Neural Network Based Wavelength Assignment in Optical Switching

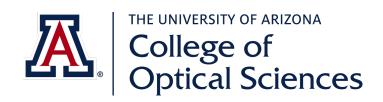
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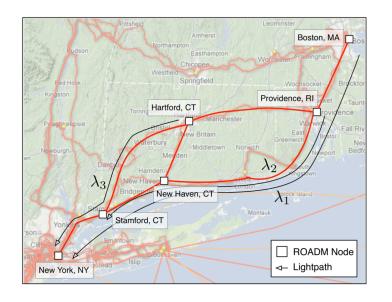
²College of Optical Sciences, University of Arizona

Aug. 21, 2017





Optical Networks





- Modern networks are static, 'set and forget' approach
 - Overprovisioned, manual configuration
- Optical devices are capable of switching and dynamic operation
 - Wavelength selective switches, modulators, tunable lasers, and filters

Dynamic Optical Networks

- Currently no real-time capacity management, wavelength reconfiguration and service provisioning in optical networks
 - Provision wavelength
 - Re-route/switch wavelength
- Service providers need to ensure reconfiguration will not affect service level agreement
 - Consider optical power dynamics: WDM channels are highly interactive
 - Disturbances grow in cascade, propagate through network
 - Current provisioning takes minutes to days per wavelength—cautious 'adiabatic' tuning to avoid disruptions
- Goal: Given active channel conditions, determine the placement of a new wavelength channel to minimize power excursions under real-time, rapid reconfiguration

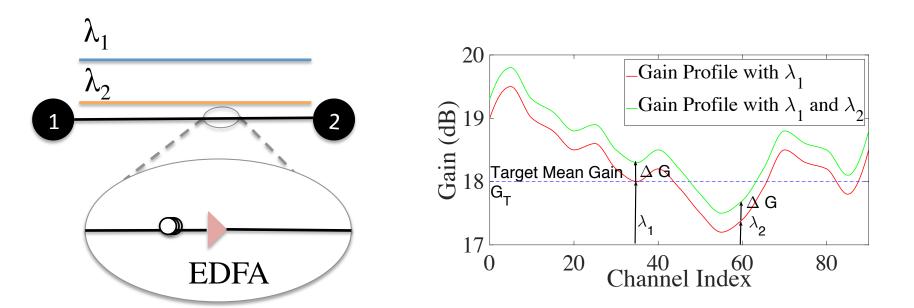
Optical Network Components



- Erbium-Doped Fiber Amplifier (EDFA): Optical **amplifier** to boost intensity of optical signal
- Reconfigurable Optical Add-Drop Multiplexer (ROADM): Allows for remotely switching traffic at wavelength layer
- Wavelength Selective Switch (WSS): Routes signals between optical fibers on a perwavelength basis
- Variable Optic Attenuator (VOA): Reduces power level of optical signal
- Optical Channel Monitor (OCM): Used to measure channel power

Power Excursions

- Erbium-Doped Fiber Amplifier (EDFAs)
 - Use Automatic Gain Control (AGC) to maintain constant target mean gain
 - Amplify input channel power to target gain
 - Results in deviations that perturb active channels causing excursions



Objective: Minimize ΔG

EDFA Gain Model

$$P_{\text{total}}^{\text{out}} = G_{\text{T}} P_{\text{total}}^{\text{in}}$$

$$P_{\text{total}}^{\text{out}} = \sum_{j=1}^{N} P_j^{\text{in}} G_j$$

$$\Delta G = \frac{NG_{\rm T} + G_{\rm T}}{NG_{\rm T} + G_{N+1}}$$

 $G_{
m T}$: target mean gain

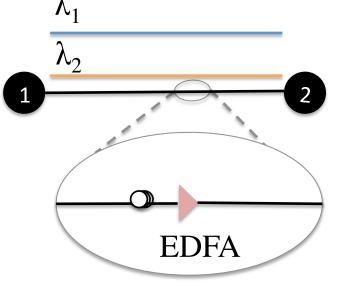
 G_j : channel gain

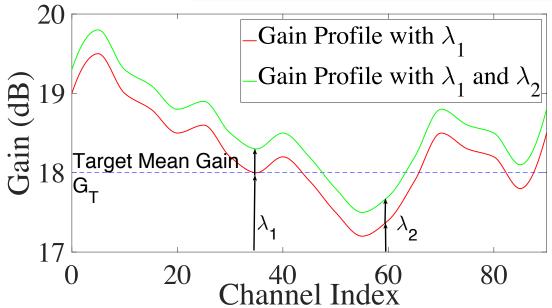
 $P_{
m total}^{
m in}$:total input power

 $P_{
m total}^{
m out}$:total output power

N : number of active channels

 ΔG : power excursion





Previous Work

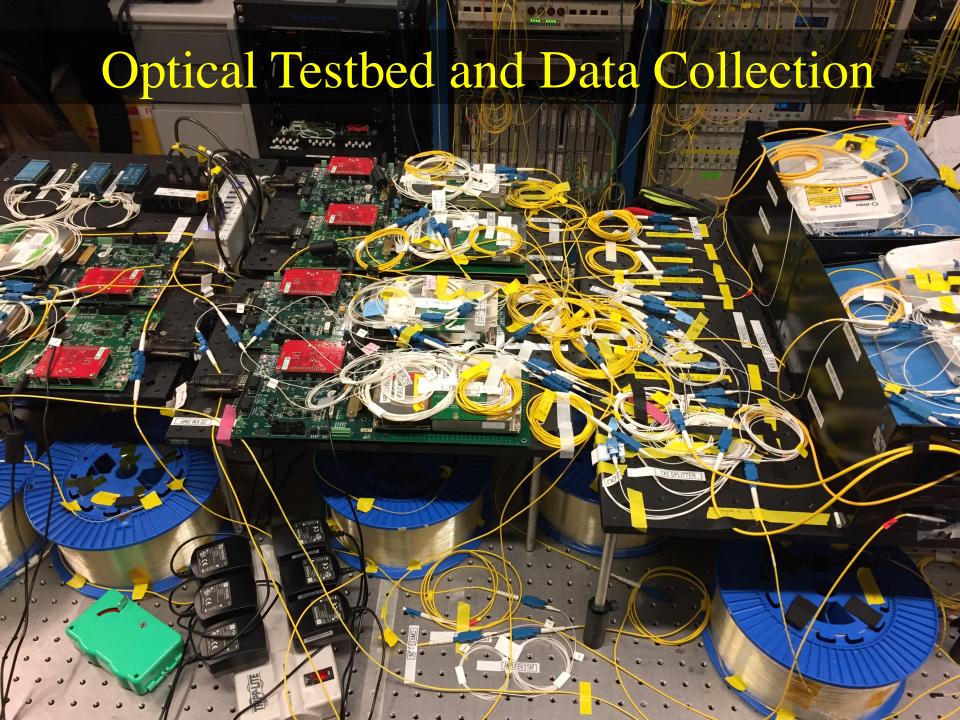
- Planning phase of dynamic optical network
 - [Angelou et al., 2012], [Doverspike et al., 2012], [Gringeri et al., 2013]
 - Dynamic optical design and architecture
 - No dynamic optical network algorithms for physical layer
- Analytical models
 - [Ishii et al., 2016], [Junio et al., 2012]
 - Non-real time (Junio), poor accuracy (Ishii)
- Machine learning for wavelength assignment
 - [Huang et al., 2017]
 - Only 24 channels, single hop system
 - Kernel Bayesian regression

Our Contributions

- Design an optical testbed
- Collect real world data on optical network performance
- Develop a scalable neural network to predict power excursions at the physical layer
- Evaluate the performance using optical testbed measurements

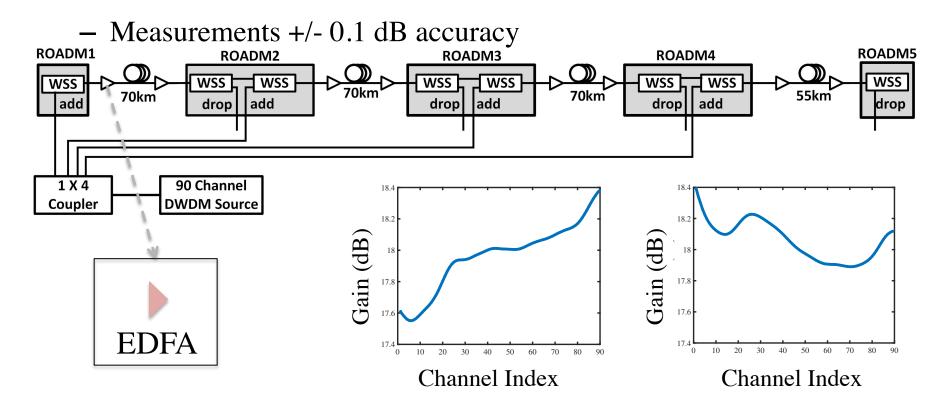




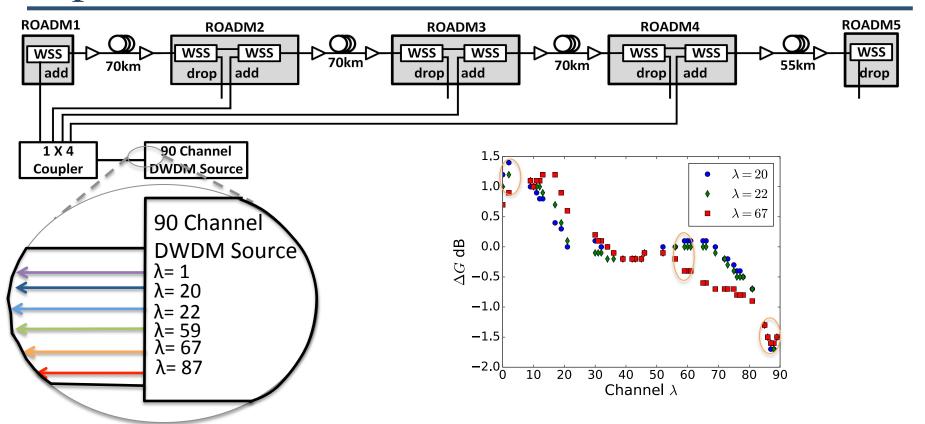


Optical Testbed

- 5-ROADM experiment setup
 - Nodes separated by 4 standard Single Mode Fiber (SMF) spans
 - Each span has 2 EDFAs
 - 90 channel DWDM source



Optical Testbed – Measurements Collection



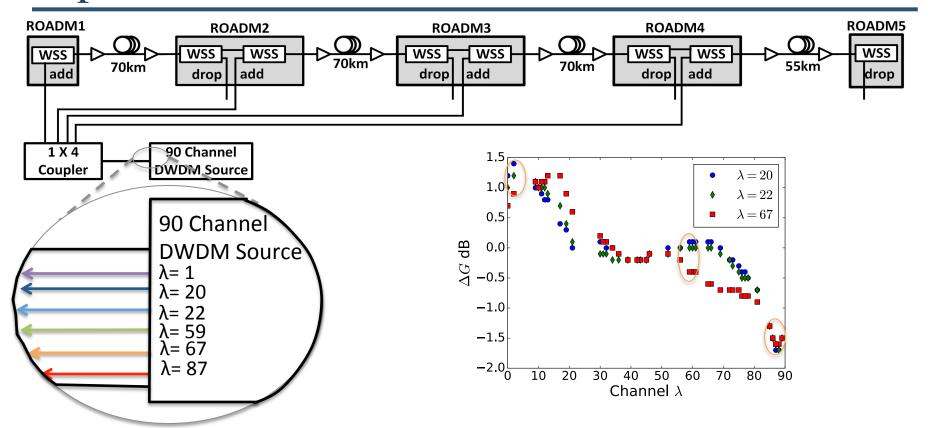
2,100 measurement cases

- 3-5 active channels
- 40 new channels added/removed one at a time
- 40 samples/case

84,000 samples

- Training: 1,680 cases (67,200 samples)
- Validation: 210 cases (8,400 samples)
- Test: 210 cases (8,400 samples)
- Data collection: ~4 seconds/sample

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Feed forward Neural Network

• Predict the maximum power excursion among all active channels

$$y^k = \max_{j \in \text{ActiveChannel}} \Delta G_j^k, \ k \in \text{Available Channel}$$

• Goal: Given initial channel conditions predict which new channel will minimize the effect of power excursion

New Channel =
$$k^* = \arg\min_{k \in \text{Available Channels}} \hat{y}^k$$

$$\vec{x} = [\vec{x}_{\text{Active}}, \vec{x}_{\text{Available}}]$$

$$= [\underbrace{x_1, \cdots, x_{90}}_{\text{ActiveChannels}}, 0, \cdots, \underbrace{1}_{(90+k^*)-\text{th}}, \cdots, 0] \in \{0, 1\}^{180} \quad \text{Input Hidden Hidden Hidden Layer 2 Layer 3 Layer 4}}_{\text{Layer 1 Layer 2 Layer 3 Layer 4}} \quad \text{Output Layer 2 Layer 3 Layer 4}$$

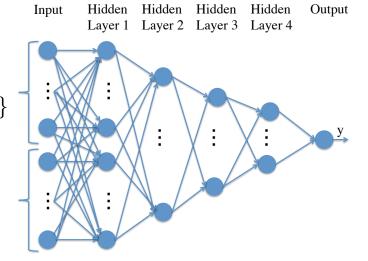
$$x_i = \begin{cases} 1, & \text{if } i \in \text{ActiveChannel}, \ \forall i \in \{1, \cdots, 90\} \\ 0, & \text{Otherwise} \end{cases}$$

$$x_{i+90} = \begin{cases} 1, & \text{if } i = k^* \\ 0, & \text{Otherwise} \end{cases}$$

Feed forward Neural Network

- Test neural network parameters
 - Activation functions
 - Number of layers
 - Number of neurons per layer
- Optimal Performance
 - 4 Hidden Layers: 180, 120, 30, 15 neurons
 - Tanh activation for hidden layers
 - Linear activation for the output layer

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Outline

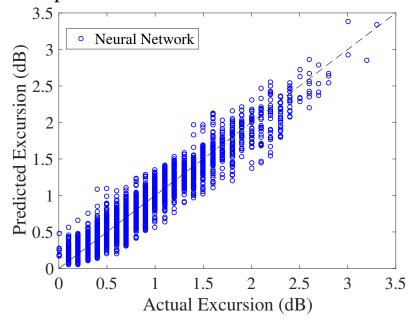
- Design an optical testbed
- Collect real world data on optical network performance
- Develop a scalable neural network to predict power excursions at the physical layer
- Evaluate the performance using optical testbed measurements
 - Prediction
 - Recommendation
 - Classification

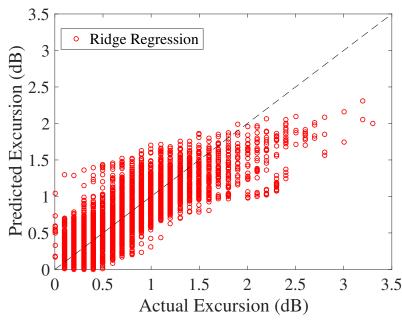
Prediction Results

- Training: 67,200 samples
- Test Points: n = 8,400 samples
- Excursion:

$$y_l = \max_{j \in \text{ActiveChannel}} \Delta G_j^k, \ k \in \text{Available Channel}, \ \forall l \in \{1, ...n\}$$

• For Neural Network (NN) comparison Ridge Regression (RR) is trained and parameters tuned on the same data set





Prediction Performance Evaluation

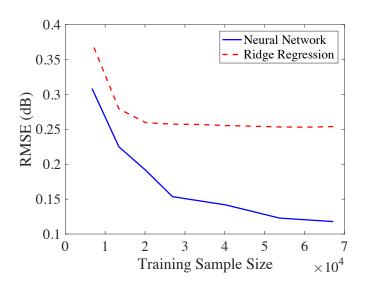
- Training: 67,200 samples
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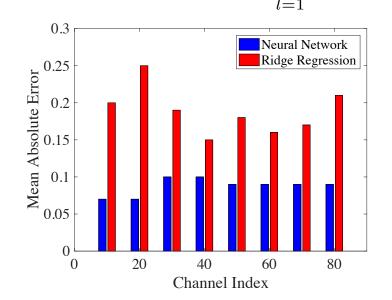
$$y_l = \max_{j \in \text{ActiveChannel}} \Delta G_j^k, \ k \in \text{Available Channel}, \forall l \in \{1, ...n\}$$

• Test data Root Mean Square Error (RMSE):

$$RMSE_{Test} = \sqrt{\frac{1}{n} \sum_{l=1}^{n} (y_l - \hat{y}_l)^2}$$
$$MAE_{Test} = \frac{1}{n} \sum_{l=1}^{n} |y_l - \hat{y}_l|$$

• Test data Mean Absolute Error (MAE):



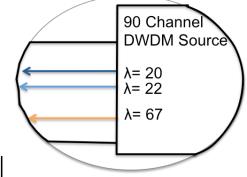


ϵ -Recommendation Accuracy

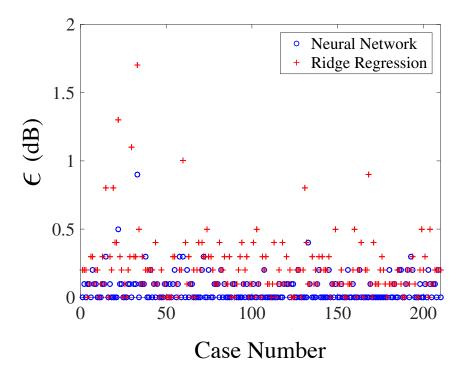
• Training: 67,200 samples

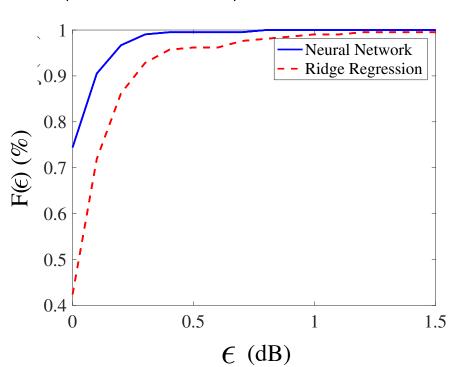
• Test Cases: 210

• Test Points: n = 8,400 samples



Recommendation Error =
$$\epsilon = |y^{\hat{k}^*} - y^{k^*}|$$





Classification Accuracy

 Classification: predict if excursion below threshold

1: Below Threshold

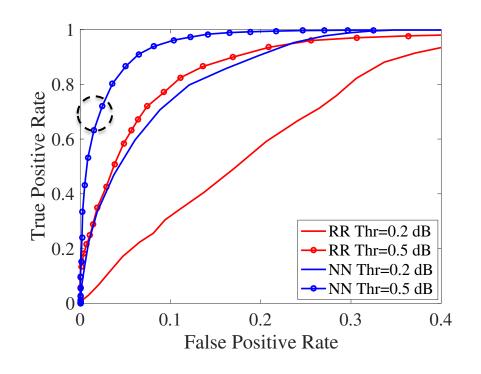
0: Above Threshold

 Set threshold of excursion to 0.5 dB

True Positive Rate (TPR) or Recall = $\frac{True Positive}{True Positive + False Negative}$

False Positive Rate (FPR) = $\frac{FalsePositive}{}$

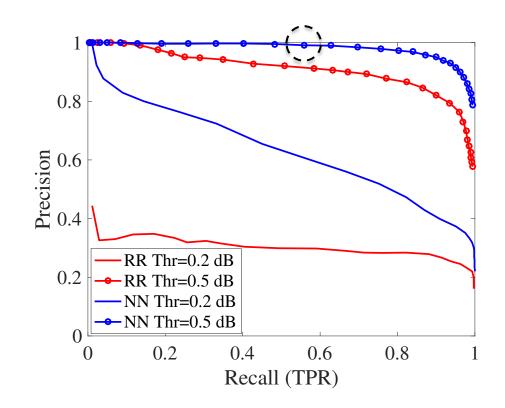
False Positive + True Negative



Classification: Precision at Recall Rate (PSRR)

- Priority for reliable optical system operation:
 - Minimize false positives: Violates SLA
 - 2. Minimize false negatives: Wastes open bandwidth

True Positive Rate (TPR) or Recall = $\frac{TruePositive}{TruePositive + FalseNegative}$ $Precision (PPV) = \\ \frac{TruePositive}{TruePositive + FalsePositive}$



Summary

- Fabricated a 90-channel multi-hop ROADM optical testbed for data collection
- Developed a neural network to predict optical power excursions
- Demonstrated very good performance
 - Prediction: Average prediction error on each channel below 0.1 dB
 - Recommendation: Pick best channel (out of 40), over 70% of the time
 - Classification: Predict maximum excursion to be less than 0.5 dB threshold with a precision of over 99% while obtaining a true positive rate greater than 55%
- Future Work:
 - Machine learning solution for ring and mesh networks
 - Implementation in Optical Software Defined Networks (OSDN)

Thank you!

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