NEURAL NETWORK BASED DYNAMIC GAIN CONTROL OF ERBIUM DOPED FIBER AMPLIFIERS

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ABSTRACT

We present an artificial neural network-based fast and dynamic gain control of a two-stage EDFA incorporating an acousto-optic fiber grating filter. A neural network (NN) module is employed which observes the power levels at the eight input and output channels within the 1520-1560nm band, and reconfigures the filter parameters. Computer simulations of the overall module show that NN was sufficiently trained and the normalized rms channel profile ripple at the module output was reduced up to 20 dB with respect to the case where no filter is used.

I. INTRODUCTION

Erbium-doped fiber amplifiers (EDFA) are widely used in WDM applications. One of the major problems in implementing amplified WDM systems is that each channel wavelength experiences a different gain due to wavelength dependent gain profile and saturation characteristics of EDFA [1]. Traditional two-stage EDFA's with non-adaptive filter systems may flatten the gain profile but changes in input signal levels require an adaptive implementation. Also, defining new filter parameters needs computationally heavy algorithm-based techniques. In this work, an artificial neural network (NN) based fast and dynamic control of EDFA module is proposed, replacing the conventional computer-interfaced techniques.

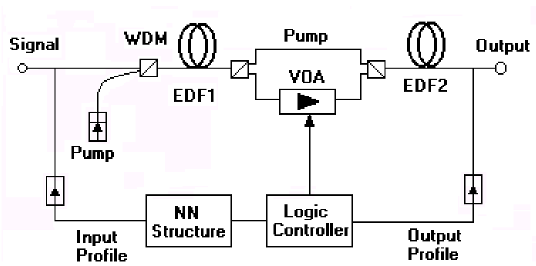
First, optimum EDFA length and optimum filter position were determined for a given pump power using mathematical model of EDFA. Then, EDFA outputs and required filter parameters to achieve flat gain were calculated for a set of variable inputs. These input-output data sets were used as training data for two-layered neural networks designed with one hidden and one output layers. The training is done to find the best NN structure by changing the number of neurons in the hidden layer. Different learning and training techniques in the literature are utilized. Computer simulations of the overall module show that the two NNs are sufficiently trained and the normalized rms channel ripple at the module output was reduced up to 20 dB with respect to the case where no filter is used.

II. MODEL

To flatten two-stage EDFA output, first stage EDFA's output profile and second stage EDFA's required input profile should be known so that the filter parameters could be set. Hence, pump, signal and ASE equations must be solved to find the non-linear EDFA behavior. In this work, two-level atomic model of Er^{+3} was used since pump power was high enough. Also, absorption and emission spectrum of ions were divided into 200 frequency windows of 100-GHz bandwidth between 1420 – 1620 nm to acquire the ASE spectrum. Two-stage EDFA rate equations were solved as a two point boundary value problem by using MATLAB. Iterations were done at forward and backward directions until the filter profile converged. These solutions were verified by comparing with those of the Oasix software for different channel, ASE and pump profiles.

III. CONFIGURATION

Two-stage EDFA with grating filter configuration is shown in Figure 1. Since the relative position of filter affects the power build-up of all four independent waves (signal, pump, forward ASE and backward ASE) and, therefore, has an impact on the gain and noise improvement [2]; optimum EDFA length and optimum filter position were calculated for different pumping configurations. Thus the most appropriate configuration turned out to be 4,13 m. for the first-stage EDFA length, 9,6 m. for the second-stage EDFA length using 100-mW 980-nm forward pump power. A neural network structure with 48 neurons and one hidden layer was used to predict EDFA channel and ASE outputs based on the knowledge of channel inputs. For each input scheme, the required second-stage EDFA input profile to achieve a flat gain profile at the output was computed by backward running of the EDFA equations. Then, filter profile was calculated by subtracting the first stage output from the second stage input. A controller algorithm that continuously observed the EDFA output and produced a feedback for gain



flattening filter was also employed.

Figure –1 Block diagram of system configuration

Two data sets which contained 900 and 100 different input power schemes for eight channels were generated as data to train and test data for the neural network. For the neural network training stage; transfer functions and training function were chosen as tangent-sigmoid and scaled conjugate gradient back propagation (trainscg), respectively. Training algorithm continued until mean square error fell under 0.01. Figure 2 shows the required filter profile obtained by direct computing and by using the NN solution for same input channel profile.

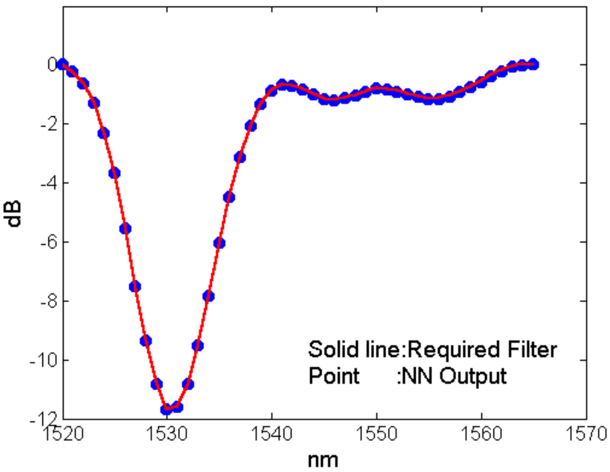


Figure 2. Required filter profile calculated (solid line) and obtained as a solution of the NN (points) for the same input channel profile.

IV. RESULTS AND DISCUSSION

All simulations were done using the computer program described above. Figure 3 shows two EDFA outputs when the input channel profile is non-uniform. Dashed line is the output channel profile of the EDFA using a constant filter profile while solid line is that of the EDFA using the neural network controlled dynamic filter. Static grating filter is enough to flatten uniform inputs but when input channels change randomly it fails to flatten the output spectrum.

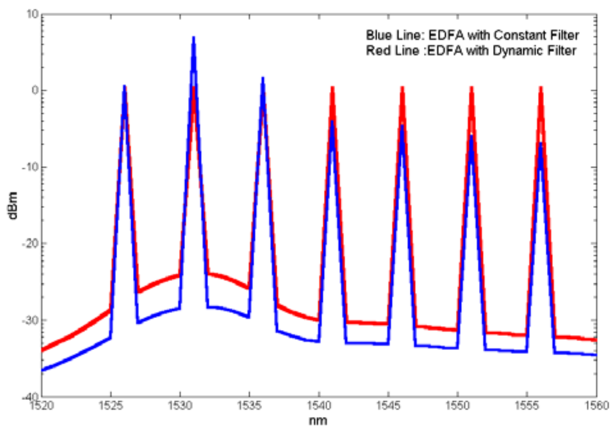


Figure 3. Output of EDFA with FGF for non-uniform input (Red line) and output of EDFA with NN controlled VOA for same input (Blue line).

Figure 4 shows controlled EDFA output ripples from different input profiles. When input ripple (channel non-uniformity) increases, the output ripple remains same until a breaking point. After that point, input power fluctuations become so great that EDFA module cannot amplify all of them to a required flat level. Figure 4 shows controlled EDFA outputs for different pump wavelengths and different pump powers. For every different pump wavelength or pump power, optimum EDFA length and optimum filter position changes. In order to use the same neural network structure at every pumping scheme, different data sets were generated and the neural network was trained again. It is obvious from Figure 4 that the same NN structure can be used to flatten outputs at different pumping schemes.

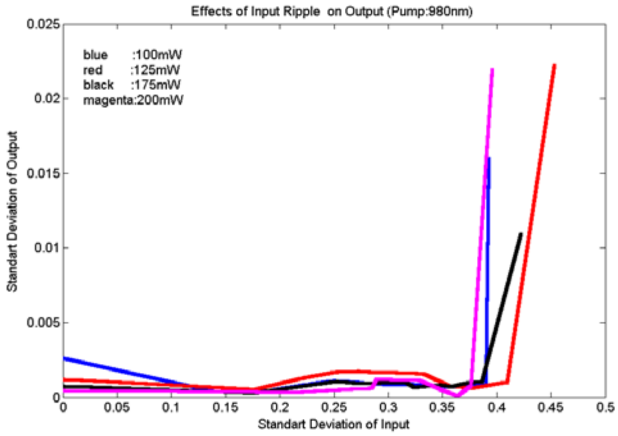


Figure 4. Output ripple change versus input ripple change.

V. CONCLUSION

In this paper a neural network based controller algorithm has been introduced to achieve a real-time, fast and effective control on a two-stage EDFA incorporating an acousto-optic tunable filter. The neural network structure was trained by different data sets and using different learning algorithms for different configurations. The resulting control structure has been tested under various working conditions. According to simulation results, output spectra remained flat at 0 dBm for different input schemes. In other works, different dynamic gain control algorithms such as [4] and [5] have been proposed but using neural networks is a new proposal and because it requires only simple calculations it is fast and appropriate for microprocessors.

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