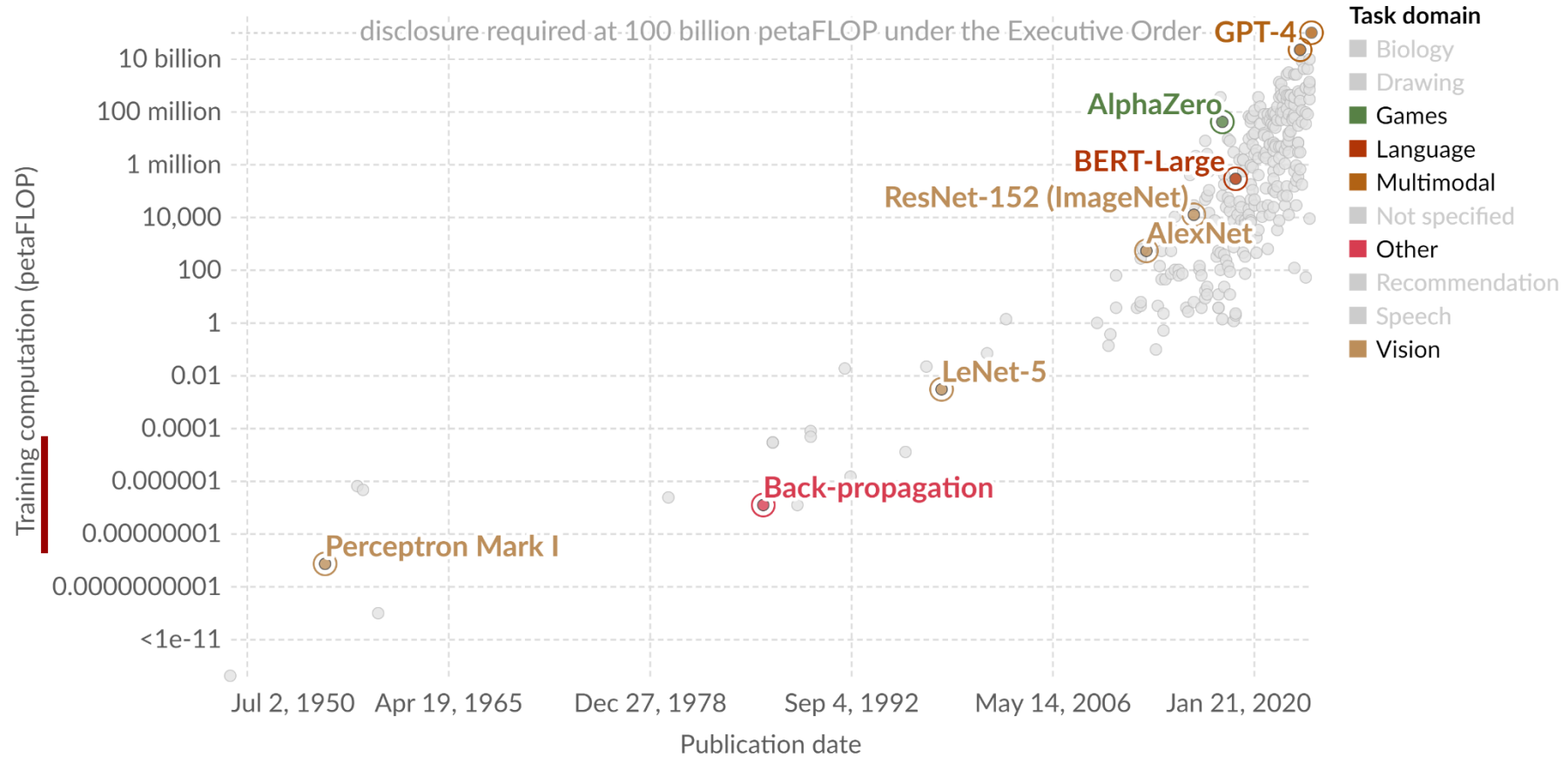


Programming photonic hardware for computing

Francesco Da Ros
fdro@dtu.dk

The computing power challenge

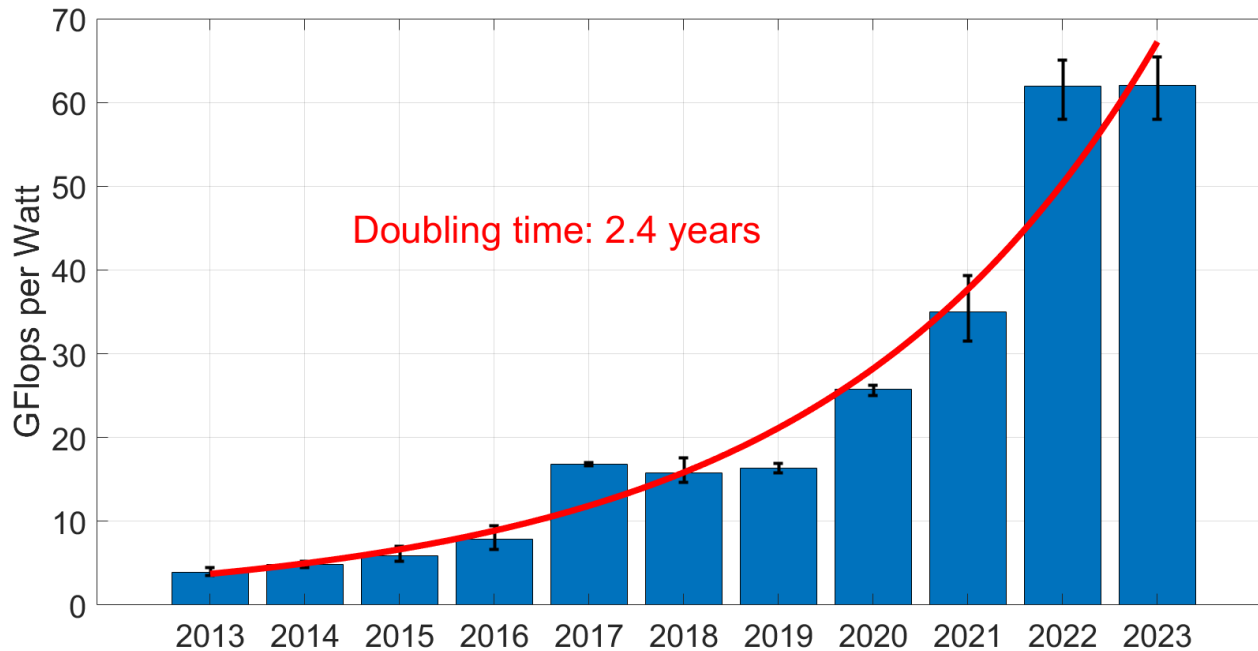


Data source: Epoch (2023)

OurWorldInData.org/artificial-intelligence | CC BY

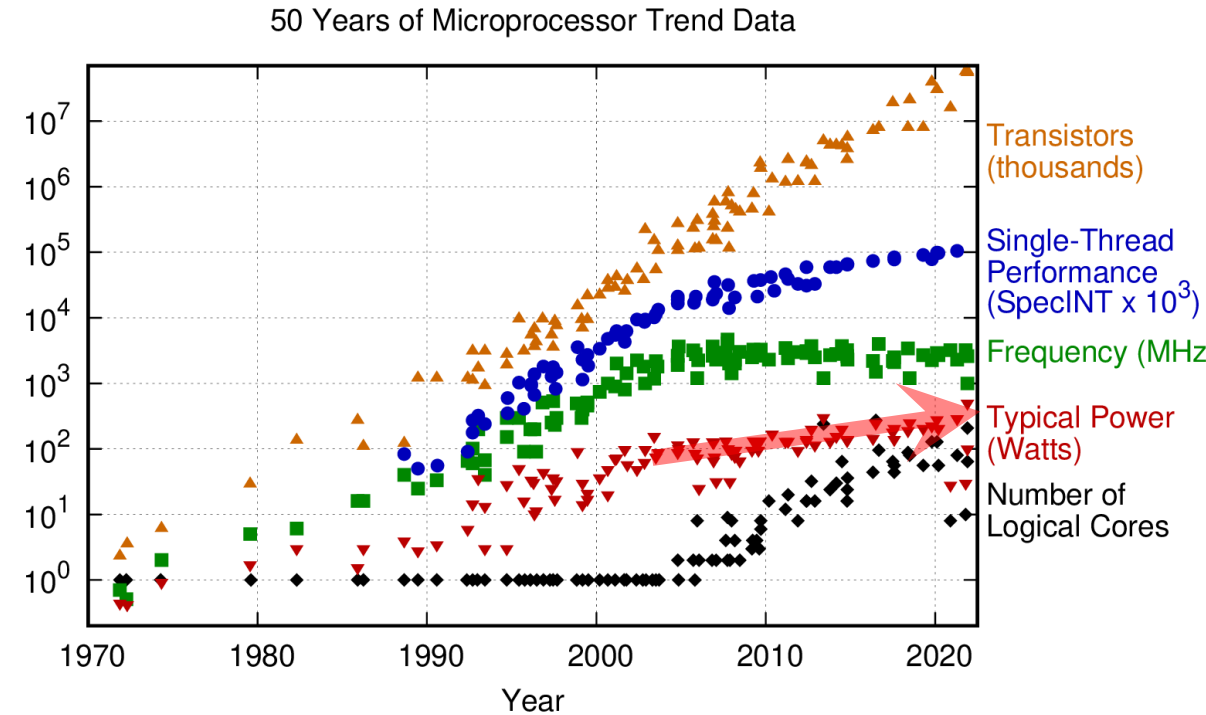
Scaling of energy efficiency in digital computing

Energy Efficiencies of Top 3 Supercomputers



Data source: Green500 list, data November 2023

End of Moore's Law?



<https://github.com/karlrupp/microprocessor-trend-data>

Scaling of energy efficiency in digital computing

Energy Efficiencies of Top 3 Supercomputers



Common carbon footprint benchmarks

in lbs of CO2 equivalent

Roundtrip flight b/w NY and SF (1 passenger)

1,984

Human life (avg. 1 year)

11,023

American life (avg. 1 year)

36,156

US car including fuel (avg. 1 lifetime)

126,000

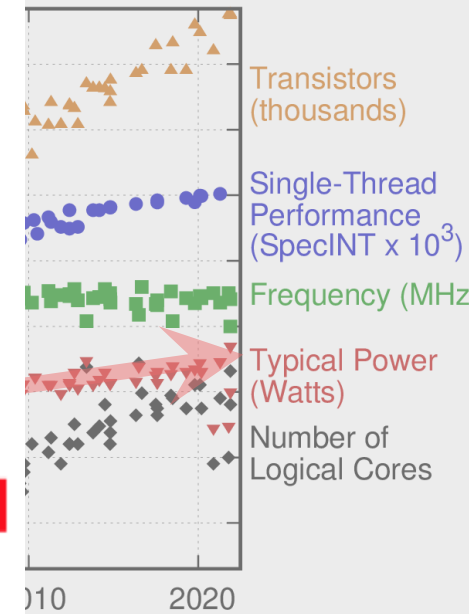
Transformer (213M parameters) w/ neural architecture search

626,155

Chart: MIT Technology Review • Source: Strubell et al. arXiv:1906.02243

End of Moore's Law?

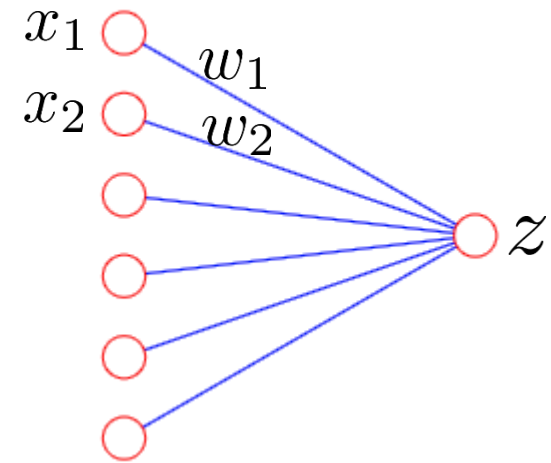
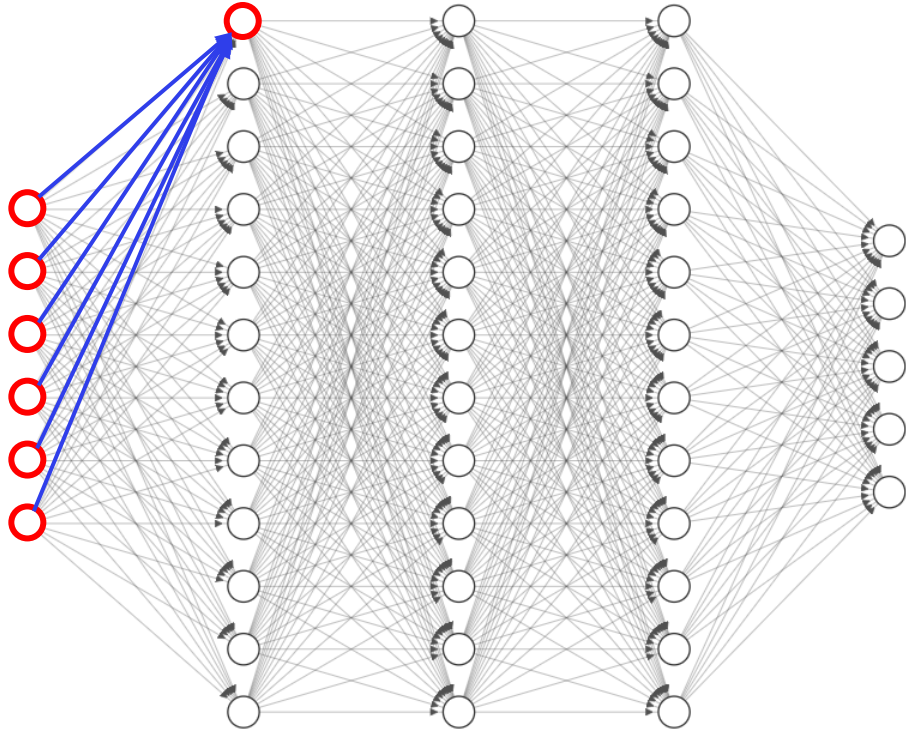
50 Years of Microprocessor Trend Data



Data source: Green500 list, data November 2023

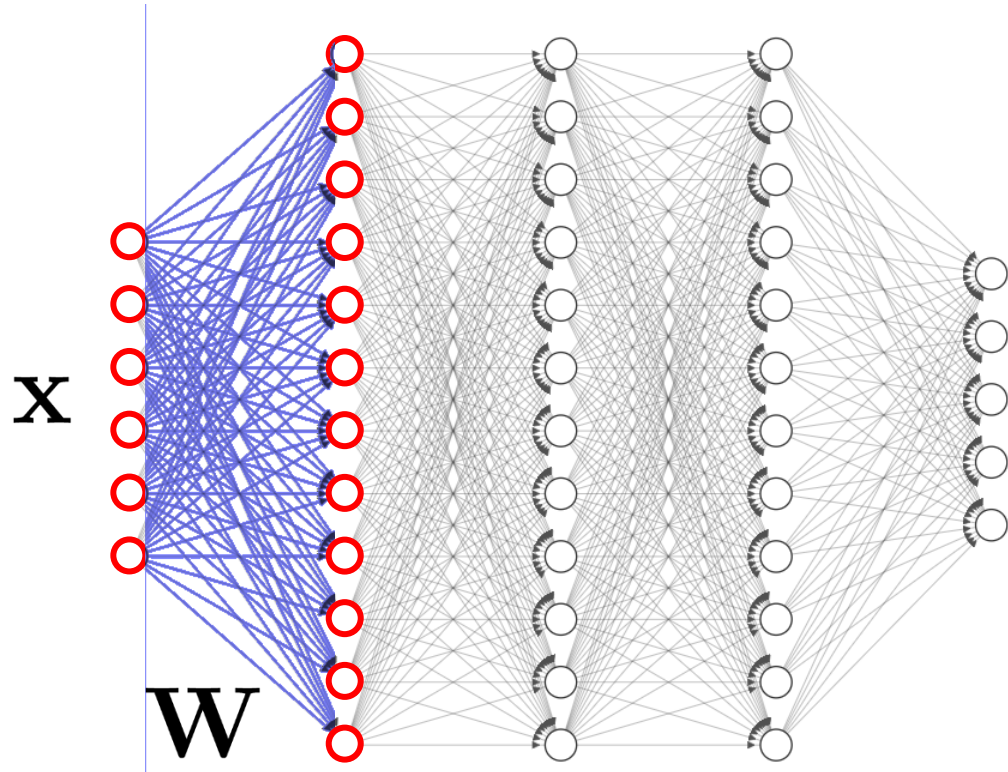
<https://github.com/karlrupp/microprocessor-trend-data>

A basic neural network



$$z = f_{act}(\mathbf{w}^T \mathbf{x})$$

Vector-Matrix Multipliers



$$Wx$$

Electronics (metal wiring)	Photonics (waveguides)
Higher energy consumption	Lower energy consumption
High loss	Low losses
Narrow freq. bandwidth	Wide freq. bandwidth
Sensitive to interference	Lower sensitivity to interference

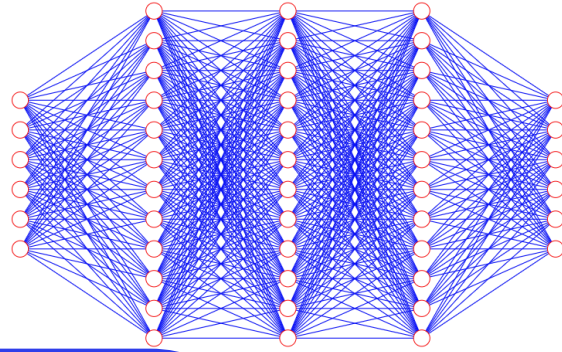
* Analog electronics for computing is also a very active research topic.

“small” NN but >400 connections/weights
 # interconnections \propto (# nodes)²

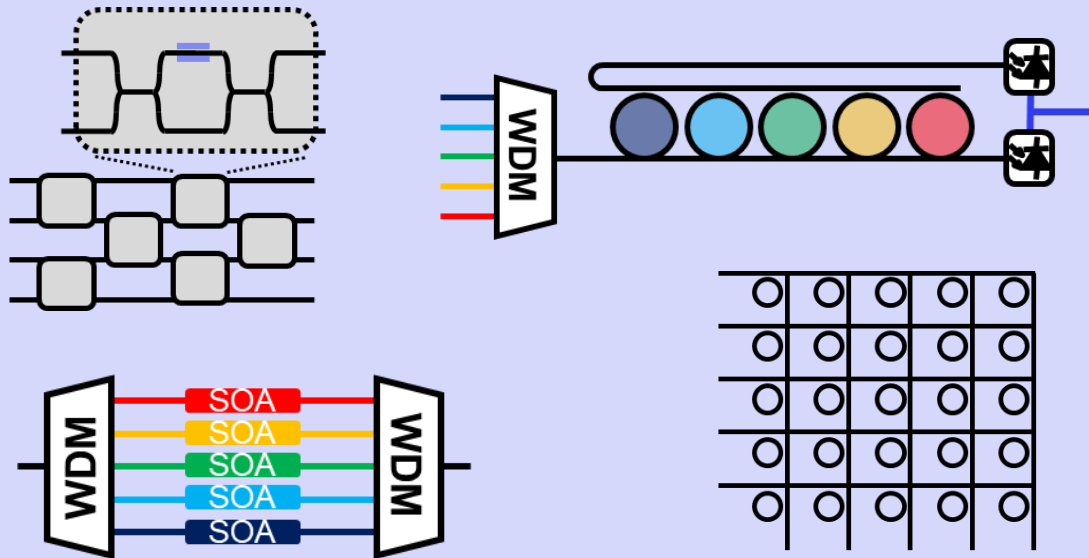
Outline of this talk

- Integrated photonics for computing
 - Building blocks and architectures
- A key challenge: **programming** the circuit
 - Why is accurate programming important?
 - Offline programming
 - Online programming
- Conclusions

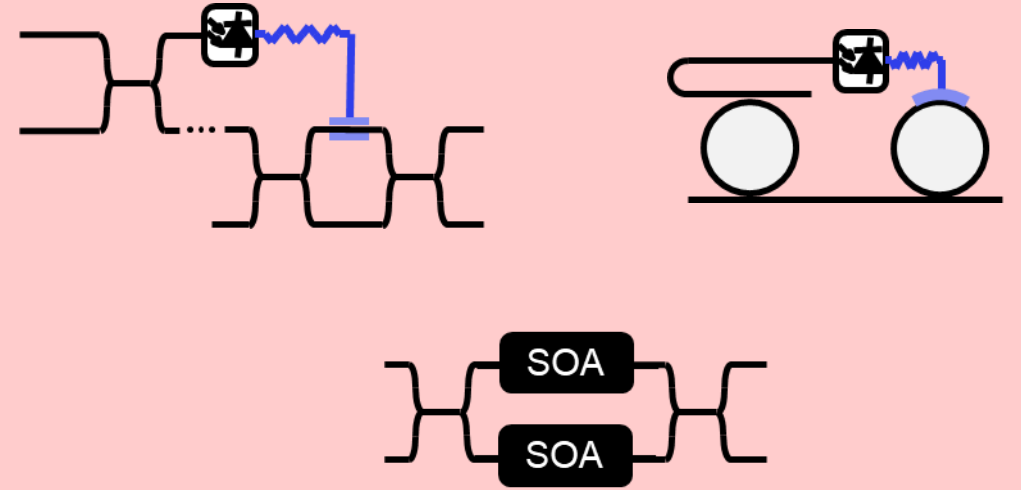
Building blocks for integrated photonic neural networks



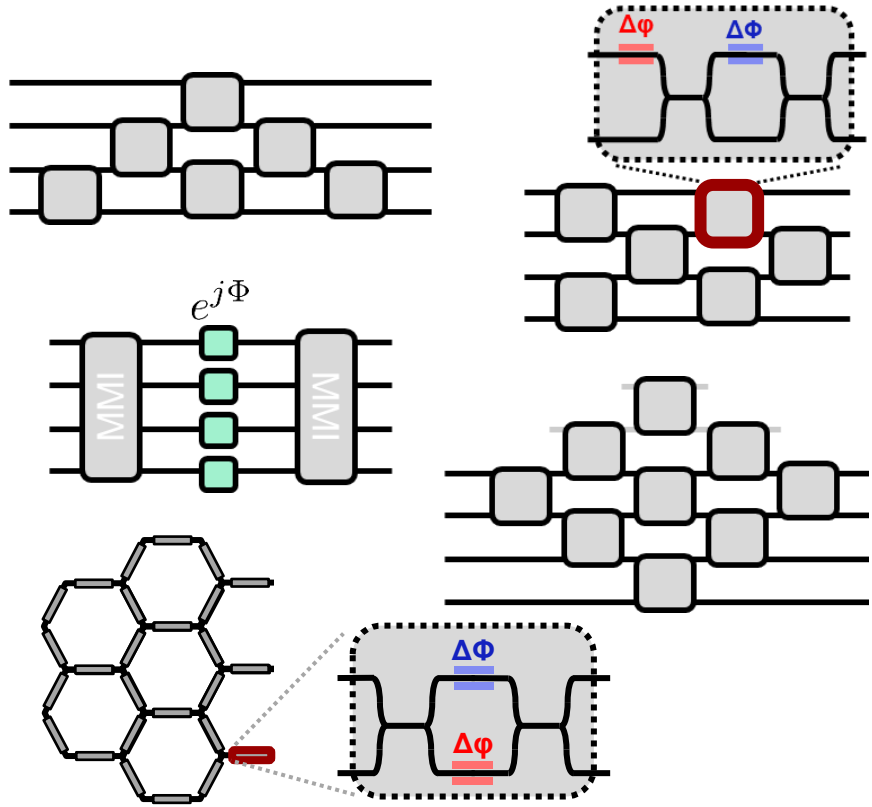
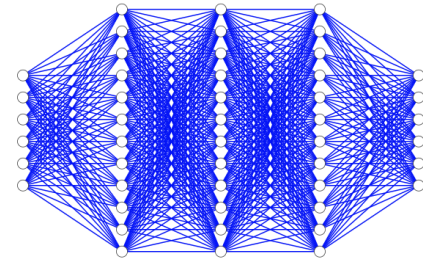
Weights – Vector-matrix multipliers



Nodes – activation functions



Vector-matrix multipliers – MZI meshes



- Several configurations proposed
 - Reck (triangular)
 - Clements (rectangular)
 - Universal generalized (UGMZI)
 - Diamond
 - Hexagonal mesh
 -
- Coherent vs. incoherent operation
- MZIs can be replaced by MRRs

Tradeoffs between scalability (# couplers/phase shifters), path loss difference, circuit depth, tolerance to errors

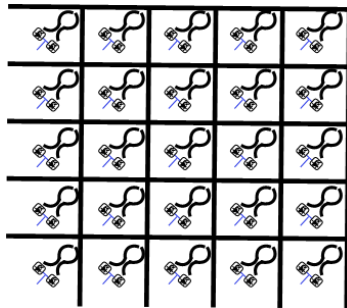
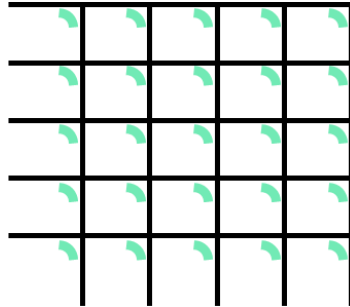
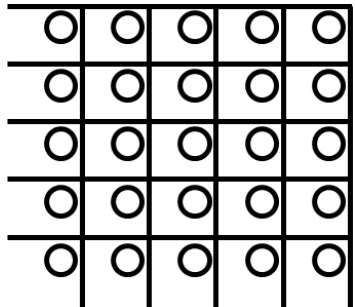
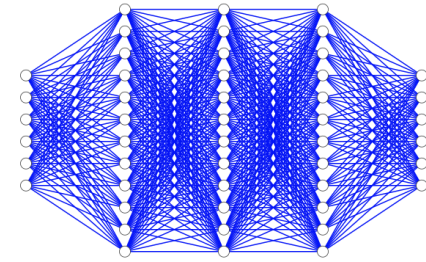
M. Reck, et al. PRL 1994
 Y. Shen, et al., Nat Phot 2017
 K. R. Mojaver Opt. Expr. 2023

W.R. Clements, et al., Optica 2016
 A. Tsakyridis, Adv. Phot. Res. 2022
 A. Cem, JLT 2023

D. Perez Lopez, et al., Nat. Comm. 2017
 R. Hamerly, PRA 2022

MZI: Mach-Zehnder interferometer
 MRR: Microring resonator
 MMI: Multimode interferometer

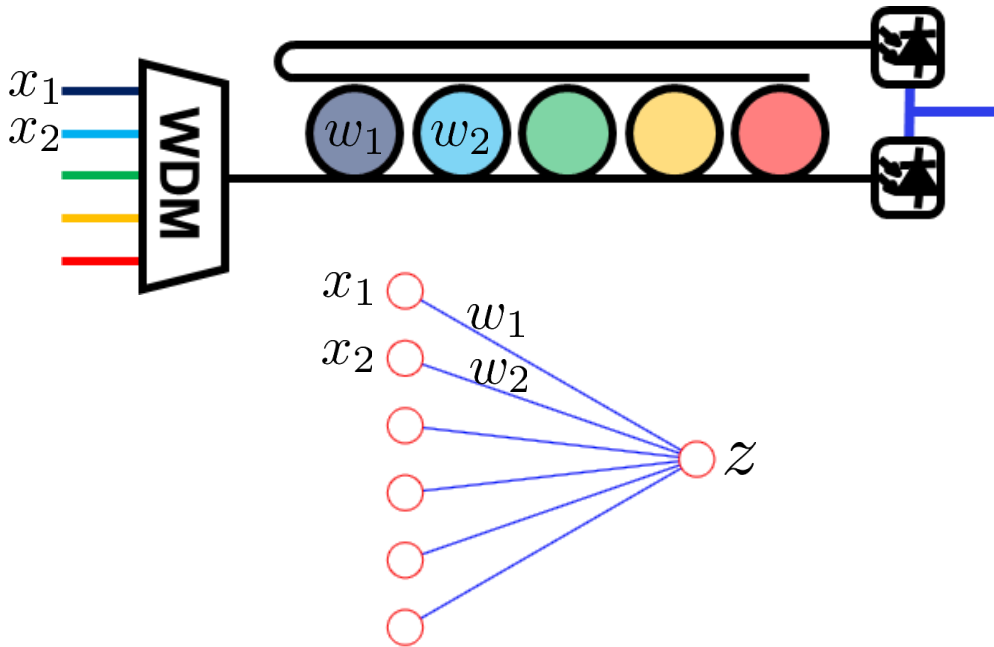
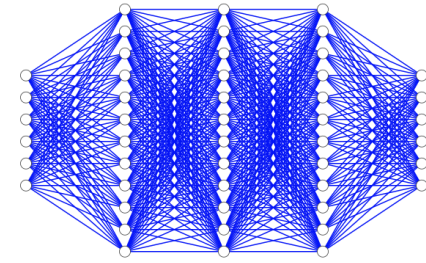
Vector-matrix multipliers – Xbar arrays



- Several configuration proposed for the weighting elements
 - MRRs
 - Phase-change materials
 - MZIs and Phase shifters
 - ...
- Coherent vs. incoherent operation
- Potential for matrix-matrix multiplication through WDM (and WDM+FM) up-scaling

Potential scaling issues and very sensitive to phase-mismatch in the optical path.

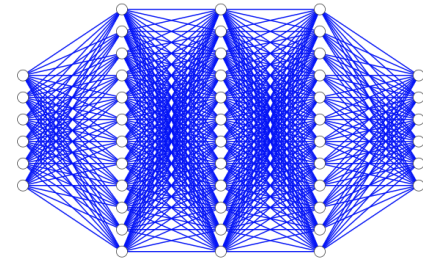
Vector-matrix multipliers – Weight & Add



- WDM dimension used for multiplexing columns
- Mainly incoherent operation

Potential scaling issues, matrix size is limited by the number of wavelengths.

Vector-matrix multipliers – SOA banks

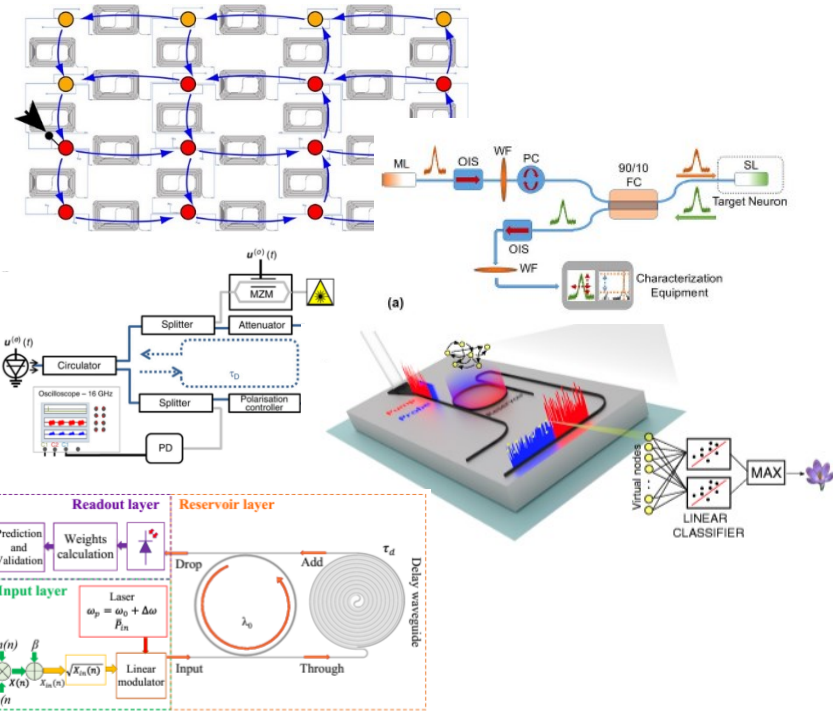


- WDM dimension used for multiplexing columns
- Mainly incoherent operation
- Allows for weights > 1

Single platform for linear and nonlinear operations and inherent signal amplification but higher energy consumption and added noise

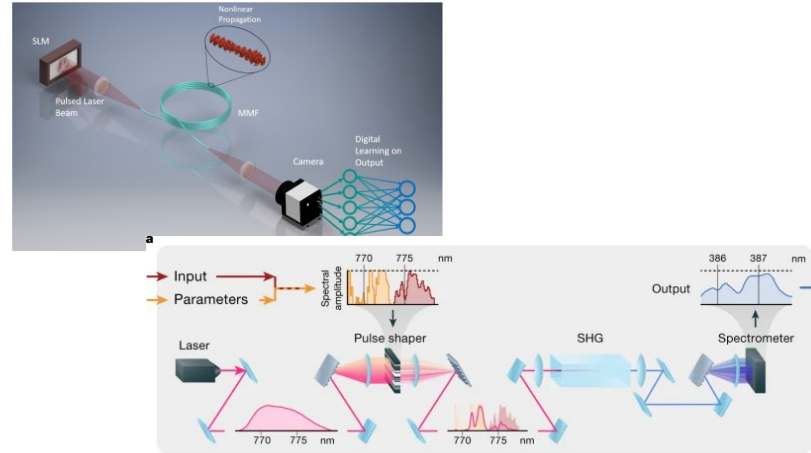
Alternative photonic NN architectures

Reservoir computing



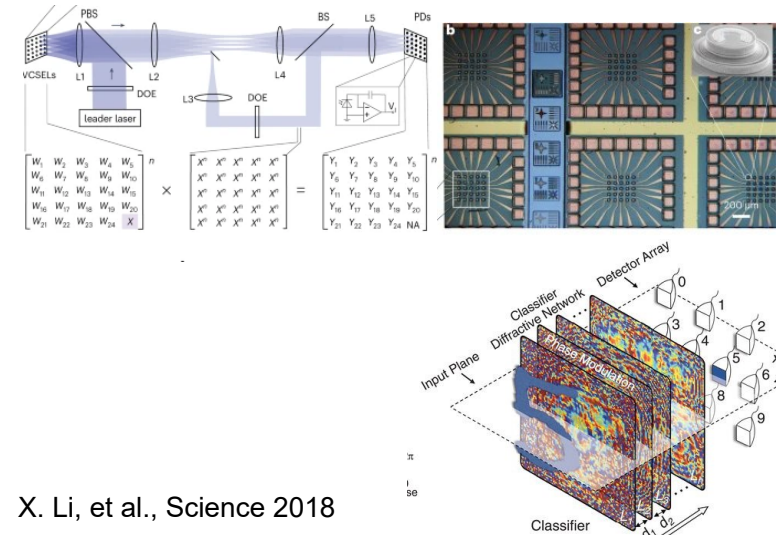
- K. Vandoorne, et al., Nat Comm 2014
- D. Brunner, et al., Nat. Comm. 2013
- C. Mesaritakis, et al., Sci. Rep. 2016
- M. Borghi, et al., Sci. Rep.. 2021
- B.J. Giron Castro, et al., Opt. Expr. 2024

Nonlinear propagation



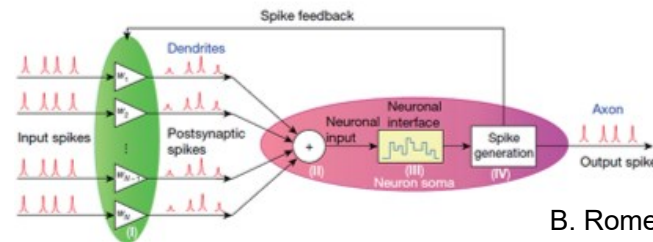
- B. Rahmani, et al., Nanophotonics 2022
- L.G. Wright, et al., Nature 2022

Diffractive networks



- X. Li, et al., Science 2018
- Z. Chen, et al., Nat. Phot. 2023

Spiking networks



- B. Romeira, et al., Neuromorph. Comput. Eng 2023

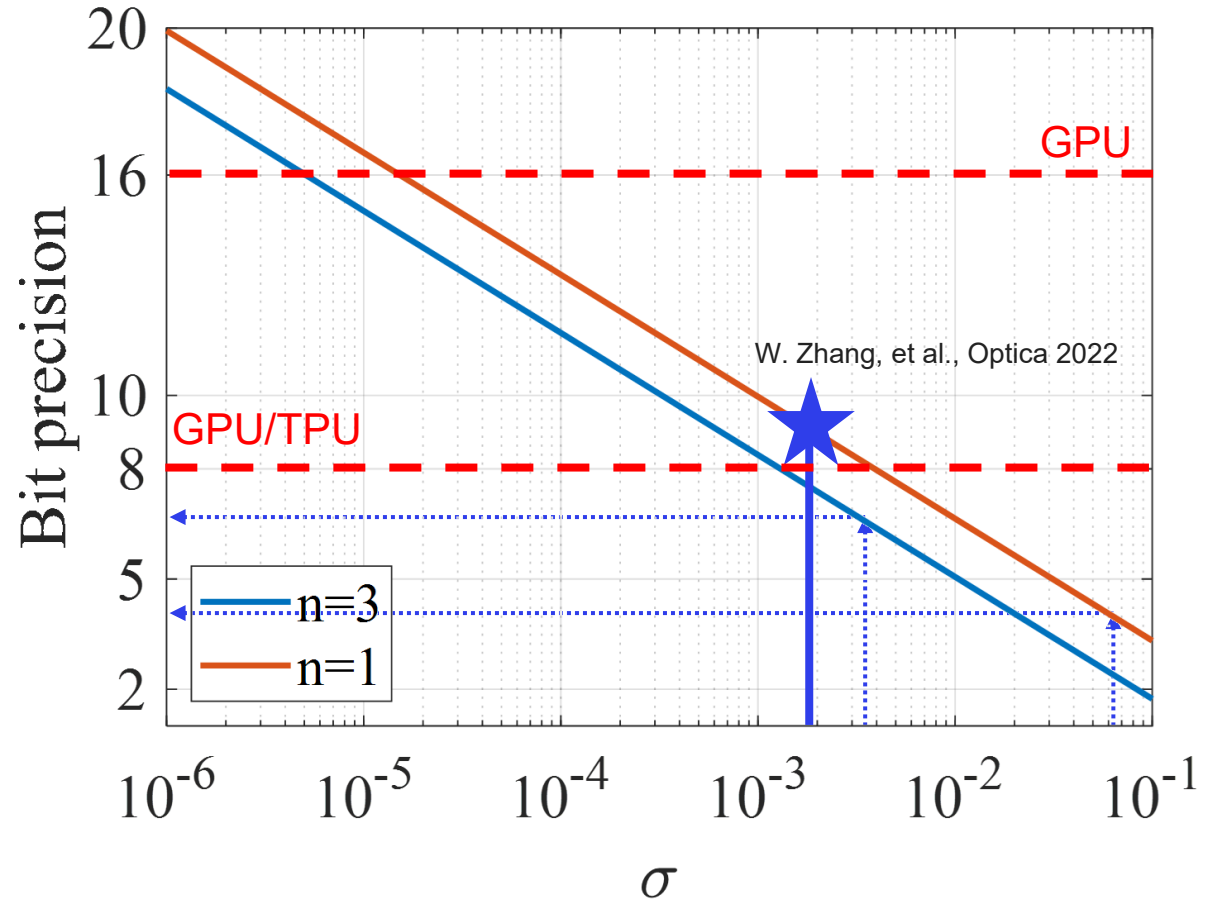
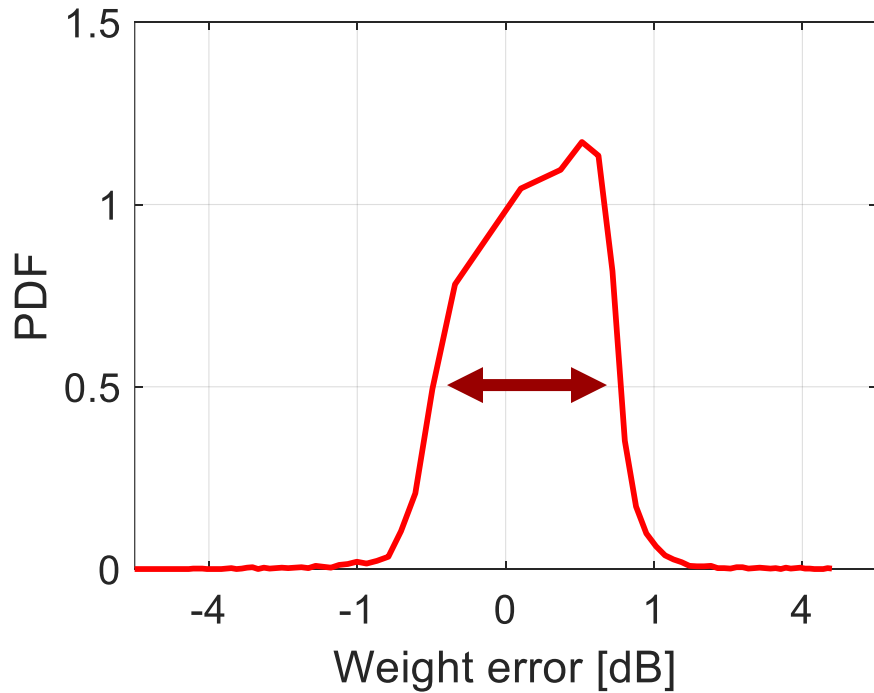
Outline of this talk

- Integrated photonics for computing
 - Building blocks and architectures
- A key challenge: **programming** the circuit
 - Why is accurate programming important?
 - Online programming
 - Offline programming
- Conclusions

Importance of programming accuracy

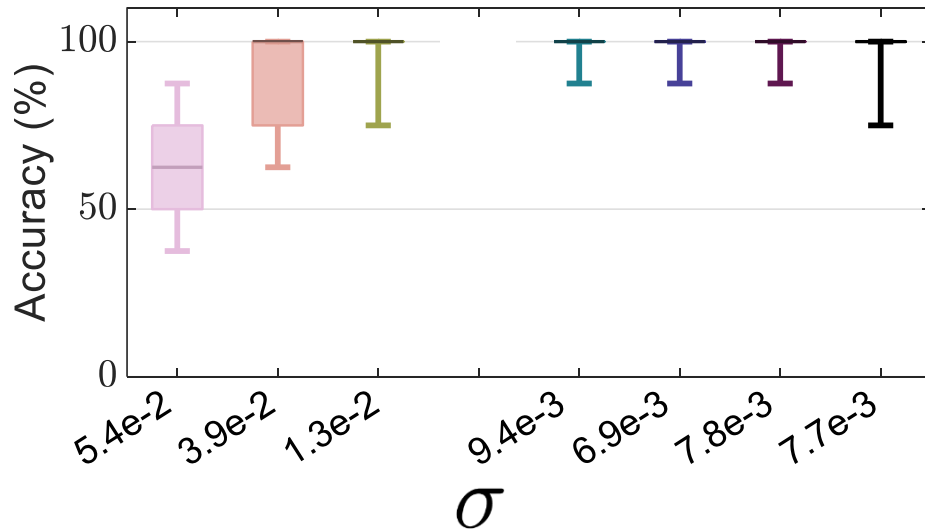
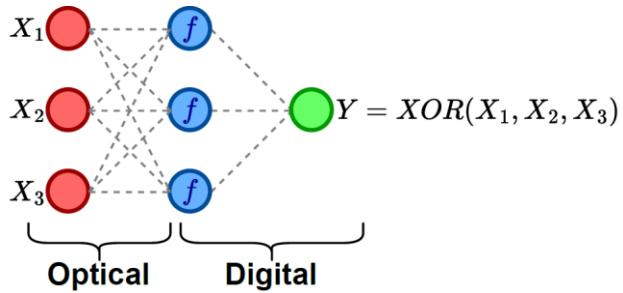
$$\text{Bit Precision} = \log_2 \left(\frac{w_{max} - w_{min}}{n \cdot \sigma} \right)$$

↑
Error in weights

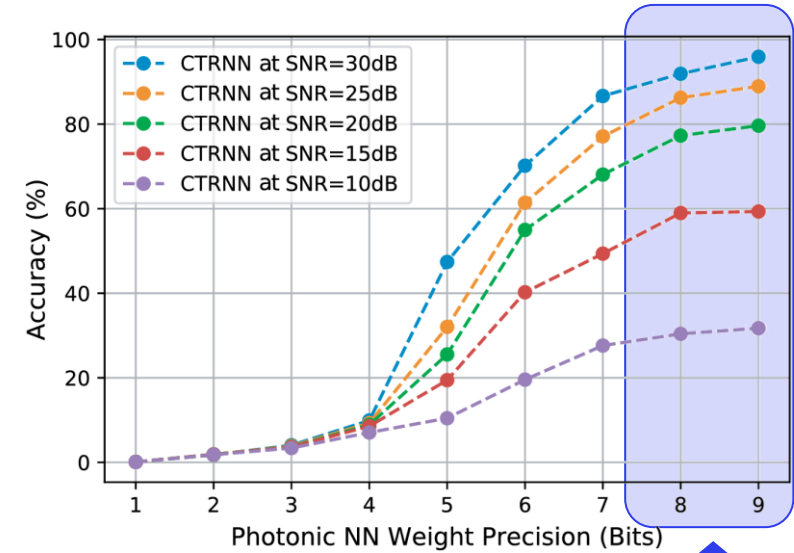


From modelling error to task performance

MZI mesh



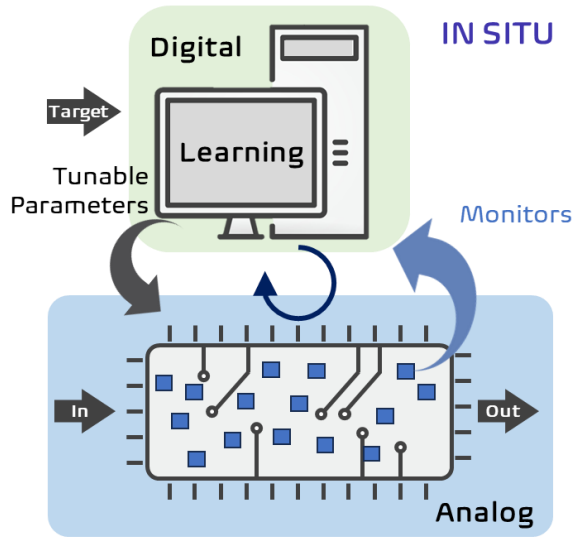
Weight & add



Active stabilization required

Training with inaccurate models leads to performance penalty during inference

Training photonic networks



On-line training (in situ)

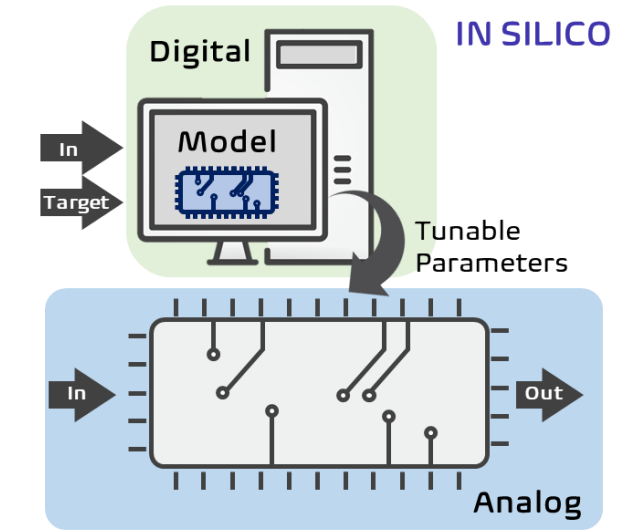
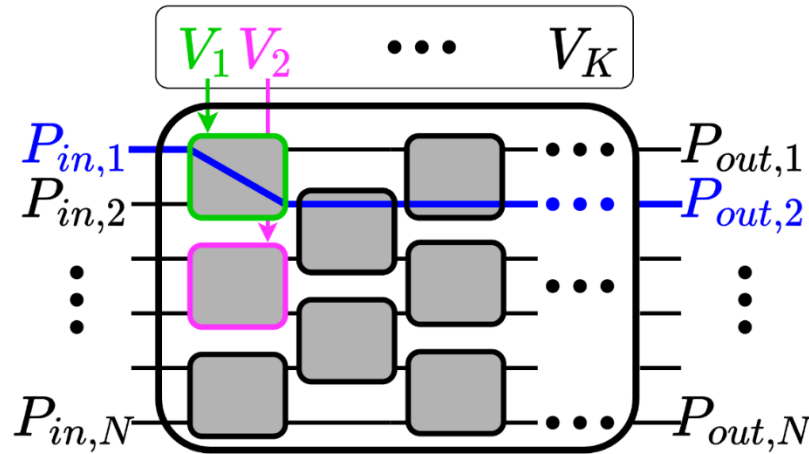
- Performed on the specific PIC
- Generally requires extra hardware
- Iterative procedure (re-train → re-start)

Z. Thang, et al., Opt. Expr. 2019

S. Pai, et al., Science 2023

M. Milanizadeh, et al., JSTQE 2020

H. Zhang, et al., ACS Phot 2021



Off-line training (in silico)

- Relies on an accurate/fast PIC model
- Allows for faster re-configurability
- Does not capture drifts

D. Pérez, et al., Nat. Commun 2017.

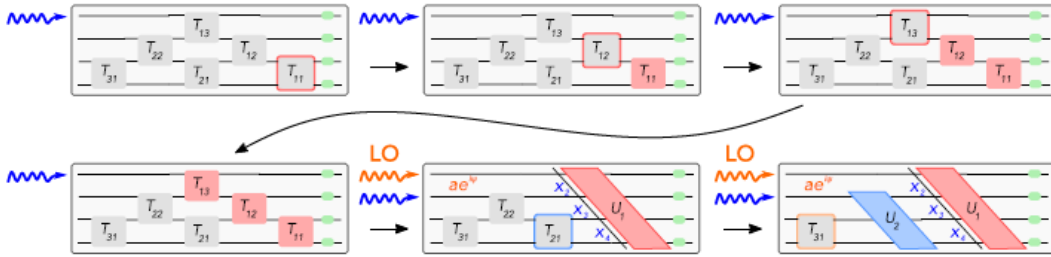
M. Fang, et al., Opt. Expr. 2019

S. Bandyopadhyay, et al., Optica 2021

A. Cem, et al., JLT 2023

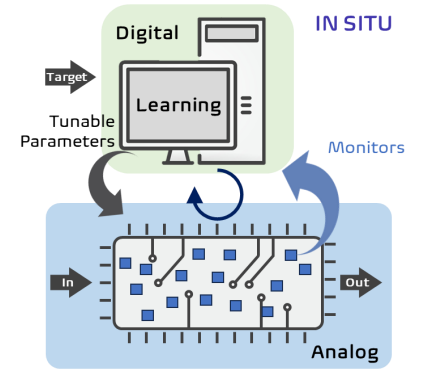
In-situ training (I)

Calibration and hardware correction

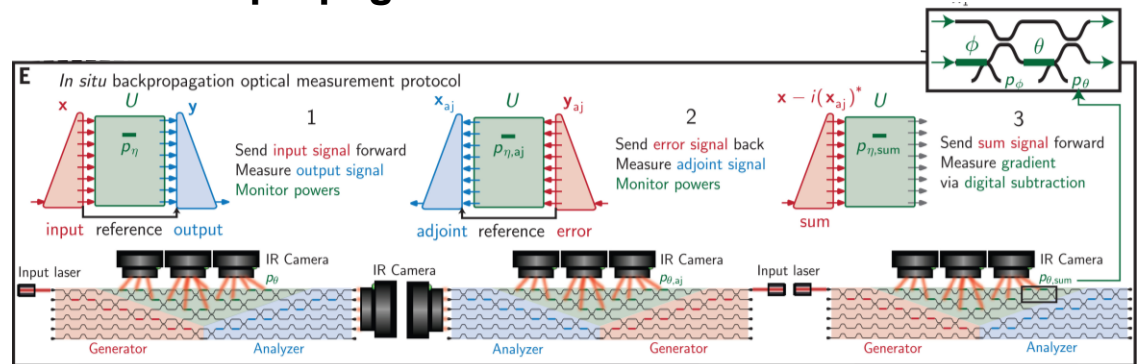


- Simple sequential procedure
- Many calibration measurements required and not easily accounting for cross-talk effects

D.A.B. Miller, Opt. Expr. 2013
 S. Bandyopadhyay, et al., Optica 2021
 K.R. Mojaver, et al., Opt. Expr 2023
 and many more...



In-situ backpropagation

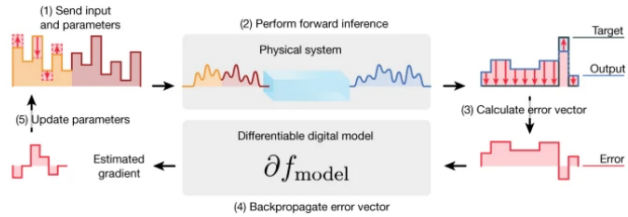


- Requires monitoring – on-chip or off-chip hardware
- Effective but scalable?

S. Pai, et al., Science 2023

In-situ training (II)

Gradient-approximation algorithms

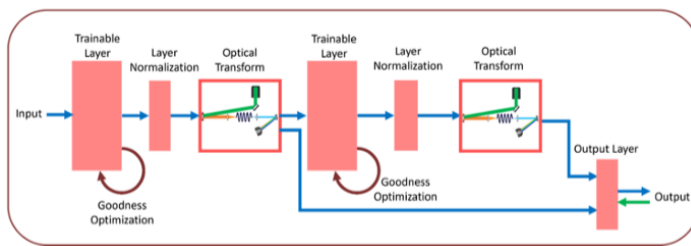


- Current demonstration/algorithms are circuit-specific

L.G. Wright, et al. Nature 2022

A. Momeni, et al., arXiv 2304.11042 2023

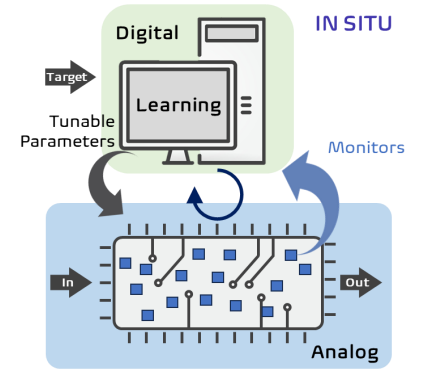
Forward-only algorithms



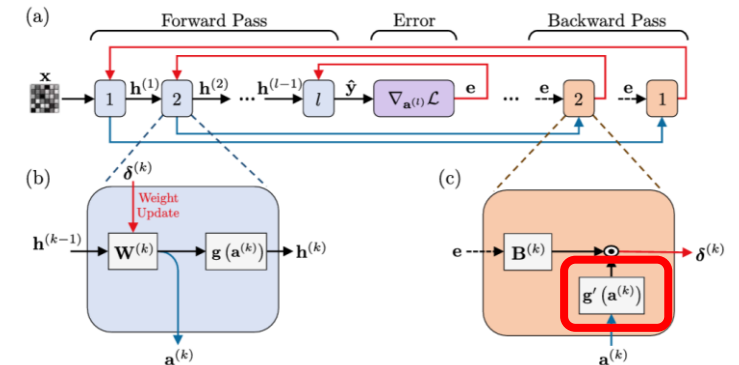
- Algorithms fine-tuned to the specific circuit

I. Oguz, Opt. Lett. 2023

E. Martin, et al., iScience 2021



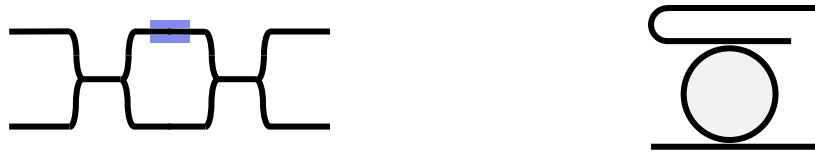
Auxiliary training circuit



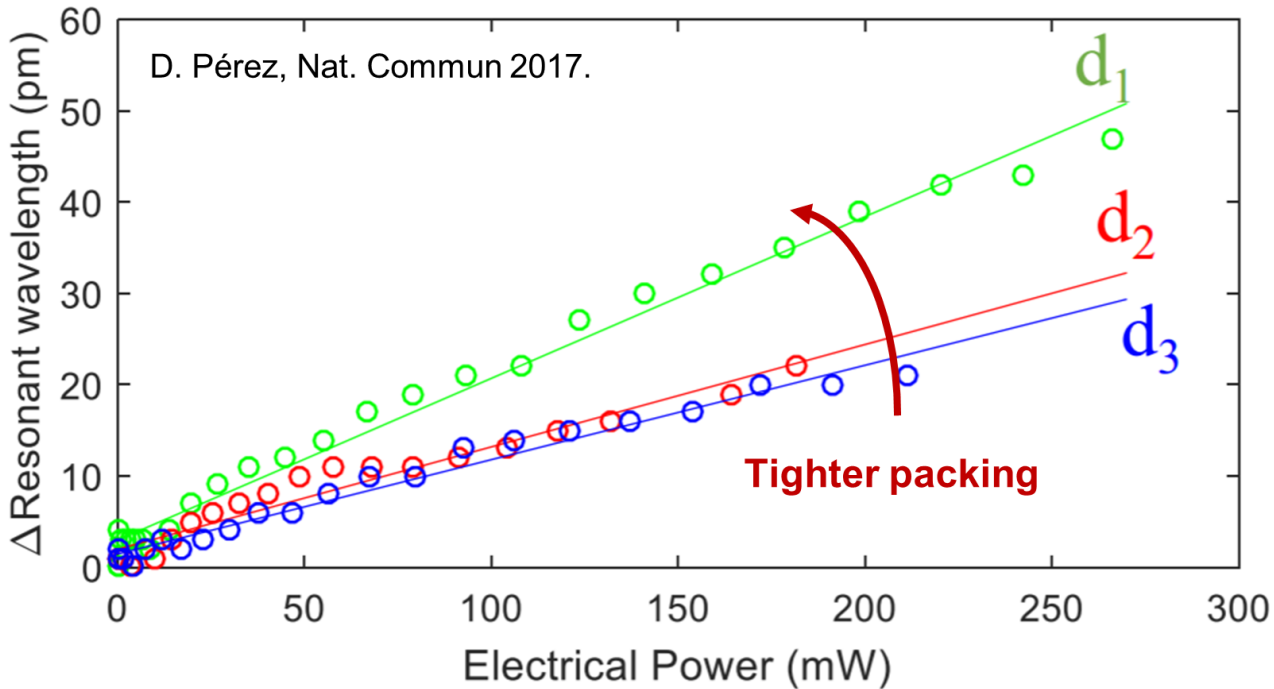
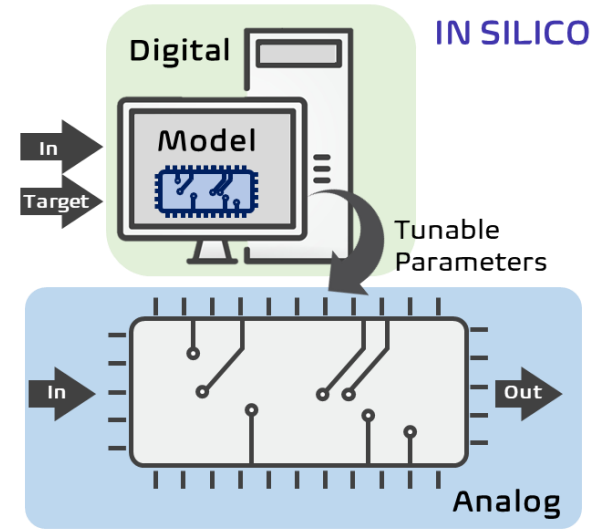
- On-chip training
- Challenges in scaling up the circuit size

M. Filipovich, et al., Optica 2022

In silico training



Accurate physical models of the building blocks exist.



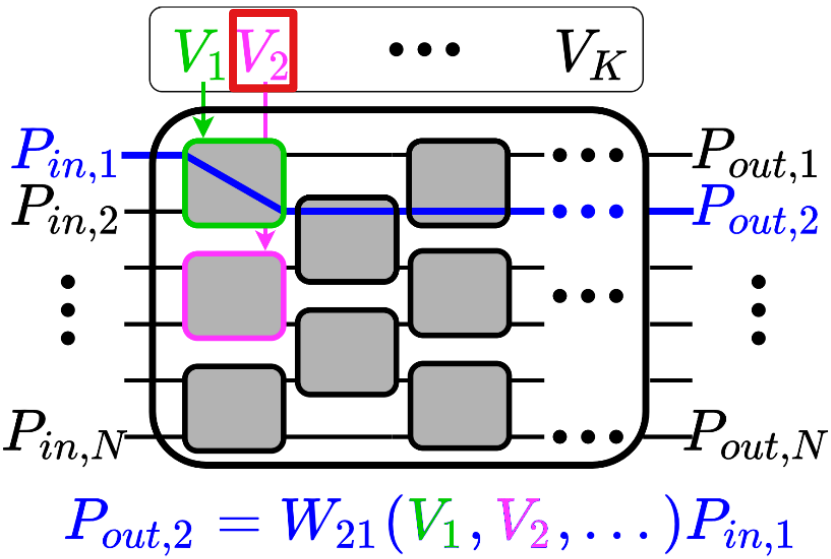
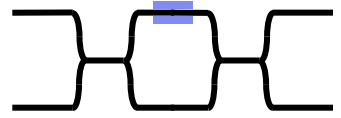
Packing MZI/MRR meshes tightly:

- Optical crosstalk – waveguide crossing
- Thermal crosstalk – thermal diffusion
- Electrical crosstalk – voltage delivery network
- Fabrication errors/tolerances



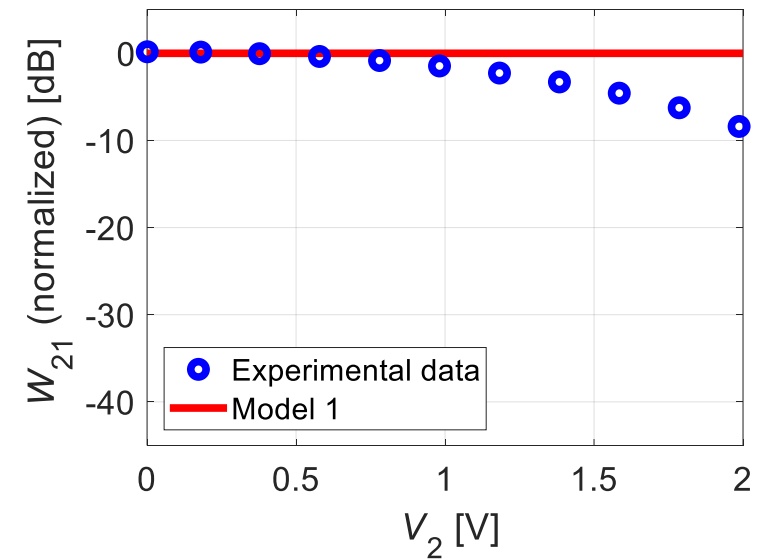
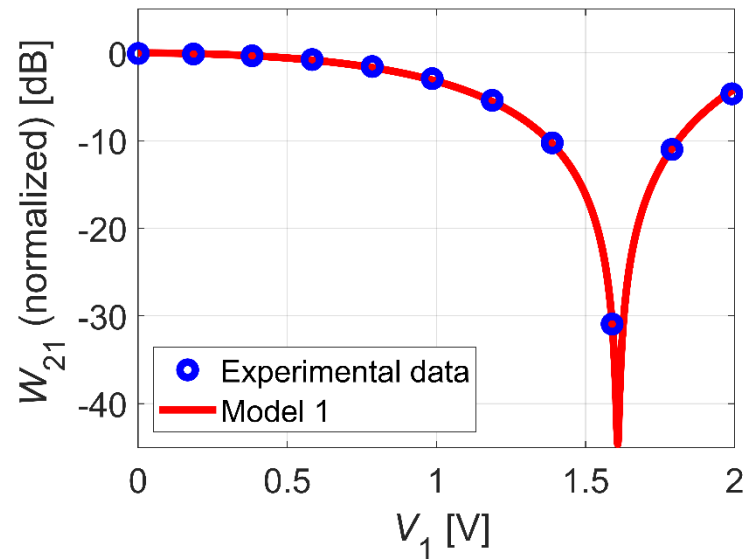
Are simple models accurate enough?

Simple MZI mesh model

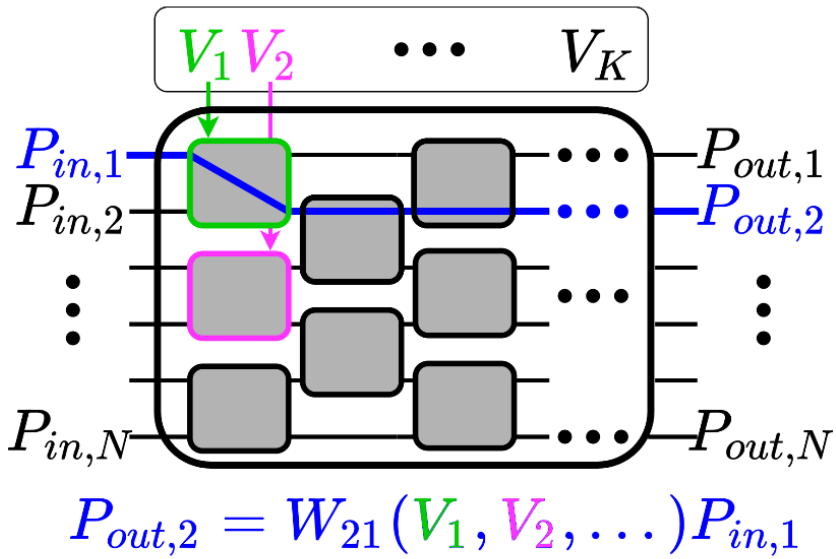


Loss Extinction ratio

$$W_{ij} = L_{ij} \prod_{k \in K_{ij}} \frac{1}{4} \left| \frac{\sqrt{ER} - 1}{\sqrt{ER} + 1} - \exp\left(\sqrt{-1}(\phi_k^{(0)} + \phi_k^{(2)}V_k^2)\right) \right|^2$$

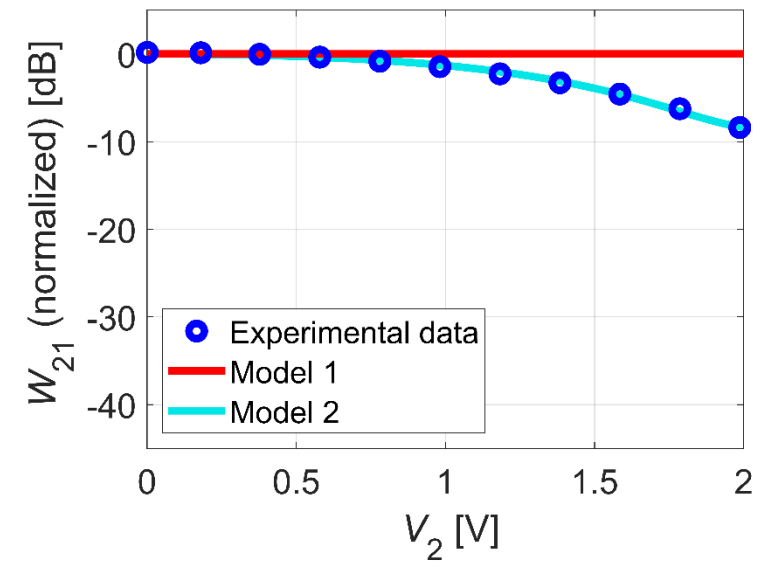
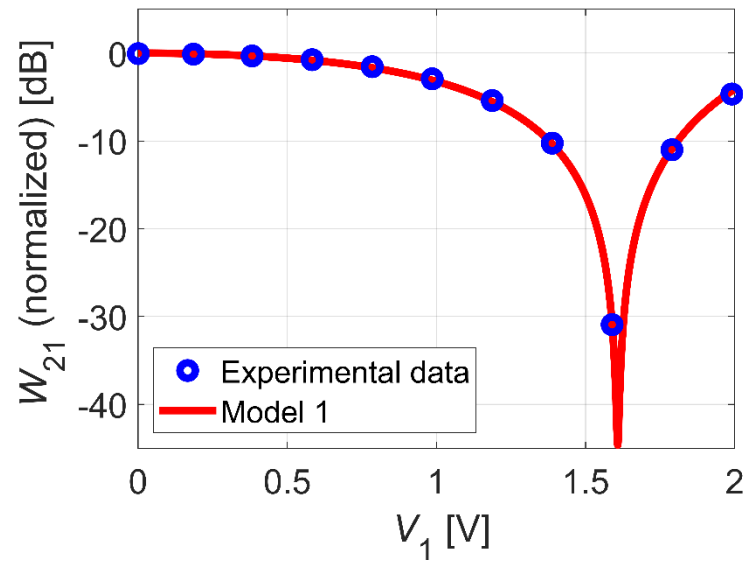


MZI mesh model with crosstalk

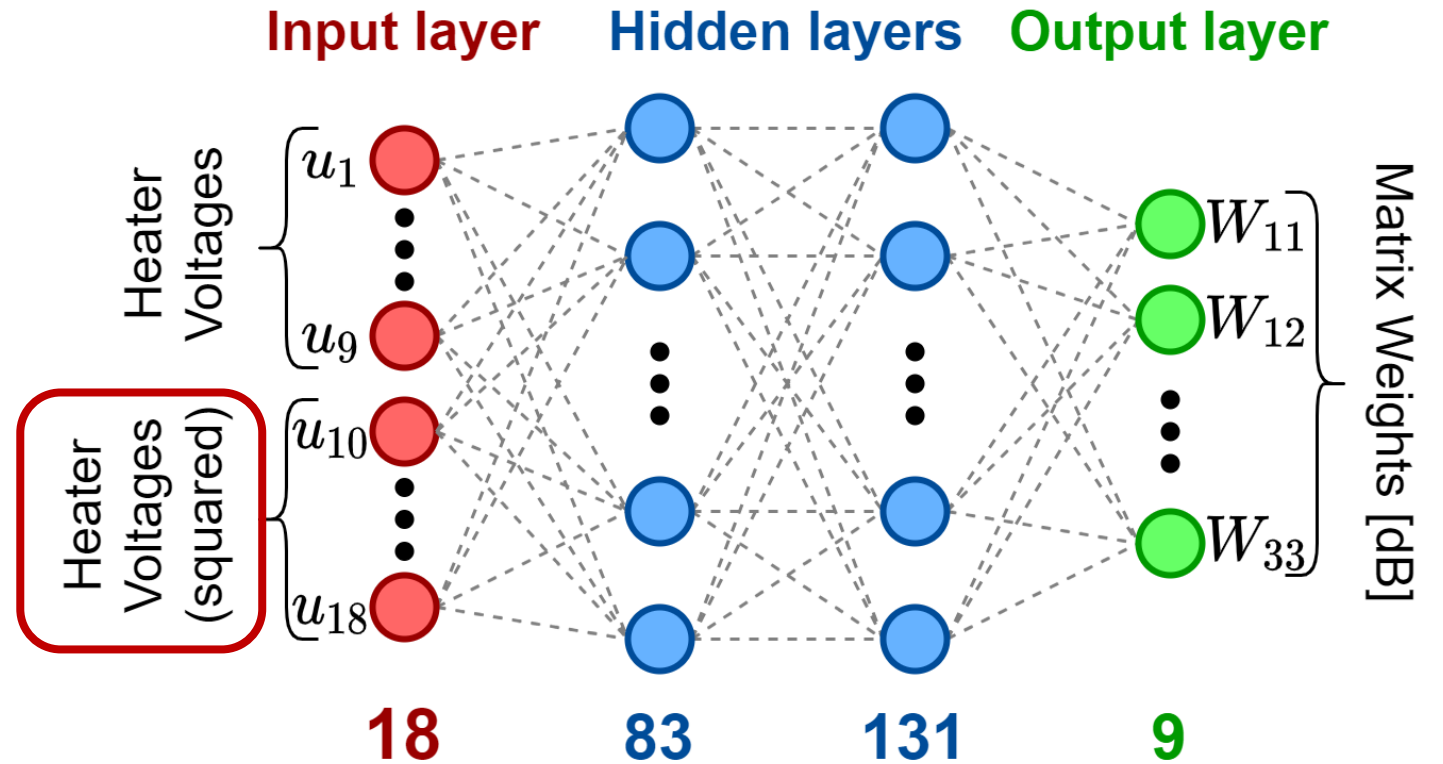
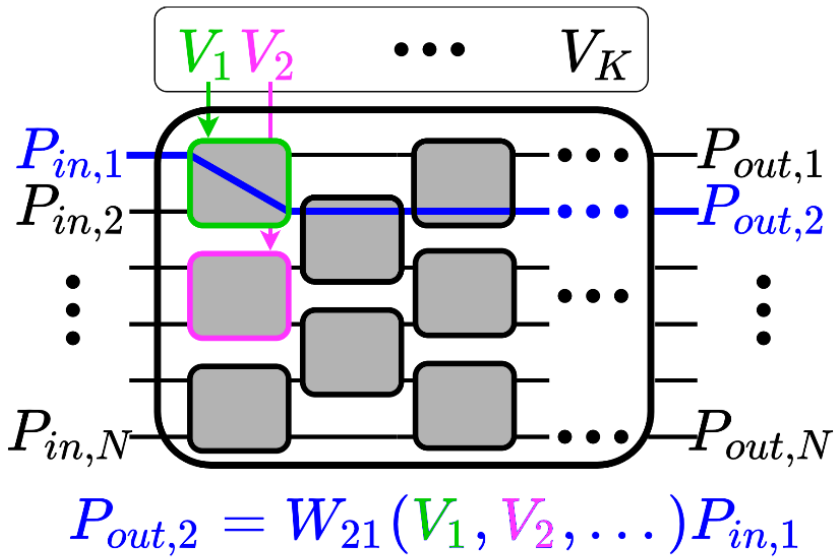


Self & crosstalk

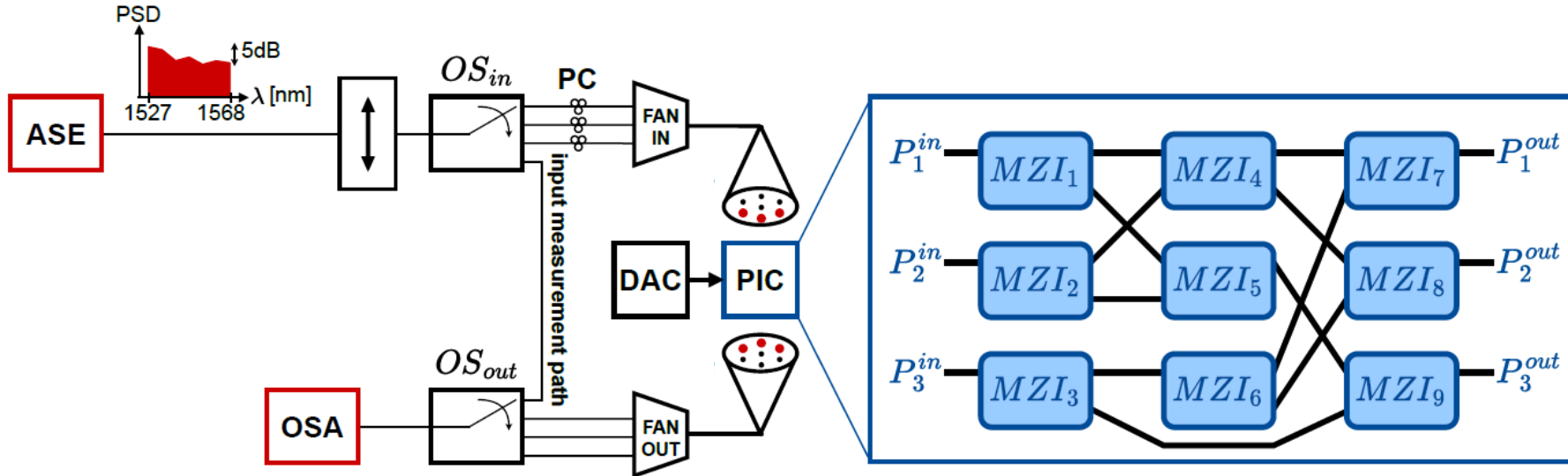
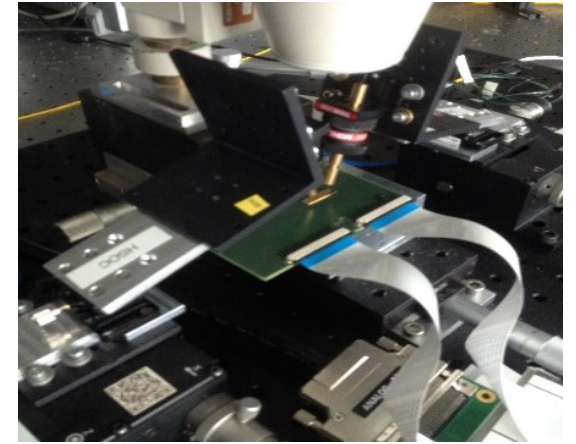
$$W_{ij} = L_{ij} \prod_{k \in K_{ij}} \frac{1}{4} \left| \frac{\sqrt{ER} - 1}{\sqrt{ER} + 1} - \exp \left(\sqrt{-1} \left(\phi_{ij,k}^{(0)} + \sum_{m=1}^M \phi_{ij,k,m}^{(2)} V_m^2 \right) \right) \right|^2$$



Grey-box NN MZI mesh model



Experimental setup and 3x3 MZI mesh



Measurements:

1. Individually sweep one voltage $[0, V_{\pi}]$
2. Randomly chosen voltages



Dataset = { Voltages | Weights }

ASE: amplified spontaneous emission
 OS: optical switch
 PC: polarization controller
 DAC: digital analog converter
 OSA: optical spectrum analyzer

Performance comparison

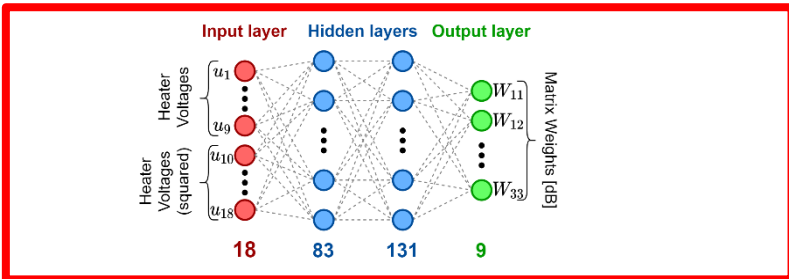
$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (w_i - \hat{w}_i)^2}$$

$$W_{ij} = L_{ij} \prod_{k \in K_{ij}} \frac{1}{4} \left| \frac{\sqrt{ER}-1}{\sqrt{ER}+1} - \exp\left(\sqrt{-1}(\phi_k^{(0)} + \phi_k^{(2)}V_k^2)\right) \right|^2$$

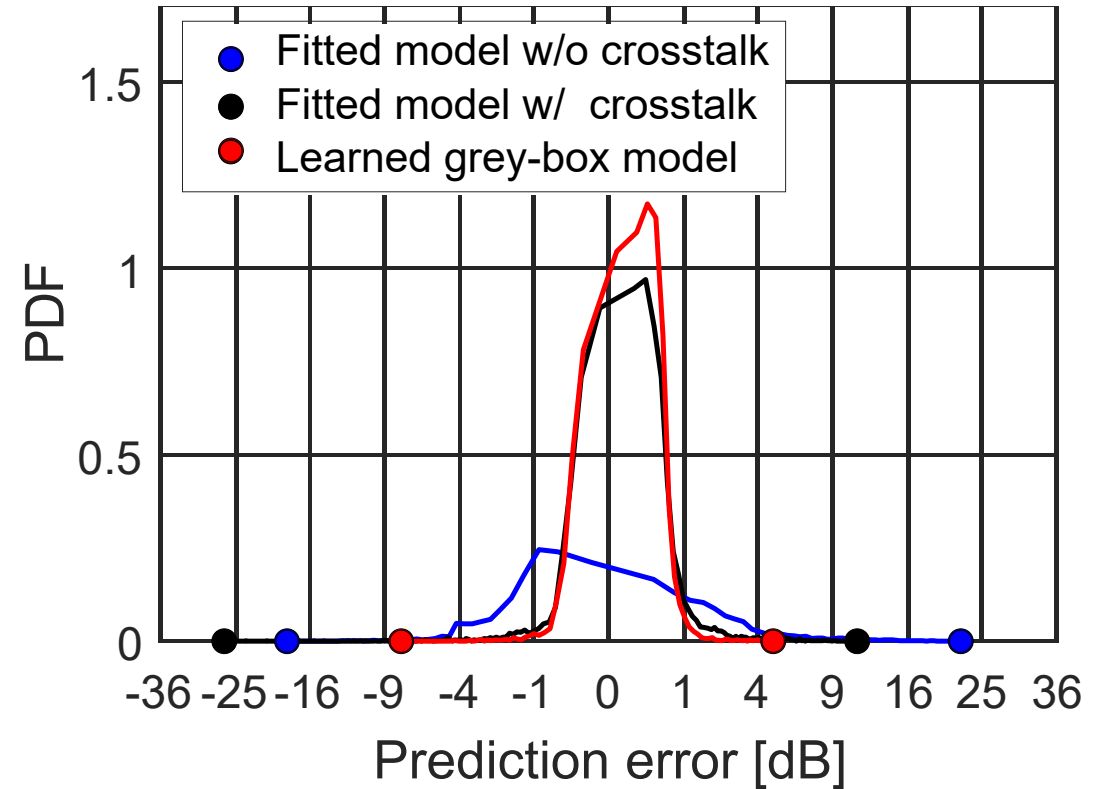
RMSE = 3.26 dB

$$W_{ij} = L_{ij} \prod_{k \in K_{ij}} \frac{1}{4} \left| \frac{\sqrt{ER}-1}{\sqrt{ER}+1} - \exp\left(\sqrt{-1}(\phi_{ij,k}^{(0)} + \sum_{m=1}^M \phi_{ij,k,m}^{(2)}V_m^2)\right) \right|^2$$

RMSE = 1.44 dB



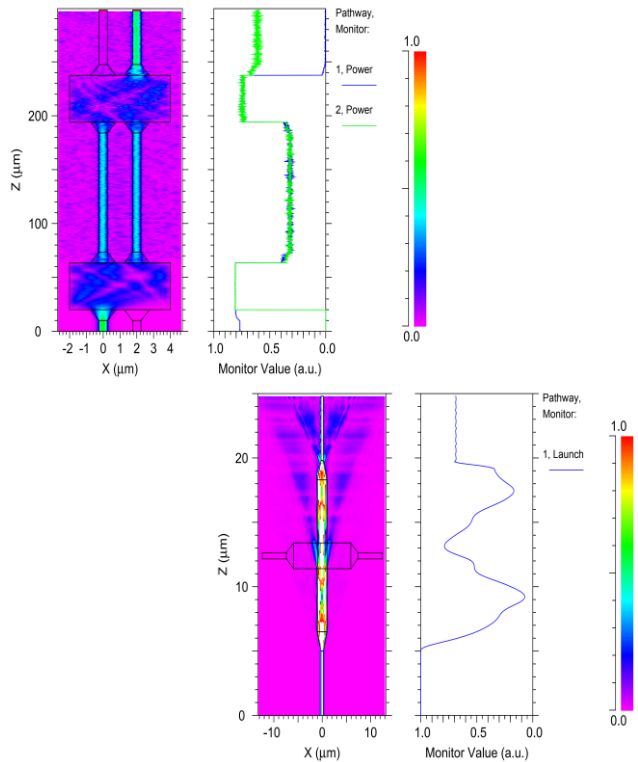
RMSE = 0.53 dB



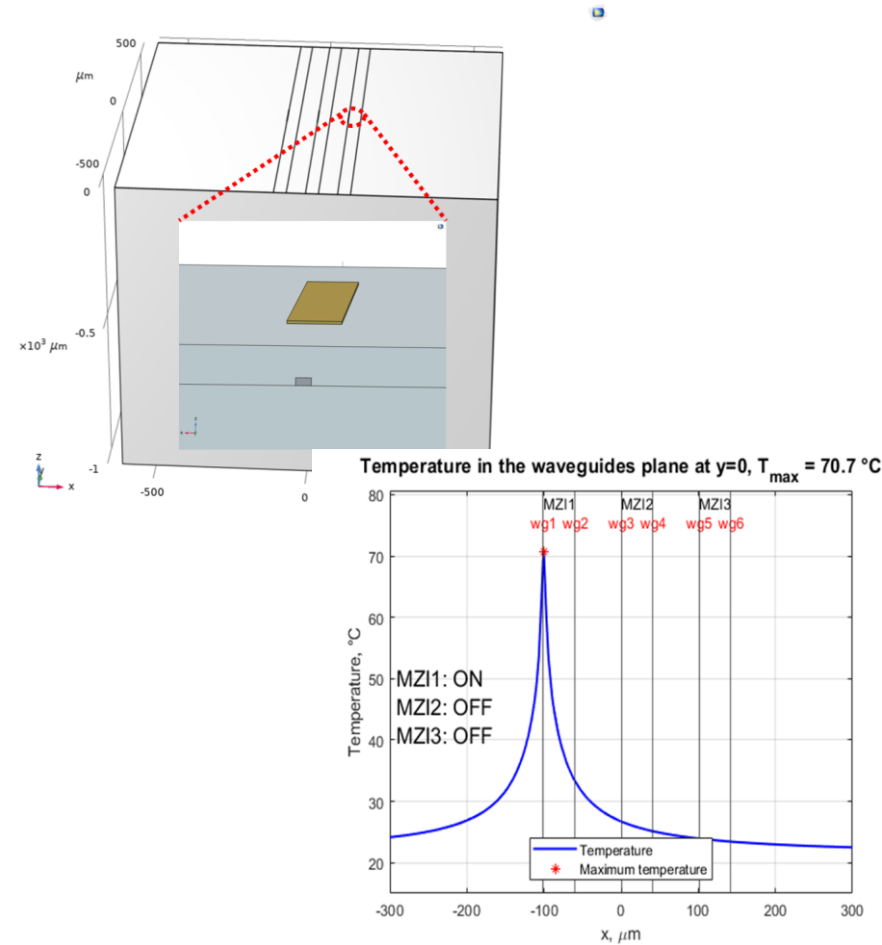
Including thermal cross-talk improves performance but not as much as a grey-box ML model.

Full model with thermal crosstalk

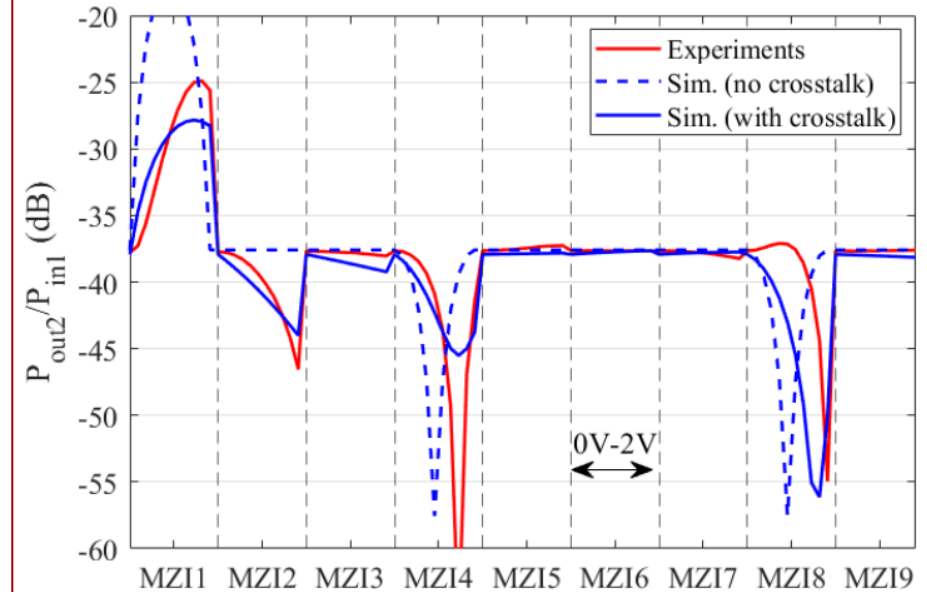
1. FTDT analysis



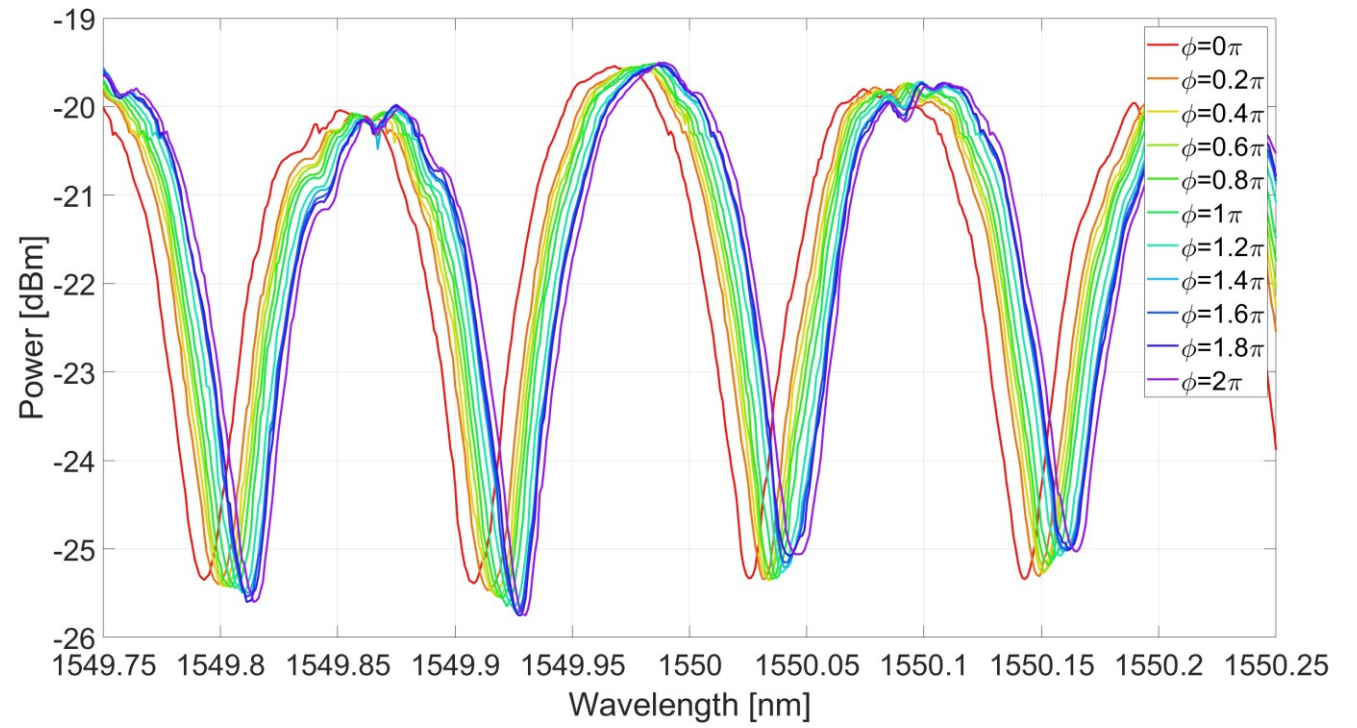
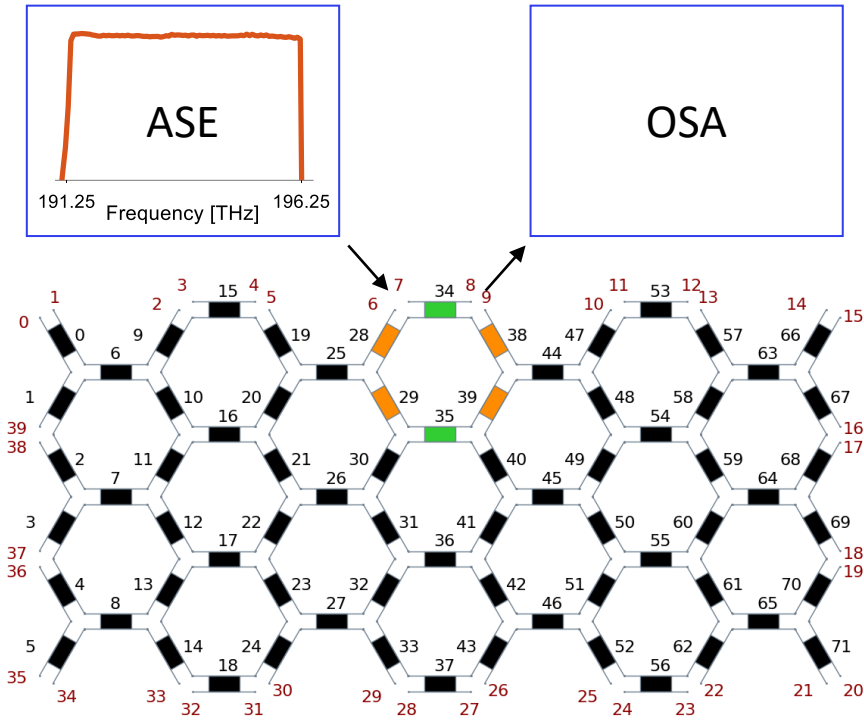
2. 3D Thermal analysis



3. Comparison w/ measurements

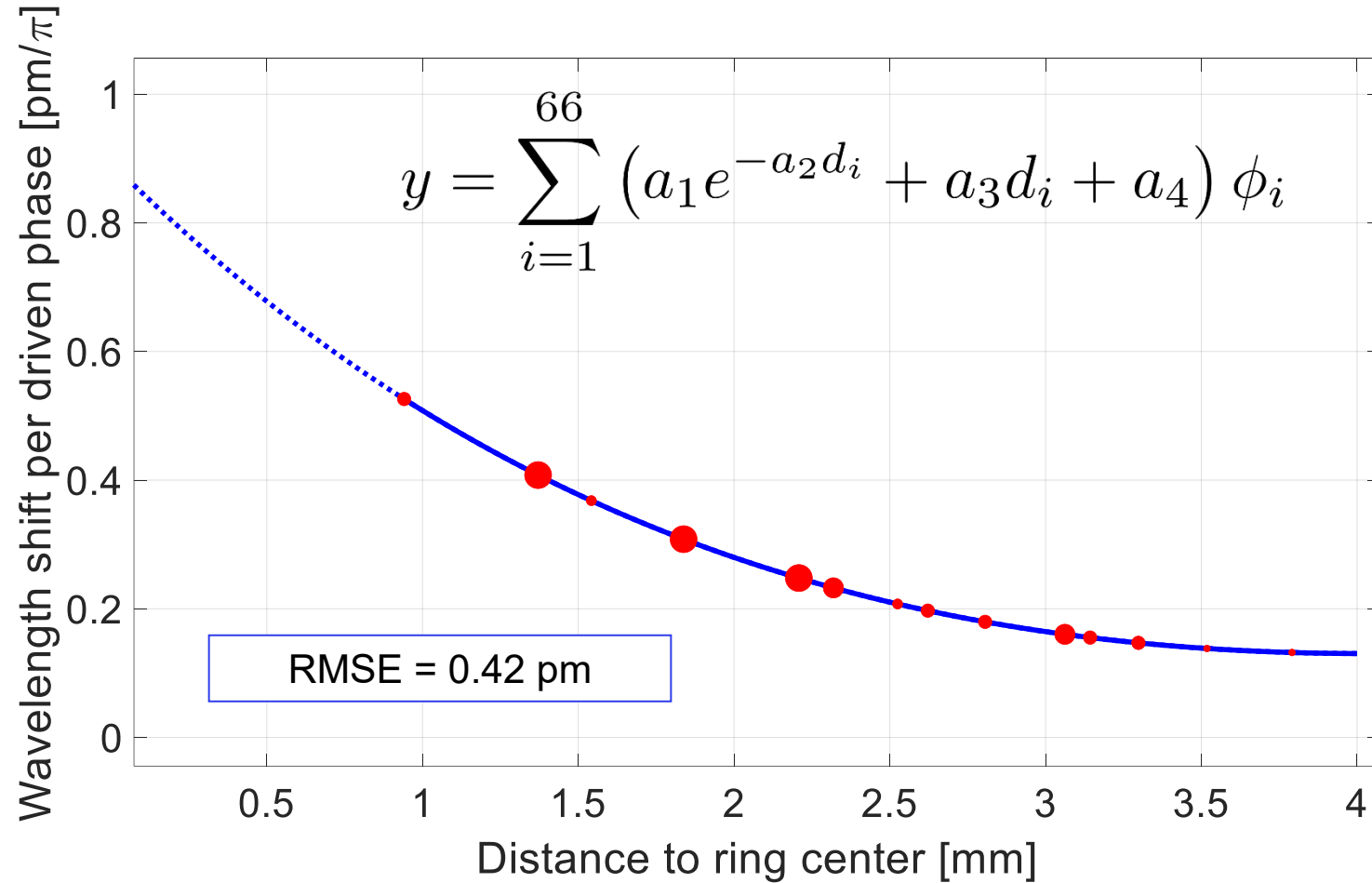


Fabrication errors, electrical and optical crosstalk not modelled

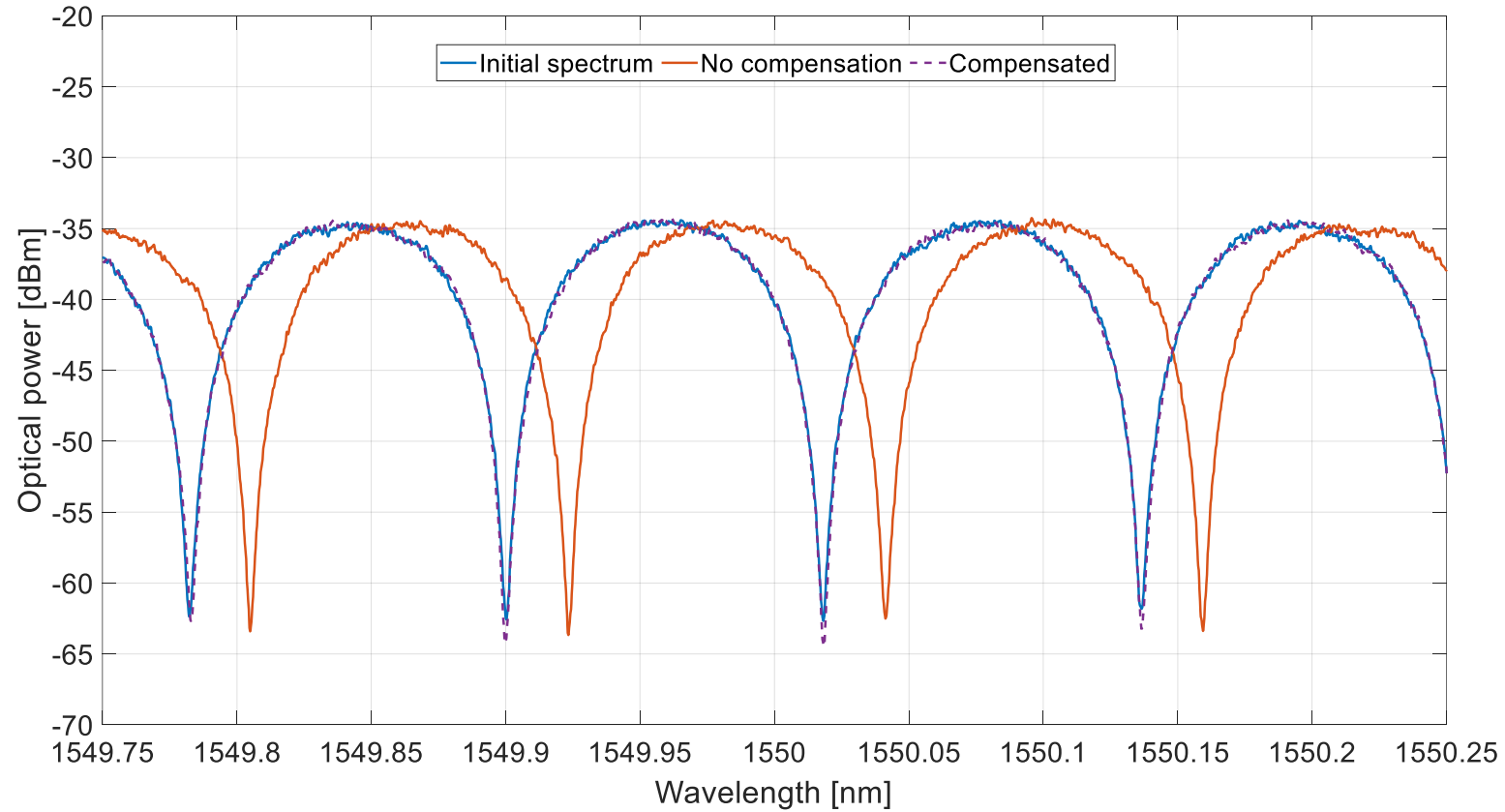
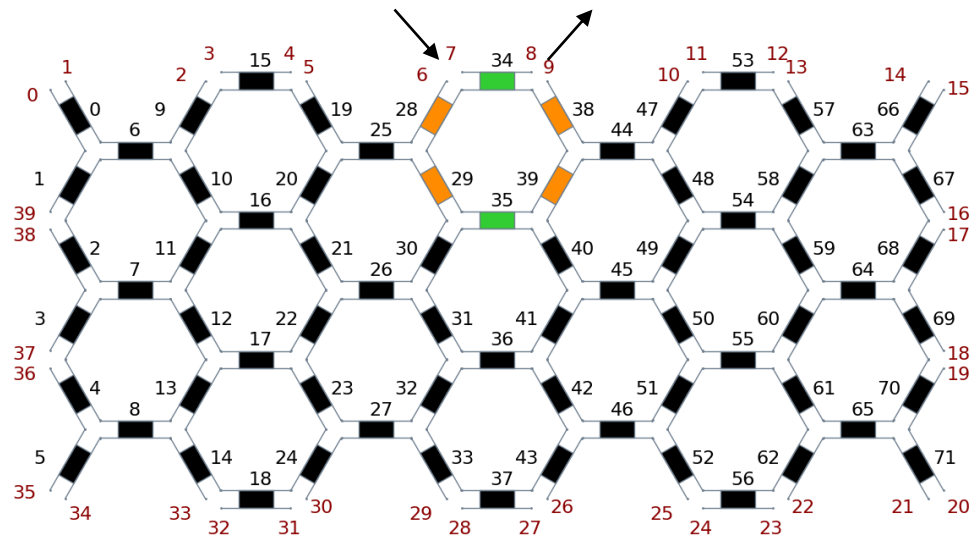


Even for chips designed to minimize the impact of crosstalk, sensitive applications can be affected.

Fitted thermal diffusion model



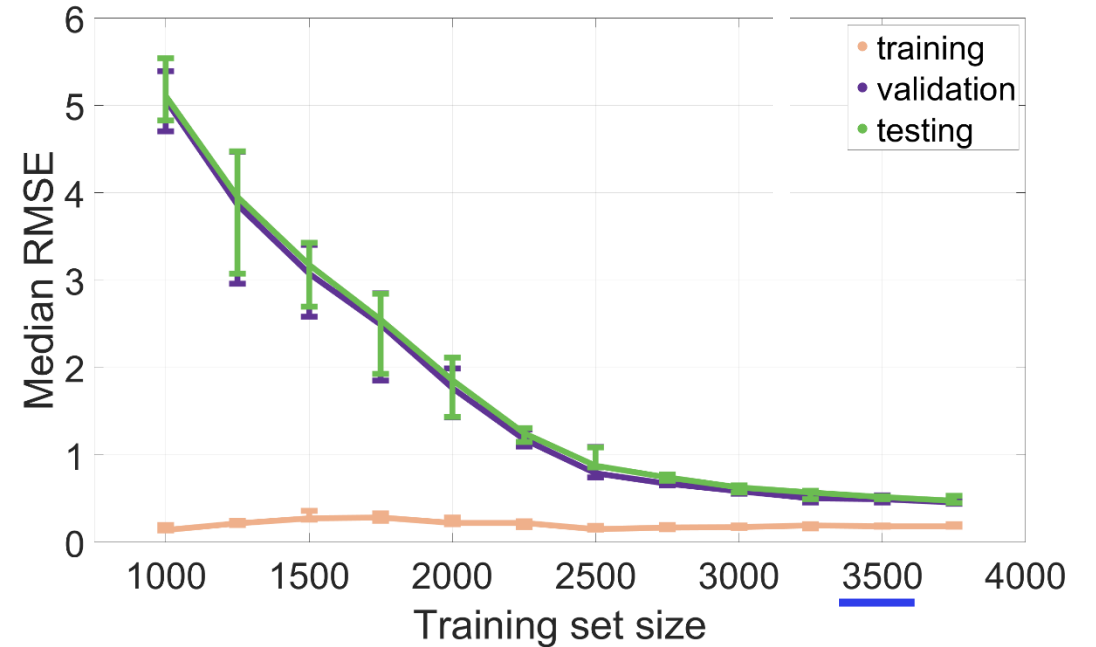
Cross-talk compensation



Data scarcity – MZI meshes



Simple Analytical Model with Thermal Crosstalk (SAM+XT)

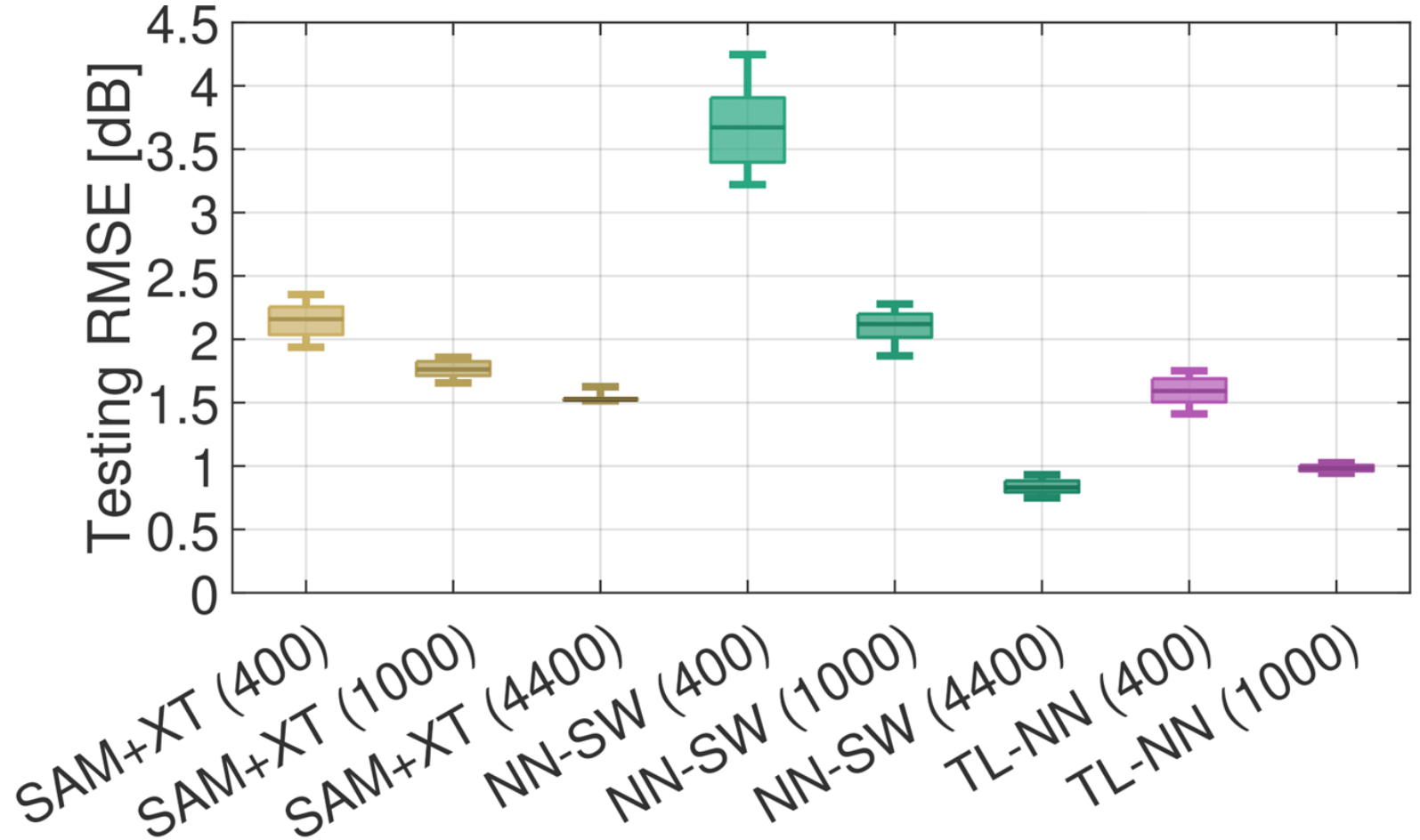


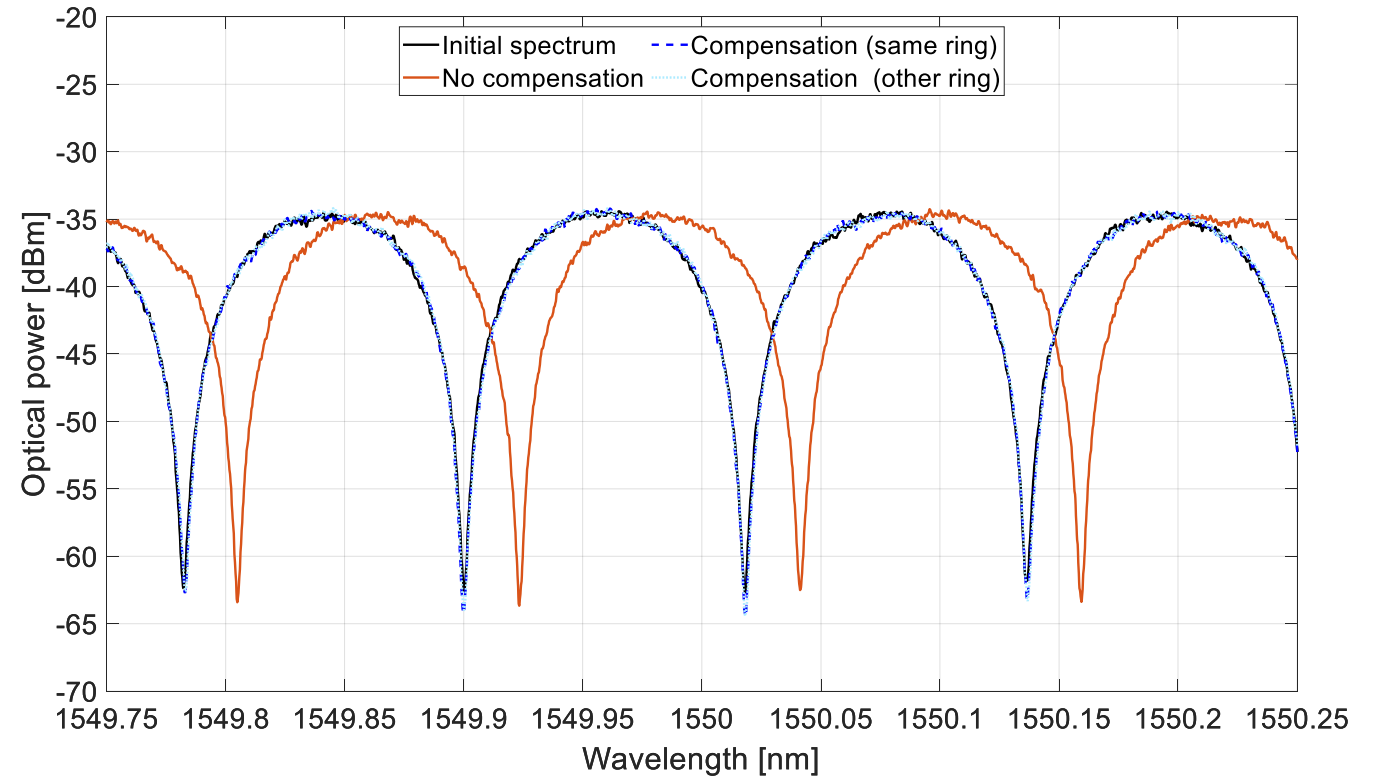
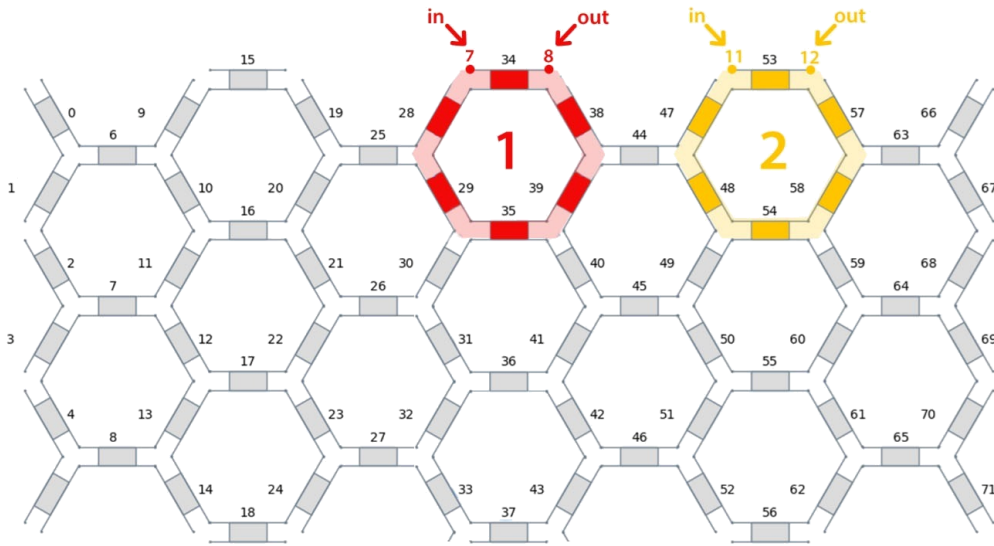
Neural Network Model (NN)

Simpler models are less accurate but more data-efficient to train

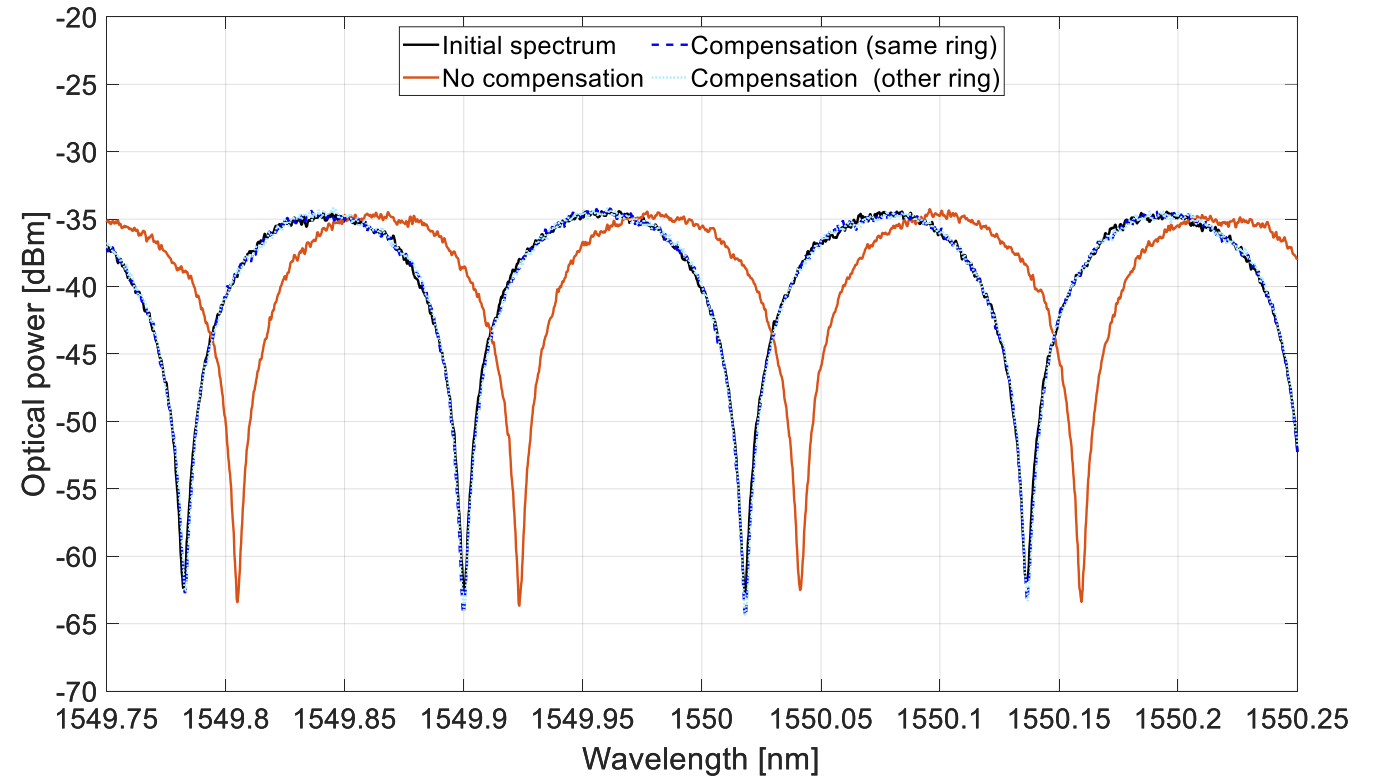
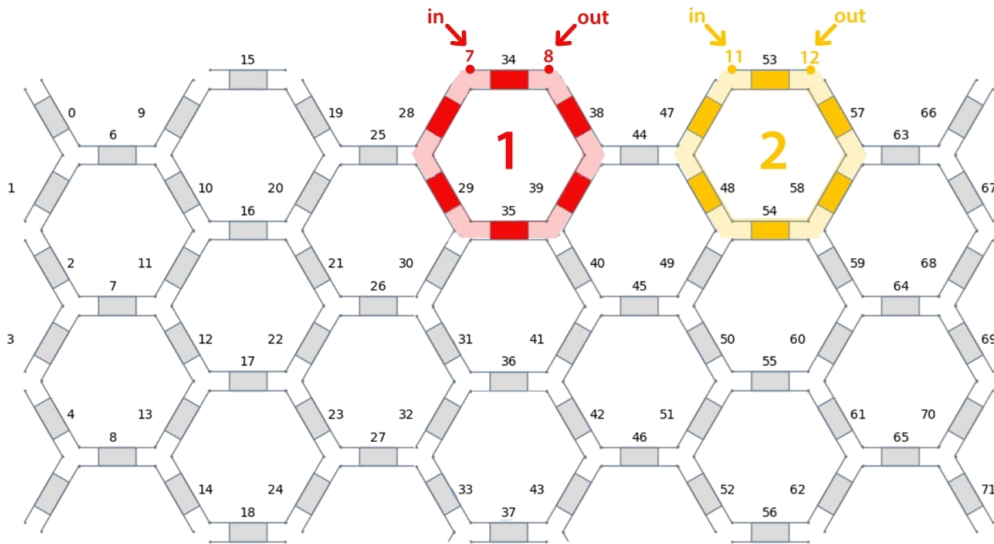
Transfer learning for data-efficient modelling

1. Train **simpler model** with **experimental data**
2. Generate **synthetic data**
3. Pre-train **NN model** with **synthetic data**
4. Re-train **NN model** with **experimental data**



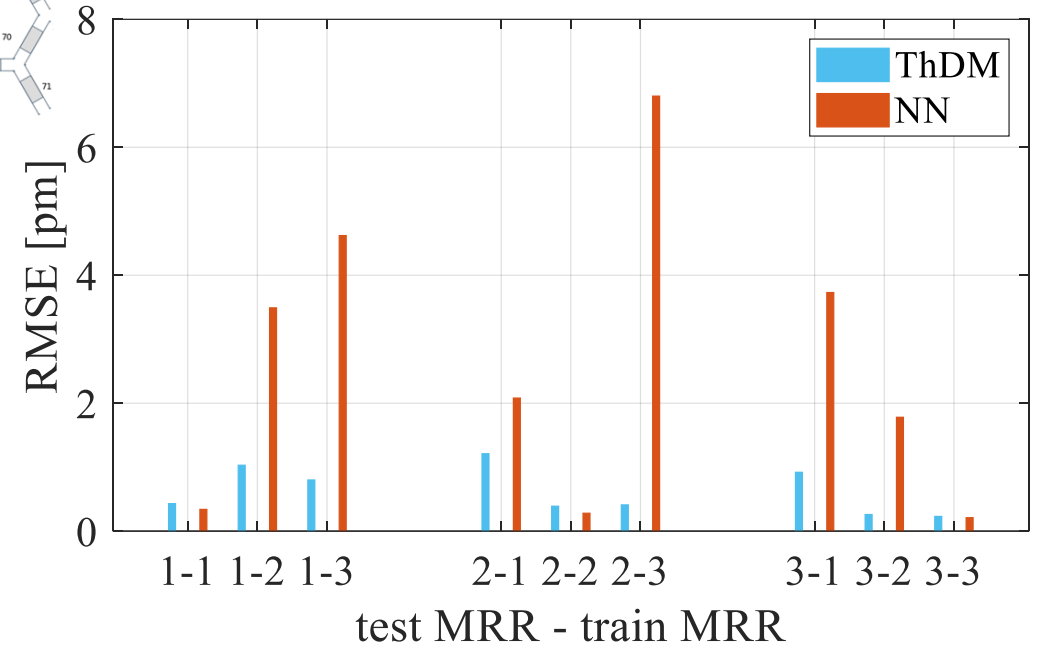
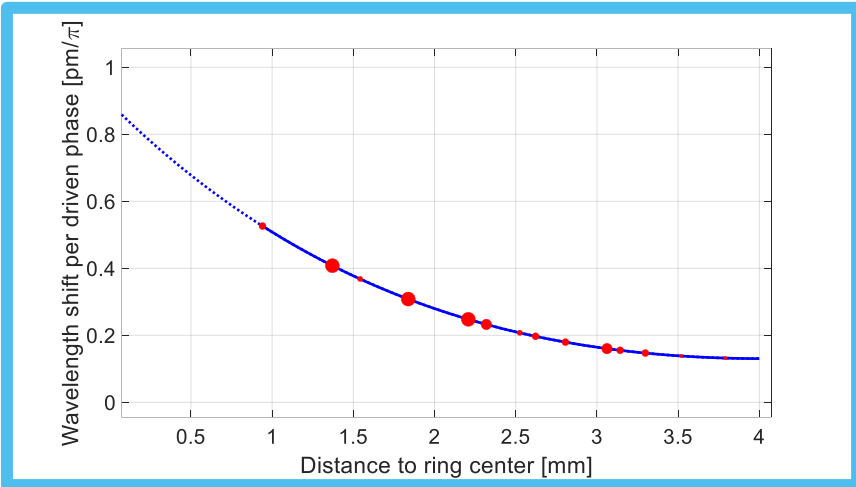
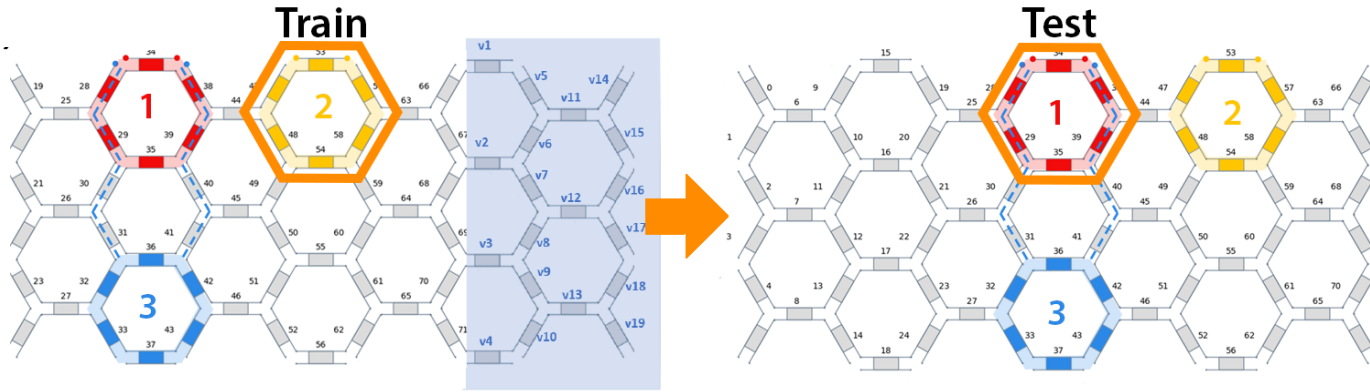


Can physics help in building more efficient/generalizable models?



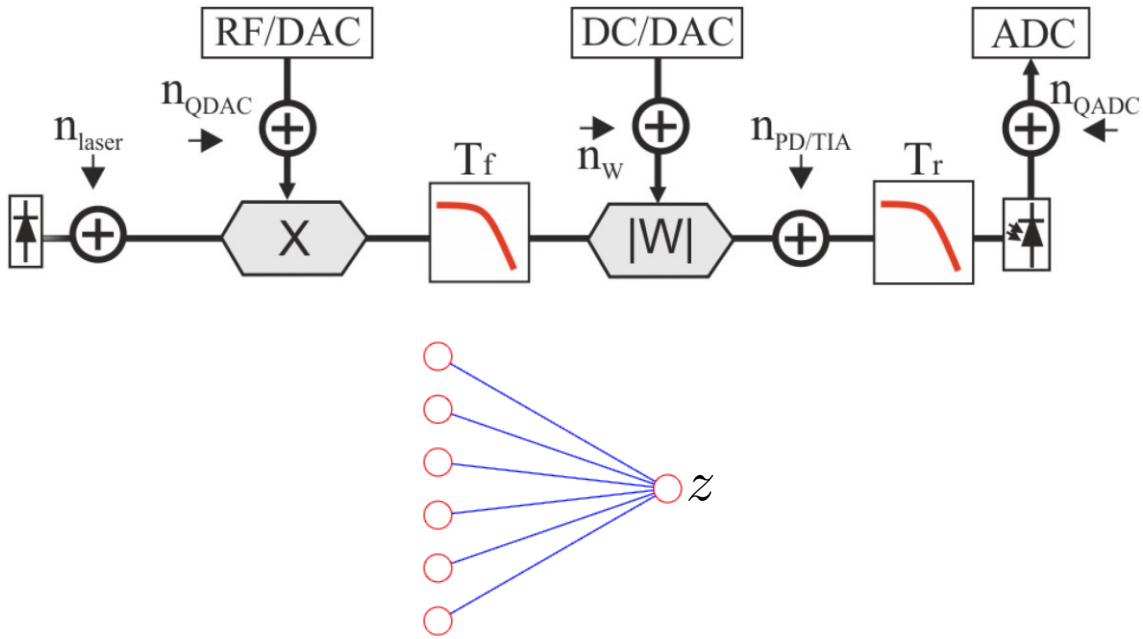
Use symmetry arguments to extend the model of a small part of the circuit

Physics-informed vs. black-box models

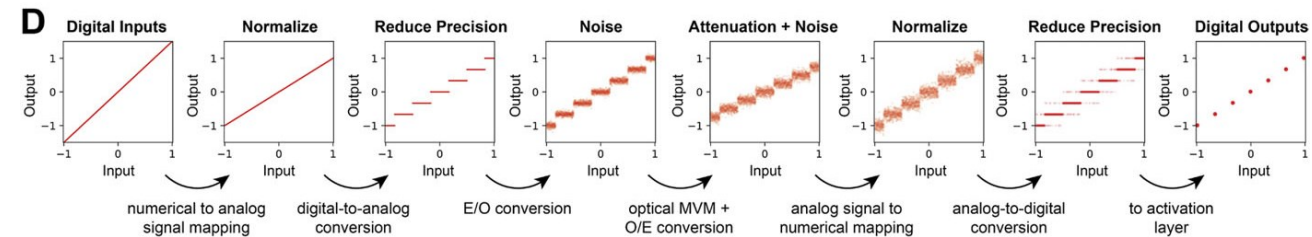
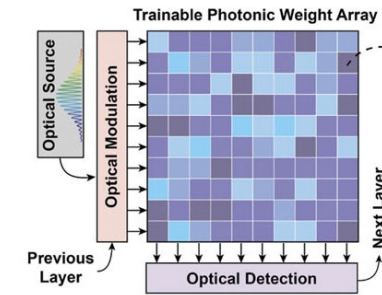


Physical knowledge allows models to generalize (e.g. by extrapolating).

Hardware-aware modelling/training



M. Moralis-Pegios, et al., JLT 2022



V. Shah, N. Youngblood, APL Mach. Learn. 2023

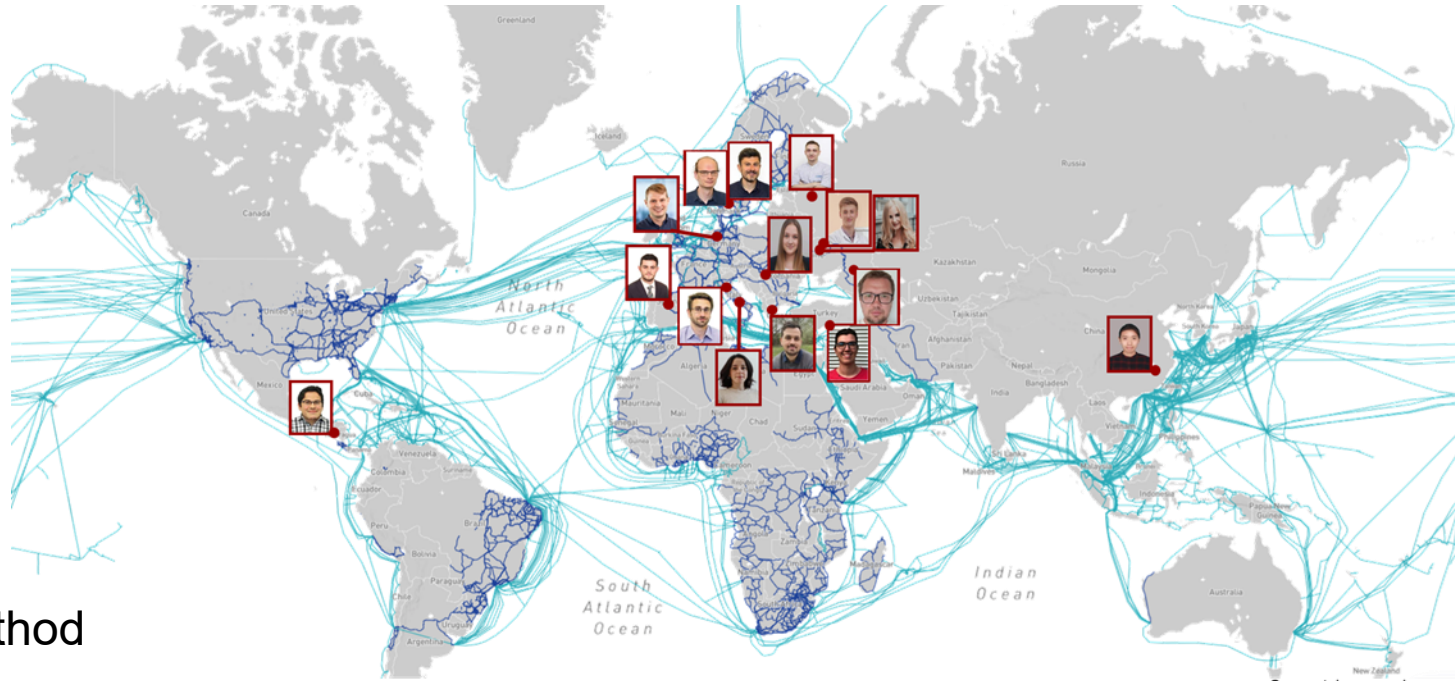
Include a physically-informed description of the photonic NN during training improves inference.

Conclusions

- Accurate training of photonic circuit is necessary to **guarantee task performance**
- In-situ and in-silico approaches provided a plethora of specific methods but with **significant trade-offs** required by every method
- No one-fits-all solution yet but lots of interesting directions
- General shift towards **physics-informed modelling** and **online algorithms tuned for photonics circuits**

Conclusions

- Accurate training of photonic circuit is necessary to **guarantee task performance**
- In-situ and in-silico approaches provided a plethora of specific methods but with **significant trade-offs** required by every method
- No one-fits-all solution yet but lots of interesting directions
- General shift towards **physics-informed modelling** and **online algorithms tuned for photonics circuits**

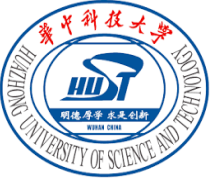


Source:telegeography.com

Questions: now and fdro@dtu.dk



Politecnico di Torino



THE VELUX FOUNDATIONS
VILLUM FONDEN × VELUX FONDEN



Acknowledgements: Villum Foundation through the Villum Young Investigator project OPTIC-AI (grant no. VIL29344), the Horizon Europe research and innovation project PROMETHEUS (grant n. 101070195), the independent research fund Denmark project QUARCOM (grant no. 10.46540/2032-00161B) and the Swedish research council project BRAIN (grant no. 2022-04798).