeå	Jönköping	14	3	17.49	18.09	17.46	17.82
EDFA2	-2.30	Karlstad	Borås	4	0	21.22	22.50	23.48	23.90
CORONET	9.00×10^{-8}	San_Diego	Boston	79	16	13.37	13.63	13.23	13.74
EDFA1	Infeasible for the PMM	Portland	Salt_Lake_City	15	0	< 9	21.18	20.56	21.67
CORONET	8.64×10^{-6}	Las_Vegas	New_York	65	10	9.90	11.49	10.53	10.68
EDFA2	-3.48	Portland	Salt_Lake_City	15	0	13.68	15.61	17.15	17.31
Mod Sweden	-2.69×10^{-4}	Norrköping	Borås	6	2	27.71	28.08	27.86	28.20
EDFA1	-7.71	Umeå	Örebro	10	1	17.41	23.93	24.76	25.37
Mod Sweden	-1.70×10^{-3}	Stockholm	Linköping	5	1	22.19	23.37	22.53	22.67
EDFA2	Infeasible for the PMM	Malmö	Norrköping	6	0	< 9	< 9	21.85	22.06
Mod CORONET	2.58×10^{-5}	Boston	Louisville	27	7	18.12	21.33	21.06	21.59
EDFA1	Infeasible for the PMM	Portland	Miami	79	9	< 9	< 9	15.50	16.53
Mod CORONET	1.47×10^{-3}	Long_Island	Boston	7	2	21.14	22.22	21.41	21.58
EDFA2	Infeasible for the PMM	Portland	Salt_Lake_City	15	0	< 9	< 9	17.90	18.12

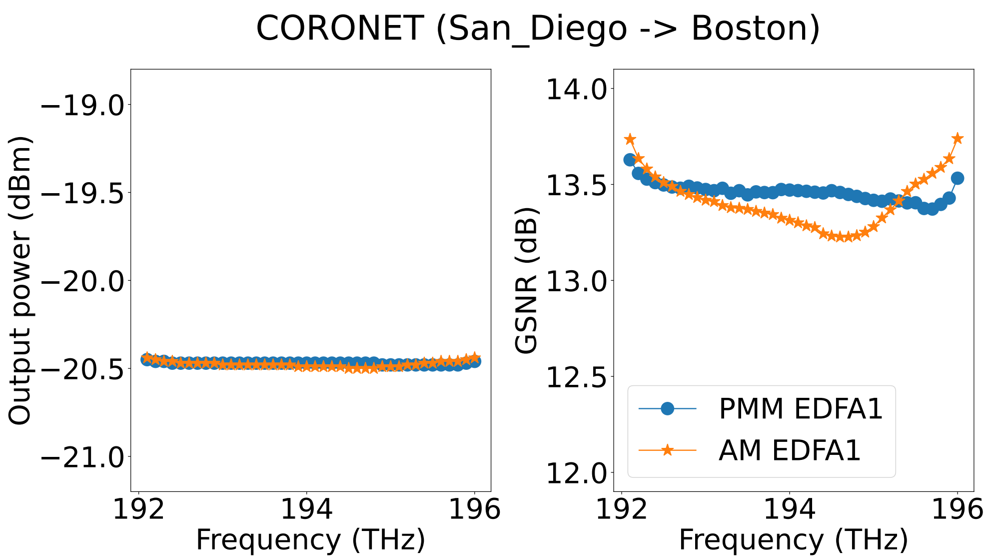


Figure 5.13: Output power and GSNR estimated by the GNPy using Power Mask Model (PMM) and Advanced Model (AM) on each channel of the CORONET network, considering the San_Diego -> Boston link, and EDFA1 amplifiers.

the links in which the PMM and AM estimations were very similar have in common the presence of intermediate ROADMs. For example, the link between San Diego and Boston has a large number of amplifiers (79), but it also has a large number of intermediate ROADMs (16).

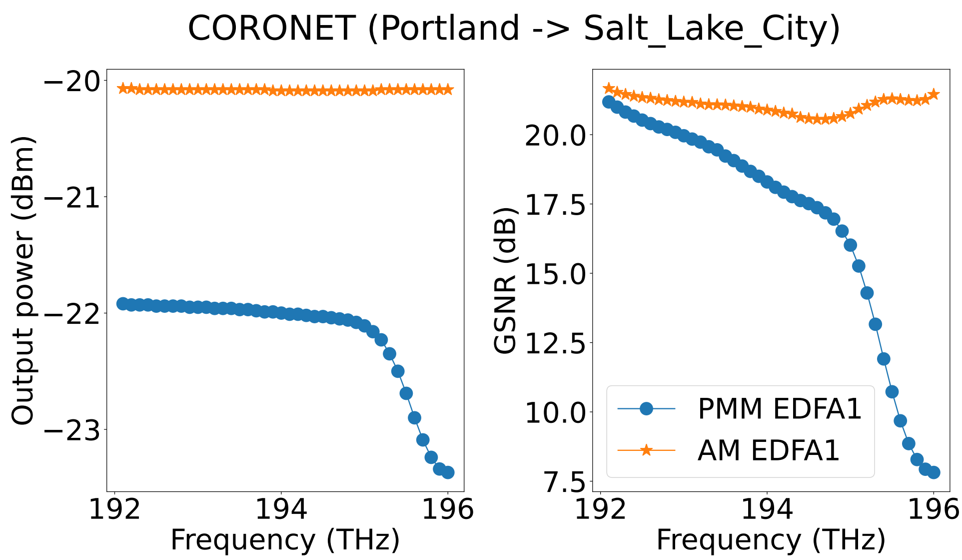


Figure 5.14: Output power and GSNR estimated by the GNPy using Power Mask Model (PMM) and Advanced Model (AM) on each channel of the CORONET network, considering the Portland -> Salt_Lake_City link, and EDFA1 amplifiers.

Since in each intermediate ROADM the signal power is equalized, the output power and the GSNR will flatten. In this case of a flat output spectrum, there is a very small difference between PMM and AM, as AM tends to estimate that the signal is flat. This can be seen in Figure 5.13 which displays the output power and GSNR spectrum of one link in which the difference was small (San Diego -> Boston). On the other hand, Figure 5.14 displays the same data for one link in which the difference was large (Portland -> Salt Lake City).

Therefore, since the AM is a simple method, it can be a good option if the amplifiers work always at the same operating point and if this operating point results in a flat response by the amplifier, as was seen in the Sweden network. However, considering the results of the single-link scenarios, the CORONET network, and the modified versions of both networks, it is valid to say that the use of PMM would be more prudent, given its greater versatility compared to AM in the GSNR estimation task. In other words, the use of AM instead of PMM can result in optimistic GSNR estimations, which can lead to channels with poor performance or even being blocked in practice.

Chapter 6

Conclusion

This work presented an evaluation of the impact of two different amplifier modelings on the estimation of QoT in optical networks. A new modeling based on the characterization of an optical amplifier, called a Power Mask Model, was added to the GNPy QoT estimator using its user-friendly modular structure. The adaptation of GNPy consisted of adding the TIP-Tilt algorithm used by the Power Mask Model to its source code, as well as adding the mask base required by the algorithm, consisting of the result of the characterization of two commercial EDFA amplifiers. Its impact was evaluated in comparison with the Advanced Model, a more traditional estimator from the literature present in the GNPy network simulator, considering both single-link and optical network scenarios. Four single-link scenarios were considered with different span, gain, and input signal power configurations, using the OptiSystem numerical simulator as a benchmark to verify the accuracy of the models' accuracy in estimation output power and OSNR. Furthermore, comparative GSNR and transmission rate estimation tests were performed with two optical network topologies already available in GNPy, where their original versions and two modified versions of them were used.

The results of this work highlight that the Power Mask Model proved to be a more accurate estimator of both signal output power and OSNR in the studied single-link scenarios, achieving test results very close to the benchmark, as well as lower error measures compared to the Advanced Model. This advantage remained in both better behaved gain and span size configurations, as in the cases of scenarios 1 and 2, and in more heterogeneous environments with different gains or noisier amplifiers, such as scenarios 3 and 4.

Now, considering the network scenarios with their default configurations, both models presented a very similar performance on the Sweden network, a network with shorter links and few amplifiers. However, in the CORONET network, a network with long links and many amplifiers, the differences between the GSNR predictions were more noticeable, especially considering the noisier EDFA2 amplifier. In this scenario, the Power Mask Model showed a tendency to estimate lower GSNR and, consequently, lower transmission rates, even going so far as to estimate several cases of connection blocking, while the Advanced Model presented more optimistic estimates, not presenting any connection blocking case.

One hypothesis for the similar performances of the Power Mask Model and the Advanced Model in most scenarios was that the amplifiers were operating in more stable regions with low ripple. The network scenarios were modified to move the operation of the amplifiers to a region with high tilt, to observe the impact on QoT and to observe whether the differences would be more significant in this scenario.

Considering both networks in their modified versions, it is observed that the differences between the GSNR estimates between the Power Mask Model and Advanced Model were greater than in their original versions, as imagined in the hypothesis. The Power Mask Model estimated GSNR considerably lower than the Advanced Model, in addition to presenting many cases of connection blockage, even more than in the original networks, while the Advanced Model did not predict any case of blockage, presenting flatter estimates.

This study was limited in some aspects. Firstly, it is possible that the results will be different from those presented here in tests with other amplifier models, whose characterizations will possibly be different from those used in the Power Mask Model mask base and will directly affect its estimations. Secondly, this work considered a modulation format set that is not as sensitive to variations at high GSNR values as a set that considers transmission rates above 400 Gb/s. Choosing a more sensitive modulation set could present more granular results in transmission rate estimation than those presented here. Furthermore, it is possible to highlight the absence of a benchmark model in the network scenario, a consequence of the impossibility of comparing all the links of the studied networks using a numerical analyzer. Future studies could aim to mitigate these limitations and expand the scope of this research, for example, by testing other amplifier models and different network topologies. In addition, other modulation formats with high transmission rates can be evaluated, as in these scenarios the impact of GSNR on the transmission rate is greater. Furthermore, a numerical simulator can be used to simulate signal transmission in some optical network links and then serve as a reference in future simulations. Finally, another research opportunity is to replicate this study in a multi-band transmission scenario, as amplifier modeling is more challenging when the S and L transmission bands are considered.

The findings of this study can be useful for optical network researchers and operators who want to have more flexible network management and optimization through simulations and software-controlled networks. Among the models covered in this work, the Power Mask Model proved to be a safer choice of use, as it presents a more detailed representation of the amplifier and, consequently, greater versatility in the QoT prediction task in relation to the scenarios presented here in comparison with the Advanced Model. On the other hand, for cases where the amplifier operates in more stable regions, presenting generally flat responses, the Advanced Model may be sufficient.

Appendix A

Code snippets

Listing A.1: Code snippet from the *eqpt_config.json* file with the new equipment added to GNPy.

```
// eqpt_config.json
{
    "Edfa":[
        {
            "type_variety": "edfa1_mask_model",
            "type_def": "power_mask_model",
            "gain_flatmax": 24,
            "gain_min": 14,
            "p_max": 21,
            "power_mask_path": "Masks/edfa1/",
            "out_voa_auto": false ,
            "allowed_for_design": false
        },
        {
            "type_variety": "edfa2_mask_model",
            "type_def": "power_mask_model",
            "gain_flatmax": 27,
            "gain_min": 17,
            "p_max": 22,
            "power_mask_path": "Masks/edfa2/",
            "out_voa_auto": false ,
            "allowed_for_design": false
        },
        {
            "type_variety": "edfa1_AdvancedModel",
            "type_def": "advanced_model",
            "gain_flatmax": 24,
            "gain_min": 14,
            "p_max": 21,
            "advanced_config_from_json": "edfa1_AdvancedModel.json",
```

```
            "out_voa_auto": false ,
            "allowed_for_design": false
        },
        {
            "type_variety": "edfa2_AdvancedModel",
            "type_def": "advanced_model",
            "gain_flatmax": 27,
            "gain_min": 17,
            "p_max": 21,
            "advanced_config_from_json": "edfa2_AdvancedModel.json",
            "out_voa_auto": false ,
            "allowed_for_design": false
        },
        ...
    ],
    ...
}
```

Listing A.2: Code snippet from the *edfa_example_network_g14.json* file containing the definition of a single-link scenario.

```
// edfa_example_network_g14.json
{
    "network_name": "EDFA_Example_Network_G14@16dBm",
    "elements": [{
            "uid": "Site_A",
            "type": "Transceiver",
            "metadata": {
                "location": {
                    "city": "Site_A",
                    "region": "",
                    "latitude": 0,
                    "longitude": 0
                }
            }
        },
        {
            "uid": "Span1",
            "type": "Fiber",
            "type_variety": "SSMF",
            "params": {
                "length":65,
                "loss_coef": 0.2,
                "length_units": "km",
                "att_in": 0,
                "con_in": 0.5,
                "con_out": 0.5
                },
            "metadata": {
                "location": {
                    "region": "",
                    "latitude": 1,
                    "longitude": 0
                }
            }
        },
        ...
        {
            "uid": "Edfa1",
            "type": "Edfa",
            "type_variety": "edfa1_mask_model",
            "operational": {
                "gain_target": 14,
                "tilt_target": 0,
                "out_voa": 0
```

```
            },
            "metadata": {
                "location": {
                    "region": "",
                    "latitude": 2,
                    "longitude": 0
                }
            }
        },
        ...
        {
            "uid": "Site_B",
            "type": "Transceiver",
            "metadata": {
                "location": {
                    "city": "Site_B",
                    "region": "",
                    "latitude": 20,
                    "longitude": 0
                }
            }
        }
    ],
    "connections": [
        {
            "from_node": "Site_A",
            "to_node": "Span1"
        },
        {
            "from_node": "Span1",
            "to_node": "Edfa1"
        },
        ...,
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        }
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}
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