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Part II – 4: Optical Power Control

Physical layer domain

Optical power control

- When adding/dropping channels into/from a WDM system, EDFA (Erbium Doped Fiber Amplifiers) gain should be adjusted to have a good balance between channels output power
- This effect is more critical in multiple-span systems



- Analytical models:
 - depend on the specific system (gain-control mechanism, EDFA gain tilt, nr of EDFAs...) and to its variations during lifetime
- ML allows to self-learn together all the parameters of any given system and adapt EDFA's features accordingly



Optical Power Control

Source 1

- Huang *et al.*, "Dynamic mitigation of EDFA power excursions with machine learning", *Optics Express*, vol. 25 n. 3, Feb. 2017
- <u>Paper objective</u>: mitigate EDFA power excursion in multiple-span WDM systems due to channel add/drop
 - input
 - $_{\odot}\,$ Historical data on power excursion vs active (ON) channels
 - output
 - o optimal wavelength assignment for the new channel
 - ML algorithms:
 - RR, Ridge Regression (linear regression with regularization)
 - KBR, Kernelized Bayesian Regression (\approx CBR)



- Testbed set-up with 24 WDM channels
 - 2 or 3 EDFA spans



- Post-EDFA power levels
 - 24 channels ON with uniform launch power
 - o ch1@192.1 THz
 - o ch24@194.4 THz
 - 100 GHz spacing





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Optical Power Control

Source 1

- ML algorithm #1 Ridge Regression
 - Input (X): 24-bits array (i-th bit = 1 if i-th channel is ON)
 - Output (y): measured post-EDFA power discrepancy (captured via STDEV of channel power levels)
 - 600 training points (historical channel ON/OFF states and power STDEV values)
 - 270 test points
 - weights are calculated with regularization (optimized with crossvalidation)





- ML algorithm #2 Kernelized Bayesian Regression
 - Kernel with radial basis function

$$K(x, x') = \alpha \exp\left(-\frac{1}{b} \|x - x'\|^2\right),$$

- Kernel is used to weight the regression output
- " α " and "b" are optimized via cross-validation
- Prediction for a new scenario: take <u>all</u> the outputs in the KB and weight them using the kernel



 Results – Impact of training set size on MSE and model complexity



Table 1. Time consumption of training and prediction for RR and KBR.

Model	RR	KBR
Time to train with 600 data points [ms]	82.2	2300
Time to predict for a single scenario [ms]	0.068	467



• Results – Single channel ADD







- Good Best Worst OFF/ON -8 Measured Post-EDFA Power [dBm] Worst, stdev=3.12 Best, stdev=2.79 -10 0 1 2 3 4 5 6 7 8 9 101112131415161718192021222324 Channels .-12 operation 3.15 measured value 3.1 -14 3.05 3 Power STDEV -16 2.95 2.9 -18 2.85 2.8 -20 1234567 8 9 101112131415161718192021222324 2.75 Channels 2.7 2.65 123456 7 8 9 101112131415161718192021222324
- Results Single channel DROP

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Channel Drop Recommender

Drop from Available Slot

• Results – Superchannel ADD (2 contiguous channels)





• Results – Superchannel ADD (3 contiguous channels)





- Mo et al., "Deep-Neural-Network-Based Wavelength Selection and Switching in ROADM Systems", *Journal of Optical Communications and Networking*, vol. 10, n. 10, Oct. 2018
- <u>Paper objective</u>: reducing power excursion in WDM system
 - Input
 - Existing and candidate add channels (wavelengths)
 - Output
 - Maximum power excursion
 - ML algorithm: Deep NN, compared against Ridge regression and Random Forest





- (combinations of lightpaths)
- 210+210 val+test pts ٠
- 40 power-excursion measurements for each point

Parameter	Value	
Neurons in hidden layers	(180, 120, 30, 15)	
Activation function	(tanh, tanh, ReLU, ReLU)	
L2 regularization	0.001	
Dropout rate	0.1	
Initial learning rate	0.005	
Number of epochs	217	



• Impact of training set size





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- Learning curves
 - Early stopping: stop training after 3 consecutive epochs with no improvement in the validation RMSE





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Results (RMSE)



3.5

2.5

(b)



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Ridge regression