Multi–band programmable gain Raman amplifier

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Abstract—Optical communication systems, operating in C–band, are reaching their theoretically achievable capacity limits. An attractive and economically viable solution to satisfy the future data rate demands is to employ the transmission across the full low–loss spectrum encompassing O, E, S, C and L band of the single mode fibers (SMF). Utilizing all five bands offers a bandwidth of up to \( \sim 53.5 \) THz (365 nm) with loss below 0.4 dB/km. A key component in realizing multi–band optical communication systems is the optical amplifier. Apart from having an ultra–wide gain profile, the ability of providing arbitrary gain profiles, in a controlled way, will become an essential feature. The latter will allow for signal power spectrum shaping which has a broad range of applications such as the maximization of the achievable information rate \( \times \) distance product, the elimination of static and lossy gain flattening filters (GFF) enabling a power efficient system design, and the gain equalization of optical frequency combs. In this paper, we experimentally demonstrate a multi–band (S+C+L) programmable gain optical amplifier using only Raman effects and machine learning. The amplifier achieves \( >1000 \) programmable gain profiles within the range from 3.5 to 30 dB, in an ultra–fast way and a very low maximum error of \( 1.6 \cdot 10^{-2} \) dB/THz over an ultra–wide bandwidth of 17.6–100 MHz (140.7–nm).

Index Terms—optical communications, multi–band systems, optical amplifiers, machine learning, neural networks.

I. INTRODUCTION

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VER the past two decades, a great evolution of optical communication systems, in terms of spectral efficiency \( \times \) distance product, has been enabled by the advances in digital coherent detection. So far, most of the efforts, on reaching the capacity of the nonlinear fiber–optic channel, have been focusing on the C–band only [1]. However, squeezing the information inside this transmission window will soon reach its theoretical limit [2]. To cope with the constant demand for higher throughput, novel solutions must be explored.

Optical communication systems operating across multi–band transmission, are an attractive solution for providing the future capacity scaling. They can provide up to 10\( \times \) higher capacity, compared to the C–band [3], on the already deployed SMF fiber infrastructure. To make multi–band systems commercially deployable in the near future, large research efforts in terms of components, system and network design are needed [4]–[11].

One of the main challenges in realizing multi–band systems is the development of optical amplifiers that are able to provide sufficiently high gains over such a wide bandwidth. Additionally, a novel feature that may become essential is the ability to provide arbitrary gain profiles in a controlled and ultra–fast way. This is because different signal channels in a multi–band system are unevenly impacted by the interaction between the Kerr nonlinearity, amplified spontaneous emission (ASE) noise and stimulated Raman scattering (SRS) [3]. Consequently, for the maximization of the achievable information rate (AIR) \( \times \) distance product, non–flat signal channel power profiles are needed. Depending on the system configuration, signal channel power profiles will be a result of a complex optimization and may assume arbitrary shapes. Moreover, to address the future requirements on high capacity optical networks, ultra–fast gain profile re–configurability is needed [12].

A current and by far the most dominant approach for performing programmable signal channel power profile shaping is by leveraging the use of wavelength selective switches (WSSs) whose primary function is to router the signals throughout the optical network. However, this approach is highly power inefficient since it adjusts the channel powers by means of attenuation.

A novel approach for realizing signal channel power shaping is by employing optical amplifiers with programmable (arbitrary) gain profiles. Such amplifiers could be a potential game changer as they would be able to simultaneously amplify the optical data signal and per-
form gain shaping. This has many impactful applications ranging from compensation of wavelength–dependent loss in devices such as modulators and frequency combs to gain–shaping in fixed-gain profile amplifiers. Especially, if integrated–combs are targeted for multi-channel sources, an efficient approach for gain shaping would be desirable. This is because for integrated–combs there is a large variation in power of their frequency components. Finally, optical amplifiers providing arbitrary gain profiles can be used in hybrid approaches to complement the gain, and overcome the limitations of other optical amplifier technologies [13]–[18].

There are several approaches and technologies for realizing optical amplifiers covering multiple bands. To date, works on multi–band optical amplifiers have focused on: rare–earth–doped fiber amplifiers (xDFAs) covering 17.56 THz over O+E–band [11] and 10.7 THz over S+C–band [19], semiconductor optical amplifiers (SOAs) for 12.7 THz on S+C+L–band [20], opto-parametric amplifiers (OPAs) with 10 THz of bandwidth on S+C+L–band [21], Raman amplifiers (RA) in combination with EDFAs, SOAs and OPAs achieving bandwidths ranging from 10.7 to 14 THz on C+L and S+C+L–band [13]–[18], and pure RAs with bandwidths of up to 19.1–THz S+C+L–band [22]–[26]. So far, the majority of works in [11], [13]–[17], [19]–[26] have focused on realizing flat gain profiles in C+L and S+C+L–band. Recently, an amplifier that relies on a hybrid SOA/Raman configuration has been demonstrated to achieve arbitrary loss/gain profile generation in S+C+L–band in 12.3 THz bandwidth [18].

Among all different solutions, RAs are most suitable for realizing arbitrary gain profiles, in a controlled way. This is because the RAs allow for a flexible gain profile design by adjusting the pump powers and wavelengths, and provide gain availability across a broad range of wavelengths, when operated in multi-pump configurations.

The challenge with Raman amplifier design is on the selection of pump powers and wavelengths that would result in a targeted gain profile. Several solutions to this optimization problem have been reported in the literature but have mainly focused on realizing flat gain profiles [24]–[28]. Recently, a machine learning framework for the ultra–fast configuration of the pump powers and wavelengths has been theoretically proposed and as a proof–of–principle experimentally demonstrated in C–band only [33], [34]. The proposed approach can be used for the design of Raman amplifiers, where an arbitrary gain profile is achievable in a controlled way. However, moving from C–band to multi–band and realizing wider gain profiles is significantly more challenging. This is partly due to the increased number of pumps that need to be controlled and also the increased nonlinearity given the higher overall powers in the optical fiber. In this paper, we use the proposed machine learning framework for the experimental realization of multi–band RAs that can provide arbitrary gains, in a controlled way, in C+L and S+C+L–band. Up to 8 pumps are employed to provide more than 5000 arbitrary gain profiles over up to 17.6-THz of bandwidth. We achieve a highly–accurate programmable set of gain profiles with a very low average maximum error, (defined between the target and realized gain profiles), per bandwidth, $E_{MAX}/BW$, of $1.6 \cdot 10^{-2}$ dB/THz.

Machine learning for broadband gain optimisation is a topic of growing interest, which is reflected in the recent work [18] reporting a root mean squared error per bandwidth, $RMSE/BW$, of 0.033 dB/THz in a 12.3 THz bandwidth SOA/distributed Raman link scenario. In this work, we achieve a close to an order of magnitude lower $RMSE/BW$ of 0.0045 dB/THz for transmission with discrete S+C+L–band Raman amplifier over a larger bandwidth of 17.6 THz. The presented work is first time demonstration of a programmable multi–band discrete Raman amplifier setting a benchmark, to be beaten, for the maximum error per bandwidth.

The structure of the paper is as following: Section II describes the experimental setup for realizing Raman amplifiers operating in C+L and S+C+L–band. We also give a brief overview of the ML framework used to obtain programmable arbitrary gain profiles. Section III presents, discusses and evaluates the experimental results. In Section IV conclusions and future work are presented and outlined.

II. EXPERIMENTAL SETUP

The experimental setup for realizing the multi–band RA is shown in Fig. 1(a). By selecting path 1 or 2, the operation in either C+L (1) or S+C+L–band (2) can be enabled. To achieve gains in the C+L, and S+C+L–band, 5 and 8 pump lasers are employed, respectively. Fig. 1(c) illustrates the spectral pump allocation and their individual contribution to the overall Raman gain. We only consider counter propagating pumps whose wavelengths are fixed and shown in Table I.

The gain profile control is performed by only adjusting the pump powers. Pump lasers $P_1...P_7$ are semiconductor laser diodes. Their output power is controlled by adjusting the driving currents. The corresponding power going into the RA is in the range from $\sim 16$ dBm to $\sim 27$ dBm. Pump laser $P_8$ is a Raman–based fiber laser and is controlled by adjusting its voltage. It provides power to the RA ranging from $\sim 20$ dBm to $\sim 27$ dBm.
Fig. 1. (a) Experimental setup for the multi–band RA: path 1 refers to the C+L–band RA and path 2 is for the S+C+L–band dual–stage discrete RA. (b) Input optical signal spectrum. (c) Pump lasers spectrum and their expected contribution to the overall Raman gain.

A. C+L–band Raman amplifier

The C+L–band RA can either be operated as a discrete, (7.5 km of inverse dispersion fiber (IDF)) or distributed (75 km span of standard SMF) amplifier. An input optical signal covering the C+L–band, for testing the performance of the RA, is generated by using two ASE sources for C and L bands channelized through a WSS to generate 90 lines placed at 100 GHz ITU-T grid covering a 9.4 THz (77 nm) bandwidth. The corresponding optical spectrum is shown in Fig. 1(b) (inside bracket 1) and is measured with a resolution of $\Delta \lambda = 0.1$ nm. The gaps between the C and L signal bands are due to the different ASE sources for these two bands. An isolator is placed at the input to the IDF to prevent pump powers entering the C+L–band signal source and to minimize the double Rayleigh backscattering induced multipath interference [35]. Finally, an optical spectrum analyser (OSA) is used to capture the optical spectrum.

B. S+C+L–band Raman amplifier

The S+C+L–band RA is implemented as a two–stage sequential discrete RA. The first stage is responsible for providing the gain in the S–band and it consists of 7.5 km of IDF and three pump lasers, $P_6$...$P_8$ used to control the gain profiles. The second stage is the same as the one used for the C+L–band RA. Note that distributing the pumps into two sequential stages reduces the strong depletion of shorter wavelength pumps [36]. The multi–band input optical signal (17.6 THz/140.7 nm) is generated by combining the optical signal from the C+L–band with a supercontinuum S–band source [37] and a single frequency laser operating at 185 THz. The resulting signal has a total of 148 frequency lines at 100 GHz ITU-T grid. The corresponding optical spectrum is shown in Fig. 1(b) (inside bracket 2). Due to the amplifier configuration, two pumps from the first stage ($P_1$−$P_2$) fall within the S-band signal. This means that some channels from the S–band need to be removed to avoid overlapping with the Rayleigh backscattered components of the pumps, leaving the gaps as shown in Fig. 1[b] [38].
C. Pump power control

The objective is to determine pump power settings that result in user defined target gain profiles such as: tilted gain, flat gain or an arbitrary gain. These settings are achieved off-line using the machine learning framework presented and then later applied on-line for the pump laser currents and voltage control [33]. As the framework in [33] is based on supervised learning, a data-set is required. This is achieved by varying the currents and the voltage of the pump lasers and measuring the corresponding gain profiles. The gain profiles are predicted, 3) the predicted currents and voltages are adjusted accordingly, i.e. fine-optimization. The fine-optimization uses iterative gradient descent by backpropagating the error through $NN_{fwd}$ to adjust the currents and voltage as described in [33]. 4) the obtained currents and voltages are and applied to the pump lasers in the experimental set-up, and new sets of measurements are performed, and 5) finally, to investigate the accuracy of the predicted pump currents and voltage, we calculate the maximum absolute error between the target and the newly measured gain profiles (i.e. $E_{MAX}$) and normalize it with the bandwidth (BW). The optimized topologies of the employed neural networks $NN_{fwd}$ and $NN_{dir}$, as well as their performance evaluation, are found in the Appendix Section.

III. RESULTS AND DISCUSSION

A. Arbitrary gain profiles

Fig. 3(a)–(c) show the probability, (PDF), and the cumulative, (CDF), density functions of the $E_{MAX}/BW$ for the C+L–band (distributed and discrete) and S+C+L–band (discrete) Raman amplifiers. The error is defined between the targeted arbitrary gain profiles, taken directly from the data-set (not used for training the machine learning framework), and the predicted gain profiles obtained from the measurement using the pump currents and voltage allocation provided by the machine learning framework. We use 2100, 2600 and 1025 target arbitrary gain profiles for the distributed C+L–band, discrete C+L–band and discrete S+C+L–band validation, respectively. We compare the accuracy of allocating pump currents and voltage, by using only the inverse mapping multi-layer neural network, ($NN_{inv}$), and both the inverse and forward mapping multi-layer neural networks, ($NN_{inv} + NN_{fwd}$), which allows for fine-optimization of pump currents and the voltage.

The PDFs shown in Fig. 3(b)–(c), illustrate that for the discrete RA, highly-accurate pump current predictions, resulting in a low mean and standard deviation, can be obtained using only $NN_{inv}$. Thus, the currents and the voltage prediction is obtained in an ultra-fast way as $NN_{inv}$ only involves matrix computations. We notice that the mean and standard deviations are decreased by a factor of $\sim 2$ when going from C+L to S+C+L–band. This is mainly because these two schemes have the same performance in terms of $E_{MAX}$ and S+C+L–band has almost two times wider bandwidth. However, qualitatively the results for C+L and S+C+L–band are comparable.

If $NN_{inv} + NN_{fwd}$ is used a slight increase in the mean and the standard deviation is observed. This is because the $NN_{inv}$ has already found pump current configuration that minimizes the mean square error.
Applying the fine-optimization introduces some small random deviations around this minimum and worsens the performance.

For both discrete RA schemes, the CDF shows that most of the cases already present an $E_{MAX}/BW$ lower than $6 \cdot 10^{-2}$ dB/THz, before the fine-optimization, i.e. 97% of the cases for the C+L–band and ~100% for the S+C+L–band.

Compared to the discrete RA, the resulting PDF for the distributed RA (Fig. 3(a)) has a higher mean and standard deviation when considering only $NN_{inv}$.

On the other hand, a significant reduction can be obtained after applying fine-optimization $NN_{inv} + NN_{fwd}$, as also illustrated by the CDF. Indeed, the fine-optimization significantly increases the number of cases with $E_{MAX}/BW$ lower than $6 \cdot 10^{-2}$ dB/THz, i.e. from 18.7% to 95.4%.

Finally, in Fig. 3(a)-(c), the resulting PDF and CDF of the RMSE per bandwidth is plotted for the distributed and discrete amplifiers. The Figure shows that very low mean and standard deviation values are achievable.
B. Flat and tilted gain profiles

Next, we investigate the ability of the machine learning framework to predict accurate pump current and voltage allocations for the design of flat and tilted gain profiles using the discrete and distributed RAs, in C+L and S+C+L–band. Flat gains ranging from 6 to 12 dB (C+L–band distributed RA), 7 to 15 dB (C+L–band discrete RA), and 14 to 20 dB (S+C+L–band discrete RA) are evaluated in steps of 1 dB. For the tilted profiles, slopes of approximately 0.24 dB/THz (C+L–band RAs) and 0.20 dB/THz (S+C+L–band RA) are considered. These values were chosen to provide an overall tilt of around 1 dB on each band.

Fig. 5 shows the predicted and target flat ((a)-(c)) and tilted (d)-(f) gain profiles, as a function of frequency, for the distributed and the discrete RA operating in C+L and S+C+L–band. Just a subset of gains (2 dB step) are shown for better visualization. The corresponding \( E_{MAX}/BW \) for all gains under consideration is shown in Fig. 5(g)-(i). We only show results obtained after using \( NN_{inv} + NN_{fwd} \) as the fine–optimization significantly reduced the error for all the amplifier schemes and their evaluated gains.

A general trend observed in Fig. 5(a)-(f) is that the predicted gain oscillates around the target gain profile. The magnitude of the oscillations has a tendency to increase for increasing gains. Moreover, for the S+C+L–band RA, the oscillation amplitude increases with the frequency, achieving up to 2 dB of maximum error compared to the target.

To understand what is happening, it is worth mentioning that it was observed some power instabilities on the supercontinuum S–band source and the Raman-based fiber laser \( P_{8} \). Additionally, recall that the broadband and nonuniform Raman gain spectrum for a single pump, with a peak located near 12.5 THz below the pump frequency for the IDF, is partially overlapped in the multiple-pump configurations considered in this work as illustrated in Fig. 1(c). On the S–band, besides pumps \( P_{6–8} \), there are also contributions of pumps \( P_{1–5} \) because the S–band lies within the Raman gain spectrum bandwidth of all these pumps. This makes the design more complex on this region. Thus, although it is expected that the machine learning framework is able to deal with these broadband effects when adjusting the pumps (once the two stages on the S+C+L–band discrete RA are jointly trained), it is also expected to achieve a higher error on the S–band.

It is observed in Fig. 5(h)-(i) that the \( E_{MAX}/BW \) for the discrete RA in C+L and S+C+L–band is similar...
for the flat and the tilted gain profiles. The $E_{\text{MAX}}/\text{BW}$ is kept below $1.1 \cdot 10^{-1}$ and $0.9 \cdot 10^{-1}$ dB/THz for the design of flat and tilted gain profiles, respectively. On the other hand, the $E_{\text{MAX}}/\text{BW}$ for the distributed RA shown in Fig. 6(g) is higher for the design of the flat gains, but it is still kept below $1.3 \cdot 10^{-1}$ dB/THz. The reason may be related to the pump distributions, i.e. the number of pumps and wavelength being more suitable to provide a tilted gain profile. This can be observed on the experimental data–set gain profiles shown in Fig. 2. The same analysis does not apply for the S+C+L–band, since there it no clear flat/tilted profile trend on its data–set gain curves. Therefore, we also need to take into account that there will be a limitation on the theoretically achievable gain tilt and flatness given experimental set–up that has fixed wavelengths of pump lasers. Fig. 5(j)-(l) shows $\text{RMSE}/\text{BW}$ and it observed that the trends are very similar to as for $E_{\text{MAX}}/\text{BW}$.

To put the presented work in the perspective, in Fig. 6 $E_{\text{MAX}}/\text{BW}$, is plotted for various experimental demonstrations of multi–band amplifiers. It is observed that the presented work results in a low–error and broad bandwidth by means of machine learning.

IV. CONCLUSION

A multi–band programmable gain Raman amplifier operating in C+L and S+C+L–band is experimentally demonstrated. The key enabling technique is the machine learning framework that allows for ultra–fast and highly–accurate prediction of the pump currents and voltage for providing the targeted gain profiles. The ability to generate arbitrary gain profiles in a controlled and fast way, may provide novel approaches for the intelligent utilization of the ultra–wideband spectrum and become a key feature for future optical communication systems. Moreover, the programmable gain optical amplifier may advance other areas of fundamental science requiring spectral shaping, such as optical frequency combs.

APPENDIX

The machine learning framework used in this paper to achieve highly accurate Raman amplifier (RA) programmable gains is based on two artificial neural networks. The first neural network $NN_{\text{inv}}$ models the RA inverse mapping, i.e. the mapping between gain profiles and pump lasers’ currents/voltage. Whereas the forward mapping, i.e., the mapping between the pump lasers’ currents/voltage and gain profiles, is learned by a second neural network $NN_{\text{fwd}}$. Here, we describe how these two NNs are trained for the different RA schemes considered in this paper. We also validate their prediction accuracy. Training and validation are performed on disjoint experimental data–sets, whose total number of elements are shown in Table II.

| RA scheme | C+L dist. | C+L disc. | S+C+L disc. |
|-----------|-----------|-----------|-------------|
| Training  | 3464      | 3000      | 3000        |
| Validation| 2100      | 2600      | 1025        |

A. Neural networks training

$NN_{\text{inv}}$ is trained using random projection (RP). This training algorithm, also known as extreme learning machine (ELM) [40], initializes the weights of the hidden layers randomly, according to a normal distribution with mean zero and a certain standard deviation $\sigma_{NN_{\text{init}}}$, corresponding to NN initialization variance. This random weight assignment is independent from the training data–set and requires a high number of hidden nodes as these weights are kept untrained. The training data–set is used to optimize only the last layer weight by regularized least squares, with a regularization parameter $\lambda$. Since it is performed in a single step, the training time is drastically reduced when compared to standard approaches that updates all the weights in a numerical interactive routine. $NN_{\text{inv}}$ models for each RA scheme are shown in Table III where $f_{\text{act}}$, $numHN$, $numHL$, $\sigma_{NN_{\text{init}}}$ and $\lambda$ were obtained after a hyperparameter optimization routine using k-fold cross validation [39].

$NN_{\text{fwd}}$ is trained differently for each RA scheme. For the C+L–band RA (discrete and distributed), $NN_{\text{fwd}}$
is trained traditionally updating all weights on the NN interactively by using the Levenberg-Marquadt (LM) method. However, the high input and output dimensions of the S+C+L-band RA scheme makes the use of LM optimization challenging due to the long convergence time. Thus, RP is applied again only for this scheme.

Table IV summarizes NN parameters for each RA scheme, where only the RP parameters \( f_{act}, numHN, \sigma_{NN_{init}} \) and \( \lambda \) were obtained after a hyperparameter optimization routine. Table IV also shows that the RP faster training comes with the cost of having a larger network, with 500 hidden nodes instead of 20 when using LM.

### B. Neural networks validation

\( NN_{inv} \)’s performance in predicting pump currents/voltage is presented in Fig. 7. The metric used is the absolute error relative to the maximum current/voltage excursion for each pump laser. Fig. 7 shows the probability density functions (PDF) and the cumulative density functions (CDF) over all the cases on the validation data-set and all pump lasers. Notice that the errors are kept bellow 2% for 95% of the cases for all the RA schemes.

The prediction performance for the \( NN_{fwd} \) is evaluated in terms of root mean squared error (RMSE\(^P\)) and maximum absolute error (\( E_{MAX}^P \)) between predicted \( G^P \) and target \( G^T \) gain profiles, extracted from the K WDM points (spectrum), given by

\[
RMSE^P = \sqrt{\frac{1}{K} \sum_{i=1}^{N} (G^P_i - G^T_i)^2},
\]

\[
E_{MAX}^P = \max \{|G^P_1 - G^T_1|, |G^P_2 - G^T_2|, \ldots, |G^P_N - G^T_N|\}
\]

we use index \( P \) for prediction to differentiate from the experimental validation errors shown in Section III and recall that \( K = 99 \) and \( K = 148 \) for C+L and S+C+L-band RAs, respectively. Fig. 8 shows the PDF for \( RMSE^P \) and \( E_{MAX}^P \) over all the cases on the validation data-set.

In Fig. 8, the overall \( NN_{fwd} \) performances for both C-L–band RAs are consistent with the ones obtained in [42], which also considers a C+L–band RA (distributed scheme only) with same NN model and training algorithms. On the other hand, the worst performance obtained here by the S+C+L–band RA scheme in terms of \( E_{MAX}^P \) can be explained by its more complex mapping relating more pumps to the gain over a wider bandwidth. S+C+L–band RA scheme was also the only model that used RP, but the same study presented in [42] showed that, for the Raman amplifier case, the performance of the LM only overcomes the RP for higher number of hidden nodes, which requires even more time to train.

The errors \( RMSE^P \) and \( E_{MAX}^P \) are non-convex and unknown functions of the pump configuration that might not share the same local minimums, i.e. the pump configuration that minimizes \( RMSE^P \) might not minimize \( E_{MAX}^P \). However, since the fine–optimization is a gradient-based procedure, it needs to use a differentiable cost function with respect to the pump parameters, which makes the MSE the only candidate for this. When the pdf curves in Fig. 8(a) and (b) present similar shapes, like for the C+L–band RAs, it might be an

### TABLE III

| RA scheme       | C+L dist. | C+L disc. | S+C-L disc. |
|-----------------|-----------|-----------|-------------|
| Training alg.   | RP        | RP        | RP          |
| \( f_{act} \)   | logsig    | sine      | sine        |
| \( numHL \)     | 1         | 1         | 1           |
| \( numHN \)     | 760       | 500       | 500         |
| \( \sigma_{NN_{init}} \) | 6.0 \cdot 10^{-3} | 2.6 \cdot 10^{-2} | 1.0 \cdot 10^{-2} |
| \( \lambda \)   | 1.0 \cdot 10^0 | 1.0 \cdot 10^3 | 1.0 \cdot 10^4 |

(*) Nguyen-Widrow initialization algorithm [41].

### TABLE IV

| RA scheme       | C+L dist. | C+L disc. | S+C-L disc. |
|-----------------|-----------|-----------|-------------|
| Training alg.   | LM        | LM        | RP          |
| \( f_{act} \)   | tanh      | tanh      | tanh        |
| \( numHL \)     | 2         | 2         | 1           |
| \( numHN \)     | 10        | 10        | 500         |
| \( \sigma_{NN_{init}} \) | *        | *        | 1.0 \cdot 10^{-3} |
| \( \lambda \)   | 0         | 0         | 1.0 \cdot 10^8 |
Fig. 8. Probability density function (PDF) of the $NN_{f,1d}$ gain prediction error: (a) $RMSEP^p$ and (b) $E_{MAX}^p$ with indication of mean, $\mu$, standard deviation, $\sigma$, and maximum (max) values.

indication that minimums of these two errors occur for similar pump configurations and, consequently, minimizing $MSE^p$ (which is proportional to the $RMSEP^p$), may also minimizes $E_{MAX}^p$. For the S-C-L-band RA, on the other hand, where $E_{MAX}^p$ and $RMSEP^p$ pdf curves have completely different shapes, it is more likely that minimizing $MSE^p$ is not the same as minimizing $E_{MAX}^p$.

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