Fast Online Optimization of Multi-pump Raman Amplifiers for Field Deployment in Multi-band Optical Networks

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Abstract: We experimentally demonstrate Raman amplifier optimization with fast pump deviation inference in different scenarios. Using less than 3 new data, accurate gain generation is achieved with low root mean square error (<0.1 dB).

1. Introduction

Opening new wavelength bands has proved to be a promising solution for expanding the capacity of optical networks [1]. Raman amplifiers (RAs) are considered right away to amplify multi-band signals for their low noise figure [2] and potential to provide arbitrary gain profiles [3]. Reasonable configuration of pumps is the prerequisite for the RA to generate specific gain profiles. However, the complex interactions between pumps and signals pose a great challenge to the configuration, especially with the increased number of pumps in multi-band optical networks. Recently, machine learning (ML) methods such as neural networks (NNs) have been widely adopted to model RAs [4] and inverse system models are trained to directly predict the configuration of Raman pumps and achieve target gain profiles in a controlled way [5,6].

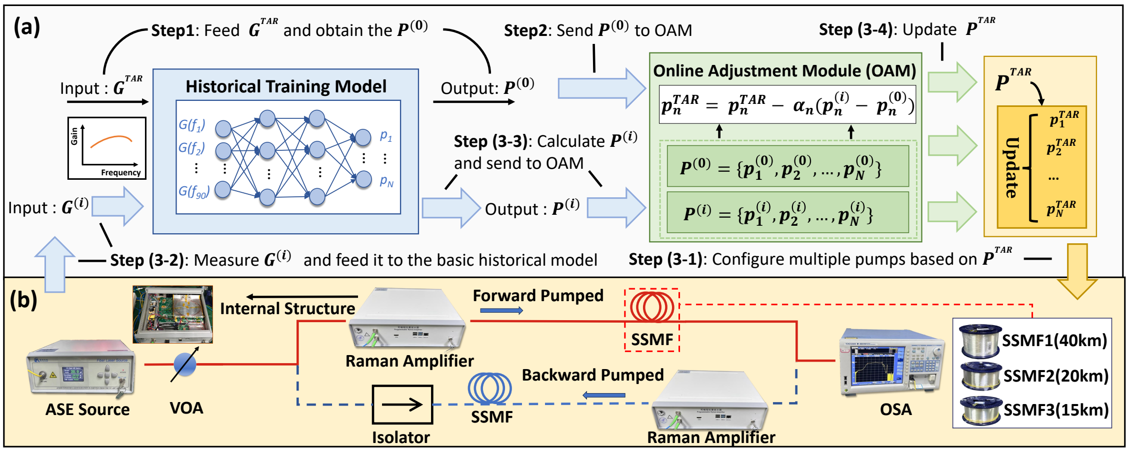
However, ML-based RA models rely on the training data and will deteriorate when the deployment scenario differs from the data collection scenario. Similar problems are studied in terms of Raman gain prediction, a general model is proposed to achieve accurate gain prediction in scenarios with different fiber lengths and fiber types [7]. However, a large dataset containing data from various scenarios is needed for the general model training. The data collection is time-consuming and the general model cannot perform well in the scenario beyond the training dataset. As for the Raman gain generation, there is still no universal method for accurately generating specific gain profiles in various deployment scenarios.

In this paper, an online optimization framework is proposed to achieve fast and accurate gain generation in various deployment scenarios. Only a few new data (1∼3 data) are needed for the optimization and the framework is applicable to various scenarios with different pump propagating direction, fiber lengths and input signal powers. The framework consists of a historical training model and an online adjustment module (OAM). The historical training model is used to assist a two-stage process to achieve fast pump deviation inference (FPDI) and the OAM iteratively updates the pump configuration according to the pump deviations. We experimentally validated the proposed framework in 7 different scenarios and various target gain profiles ranging from 7 dB to 20 dB are generated. Results show that, in all scenarios, the maximum root mean square error (RMSE) between the target gain profiles and the generated gain profiles is reduced to <0.1 dB within 3 optimization iterations. Compared with no optimization, 96.2% improvement in gain generation accuracy is achieved, demonstrating the great performance of the proposed framework.

2. Online Optimization Framework with Fast Pump Deviation Inference

The optimization is to find a set of pump setting parameters (P^{TAR}) to achieve the target gain profile (G^{TAR}) in the deployment scenario. As the number and wavelength of pumps are usually fixed in commercial RA modules, the power of pumps is used as the optimization parameter.

The historical training model contained in the framework is constructed by the neural network and learns the mapping from Raman gain profiles to pump powers [6] in a given scenario which is defined as the modeling scenario. The key of the proposed framework is the fast pump deviation inference (FPDI) which infers the pump deviation between current pump settings and the pump settings of achieving the target gain profile in the deployment scenario. It is a two-stage inversion inference process assisted by the historical training model. The first stage of FPDI is to infer the pump configuration difference between two gain profiles in modeling scenarios based on



Tab.1. The settings of 8 constructed scenarios.

Scenarios	Sce. 1	Sce. 2	Sce. 3	Sce. 4	Sce. 5	Sce. 6	Sce. 7	Sce. 8
Pump Direction	Forward	Backward	Backward	Backward	Forward	Forward	Forward	Forward
Fiber Length [km]	75	75	60	40	60	60	40	40
Input Power [dBm]	-30	-30	-15	-15	-15	-30	-30	-15

Fig. 1. Process of the online optimization framework: (a) the historical training model and the online adjustment module (OAM); (b) experimental setup for constructing different scenarios.

the historical training model. The second stage is to reflect the pump configuration difference from the modeling scenario to the deployment scenario and infer the pump deviations. The reflection process in the second stage is based on the similarity of RA mappings in different scenarios. An online adjustment module (OAM) iteratively updates pump configurations according to the pump deviation. The detailed process of the framework is shown in Fig. 1 and can be divided into 3 steps:

Step1: Feed the target gain profile G^{TAR} to the historical training model, and obtain the initial pump settings $P^{(0)} = \{p_1^{(0)}, p_2^{(0)}, \ldots p_N^{(0)}\}$. N is the number of pumps.

Step2: Send $P^{(0)} = \{p_1^{(0)}, p_2^{(0)}, \ldots p_N^{(0)}\}$ to OAM, and initialize $P^{TAR} = \{p_1^{TAR}, p_2^{TAR}, \ldots p_N^{TAR}\}$ with $P^{(0)}$.

Step3: Iterations. Step (3-1): Configure multiple pumps in RA in the deployment scenario based on the current P^{TAR}. Step (3-2): Measure the actual on-off gain profile $G^{(i)}$ achieved with the current pump configuration and feed $G^{(i)}$ to the historical training model. Step (3-3): Obtain the predicted pump configuration $P^{(i)} = \{p_1^{(i)}, p_2^{(i)}, \ldots p_N^{(i)}\}$ of $G^{(i)}$ through the historical training model and send it to OAM. Step (3-4): OAM updates P^{TAR} by:

$$p_n^{TAR} = p_n^{TAR} - \alpha_n(p_n^{(i)} - p_n^{(0)}), n = 1, 2, \ldots N \tag{1}$$

α_n is defined as the adjustment coefficient and set as $p_n^{TAR}/p_n^{(0)}$, and it evolves with the updates of P^{TAR}. The root mean square error (RMSE) between $G^{(i)}$ and G^{TAR} is used as the metric for assessing optimization performance. Step 3 is executed iteratively until the number of iterations is reached or the RMSE is lower than the set threshold.

3. Experimental Setup and Results

The C+L-band optical system from 187.2 THz to 196.2 THz with 90 channels (ITU-T, 100GHz) is considered. 8 transmission scenarios listed in Tab. 1 are constructed in Fig. 1(b). We develop a multi-pump RA and it contains 6 pumps (1425 nm∼1500 nm) with adjustable powers and a control module embedded with the proposed optimization framework. An amplified spontaneous emission (ASE) source is used to generate C+L-band optical signals. A variable optical attenuator is connected after the ASE source to adjust the input optical signal power. Standard single-mode fibers(SSMF) with different lengths(15 km, 20 km,40 km) are selectively connected to the system. At the fiber output port, an optical spectrum analyzer(OSA) is used to capture the power spectrum. The connection position of RA depends on the pump propagating direction. In backward-pumped scenarios, an isolator must be connected to the fiber input port to protect the ASE source.

As for the historical training model construction, 2300 samples are collected in Sce. 1. 1300 samples are used for model training and 1000 are used for model testing. Each sample contains the power of 6 pumps (range from 0 mW to 260 mW) and the corresponding on-off gain profile. The model consists of 3 layers, each with 200 nodes and employing the *tanh* activation function. Training is performed using gradient descent (GD) with the Adam optimizer. 1000 sets of pump powers are predicted by the model after feeding 1000 testing gain profiles. In Sce. 1, 1000 actual generated gain profiles achieved by corresponding predicted pump powers are measured. The mean and standard deviations ($\mu \pm \sigma$) of the root mean square error (RMSE) between the testing gain profile and the generated gain profile is (0.113 ± 0.063dB), indicating the high-accurate gain generation performance of the

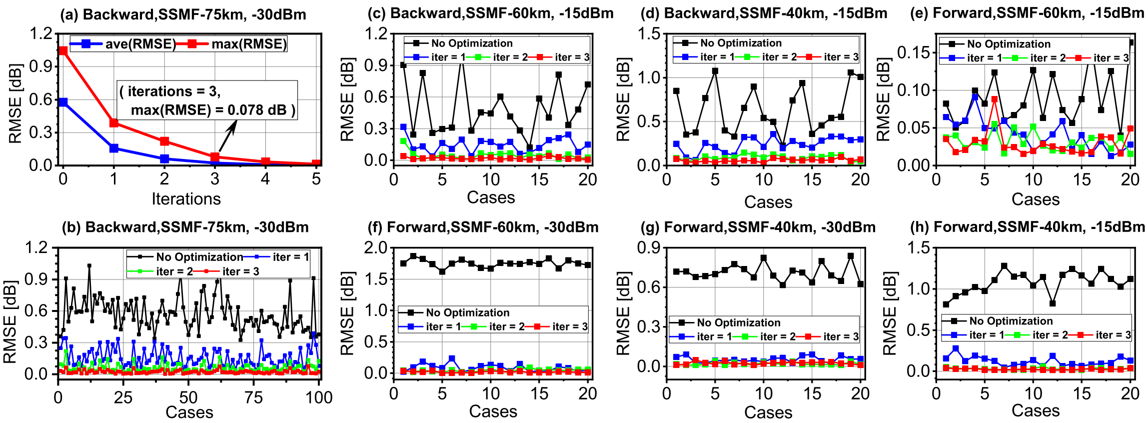


Fig. 2. (a) The variation of the average (blue) and the maximum (red) RMSE with optimization iteration in Sce. 2; (b)-(h) the RMSE of each case with optimization iterations of 0, 1, 2, and 3 in Sce. 2∼Sce. 8.

historical training model under Sce. 1.

We validate the performance of the proposed framework in the scenario with different pump propagating direction, the generation of 100 target gain profiles ranging from 7 dB to 20 dB are used as cases in a backward-pumped scenario (Sce.2). The optimization metric is set as the RMSE between the target gain profile and the generated gain profile. Fig. 2(a) shows the variation of the maximum RMSE and the average RMSE among 100 cases with optimization iteration. In the third iteration, the RMSE of all cases are reduced to <0.08 dB. Fig. 2(b) shows the RMSE of 100 cases with optimization iterations of 0, 1, 2, and 3, respectively. The black line (iterations = 0) represents the gain generation performance of the historical training model in Sce. 2 and the RMSE of some cases even exceed 1dB, indicating the model degradation in Sce. 2. Compared with no optimization, the gain generation accuracy in Sce.2 is significantly improved by 96.1% after 3 iterations.

To validate that the framework is applicable to various scenarios, further validation is conducted in Sce. 3∼Sce. 8. 120 cases are tested and the results are shown in Fig. 2(c)∼Fig. 2(h). Compared with no optimization, the gain generation accuracy are improved by 96.0%, 90.7%, 98.8%, 96.5%, 67.7%, and 97.7% after 3 iterations in Sce. 3∼Sce. 8, respectively. The insignificant improvement in Sce. 5 (Fig. 2 (g)) is due to the RMSE before optimization is already low (below 0.2 dB). Nonetheless, further improvement has been achieved through our framework.

Overall, within 3 iterations, the RMSE of all cases are reduced to <0.1dB and the average RMSE is improved by 96.2% in scenarios from Sce. 2 to Sce. 8, demonstrating the effectiveness of the proposed framework in fast multi-pump RA optimization.

4. Conclusion

We propose an online optimization framework with fast pump deviation inference (FPDI) and experimentally validate it in 7 scenarios with different pump propagating direction, fiber lengths and input signal powers. Results show a low RMSE (<0.1 dB) is achieved within 3 iterations in the generation of various target gain profiles ranging from 7 dB to 20 dB, and the accuracy is improved by 96.2% after using the proposed framework.

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