Machine Learning Based Prediction of Erbium-Doped Fiber WDM Line Amplifier Gain Spectra

Shengxiang Zhu, Craig L. Gutterman, Weiyang Mo, Yao Li, Gil Zussman, Daniel C. Kilper
Software-Defined Network in

Power variation > 6 dB!

In QoT estimation, GN model needs OCM in each amplifier (more cost).

Open Networking Foundation 2018
S. Zhu, et. al, OFC 2017
M. Filer, et. al, JLT 2018
Wavelength Division Multiplexing Gain Models

\[ \hat{g}(\lambda_i) = \frac{G_{TC}}{G_M} \left[ \frac{\sum_j P_j + N_I + N_C}{\sum_j P_j g_j t_j + g_R N_R + g_I N_I} \right] g(\lambda_i) \]

EDFA gain excursion due to a change in channel powers \( P_j \)

Equation: J. Junio, et al., JOCN 2012
Figures: S. Zhu, et al., OFC 2017

Single channel/WDM gain spectrum

Optical channel power excursion

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Wavelength Division Multiplexing (WDM) Gain Models

Supposed gain spectrum for single channel input of $\lambda_a, \lambda_b, \lambda_c$

Gain curve for WDM input, $g(\lambda)$

Gain curve for single channel input, $g_s(\lambda)$

Gravity center among the three supposed gain spectra = Gain spectrum for the three wavelengths input; $\lambda_a, \lambda_b, \lambda_c$

Figure: K. Ishii, et al., OFC 2014
Given the input status (input spectrum) of an EDFA, predict its gain spectrum (or equivalently output spectrum).

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Input Vector</td>
<td>$[P_{ch1}, P_{ch2}, P_{ch3}, \ldots, P_{ch90}]$</td>
</tr>
<tr>
<td>Output Vector</td>
<td>$[P_{ch1}]$ for $i$ in $[1, 90]$ # $i$ is index of the 90 NNs</td>
</tr>
<tr>
<td>Transfer Func.</td>
<td>[ReLU, Linear, ReLU, Linear, ReLU]</td>
</tr>
<tr>
<td>Training Target</td>
<td>Min{MSE}</td>
</tr>
<tr>
<td>Training Method</td>
<td>Stochastic Gradient Descent (SGD)</td>
</tr>
<tr>
<td>Batch Size ($m$)</td>
<td>$m = 60$</td>
</tr>
<tr>
<td>Learning Rate ($\alpha$)</td>
<td></td>
</tr>
<tr>
<td>Training Time</td>
<td>$&gt; 15000$ iterations</td>
</tr>
</tbody>
</table>
Experiment Setup

• Validate/test existing models (CM model).
• Capture true value of input and output spectrum
• Capture ML training data, validation data, test data.
Test Result (CM model vs. ML model)

\[ \hat{g}(\lambda_i) = g(\lambda_i) + \frac{\sum_{j=1}^{n}[g_s(\lambda_j) - g(\lambda_j)]}{n} \]

Error distribution of CM model with dynamic range of +/- 3, 6, 9 dB.
Test Result (CM model vs. ML model)

<table>
<thead>
<tr>
<th>Dynamic range [dB]</th>
<th>CM [dB]</th>
<th>ML [dB]</th>
</tr>
</thead>
<tbody>
<tr>
<td>+/- 3</td>
<td>0.247</td>
<td>0.081</td>
</tr>
<tr>
<td>+/- 6</td>
<td>0.359</td>
<td>0.180</td>
</tr>
<tr>
<td>+/- 9</td>
<td>0.410</td>
<td>0.266</td>
</tr>
</tbody>
</table>

RMSE of analytical model and ML model.

Error distribution of CM model and ML model with gain value of 14 dB and 22 dB.

Error distribution of CM model and ML model with dynamic range of +/- 3, 6, 9 dB.
Conclusion

1. In this work, a machine learning based modeling method is implemented and studied.

2. Using captured samples of input and output spectrum, Machine learning based model is shown to reduce the gain estimation error compared with analytical model using center of mass method.

3. In the future, this model is to be used to predict QoT in large scale optical networks.
Thank you! (Welcome to talk with us later about questions and collaborations)

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