

# Intelligent gain flattening of FMF Raman amplification by machine learning based inverse design

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**Abstract:** We report an intelligent gain flattening method for rapid, precise and objective-driven FMF Raman amplifier design, by using machine learning based inverse design method to optimize the pump wavelengths, powers and mode contents. © 2020 The Author(s)

## 1. Introduction

Mode division multiplexing (MDM) on few-mode fibers (FMF) is an attractive scheme to overcome the transmission capacity crunch of single-mode fiber caused by Shannon limit and nonlinear effects [1]. In MDM systems, several modes in FMF are simultaneously employed as independent channels to transmit signals. Optical amplifiers are significantly important to compensate the loss of fiber links. Distributed Raman amplifiers (DRA) have many advantages compared to Erbium-doped fiber amplifier (EDFA), such as low noise figure, reduced nonlinear effects and flexible gain spectrum. Moreover, in MDM systems, DRAs have superiority to reduce MDG by adjusting pump content [2]. To mitigate relative intensity noise (RIN), random fiber laser is applied to DRAs using second order Raman pumps and FBGs, which has resulted in a significant improvement in experiments [3]. We apply this scheme to the MDM systems to obtain few-mode DRAs with gain flatness in C-band and low MDG, which is a quite complex optimization involving the selection of wavelengths, powers and mode content.

The challenge for few-mode DRAs with gain flatness is that many parameters should be optimized simultaneously. Traditional optimization algorithm, such as genetic algorithm(GA), might need long time and complicated process to get target results. In some cases, the solution may not converge[5].

According to this situation, machine learning (ML) will be a valid method. Through training of neural network (NN), we can get the mapping between input and output coefficients. Because of large input dimension limit, NN can optimize multiple parameters simultaneously. When NN is highly accurate, the weight matrix can fit the results of the physical equation to some extent.

This paper will give general approach to solving mapping problems by machine learning and multiple parameters optimization simultaneously in FMF system. This approach need not solve the integration of propagation equation and it can give high accurate prediction in a short time. For a second-order FMF DRA with four first-order pumps, we show that 1.0-dB flatness over C band with 0.63-dB MDG at 14-dB gain level can be realized based on our inverse design method. And the optimization is 480-times faster than conventional method like genetic algorithm.

## 2. Machine learning procedure

In Fig 1(b), the configuration of few-mode DRA with C-band gain spectrum based on random fiber laser is shown. Four first order pumps and a single second order pump is employed, whose wavelengths are to be optimized. The powers of LP11 mode are averaged into LP11a and LP11b imports. Signals and pumps are coupled and launched into FMF by ideal mode (de)multiplexers at both ends of the fiber. Four FBGs are placed near output end of the 70km FMF, reflecting first order pumps and converting their mode into the other mode [4]. The FMF attenuation of C-band(4 THz band between 192 and 196 THz), first order Raman pump and second order Raman pump is 0.2dB, 0.277dB and 0.349 dB, respectively. Totally 36 signal wavelengths from 1530nm to 1565nm(C-band) were utilized and the input power is -10dBm per wavelength per mode channel. The intensity overlap integrals and Raman coefficients of the FMF we use are shown in [6].

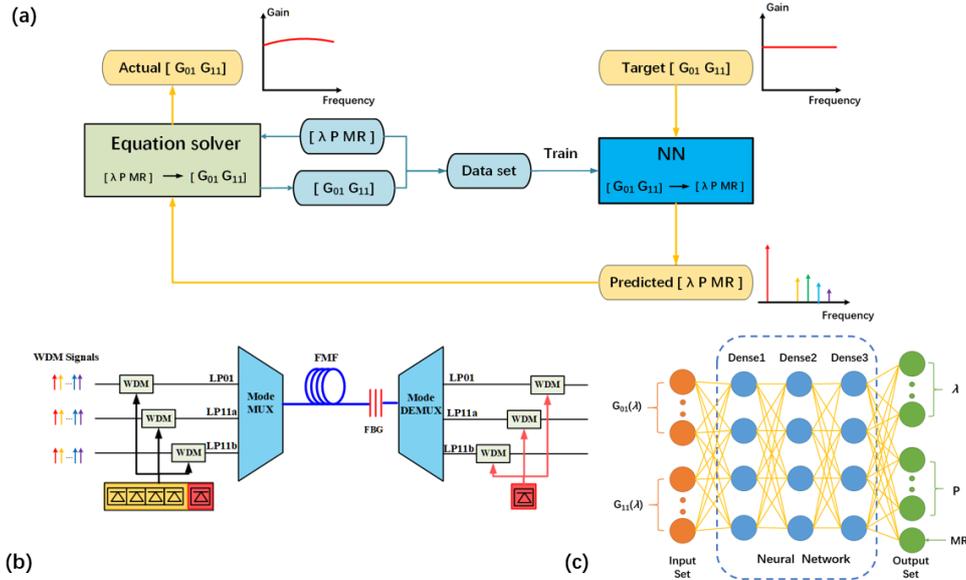


Fig. 1. (a)The procedure in this task, orange line represents process of prediction and blue line is process of data preparation (b) setup of FMF system (c) structure of neural network for this task

From above case, the procedure in this task is shown as Fig 1(a), data set is obtained by solving propagation equations governing pumps and signals presented in Ref. [6] and divided into input and output set. Input set is gain spectrum in two modes (LP01 and LP11). Each spectrum is applied in 36 signal wavelengths as  $[G_{01}(\lambda_1, \dots, \lambda_{36}), G_{11}(\lambda_1, \dots, \lambda_{36})]$ . In output set, pump coefficients are  $[\lambda_1, \dots, \lambda_5][P_1, \dots, P_6]$ . Another parameter is mode ratio shown as  $[MR]$ . Data set in the scale of 5000 will be input to a neural network (NN) which is composed of three dense layers shown in Fig. 1(c). After training, we get a mapping from input on 72 dimensions to output on 12 dimensions. Test set is given to predict optimized parameters and get actual target curve. As for processing data set, the normalization of visibility is the most essential task in processing data sets. It is necessary to ensure that the range of data must be within the scope of the loss function, and normalization can't change the weight affecting results. Since the results of the model giving the test set must itself be able to be restored to usable data, the visualization has a large impact on the accuracy of the final result. Reasonable normalization can be made based on experience and physical equation characteristics, and adjusted according to the results.

To establish proper network, it's essential to adjust the structure of NN. In essence, this problem can be classified as a classification problem, and the accuracy of the mapping decides the accuracy of the classification. Dense layer can be applied in deep NN, and the number of layers can be flexibly adjusted according to different experimental conditions. Meanwhile, we must also pay attention to the condition of over fitting, Dropout layer is applied to weaken it and the activation function is selected by the classical classification network with combination of linear rectification function ReLU and function Sigmoid.

Then another key step is the selection of the loss function. In classification, there are mainly three loss functions. Hinge function can be used in SVM, but in this task, its output covers only 0 and 1. Then mean square error (MSE) and binary crossentropy both work in this situation. MSE has good linearity in optimization. Binary crossentropy is sensitive to fine changes. We select binary crossentropy as loss function because of better performance in this task. The comparison between the two loss functions is demonstrated in Fig 2(a). We can obviously see that using binary cross entropy will get better gain flatness.

### 3. Results and analysis

The considered on-off gain levels range from 9 to 14.5 dB. As Fig 2(a) shown, it fits the target curve with small error. And the discrepancy between two modes is limited to a very small extent. The calculated gain flatness of different on-off gain is illustrated in Fig 2(b), we can easily see the flatness of 4 groups and two nearly undifferentiated mode gain spectrum. Gain flatness limits below 1.21 dB and MDG will be under the level of 0.63 dB.

Table 1 demonstrates comparison between GA and NN presented in this paper. We can obviously recognize that GA can't optimize power and wavelength simultaneously. Meanwhile, as for the speed of running, the speed of ML will be 480 times faster than GA. The results of ML will be also a little bit better. From above, for FMF

system, applying machine learning method to complex parameters optimization is feasible. It consumes less time than traditional algorithm. The whole process only needs a small amount of data sets and trained model can be reserved and used many times. Fine-tuning classification NN can sense minor changes in data and get more accurate results.

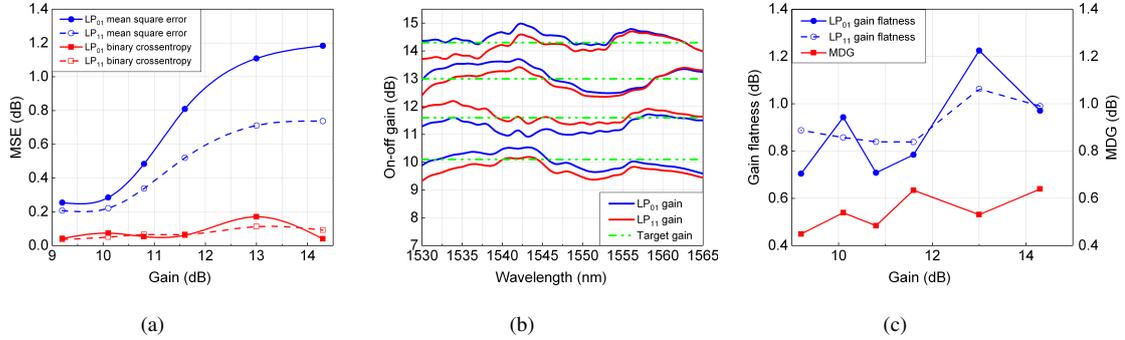


Fig. 2. (a) comparison between mse and binary crossentropy loss function., y axis represents for mean square error of predicted curve in two loss functions (b) Results of C-band Gain flatness, each curve group covers predicted G(LP01), G(LP11) and given G(target) (c) MSE in two modes and maximum dependent gain (MDG) gain error over C-band

Table 1. Comparison between GA and ML

Algorithm(optimization parameter)	Time	Gain flatness (14dB)	Performance
GA(power)	2h	0.92dB	work well but time-consuming
GA(power&wavelength)	×	×	not work
ML(power&wavelength)	15s	0.87dB	multi-optimization permitted and fast

#### 4. Conclusion

Optimization for few-mode Raman amplifier system by machine learning method has been presented. It has been demonstrated that machine learning can optimize this system by less time and a small amount of datas. Another advantage is that it can accurately optimize more parameters compared to traditional optimization algorithm. We achieved a flat gain for FMF systems with below 1.0- dB gain flatness and below 0.63-dB MDG by NN.

#### Acknowledgement

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#### References

- [1] Jiexiong Li, et al., "Second-order few-mode Raman amplifier for mode-division multiplexed optical communication systems," *Optics Express*, 25(2), 810-820 (2017).
- [2] Jiexiong Li, et al., "Ultra-Low-Noise Mode-Division Multiplexed WDM Transmission Over 100-km FMF Based on a Second-Order Few-Mode Raman Amplifier," *Journal of Lightwave Technology*, 36(16), 3254-3260 (2018).
- [3] M. Tan, et al., "RIN Mitigation and Transmission Performance Enhancement With Forward Broadband Pump," *IEEE Photonics Technology Letters*, 30(3), 254-257 (2018).
- [4] Muhammad M. Ali, et al., "Characterization of Mode Coupling in Few-Mode FBG with Selective Mode Excitation," *IEEE Photonics Technology Letters*, 27(26), 1713-1716 (2015).
- [5] D. Zibar, A. Ferrari, V. Curri, and A. Carena, "Machine learning-based Raman amplifier design," in *Optical Fiber Communication Conference (OFC) 2019, OSA Technical Digest (Optical Society of America, 2019)*, paper MIJ.1.
- [6] Jiexiong Li, et al., "Experimental demonstration of a few-mode Raman amplifier with a flat gain covering 1530-1605 nm," *Optics Letter*, 43(18), 4530-4533 (2018).