

# Hybrid Machine Learning EDFA Model

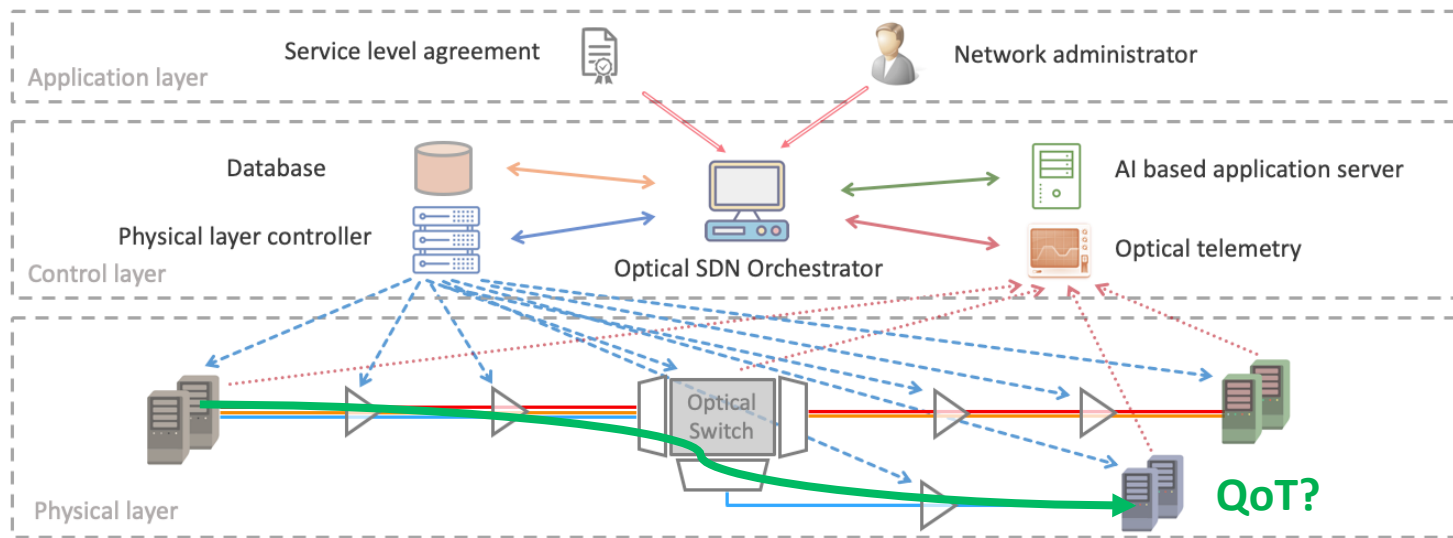
Shengxiang Zhu<sup>1</sup>, Craig Gutterman<sup>2</sup>, Alan Montiel<sup>3</sup>, Jiakai Yu<sup>1</sup>,  
Marco Ruffini<sup>3</sup>, Gil Zussman<sup>2</sup>, Daniel Kilper<sup>1</sup>

<sup>1</sup> University of Arizona, Tucson, AZ, United States.

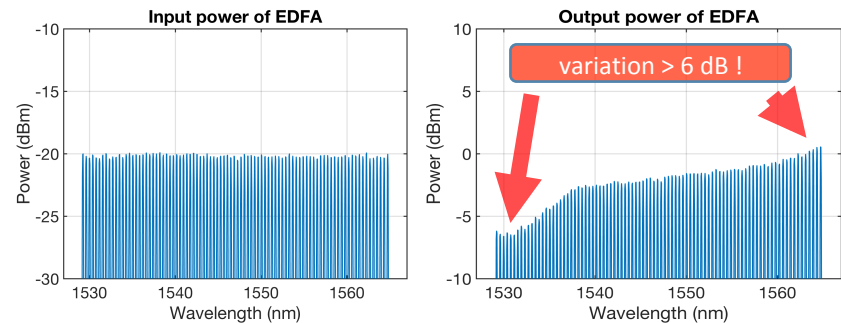
<sup>2</sup> Columbia University, New York, NY, United States.

<sup>3</sup> Trinity College Dublin, Dublin, Ireland.

# Why do we need an accurate EDFA model?



- Minimize Quality of Transmission (QoT) estimation error before channel provisioning.
  - Real time SDN control
  - Disaggregated systems
- EDFA gain spectrum dependent on input channel loading
- Tighter margins for less regeneration/higher spectral efficiency/lower cost

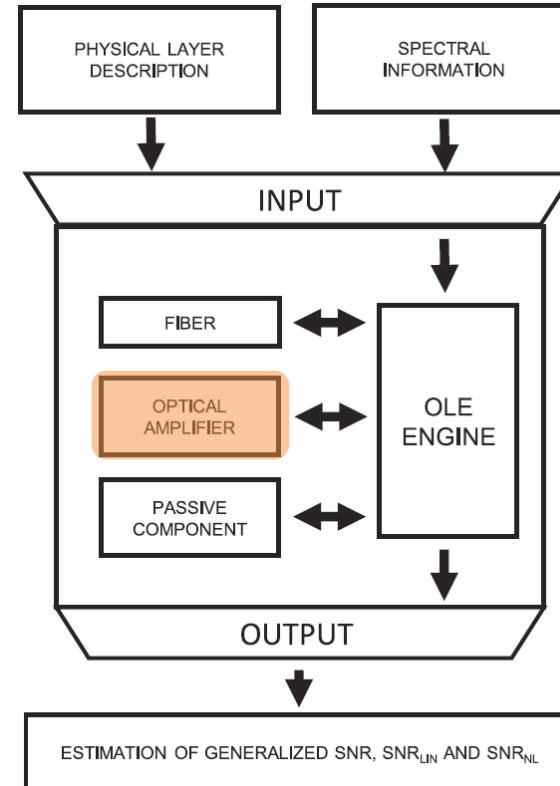


S. Zhu, et. al, OFC 2017

# ML Model for SDN Controllers

In QoT estimation, amplifier model determines launch power and ASE noise

- Accurate EDFA model
  - > improve the GN model accuracy
  - > better QoT estimation



M. Filer, et. al, JLT 2018

# Problem statement

- Purpose of having an accurate EDFA model:
  - Better predict optical channel power
  - Better **predict end-to-end Quality of Transmission**
  - Better network planning, e.g. improved Gaussian Noise (GN) model
- Difficulties of building an EDFA model:
  - Gain is dynamic: gain spectrum depends on input channel loading
  - Hard to find a pure mathematical formula based on physics
  - Empirical formula is not accurate
- Ideal EDFA model:
  - Given input power spectrum and EDFA settings (e.g. gain, tilt, middle stage loss, etc.), find output power spectrum
  - `func edfa_model(input_spectrum: List[float], edfa_settings: Dict)`  
    `-> output_spectrum: List[float]`

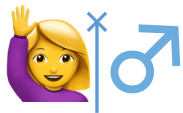
# Two models: Analytical vs. ML

$$g(\lambda \downarrow i) = g(\lambda \downarrow i) + \sum_{j=1}^n [g(\lambda \downarrow j) - g(\lambda \downarrow i)] / n$$

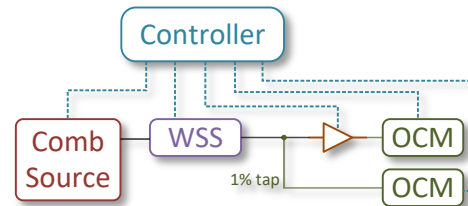
K. Ishii, et al., OFC 2014

## Analytical

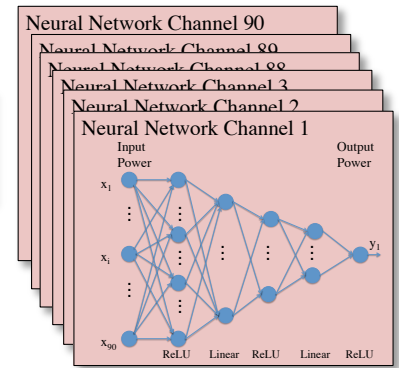
- Simple model 👍
- Fast characterization 👍
- Quick calculation 👍
- Dynamic range is limited
- Accuracy is limited



Can we combine the pros of the two approaches?



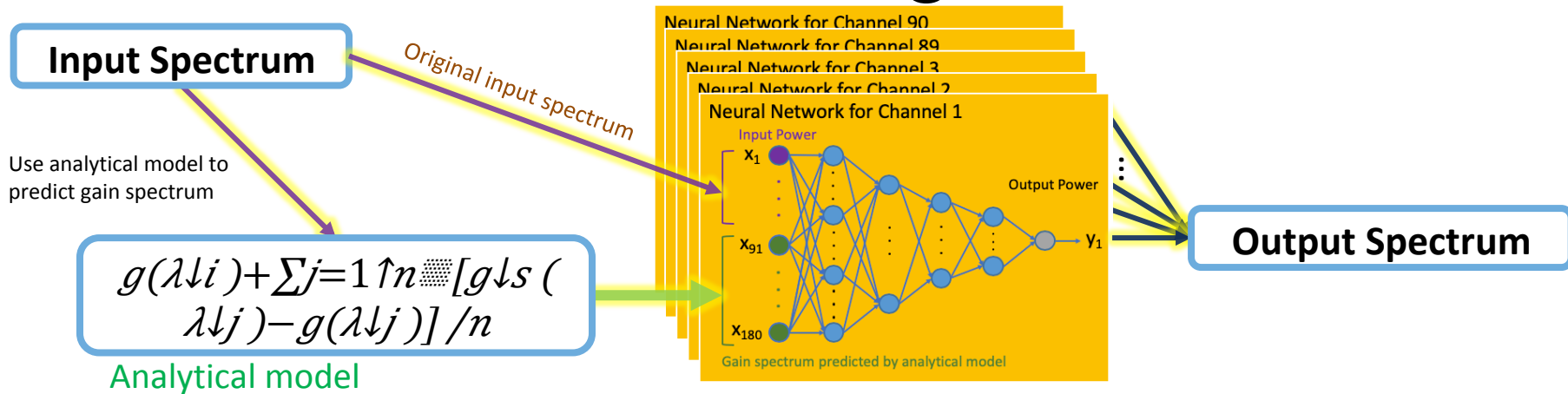
S. Zhu, et al., ECOC 2018



## ML

- Slow data capture process (~20k)
- Complex training process
- Quick calculation 👍
- Dynamic range is wide 👍
- Accuracy is highest 👍

# Hybrid Machine Learning (HML) Modeling



## Input of model:

EDFA input spectrum,  
Gain spectrum by analytical  
model

## Output of model:

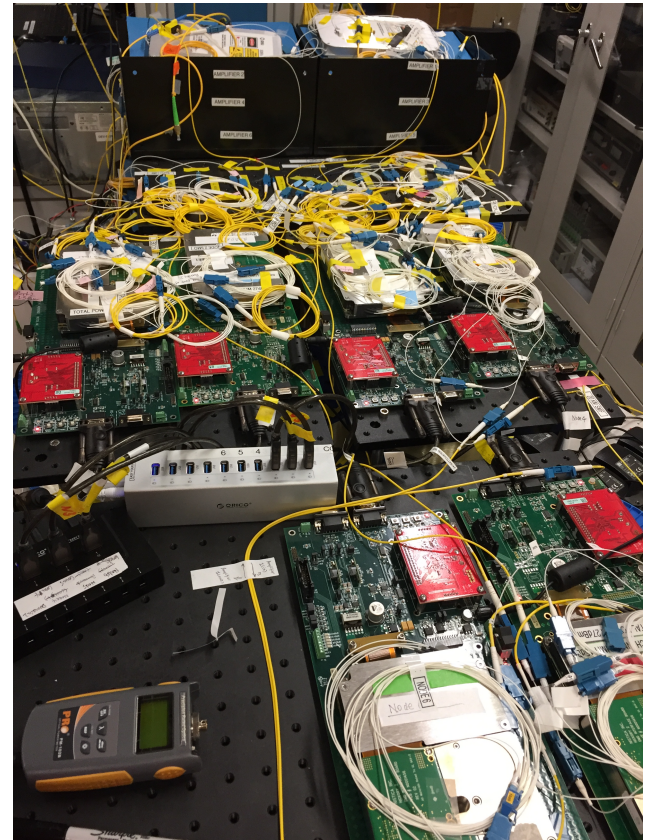
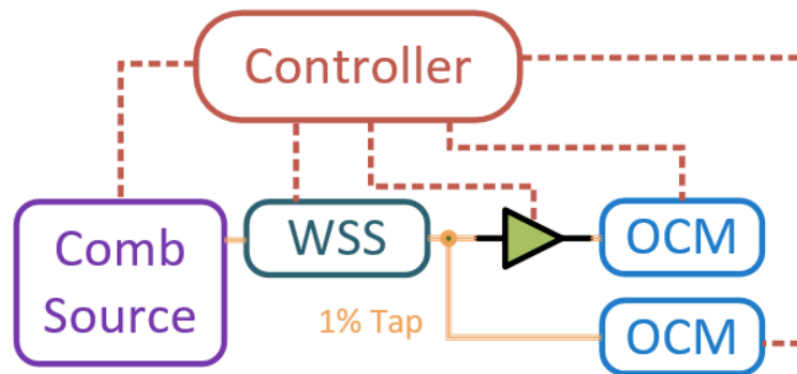
EDFA output spectrum  
(or equivalently gain spectrum)

Parameter	Value
Input Vector	$[P_{ch1}, \dots, P_{ch90}, G_{ch1}, \dots, G_{ch90}]$
Output Vector	$[P_{chi}]$ for $i$ in $[1, 90]$ # $i$ is index of the 90 NNs
Transfer Func.	[ReLU, Linear, ReLU, Linear, ReLU]
Training Target	Min{MSE}
Training Method	Stochastic Gradient Descent (SGD)
Batch Size ( $m$ )	$m = 60$
Learning Rate ( $\alpha$ )	$\alpha = 0.00025$
Training Time	> 15000 iterations

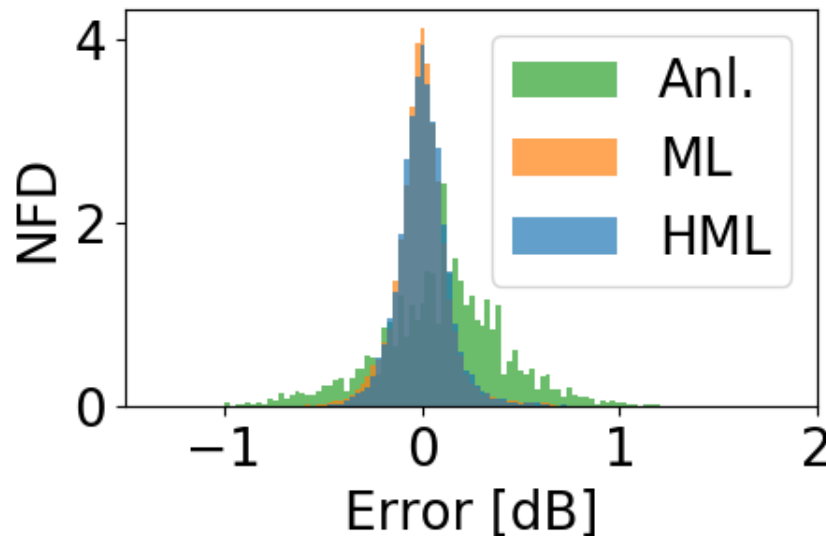
# Experiment Setup

We take the data from previous results, as we reported in *S. Zhu, et al., ECOC 2018*.

- Characterize single channel and fully loaded gain profile for EDFA.
- Capture *true* value of input and output spectrum.
- Capture ML *training data, validation data, test data*.



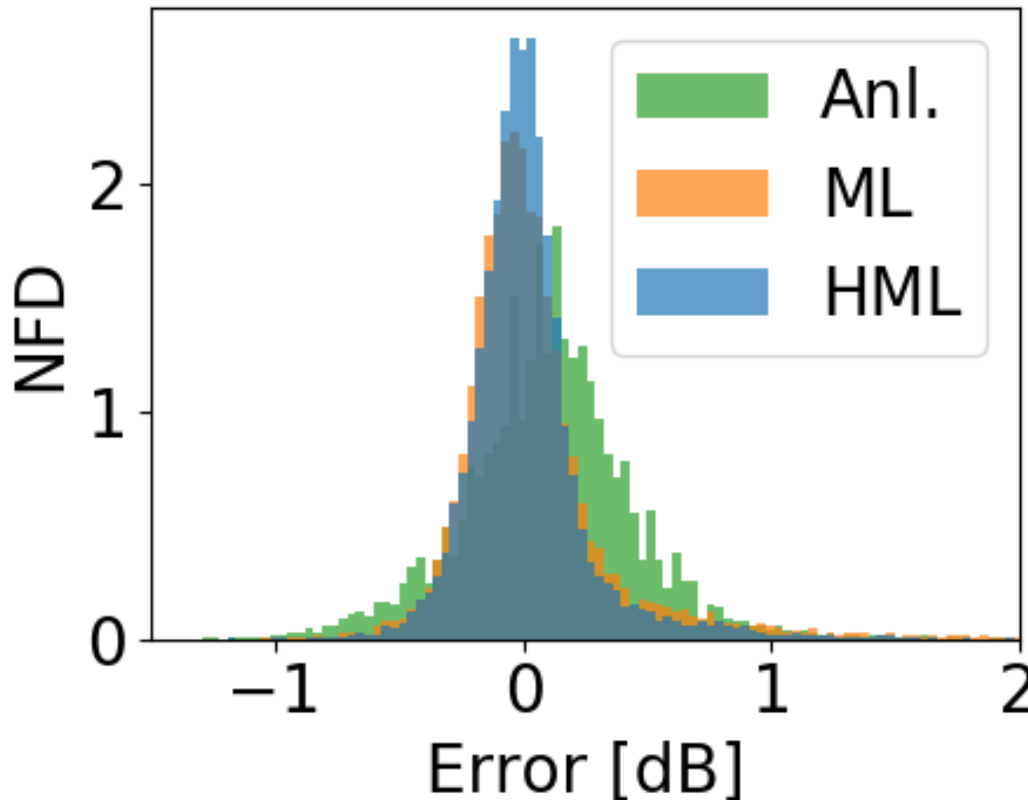
# Accuracy of prediction given abundant training data and unlimited training time (12000 samples and 25000 iterations)



Model	MSE Error	Max Error
Analytical	0.36 dB	2.6 dB
ML	0.16 dB	2.6 dB
HML 👍	0.14 dB	1.6 dB

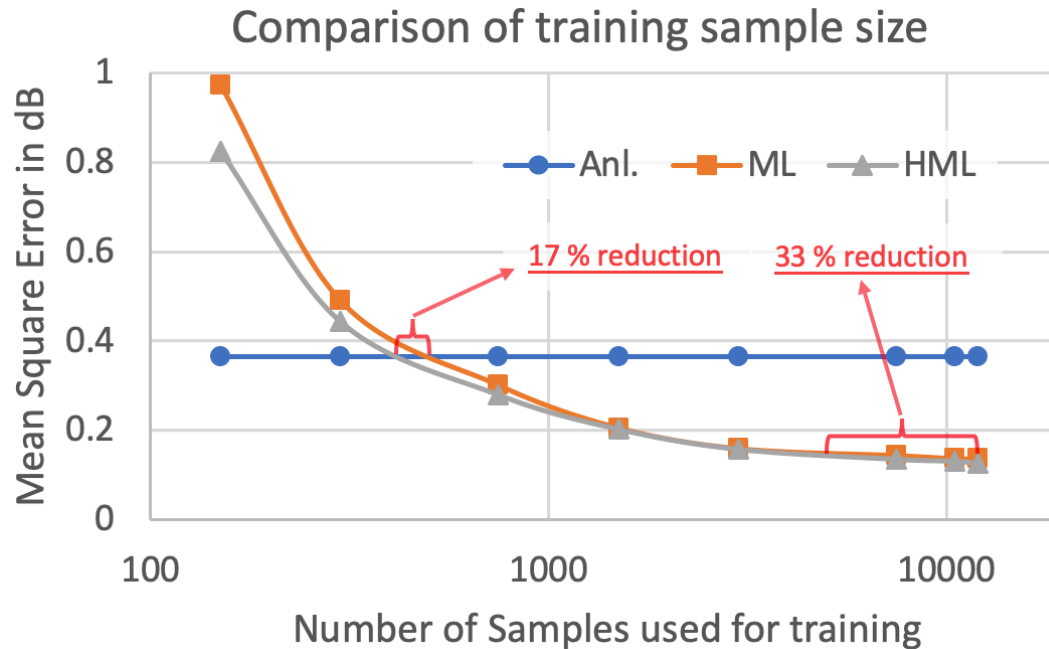


# Accuracy of prediction given abundant training data and limited training time (12000 samples and 5000 iterations)



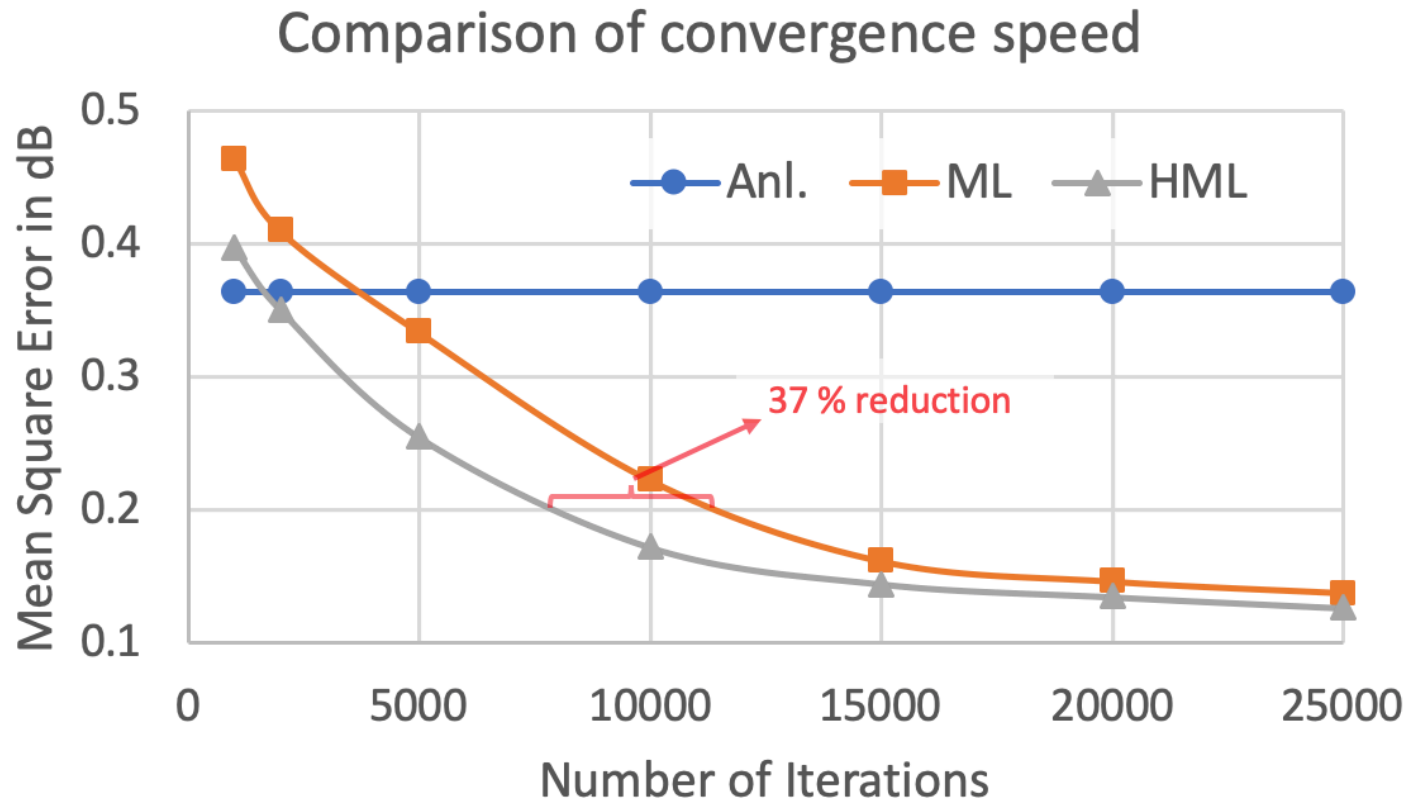
- HML has **much better accuracy** given limited training time.
- To achieve the same accuracy (e.g. 0.2 dB), HML takes **37% less** time than ML.

# Prediction error vs. number of training samples



- HML shows ability of achieve same level of accuracy with less training data.
- In figure: 33 % reduction with target MSE of 0.134 dB / 3 % in linear scale).
- Note: The target MSE value of 0.134 dB is very close to measurement error of typical power reading device (0.1 ~ 0.2 dB).

# Comparison: error convergence speed



- HML shows ability of achieve same level of accuracy with less time.  
(37 % reduction with target MSE of 0.2 dB / 5 % in linear scale)

# Conclusion

1. HML has the following advantages:
  - a. Quicker convergence and use less training data
  - b. Reduce max prediction error
2. Both HML and ML can achieve a good prediction accuracy. Both have MSE error below 0.2 dB, which is close to typical error of optical power measurement. HML accelerates the training process and reduces the size of training data.

# *Hybrid Machine Learning EDFA Model*

## Thank you!

Shengxiang Zhu: [szhu@optics.arizona.edu](mailto:szhu@optics.arizona.edu)

TOAN Lab: <https://wp.optics.arizona.edu/dkilper/>

WIMNET Lab: <https://wimnet.ee.columbia.edu/research/>

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