ML applications to optical systems and devices: from the design of Raman amplifiers to the management of NxN switches

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OPTCOM - Optical Communications Group – Politecnico di Torino, Torino – ITALY

OUTLINE

PART ONE

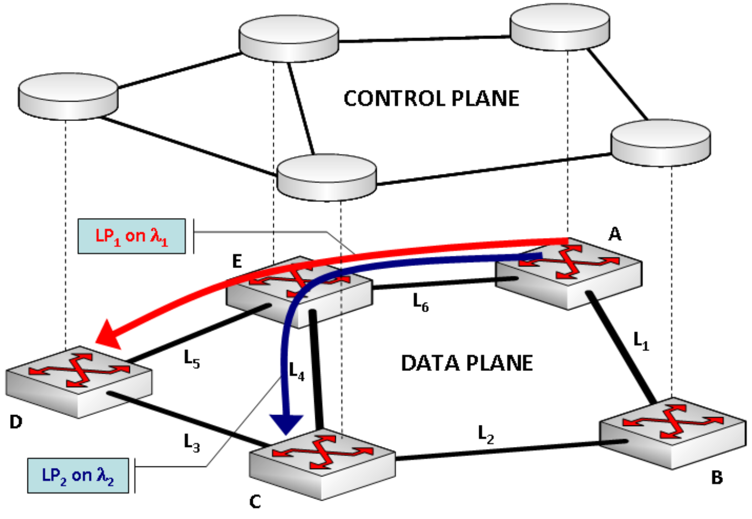
ML applied to design and analysis of Raman amplifiers

PART TWO

ML applied to the management of NxN switches

COMMON SCENARIO: DYNAMIC NETWORKS

- Reconfigurable optical networks allow and to dynamically adapt to traffic demand
- Network control plane must implement efficient resource allocation
  - Physical layer awareness is fundamental for the evaluation of Quality of Transmission
- Application of SDN paradigm through virtualization of network elements and functions
- All network elements (i.e amplifiers, switches et al.) must be abstracted to allow fast reconfiguration
  - Real-time models are needed
  - Machine Learning can be a solution



PART ONE

ML applied to design and analysis of Raman amplifiers

PART ONE - ACKNOWLEDGEMNTS

This work has been carried out in collaboration with:

- DTU
- Aston University

Thanks to :

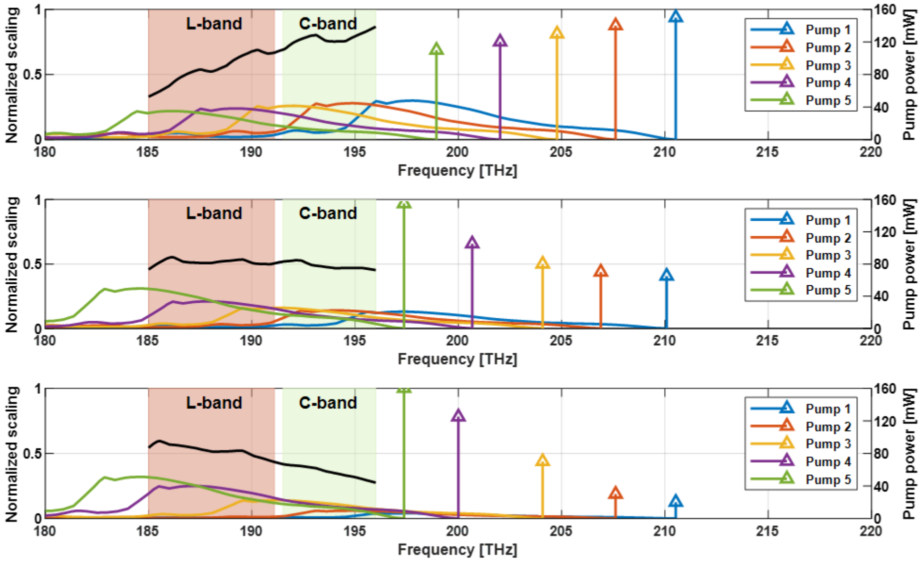
- A.M. Rosa Brusin
- Prof. D. Zibar and his group @DTU
- Prof. W. Forysiak, Prof. S. Turitsyn and their group @Aston University

OUTLINE – PART ONE

WHY RAMAN AMPLIFICATION?

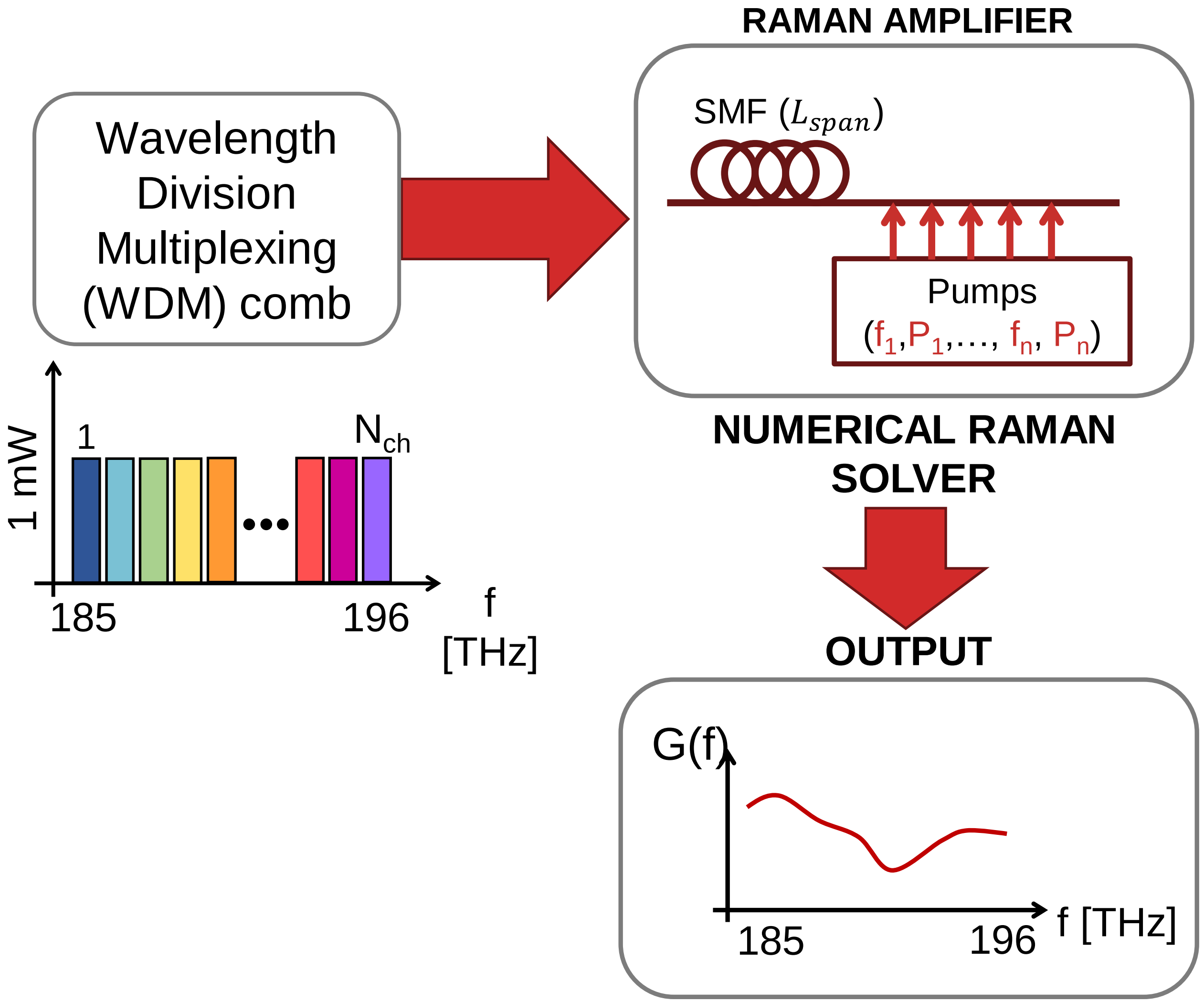
Politecnico di Torino

- Raman amplification is a promising solution for multi-band optical systems
  - Availability of amplification in any bands
  - Broadband amplification in multi-pump configuration
  - Flexible and programmable gain by properly adjusting pump powers and frequencies
    - Arbitrary gain profiles compensating for tilts and ripples in hybrid solution
    - It allows to avoid Gain-Flattening Filters
  - Lower noise figure than other amplification solutions because it is a distributed gain



ONE.1
RAMAN AMPLIFIERS
AND MACHINE LEARNING

THE RAMAN AMPLIFIER



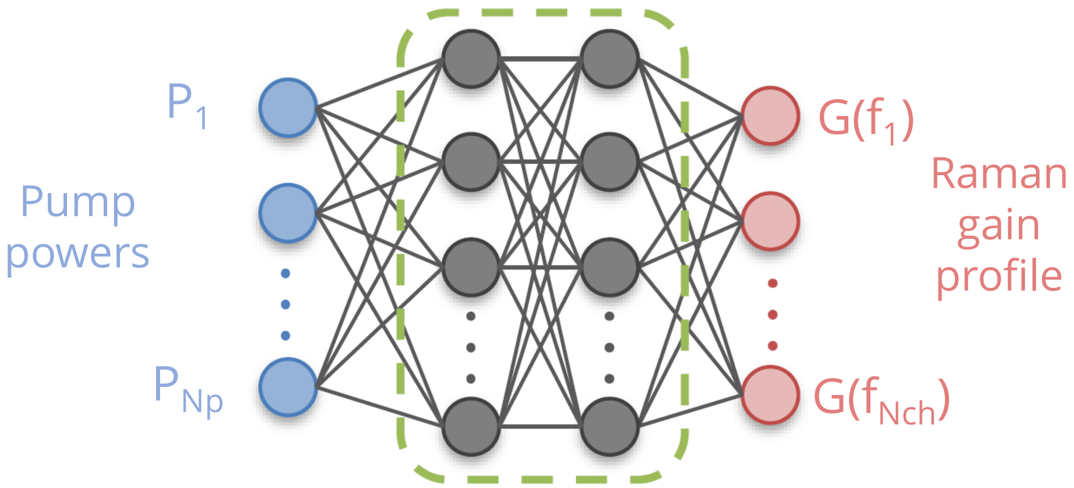
$$\frac{dP_s}{dz} = -\alpha_s P_s + C_R(\lambda_s, \lambda_p)\left[P_p^+ + P_p^-\right] P_s \quad (1)$$

$$\pm\frac{dP_p^\pm}{dz} = -\alpha_p P_p^\pm - \left(\frac{\lambda_s}{\lambda_p}\right) C_R(\lambda_s, \lambda_p)\, P_s\, P_p^\pm \quad (2)$$

$$\pm\frac{dP_A^\pm}{dz} = -\alpha_A P_A^\pm + C_R(\lambda_A, \lambda_p) P_p P_A^\pm + C_R(\lambda_A, \lambda_p)[1+\eta(T)] h\nu_A B_{ref} P_p \quad (3)$$

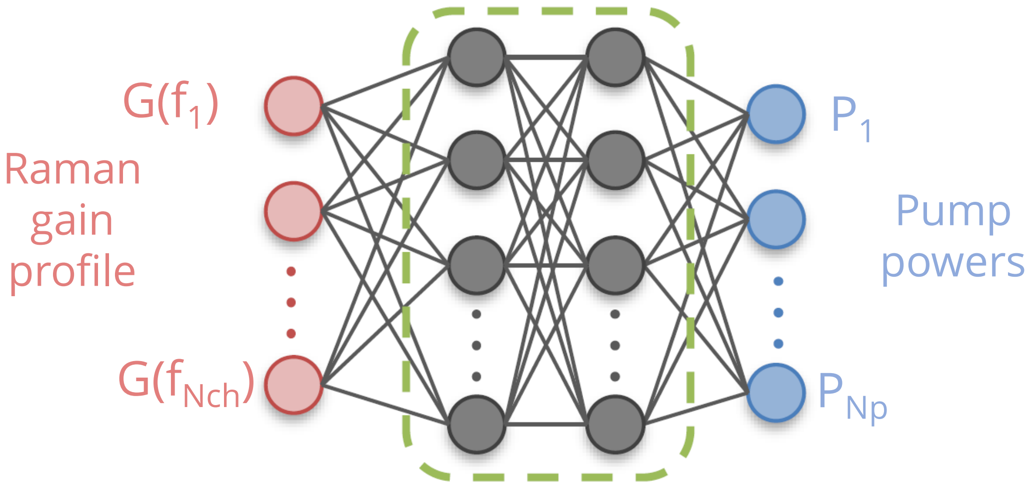
- [J. Bromage, '*Raman Amplification for Fiber Communications Systems*', Journal of Ligthwave Technology, vol. 22, no. 1, pp. 79-93, 2004.

DIRECT PROBLEM



$\boldsymbol{x}$ $\quad y = f(x) \quad$ $\boldsymbol{y}$

INVERSE PROBLEM



$\boldsymbol{y}$ $\quad x = f^{-1}(y) \quad$ $\boldsymbol{x}$

ONE.2
LITERATURE REVIEW

LS-SVR based RA design

IOP Publishing — Journal of Optics
J. Opt. **20** (2018) 025702 (6pp) https://doi.org/10.1088/2040-8986/aaa2a6

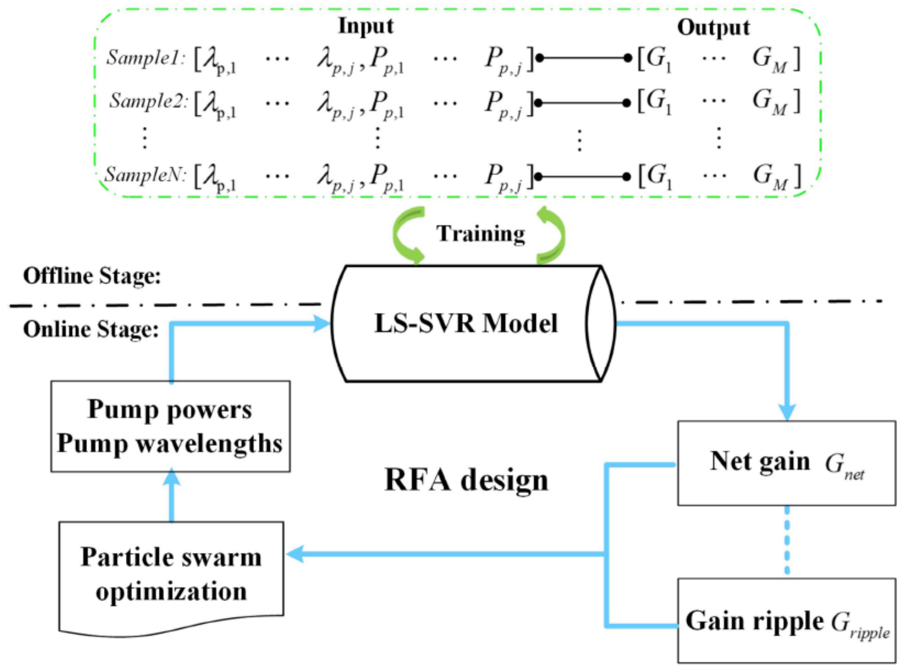
Efficient design of gain-flattened multi-pump Raman fiber amplifiers using least squares support vector regression

Jing Chen, Xiaojie Qiu, Cunyi Yin and Hao Jiang

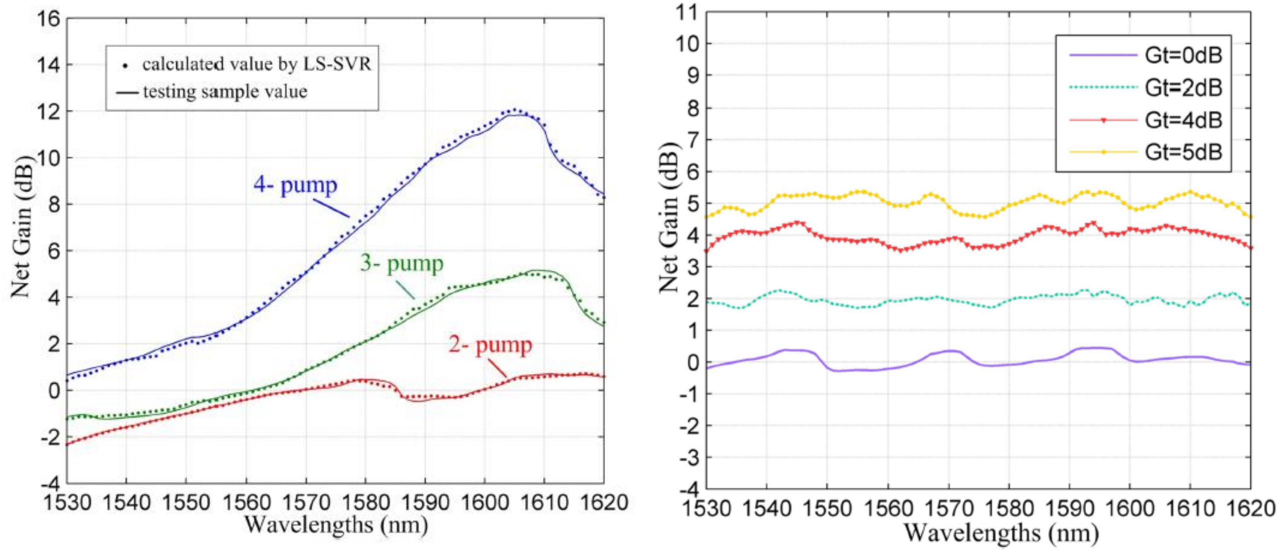
College of Electrical Engineering and Automation, Fuzhou University, Fuzhou 350116, People's Republic of China

E-mail: jiangh@fzu.edu.cn

LS-SVR MODEL



RESULTS



- Jing Chen et al 2018 J. Opt. **20** 025702, https://doi.org/10.1088/2040-8986/aaa2a6

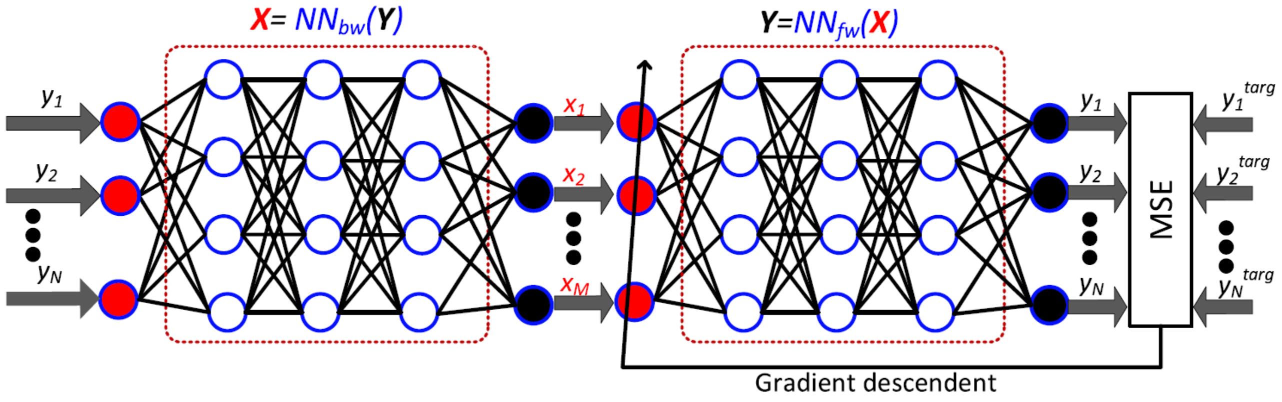
ML-based RA design

JOURNAL OF LIGHTWAVE TECHNOLOGY

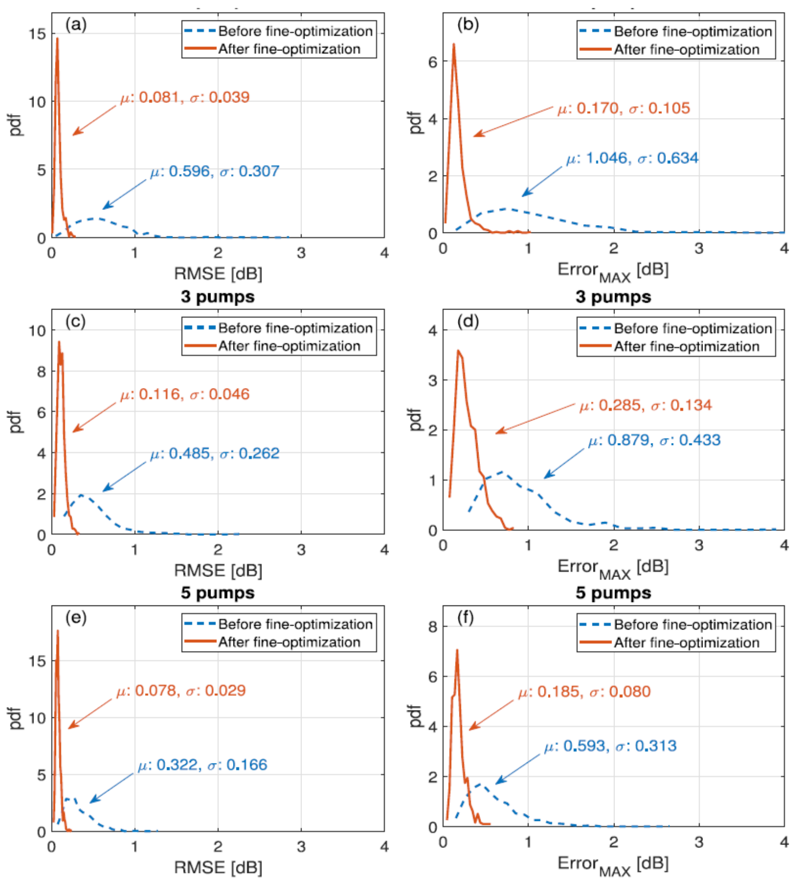
Inverse System Design Using Machine Learning: The Raman Amplifier Case

Darko Zibar, Ann Margareth Rosa Brusin, Uiara C. de Moura, Francesco Da Ros, Vittorio Curri, and Andrea Carena

NN SETUP



RESULTS



- D. Zibar, A. Ferrari, V. Curri and A. Carena, “Machine Learning-based Raman amplifier design”, *2019 Optical Fiber Communications Conference and Exhibition (OFC)*, 2019.
- D. Zibar , A. M. Rosa Brusin, U. C. de Moura, F. Da Ros, V. Curri, and A. Carena “Inverse System Design Using Machine Learning: The Raman Amplifier Case," in *Journal of Lightwave Technology*, doi:10.1109/JLT.2019.2952179

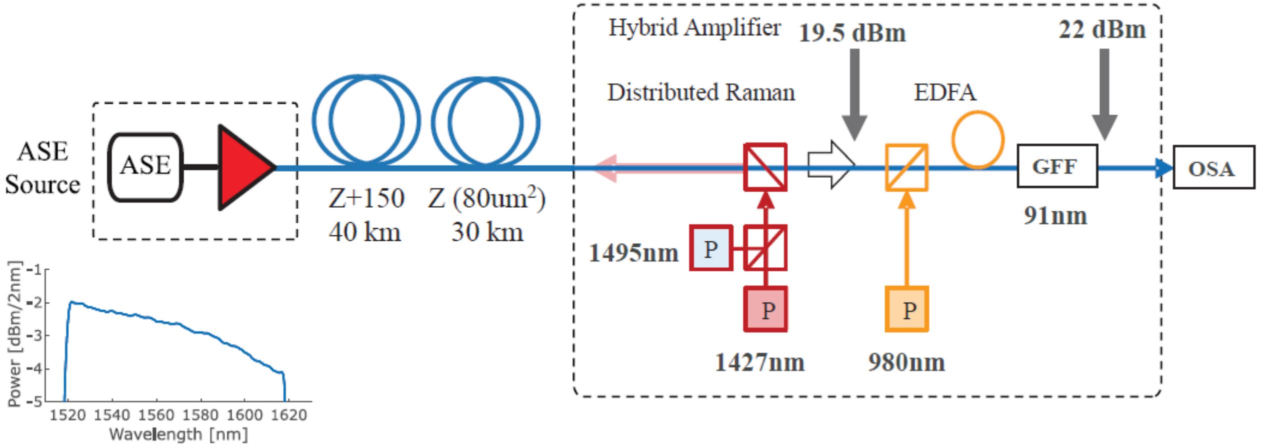
ML-based RA+EDFA design over C+L-band

ICTON 2019 We.B7.3

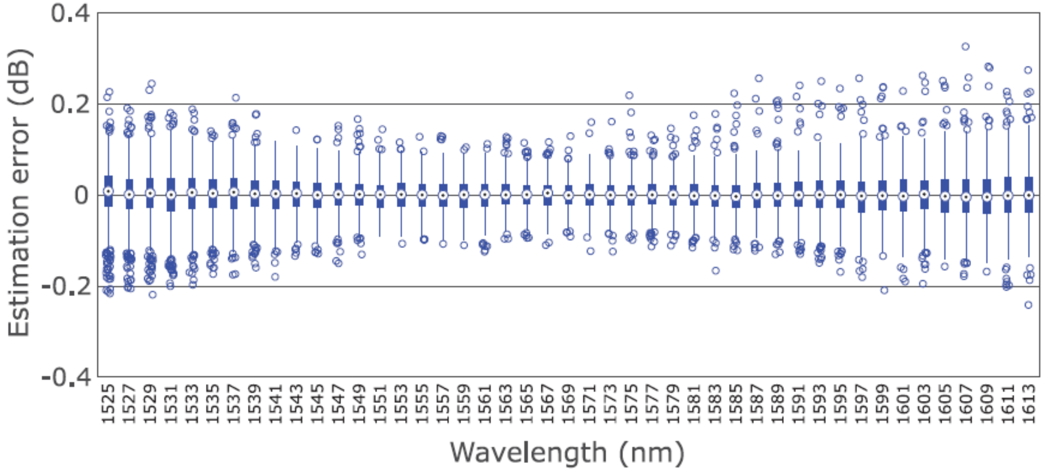
Machine Learning for Ultrawide Bandwidth Amplifier Configuration

Maria Ionescu*
Nokia Bell Labs Paris-Saclay, Nozay, 91620, France
**e-mail: maria.ionescu@nokia-bell-labs.com*

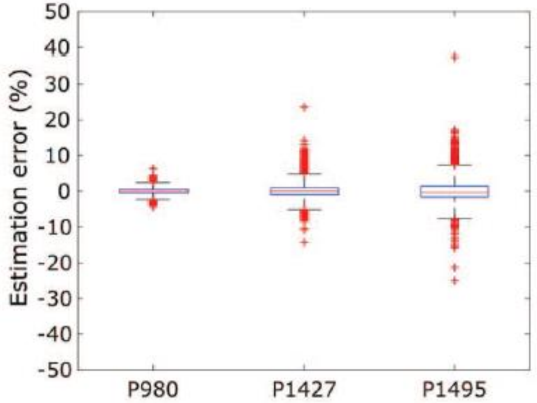
EXPERIMENTAL SETUP



RESULTS



Configuration	980 nm pump [mW]	1427 nm pump [mW]	1427 nm pump [mW]	1495 nm pump [mW]	1495 nm pump [mW]
(a) Best fit	529.7	225.5	226.7	235.7	237.1
(b) Human	500	230	230	230	230
(c) NN Model	519.1	223.5	224.2	246.8	245.7



• M. Ionescu, "Machine Learning for Ultrawide Bandwidth Amplifier Configuration," *2019 21st International Conference on Transparent Optical Networks (ICTON)*, 2019, doi: 10.1109/ICTON.2019.8840453.

ML-based RA design over S+C+L-band

W1K.3.pdf OFC 2020 © OSA 2020

Experimental Prediction and Design of Ultra-Wideband Raman Amplifiers Using Neural Networks

Xiaoyan Ye, Aymeric Arnould, Amirhossein Ghazisaeidi, Dylan Le Gac and Jeremie Renaudier
Nokia Bell Labs, Paris-Saclay, France (aymeric.arnould@nokia.com)

EXPERIMENTAL SETUP

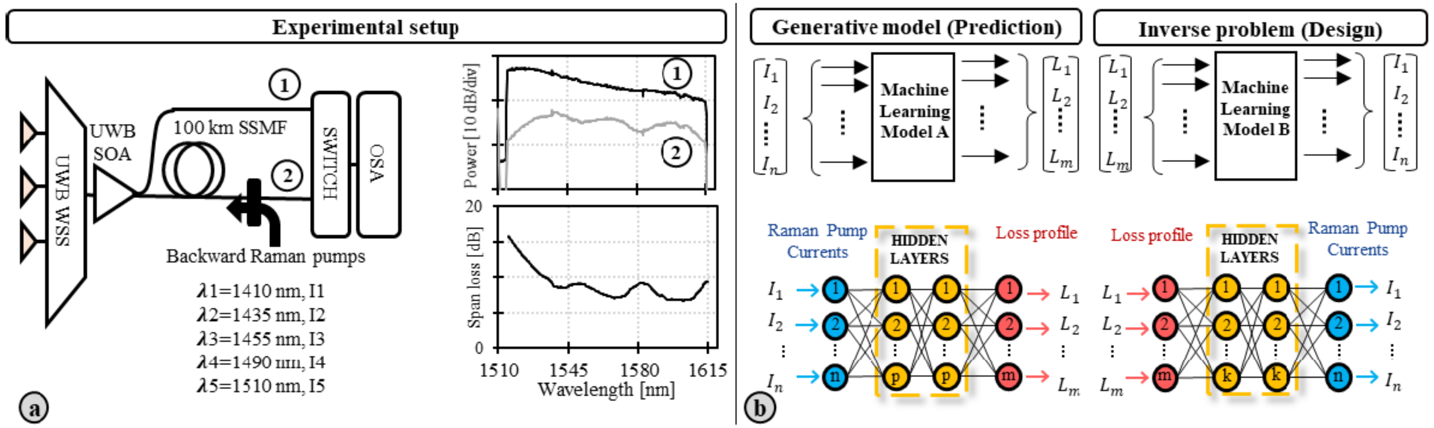
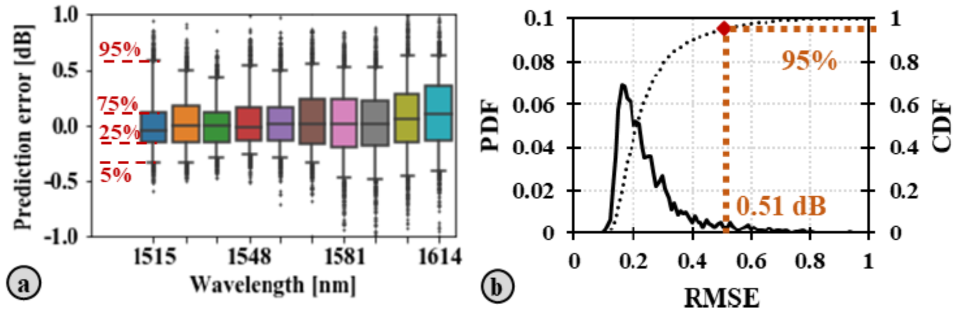
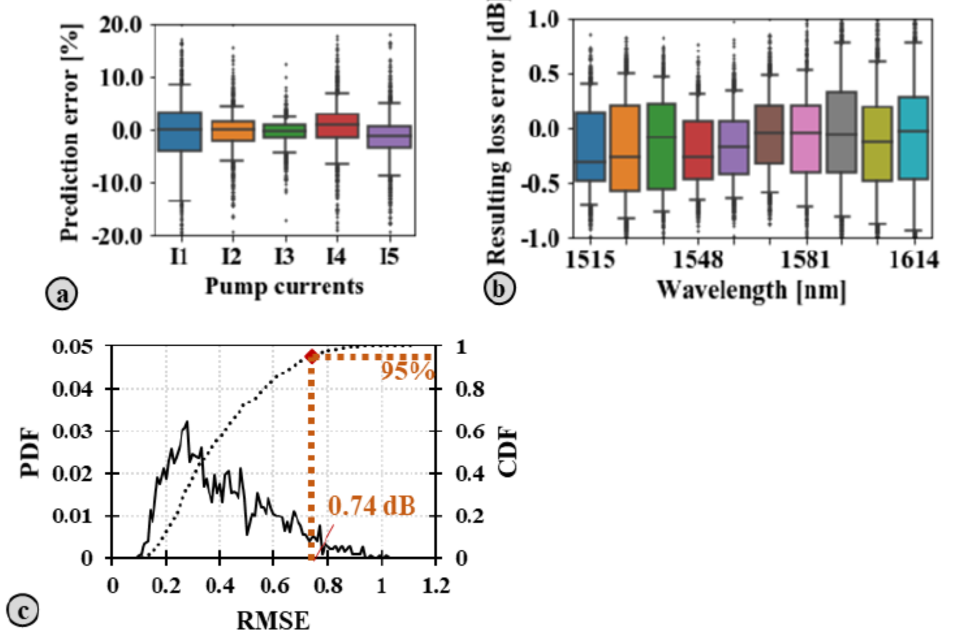


Fig. 1. (a) Single span characterization setup with 5 pumps Raman amplifier and SOA: span input and output power profiles are measured with the OSA (respectively labelled 1 and 2 in top inset) and span loss profile (bottom inset) is deduced. (b) ML models and artificial neural networks (ANN) architectures for span loss profile prediction (model A) and pump current value prediction (model B)

GENERATIVE MODEL RESULTS



INVERSE MODEL DESIGN RESULTS



• X. Ye, A. Arnould, A. Ghazisaeidi, D. Le Gac and J. Renaudier, "Experimental Prediction and Design of Ultra-Wideband Raman Amplifiers using Neural Networks," *2020 Optical Fiber Communications Conference and Exhibition (OFC)*, 2020.

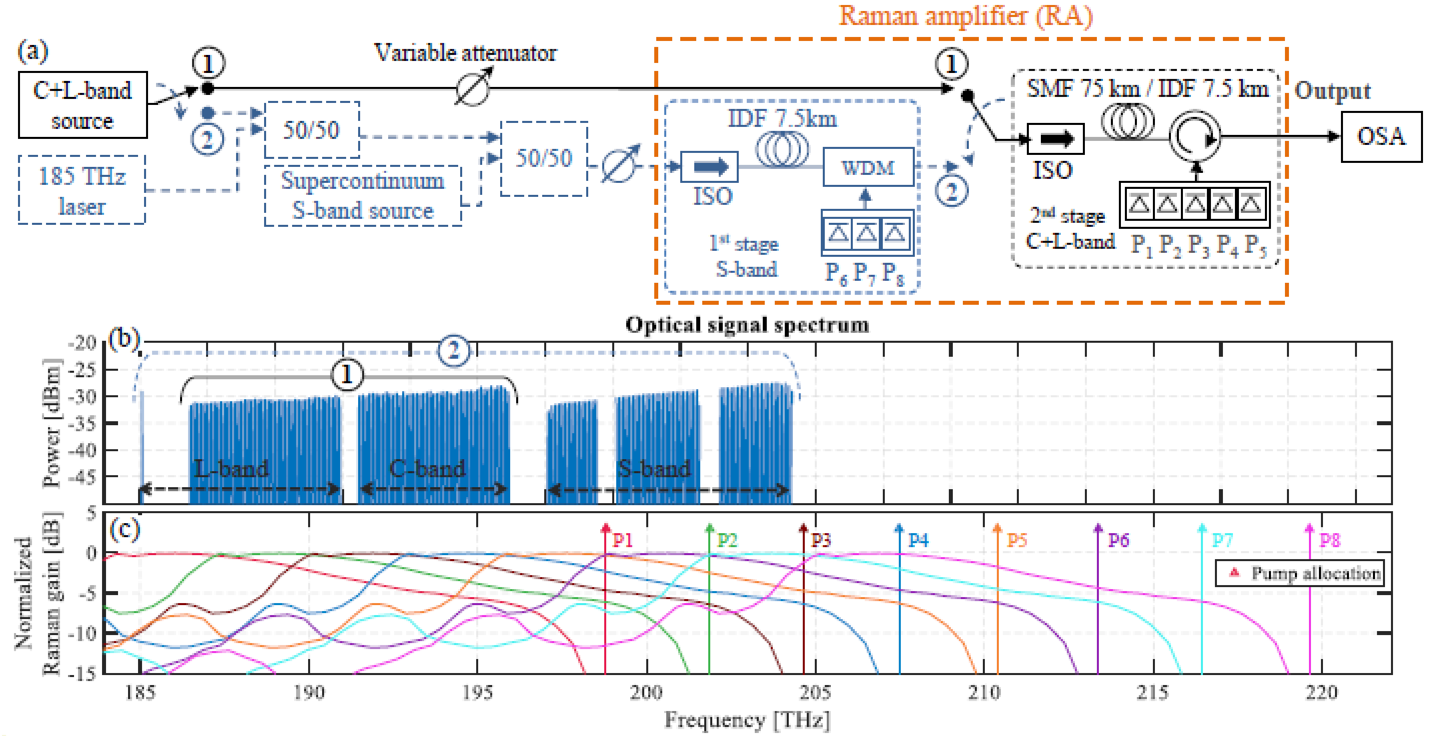
ML-based RA design over S+C+L-band

JOURNAL OF LIGHTWAVE TECHNOLOGY

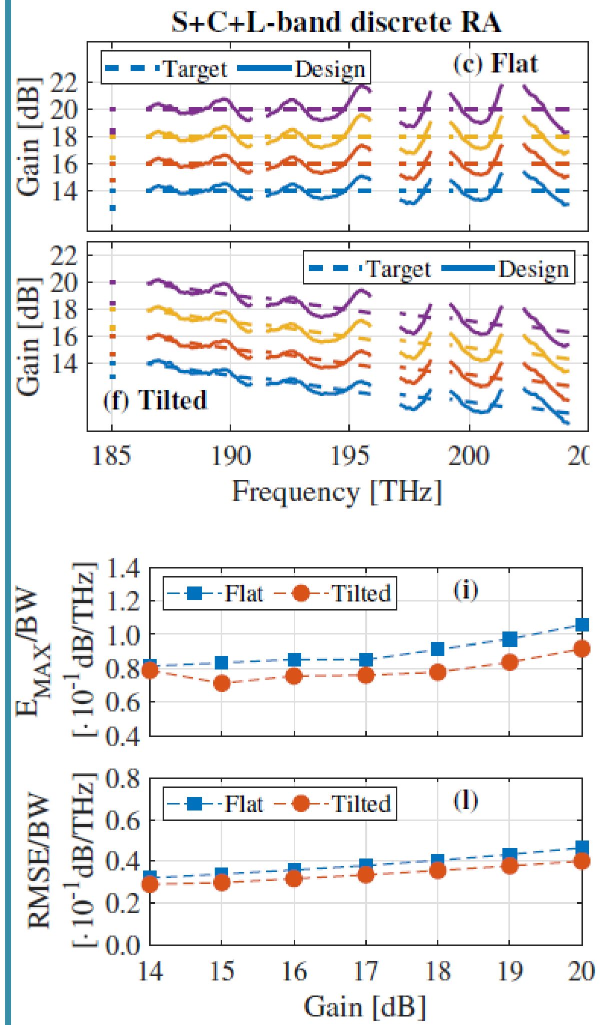
Multi–band programmable gain Raman amplifier

Uiara Celine de Moura, Md Asif Iqbal, Morteza Kamalian, Lukasz Krzczanowicz, Francesco Da Ros, Ann Margareth Rosa Brusin, Andrea Carena, Wladek Forysiak, Sergei Turitsyn, and Darko Zibar

EXPERIMENTAL SETUP



RESULTS



(c),(f): Predicted and target flat and tilted (on–off) gain profiles with respect to frequency
(i): Maximum error of gain prediction with respect to total bandwidth
(l): Root-mean-square-error of gain prediction with respect to total bandwidth.

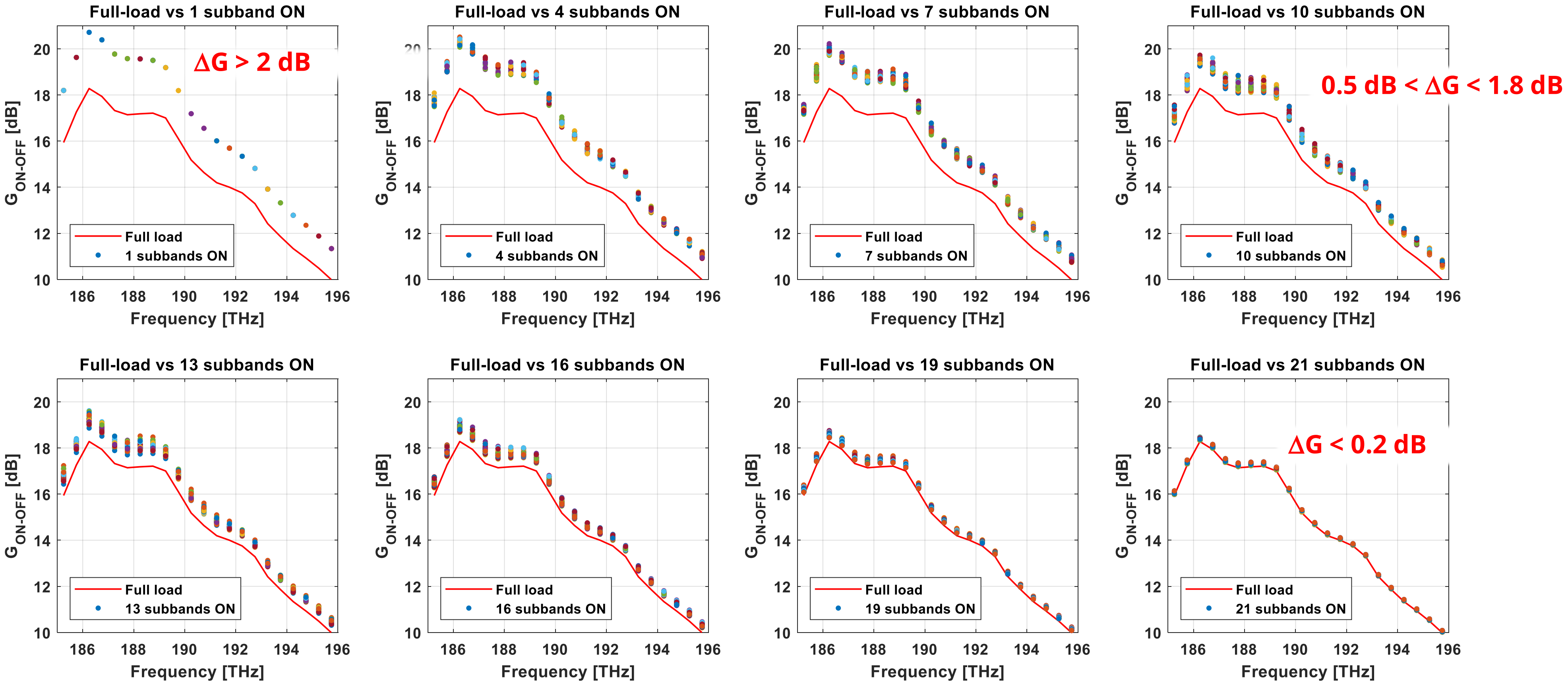
- U. C. De Moura et al., "Multi-band programmable gain Raman amplifier," in *Journal of Lightwave Technology*, doi: 10.1109/JLT.2020.3033768.

THE COMMON FACTOR

- All these works presented in previous slide have a COMMON FACTOR: they assume at the input of the Raman Amplifier FULL LOAD condition

- In dynamically reconfigurable networks, optical links operate with PARTIAL LOADS
  - Does this have an impact on the behaviour of the Raman amplifier?

EFFECT OF PARTIAL LOADS ON RA



Fixed pump powers and frequencies:

- f_p=[210.51 207.28 204.15 201.11 198.16] THz
- P_p=[246.7,237.7,194.2,192.7,168.8] mW

ONE.3
LOAD AWARE
RAMAN AMPLIFIER ANALYSIS

MACHINE LEARNING FRAMEWORK

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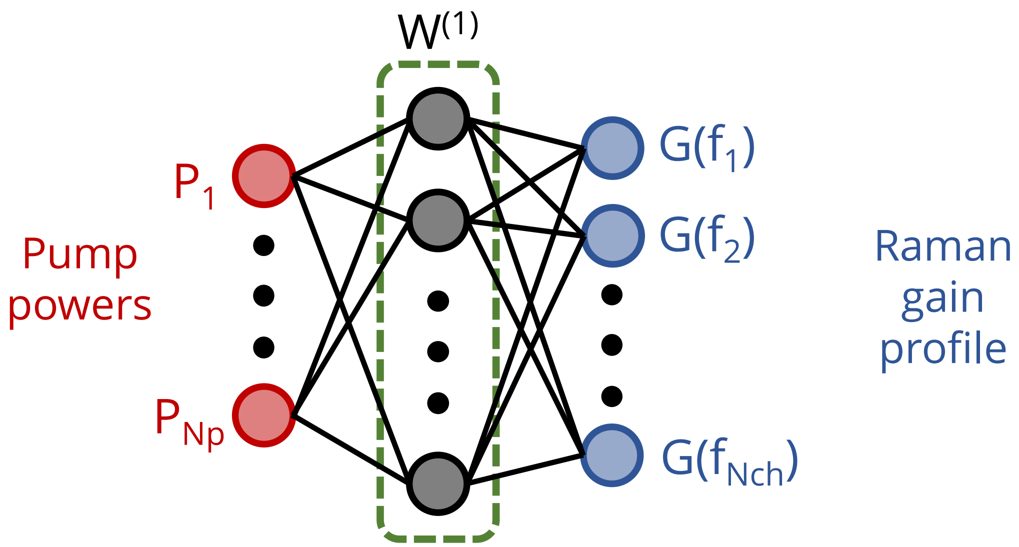
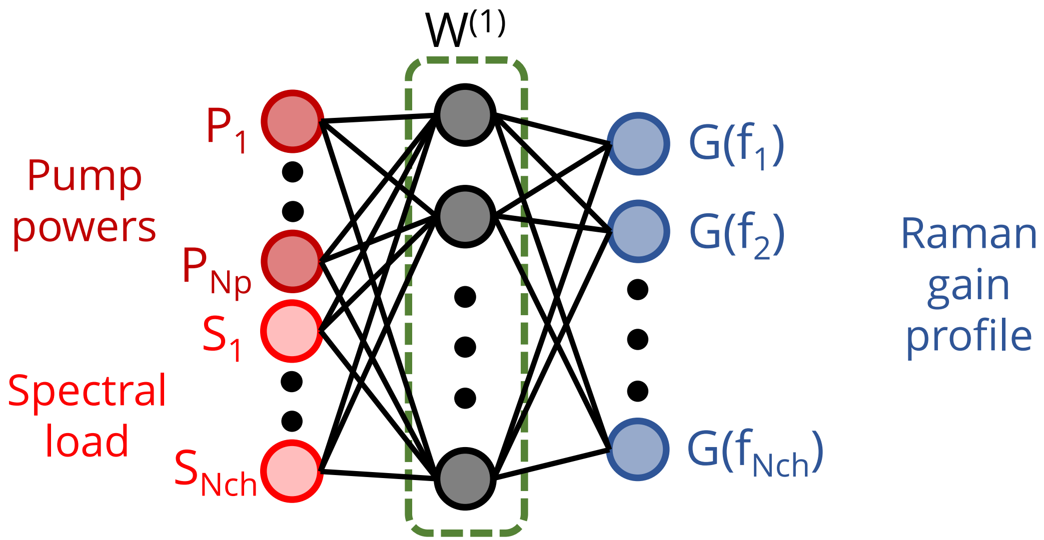
Load Unaware NN (LU-NN)



$\boldsymbol{x}$ $\quad \boldsymbol{y} = f(\boldsymbol{x}) \quad$ $\hat{\boldsymbol{y}}$

Load Aware NN (LA-NN)



$\boldsymbol{x}$ $\quad \boldsymbol{y} = f(\boldsymbol{x}) \quad$ $\hat{\boldsymbol{y}}$

SIMPLIFYING THE PROBLEM

- C+L bands: 220 frequency slots of 50 GHz
  - Partial load: each frequency slot can be ON or OFF
- In partial load scenario: 2^{220} possible combinations + pump powers arbitrariness

TOO LARGE!

SOLUTION

- 10 adjacent frequency slots grouped together to form a sub-band
- Each sub-band is 500 GHz wide and can assume two states: ON or OFF
- Total of 22 sub-bands over the entire 11 THz C+L-band
  - 12 sub-bands in the L-band
  - 10 sub-bands in the C-band

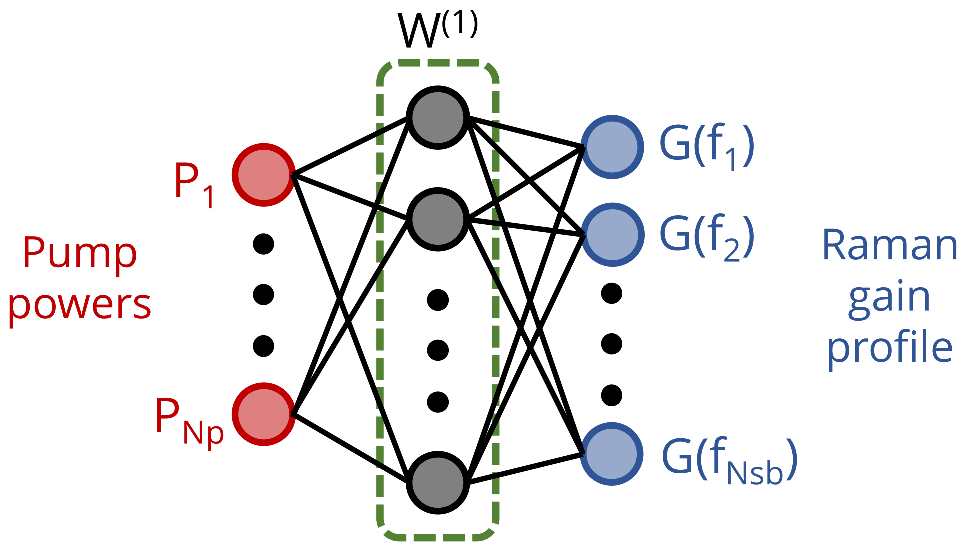
DATASET GENERATION

- General data
  - Five pumps
  - Fixed pump frequencies f_p=[210.51 207.28 204.15 201.11 198.16] THz
  - C+L band: $f \in [185,196]$ THz
  - 22 sub-bands: 500 GHz each
- We generate 11000 different **partial loads** configurations
  - To emulate all load conditions, we consider different classes (C, L and C+L) and sub-classes (number of sub-band ON) of elements with randomly selected sub-band positions
- Using the numerical Raman solver included in GNpy we generate the corresponding gain and noise profiles

MACHINE LEARNING FRAMEWORK

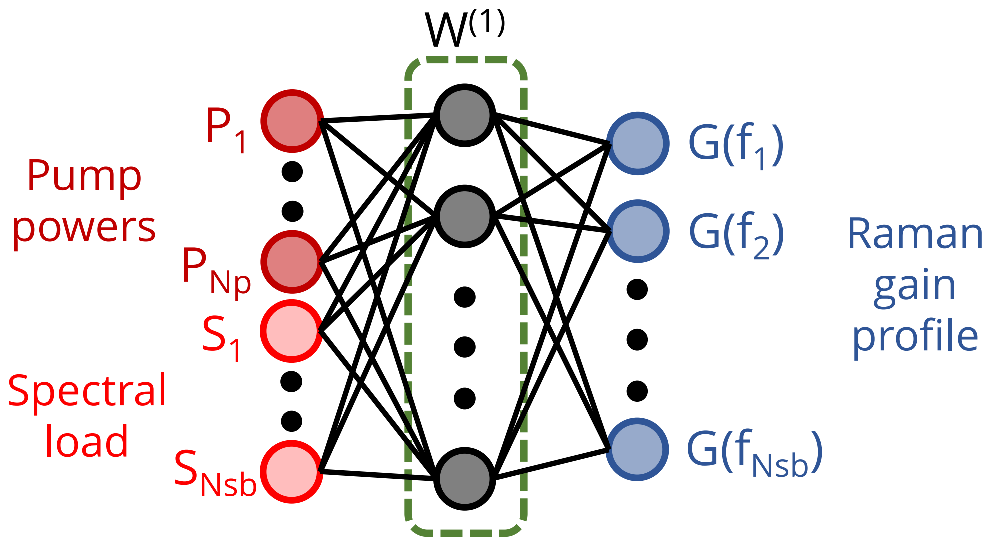
Politecnico di Torino

Load Unaware NN (LU-NN)



$\boldsymbol{x}$ $\quad \boldsymbol{y} = f(\boldsymbol{x}) \quad$ $\hat{\boldsymbol{y}}$

Load Aware NN (LA-NN)



$\boldsymbol{x}$ $\quad \boldsymbol{y} = f(\boldsymbol{x}) \quad$ $\hat{\boldsymbol{y}}$

- Training method: Random projection
- 1 hidden layers, 1980 neurons per layer, activation function: tanh
- Same approach can also be used to predict ASE noise profile generated by Raman amplifier

TESTING PROCESS

$\left[P_1, P_2, \dots, P_{N_p}\right]$

or

$\left[P_1, P_2, \dots, P_{N_p}, S_1, S_2, \dots, S_{N_{sb}}\right]$

LU-NN

or

LA-NN

NUMERICAL RAMAN SOLVER

TRAINED NEURAL NETWORK

Target profile G_{target}

Predicted profile G_{pred}

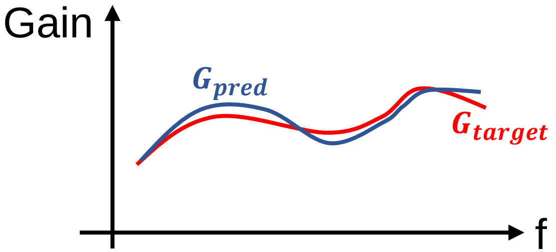
COMPARISON

Maximum error:

$$Error_{MAX} = \max_{i \,\epsilon\, \{1, N_{sb}\}} \left| G_{pred,i}(f) - G_{target,i}(f) \right|$$

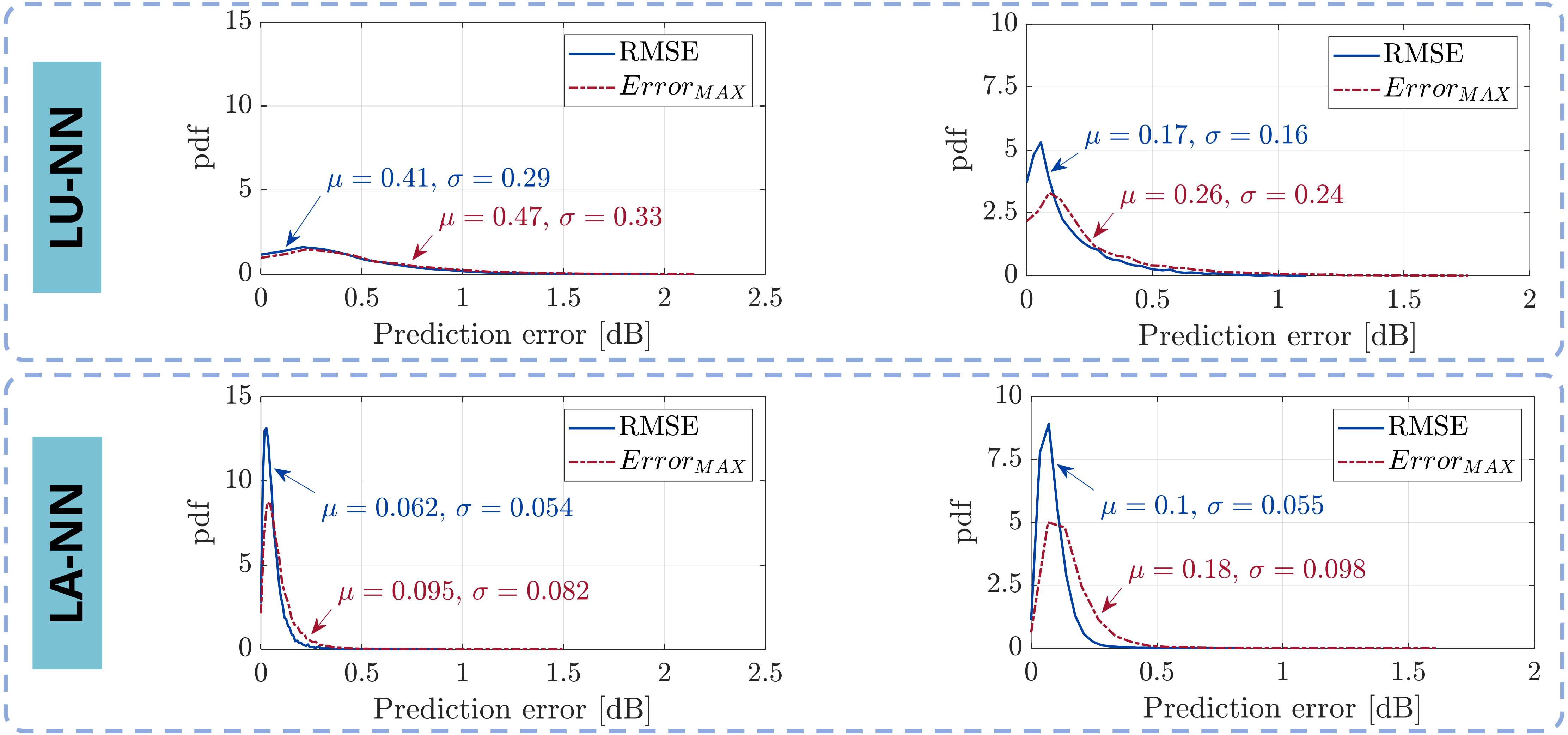
Root-mean-square-error (RMSE):

$$RMSE = \sqrt{\frac{1}{N_{sb}} \sum_{i=1}^{N_{sb}} \left(G_{pred,i}(f) - G_{target,i}(f) \right)^2}$$



TESTING RESULTS: LU-NN vs LA-NN

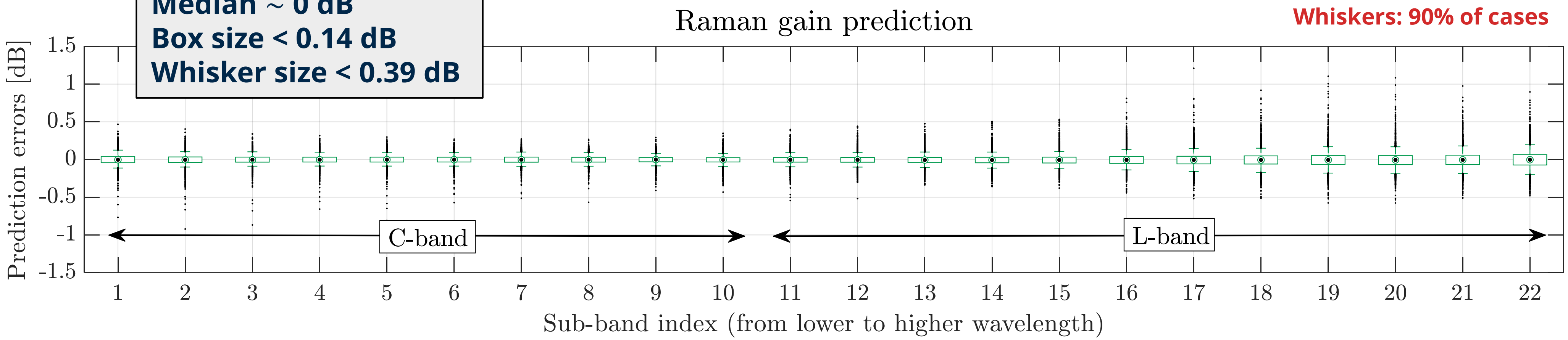
RAMAN GAIN PREDICTION | **ASE NOISE PREDICTION**

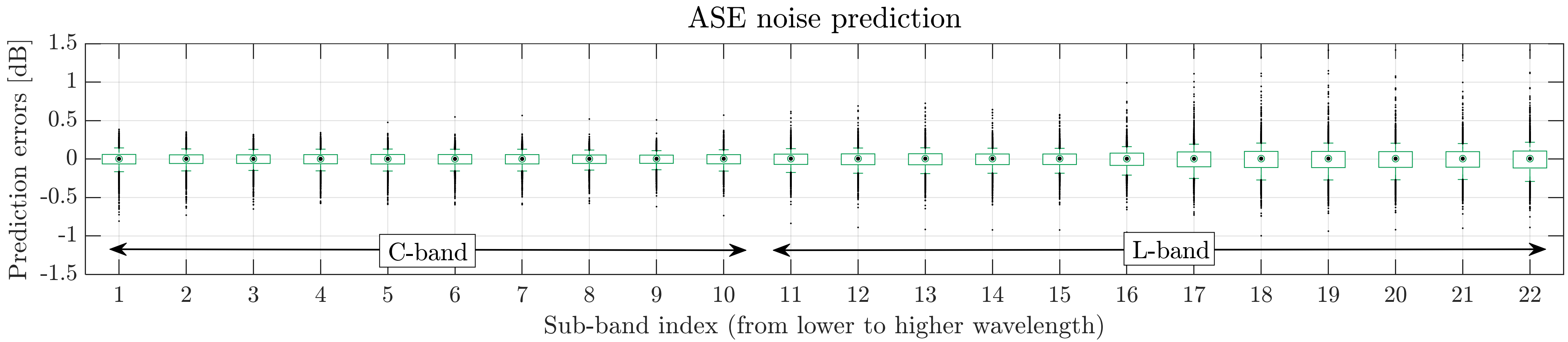


TESTING RESULTS: LU-NN vs LA-NN

Median ~ 0 dB
Box size < 0.14 dB
Whisker size < 0.39 dB

Box: 50% of cases
Whiskers: 90% of cases



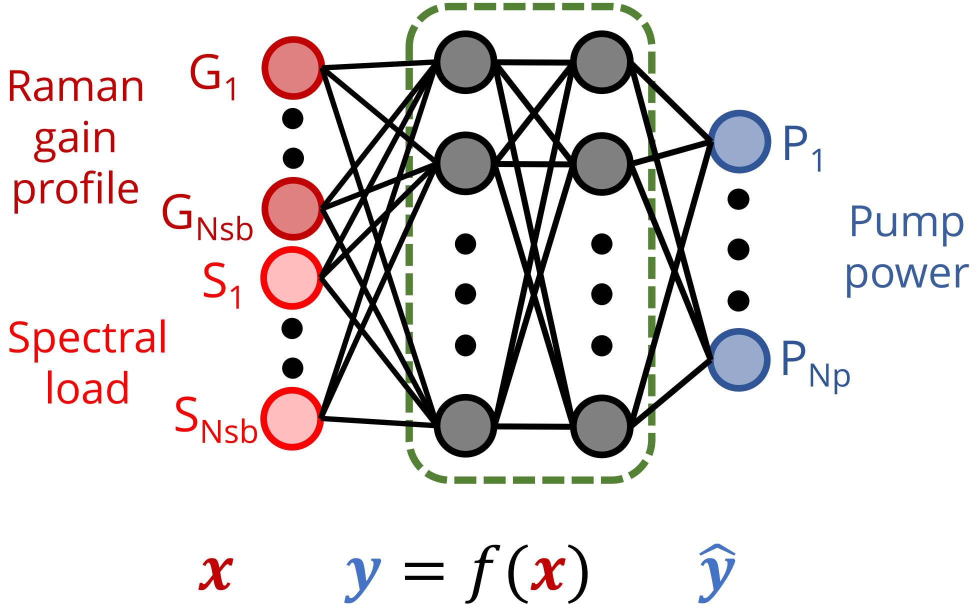


A. M. Rosa Brusin, U. C. de Moura, V. Curri, D. Zibar and A. Carena, "Introducing Load Aware Neural Networks for Accurate Predictions of Raman Amplifiers," in *Journal of Lightwave Technology*, vol. 38, no. 23, pp. 6481-6491, Dec. 1, 2020, doi: 10.1109/JLT.2020.3014810.

ONE.4
LOAD AWARE
RAMAN AMPLIFIER DESIGN

Politecnico di Torino

Load Aware NN (LA-NN)



- Training method: Levenberg-Marquardt
- 2 hidden layers, 40 neurons per layer, activation function: tanh

TESTING PROCESS

$[G_1, G_2, \dots, G_{N_{sb}}, S_1, S_2, \dots, S_{N_{sb}}]$

G_{target}

TRAINED
LA-NN

Predicted pumps power
P_{pred}

NUMERICAL
RAMAN SOLVER

Predicted
profile
G_{pred}

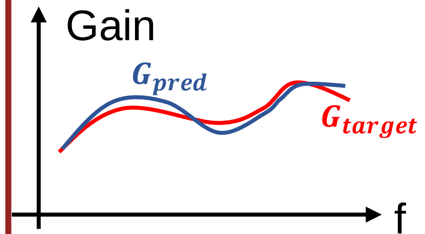
COMPARISON

Maximum error:

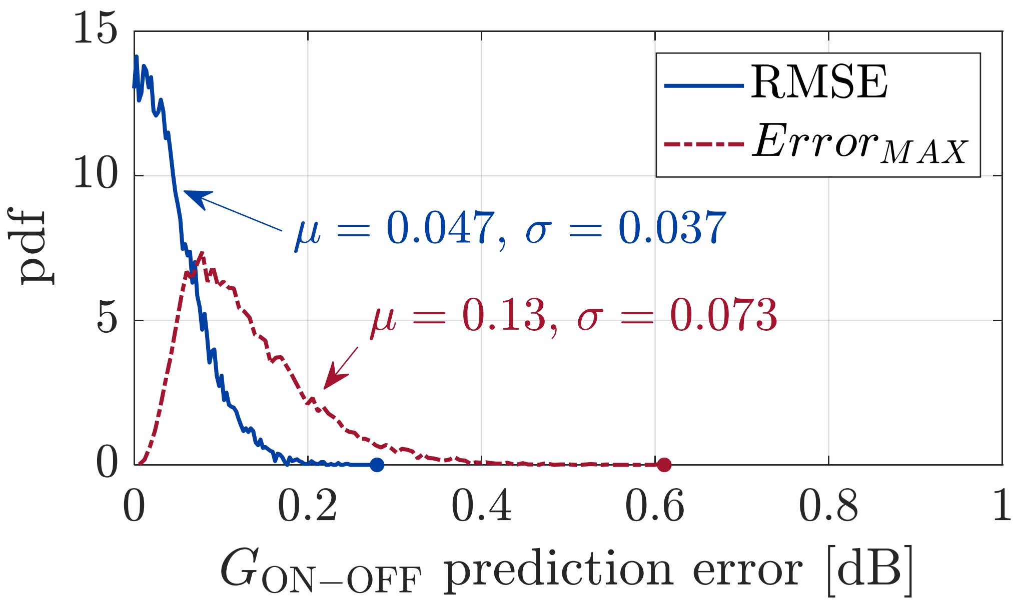
$$Error_{MAX} = \max_{i \in \{1, N_{sb}\}} \left| G_{pred,i}(f) - G_{target,i}(f) \right|$$

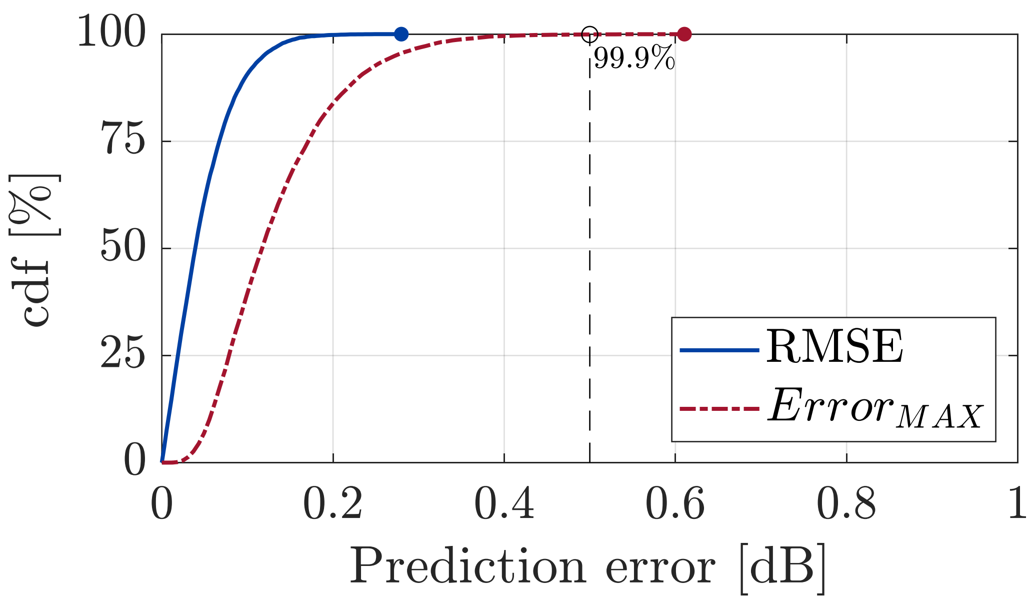
Root-mean-square-error (RMSE):

$$RMSE = \sqrt{\frac{1}{N_{sb}} \sum_{i=1}^{N_{sb}} \left(G_{pred,i}(f) - G_{target,i}(f) \right)^2}$$



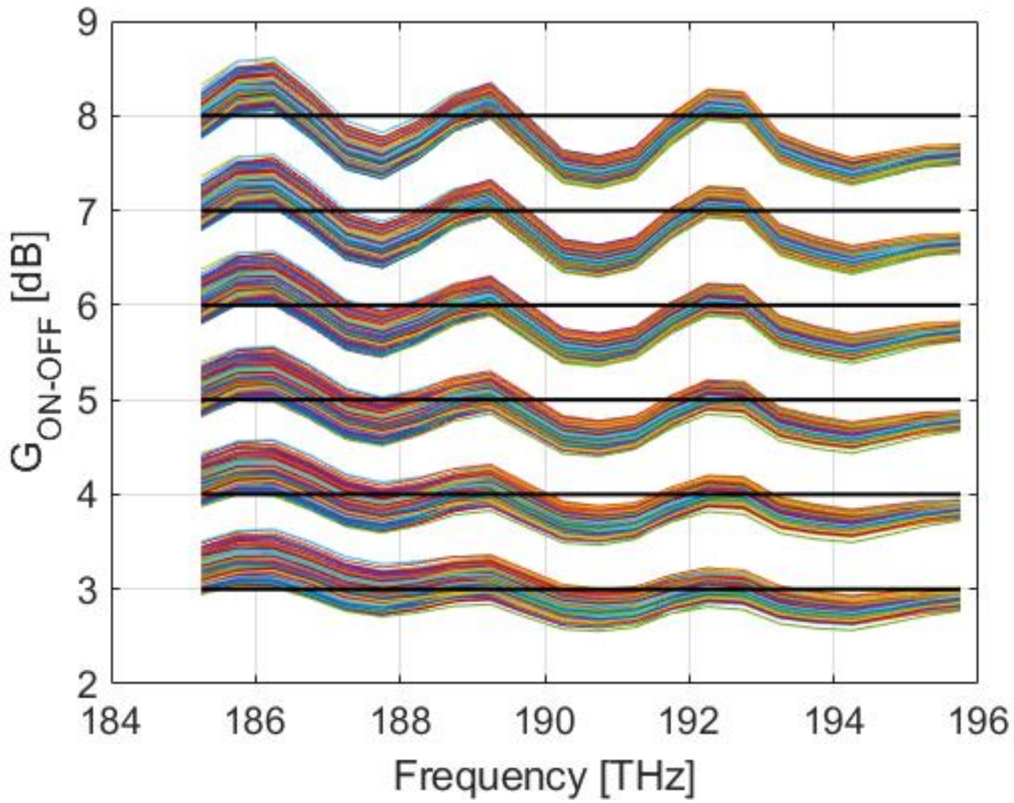
TESTING RESULTS: ARBITARY PROFILES





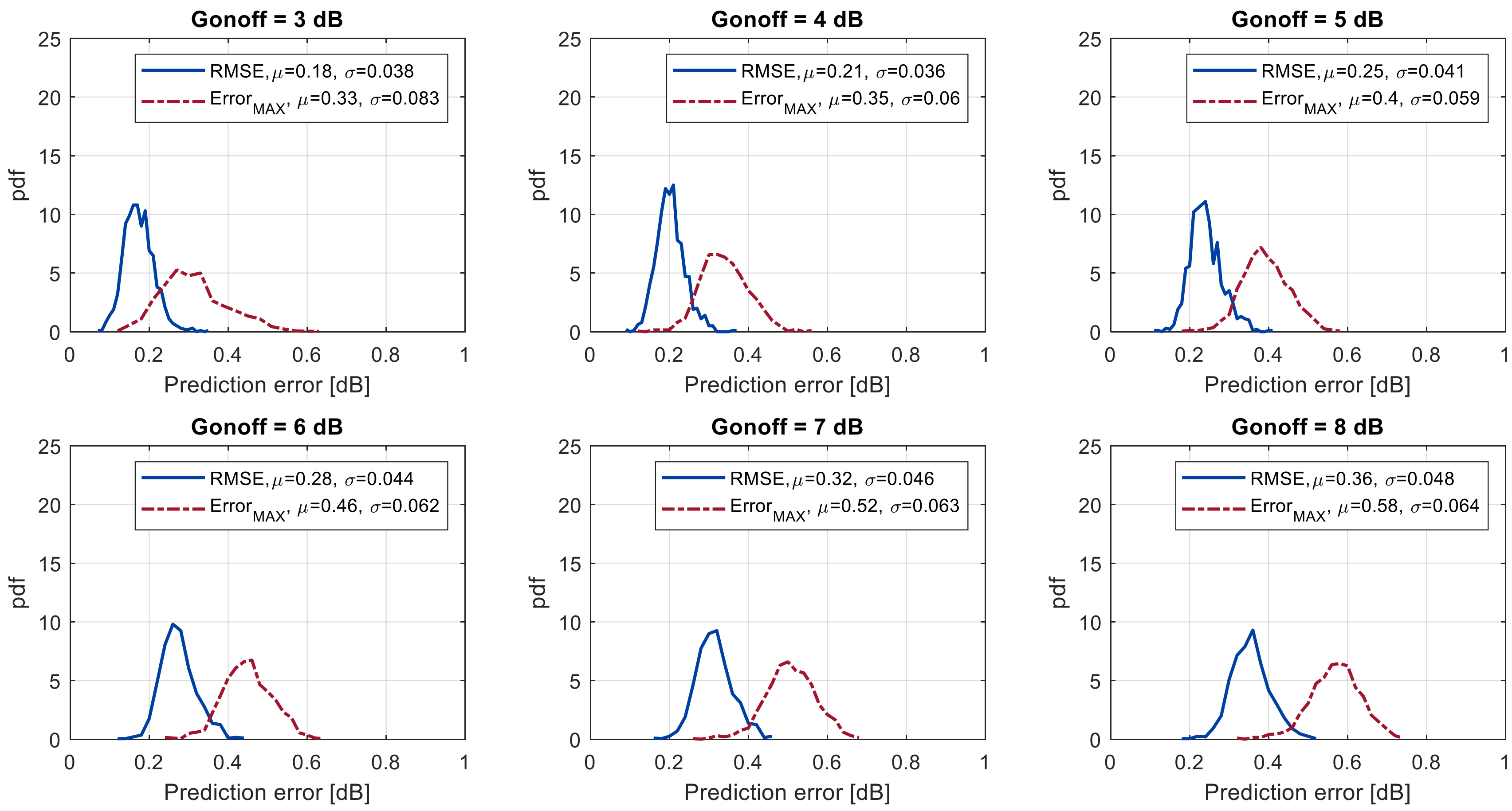
TESTING RESULTS: FLAT PROFILES

- 1000 different partial loads



TESTING RESULTS: FLAT PROFILES

- 1000 different partial loads



ONE.5
CONCLUSIONS

PART ONE - CONCLUSIONS

- For ultra-wide band transmission, Raman amplification is an enabler to deliver arbitrary gain profiles at any wavelengths
- Machine Learning based methods allow for fast and accurate Raman amplifier analysis and design
- Load awareness is fundamental for applications in dynamically reconfigurable networks
  - Direct NN predicts gain and noise profile to be effectively used in network controller
  - Inverse NN predicts pump powers to design the required gain profile

PART TWO

ML applied to the management of NxN switches

PART TWO - ACKNOWLEDGEMNTS

This work has been carried out in collaboration with:

- Synopsys, Inc. (USA)

Thanks to:

- PoliTo colleagues: Prof. V. Curri and Prof. P. Bardella
- PoliTo PhD students: L. Tunesi, I. Khan and M.U. Masood
- Synopsys team lead by E. Ghillino

OUTLINE – PART TWO

TWO.1 PIC and Machine Learning
TWO.2 NxN switch: topologies and implementations
TWO.3 Predicting control signals in a NxN switch
TWO.4 Estimating QoT in a NxN switch
TWO.5 Conclusions

TWO.1

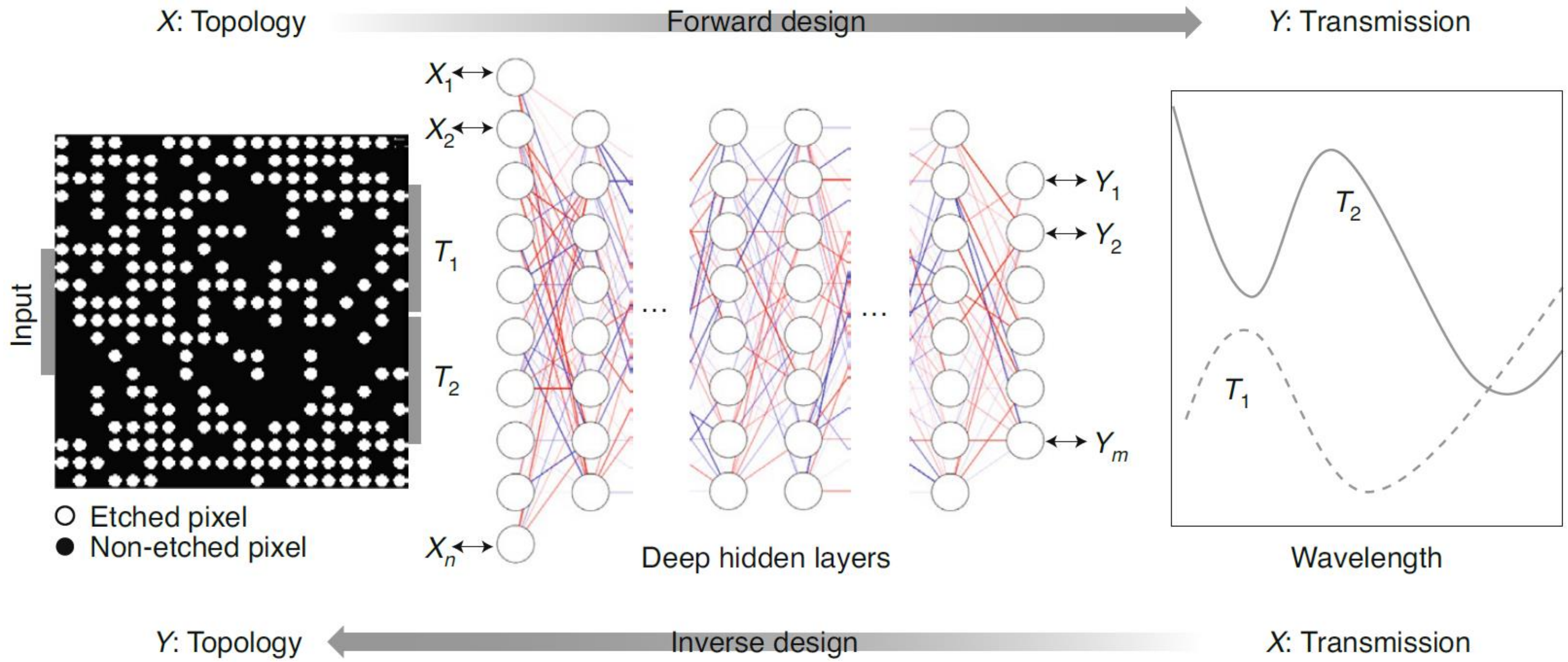
PIC and Machine Learning

PIC

- Photonic Integrated Circuits (PICs) are an enabling technology for future optical networks
  - Silicon Photonics is becoming a mature PIC technology
- PIC can implement complex functionalities at the photonic level
- Network elements, especially photonic switching systems, can be implemented as PIC
- Future ROADM architectures will possibly be based on WSS and switching elements based on PIC
  - Small footprint
  - Low energy consumption
  - Low latency

ML-based PIC design

- An interesting innovative application of ML to PIC is to apply it to the design of physical structures



- Ma, W., Liu, Z., Kudyshev, Z.A. et al. Deep learning for the design of photonic structures. Nature Photonics 15, 77–90 (2021). https://doi.org/10.1038/s41566-020-0685-y

QoT estimation and Control Signals prediction

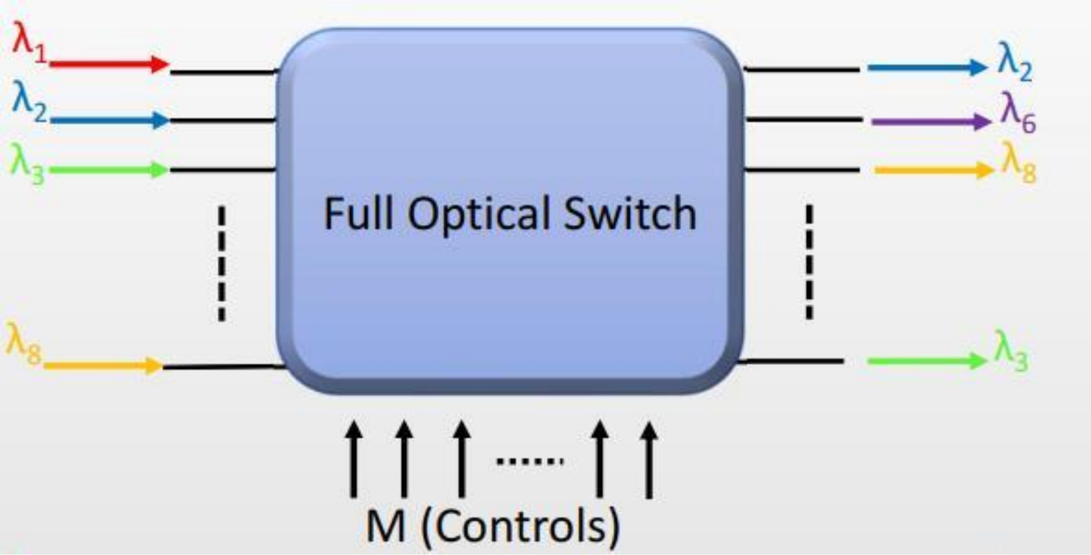
- In recent years several works targeted Machine Learning application to evaluate Quality of Transmission (QoT) of lightpaths
- Most of these works consider only the impact of propagation effects
  - ASE noise accumulation and fiber non-linear effects
- In flexible and dynamic optical networks, the impact of ROADM is not negligible
  - Filtering and switching sections must be properly analyzed
- ML can be applied to estimate QoT degradation in complex PIC structures
- A further novel application we have targeted is the prediction of control signal for complex PIC structures

- Rui Manuel Morais and João Pedro, "Machine Learning Models for Estimating Quality of Transmission in DWDM Networks," J. Opt. Commun. Netw. 10, D84-D99 (2018)
- Cristina Rottondi, Luca Barletta, Alessandro Giusti, and Massimo Tornatore, "Machine-Learning Method for Quality of Transmission Prediction of Unestablished Lightpaths," J. Opt. Commun. Netw. 10, A286-A297 (2018)
- Ihtesham Khan, Muhammad Bilal, M. Umar Masood, Andrea D'Amico, and Vittorio Curri, "Lightpath QoT computation in optical networks assisted by transfer learning," J. Opt. Commun. Netw. 13, B72-B82 (2021)

TWO.2
NxN switch:
topologies and implementations

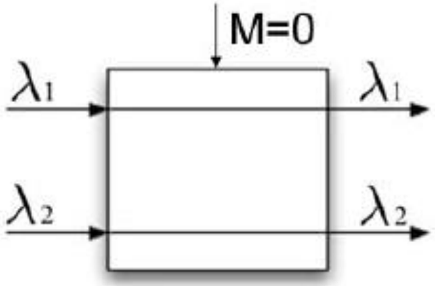
Switching application

- We consider the following NxN switch application:
  - At each of the N inputs we have a channel at a specific wavelength
  - Based on M electrical control signals, we define a switch state where at the output ports we have a specific channel permutation

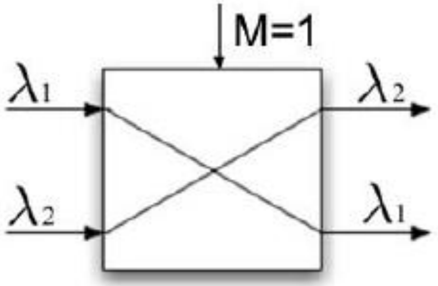


Switching topologies

- Physical layouts
  - Beneš network
  - Honey-Comb Rearrangeable Optical Switch (HCROS)
- In all cases, the elementary Optical Switching Elements is a 2 x 2 unit

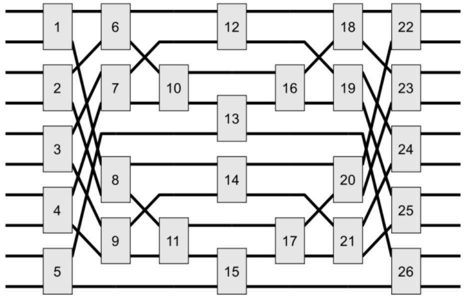


Bar



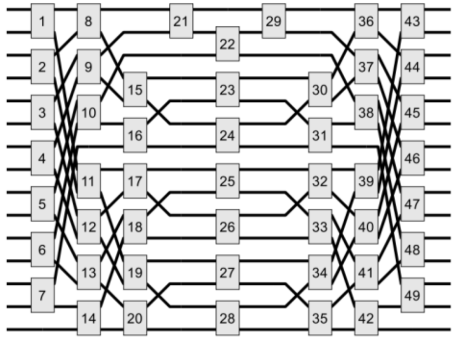
Cross

Beneš 10x10



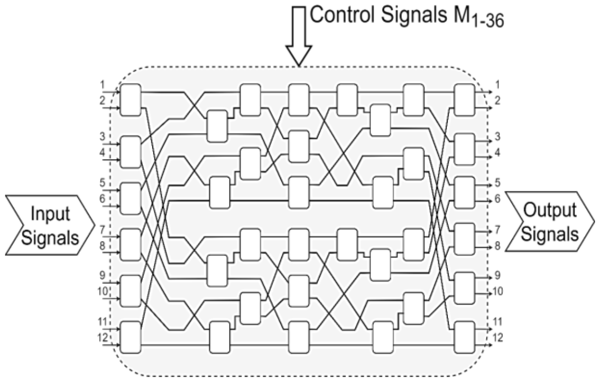
M=26

Beneš 15x15



M=49

HCROS 10x10



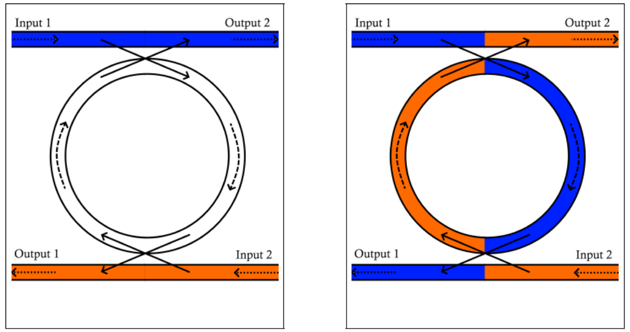
M=36

Optical Switching Elements (OSE)

- Several topologies are available to implement an OSE as a PIC
  - Micro-Ring Resonators (MRR)
  - Mach-Zehnder Interferometers (MZI)

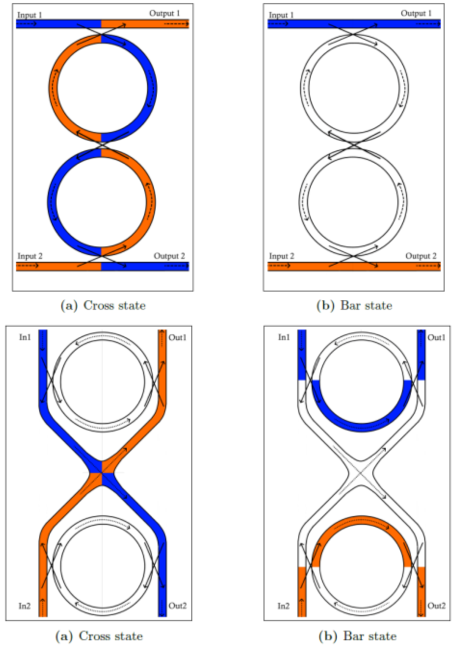
MRR

FIRST ORDER MRR

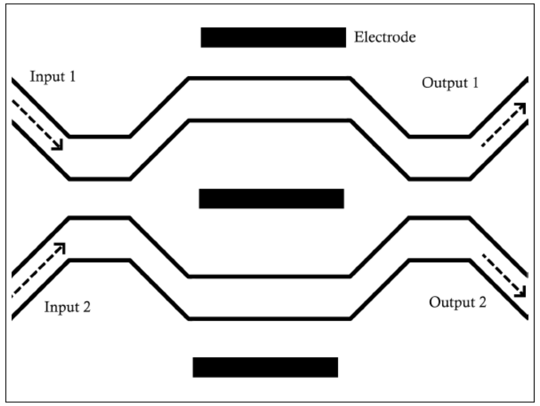


(a) Bar state (b) Cross state

SECOND ORDER MRR



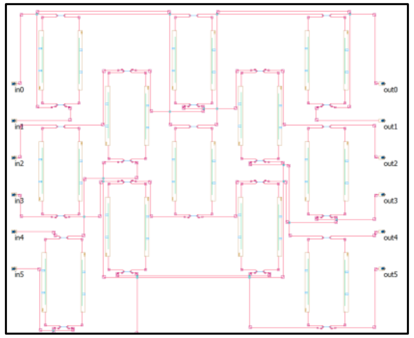
MZI



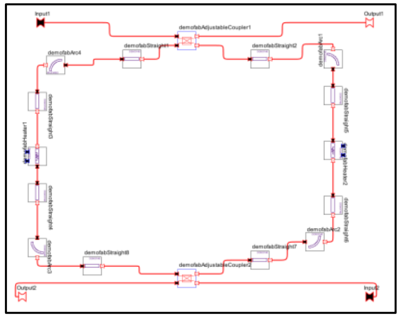
Physical layer simulations

- Synopsys design suite allows a VERTICAL approach in simulation analysis

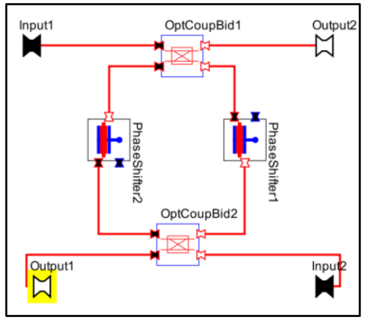
PRODUCTION-READY
LAYOUT MASK



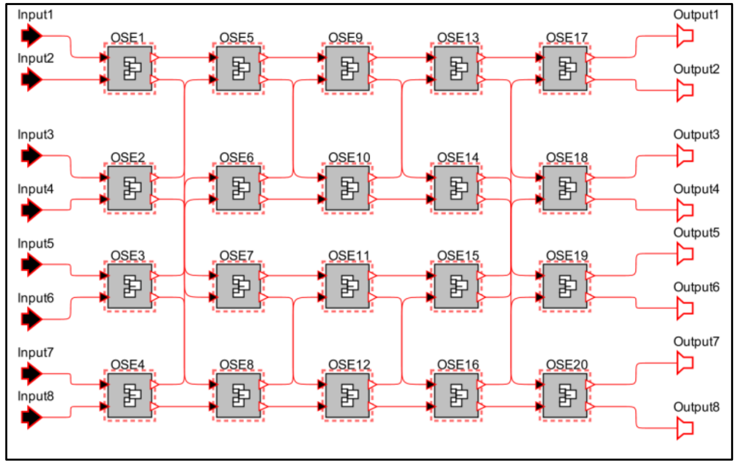
PDK-BASED
MODEL



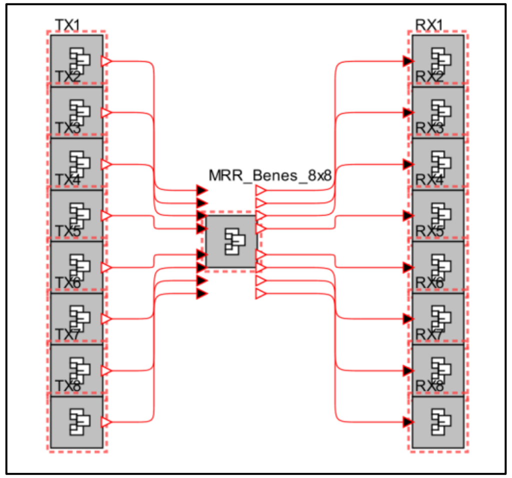
OSE
OptSim MODEL



NxN SWITCH
OptSim MODEL
(8x8 Benes)



FULL SYSTEM
OptSim MODEL

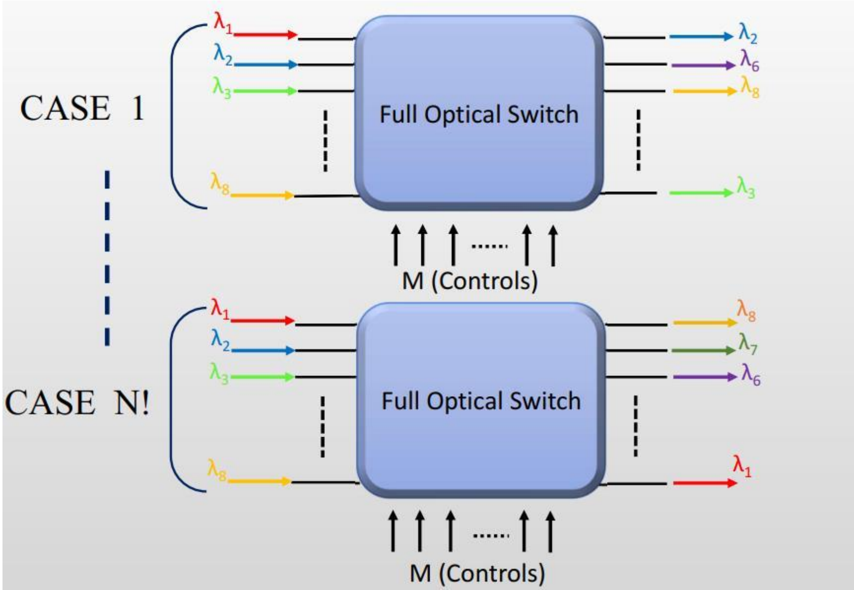


TWO.3

Predicting control signals in a NxN switch

Switching operations

- Each state of the switch is defined by its unique control vector comprising of M control signals having 2^M combination
- At each state corresponds a permutation of the input wavelengths at the output ports

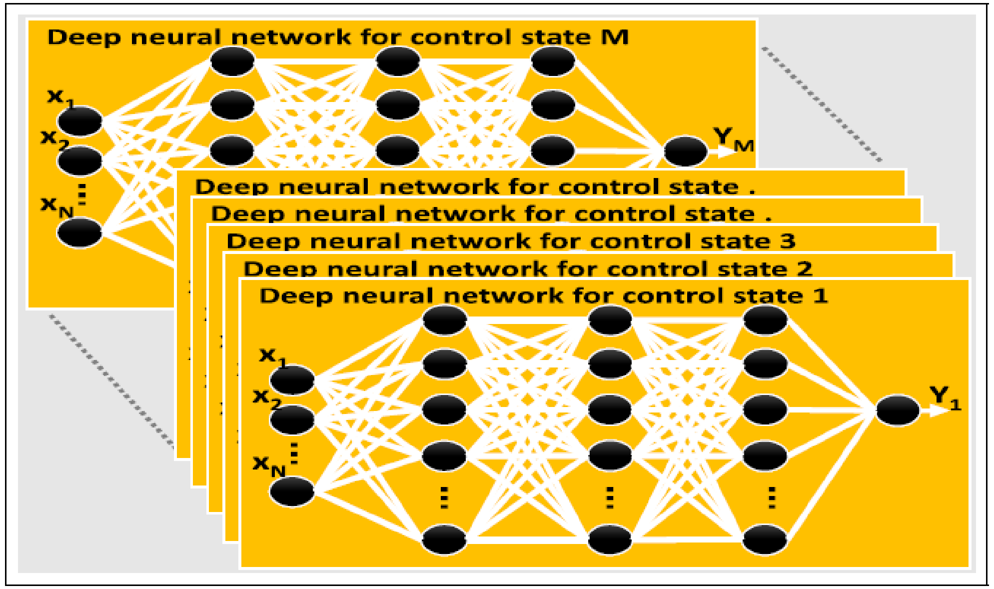


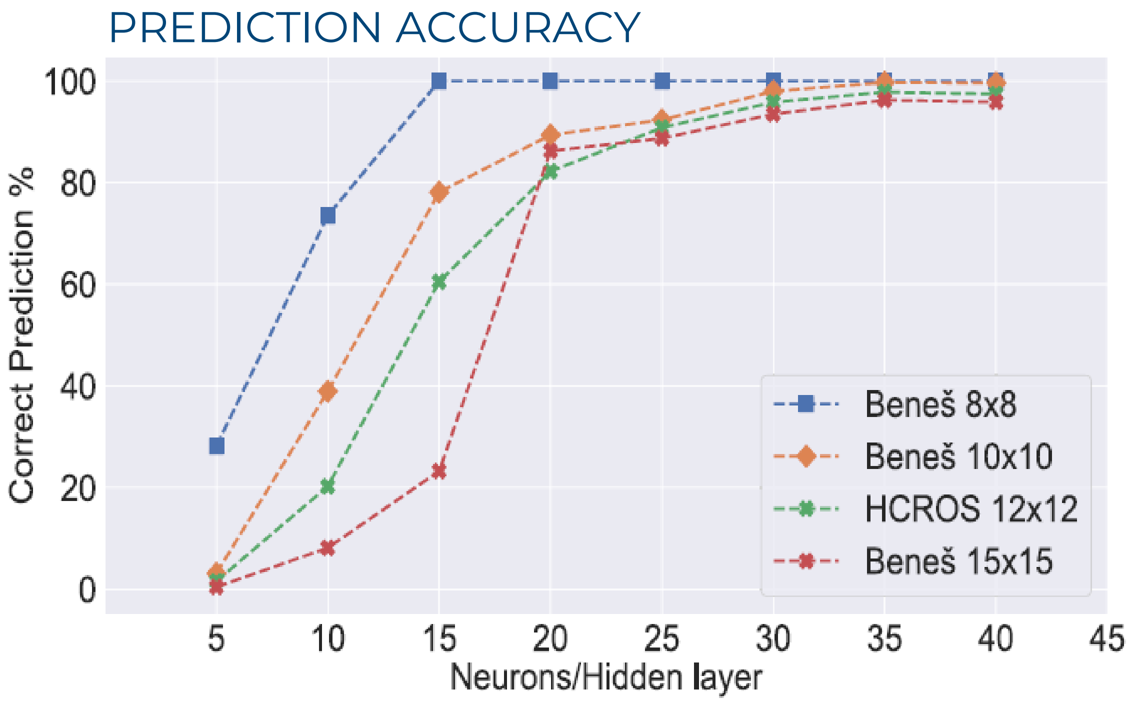
Network type Size ($N \times N$)	Beneš 8x8	Beneš 10x10	HCROS 12x12	Beneš 15x15
Permutations ($N!$)	40,320	3,628,800	479,001,600	$1{,}307 \times 10^9$
Switches (M)	20	26	36	49
Combinations (2^M)	1,048,576	67,108,864	68×10^9	562×10^{12}
Dataset	100,000	300,000	300,000	1,000,000

- Black-box approach
- Reduced number of elements in the dataset: no need to analyze the full space

Control signal predictions

- We trained M-parallel neural networks to predict the control states based on the required output wavelength permutation
- It is an inverse design approach



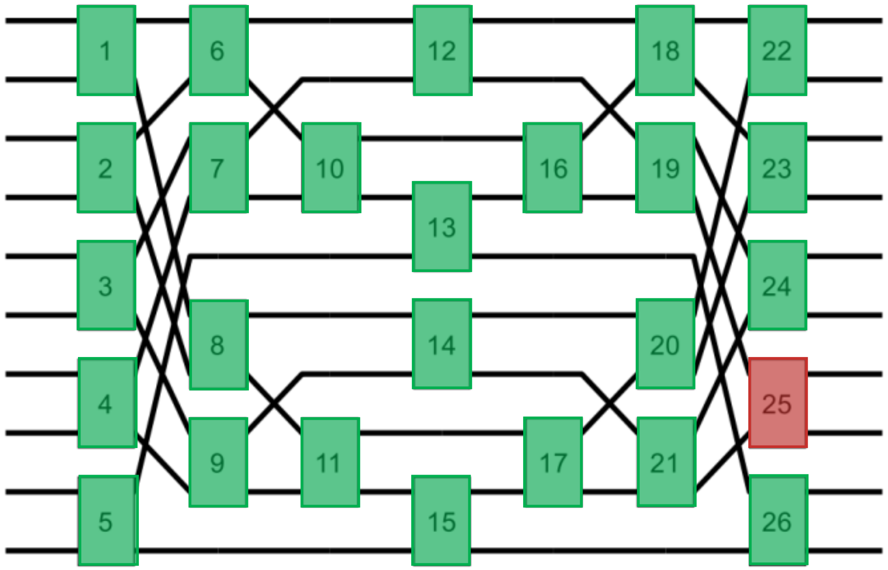


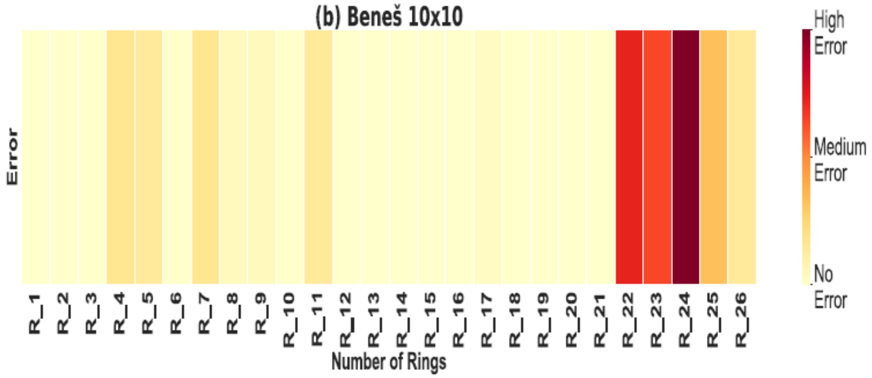
Improve prediction performances

- Analyzing control state predictions, we found that in ALL cases we have single errors, mainly in the last stage of the topology
- We proposed a simple heuristic: flipping one at a time each of the M control signals, we can find the correct state

Beneš 10x10

M=26



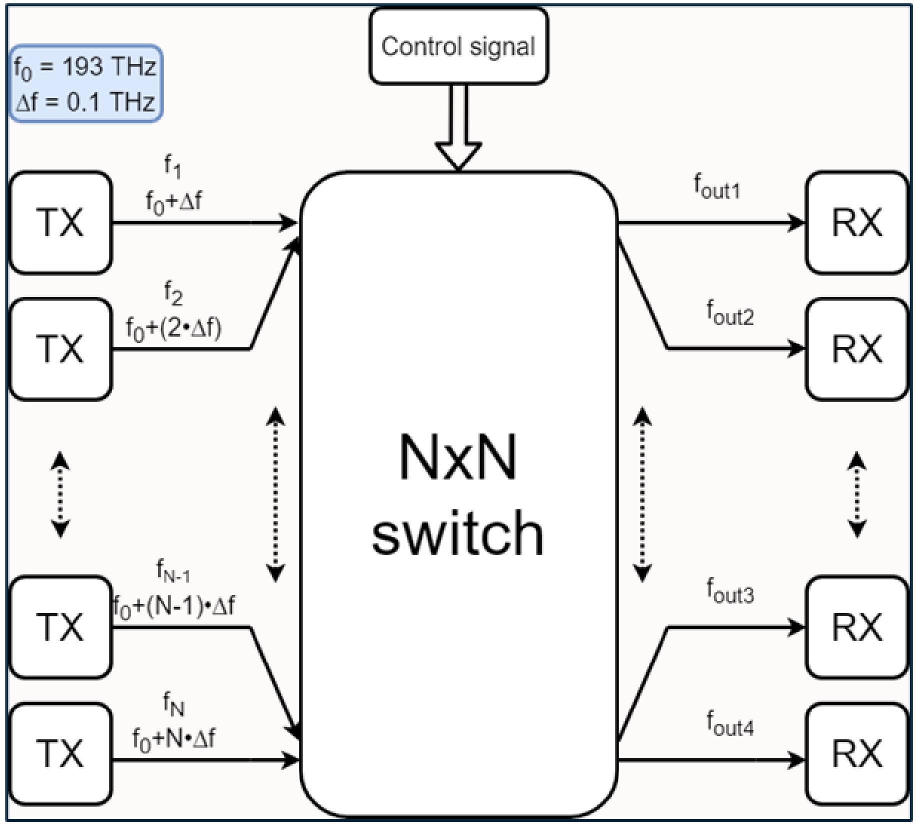


Network type Size ($N \times N$)	Beneš 8x8	Beneš 10x10	HCROS 12x12	Beneš 15x15
Neurons per hidden layer	15	35	35	35
Accuracy (no heuristic)	100%	99.72%	97.83%	96.25%
Single switch control error	0%	0.28%	2.17%	3.75%
Multiple switch control error	0%	0%	0%	0%
Accuracy (with heuristic)	100%	100%	100%	100%

TWO.4
Estimating QoT in a NxN switch

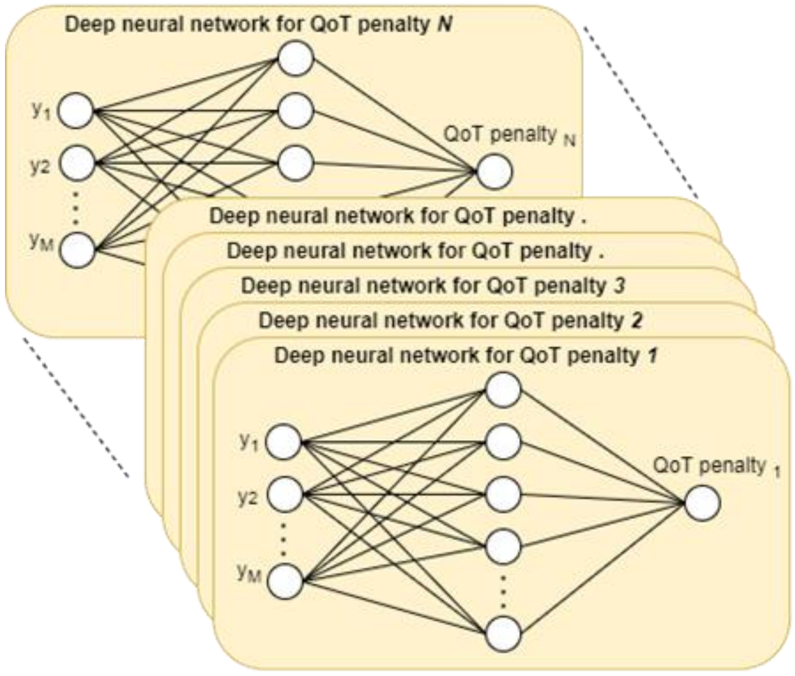
QoT analysis for a 600G system

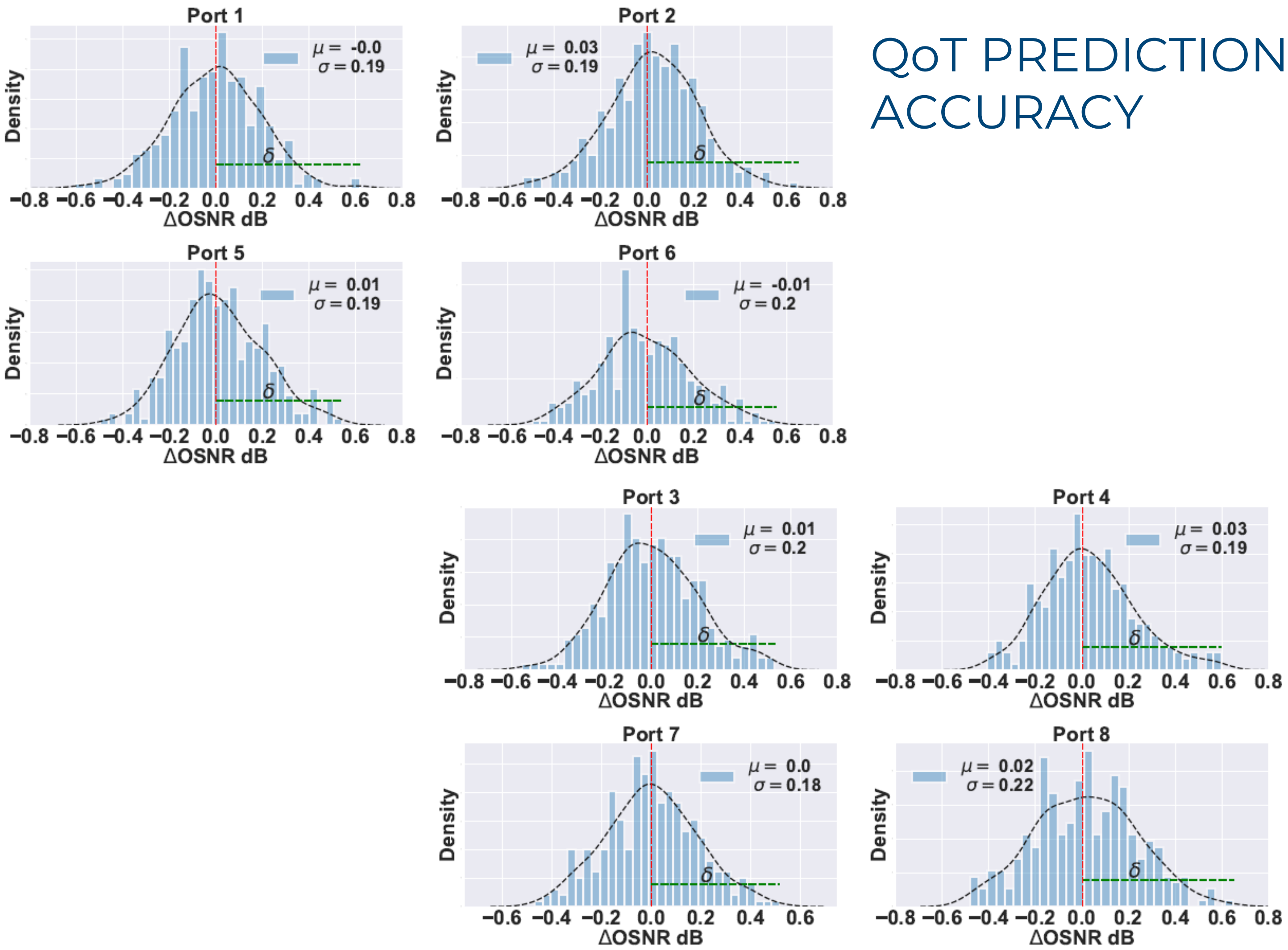
- Transmission Model
  - Inputs and outputs stages are connected to a transmitter and receiver module
  - PM-64QAM modulation format (Symbol rate 50 GBaud)
  - OSNR penalty as QoT metric
  - BER counting technique
    - Target Bit-Error Rate (BER): $5{\cdot}10^{-3}$
  - Simulations are performed using OptSim



QoT predictions

- Beneš 8x8





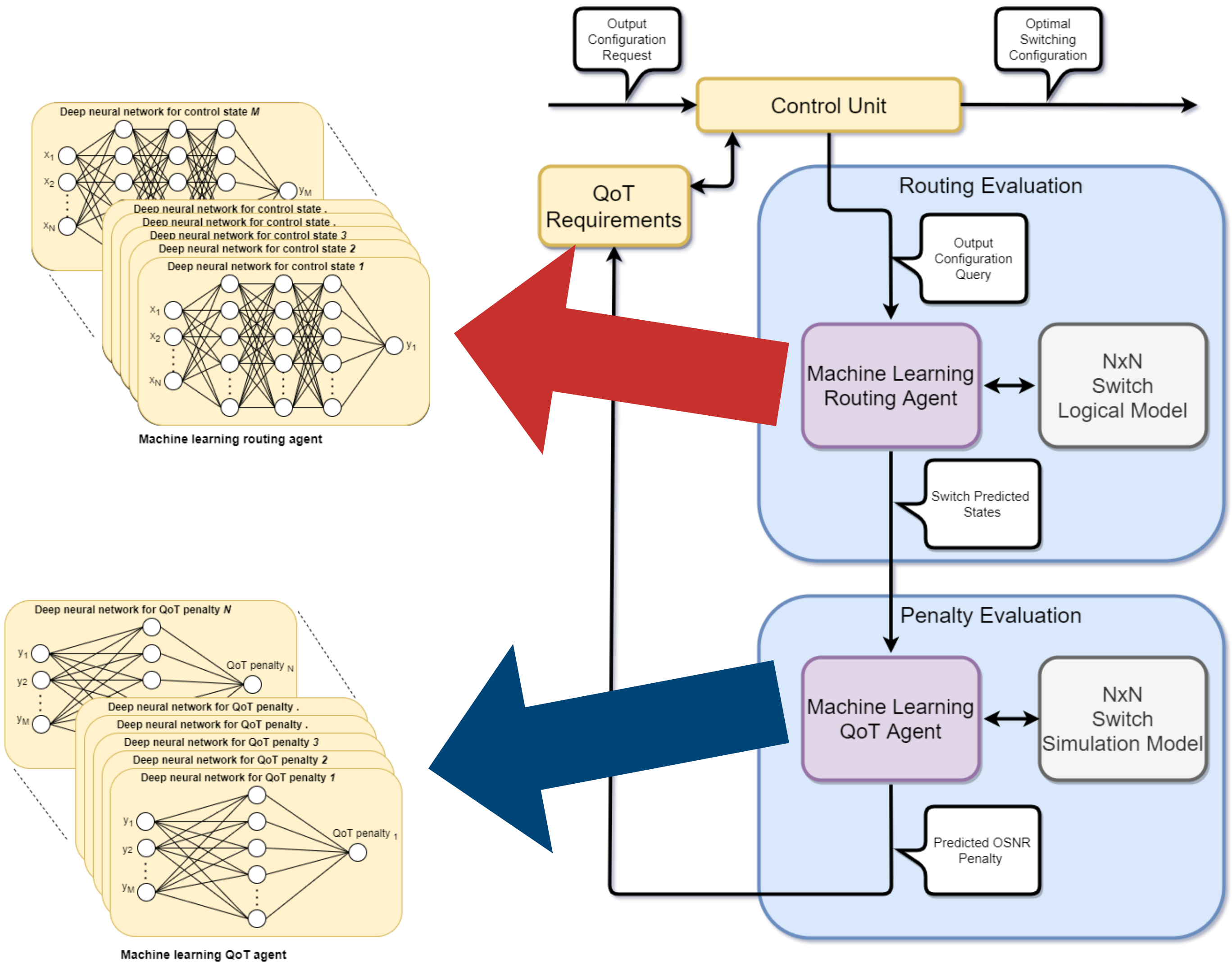
QoT PREDICTION ACCURACY

TWO.5

Conclusions

PART ONE - CONCLUSIONS

- We demonstrate the operation of two ML agents that allow for an autonomous management of PIC based NxN switches
- They are enabling solutions to implement SDN paradigm down to the physical layer of dynamic optical networks



Politecnico di Torino

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Thank you for your attention!

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Slides available at: https://www.optcom.polito.it/talks

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