AI-ASSISTED CONTROL OF OPTICAL DATA TRANSPORT

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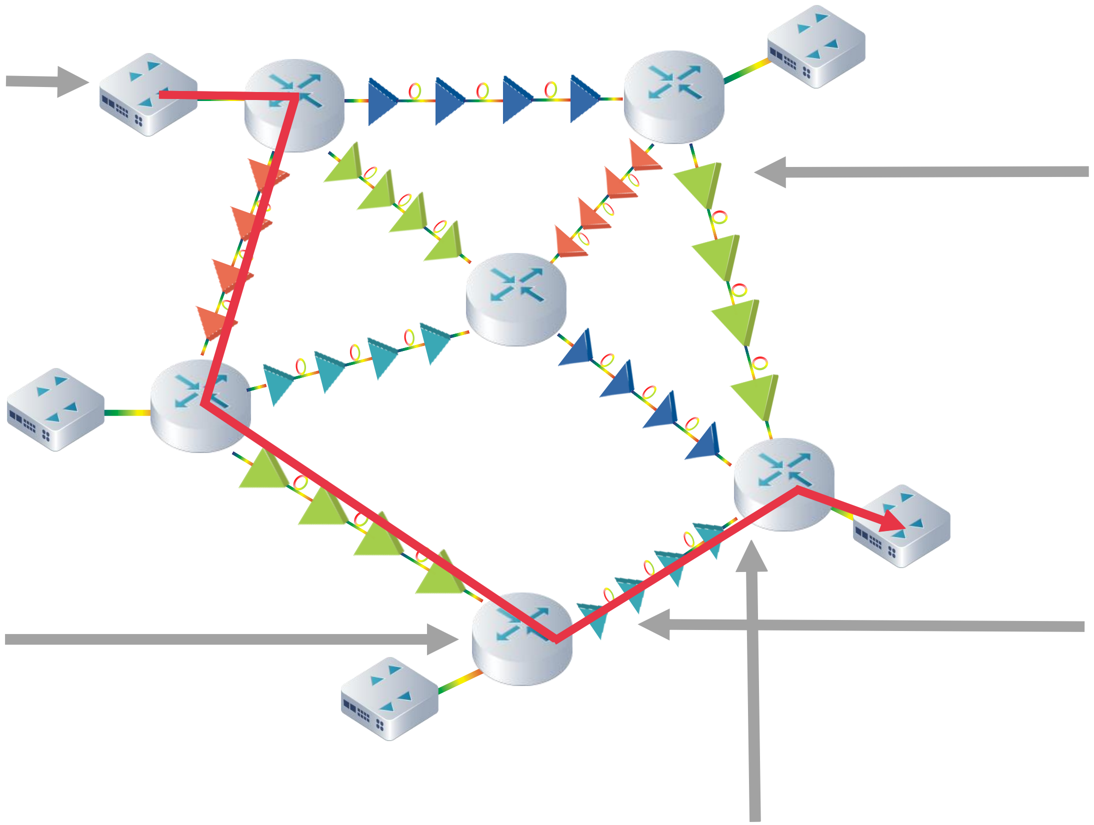
WORKSHOP GARR 2021

NET MAKERS

OPTICAL TRANSPARENT NETWORKS

Optical transponders:
Tx/Rx a LP at λ in B_{opt} operating at R_b over WDM grid using DP coherent optical technologies

ROADMs:
Transparently routes any λ in B_{opt} from any input direction to any output direction according to the WDM grid



Transparent lightpath

Optical amplifiers:
Transparently amplify all λ in B_{opt}

Optical fibers:
Transparently transport all λ in B_{opt}

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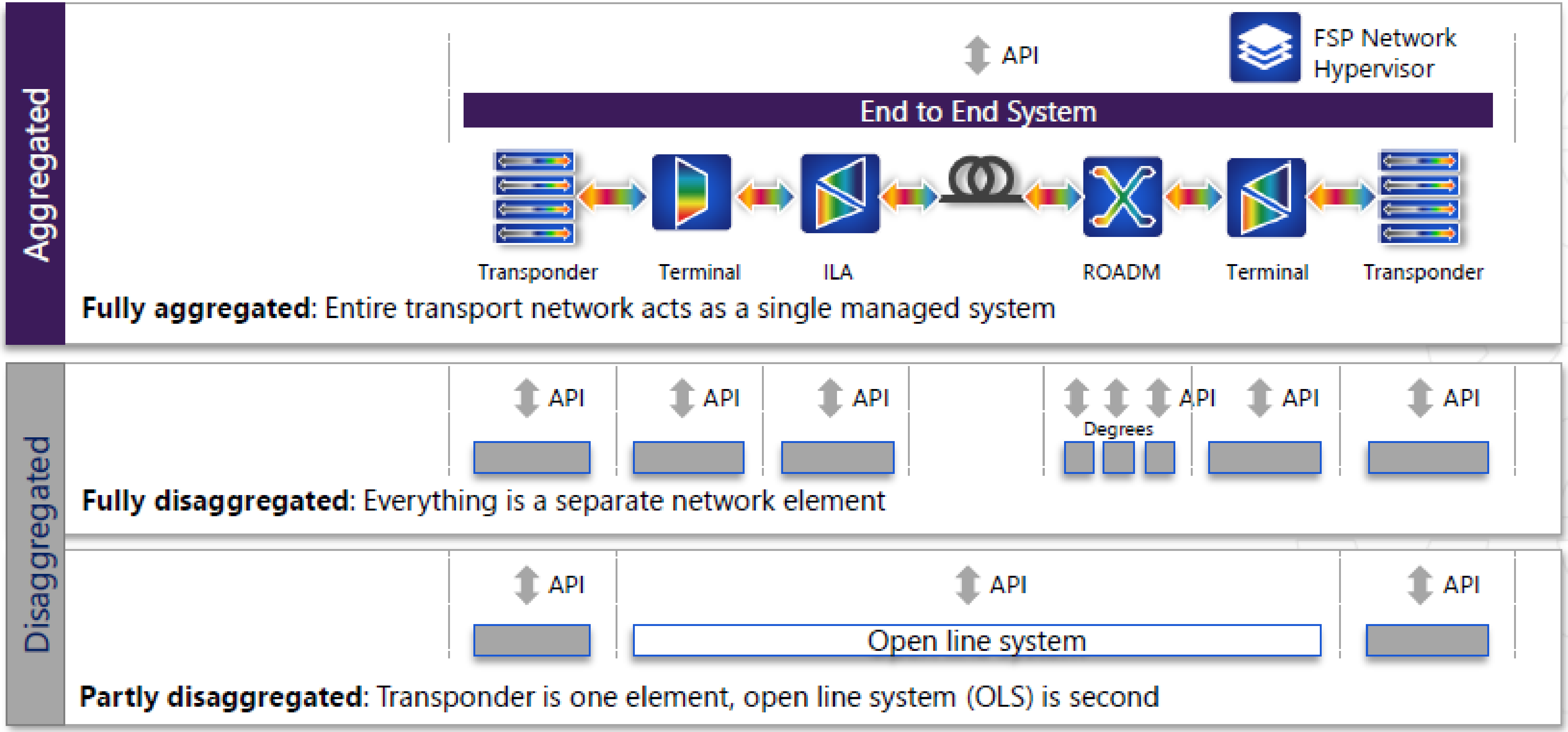
AGGREGATED AND DISAGGREGATED NETWORKS

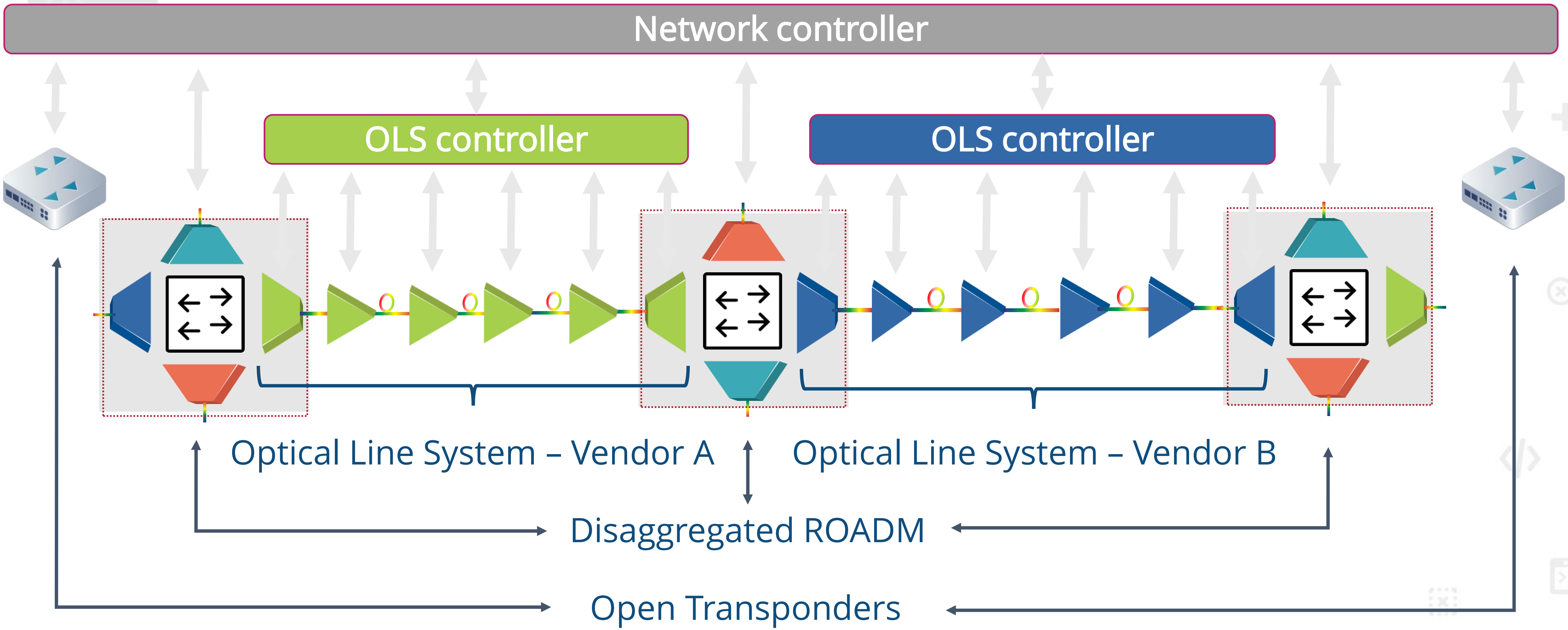


Fully aggregated: Entire transport network acts as a single managed system

Fully disaggregated: Everything is a separate network element

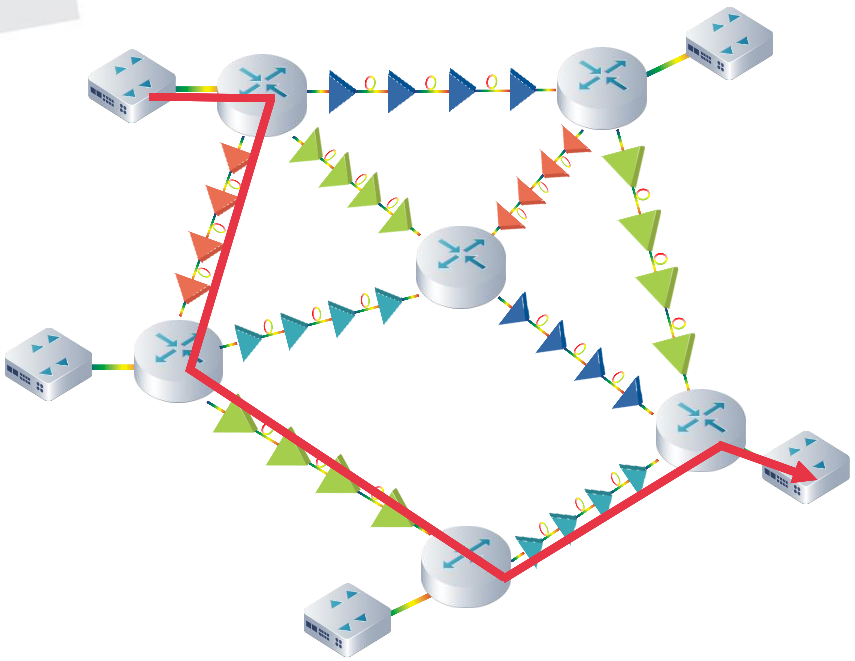
Partly disaggregated: Transponder is one element, open line system (OLS) is second

PARTIALLY DISAGGREGATED NETWORKS



- E. Riccardi et al, An operator view on the introduction of white boxes into optical networks, JLT, 2018
- J. Kundrát et al, Opening up ROADMs: let us build a disaggregated open optical line system, JLT ,2019
- C. Xie et al, Open and disaggregated optical transport networks for data center interconnects, JOCN, 2020
- M. Birk et al, The OpenROADM initiative, JOCN, 2020
- H. Nishizawa et al, Open whitebox architecture for smart integration of optical networking and data center technology, JOCN, 2021

LIGTHPATH = AWGN NONLINEAR CHANNEL

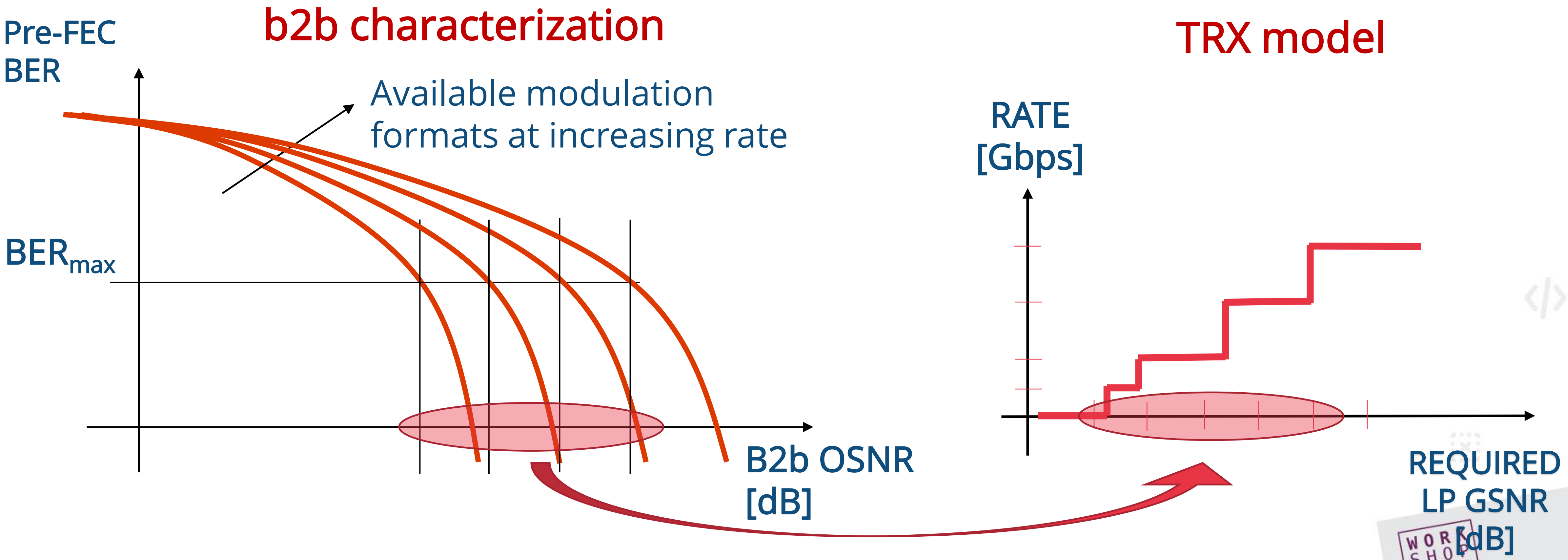


$$GSNR = \frac{P_{ch}}{P_{ASE} + P_{NLI}}$$

- Each LP is a transparent point-to-point digital connection deploying DP coherent optical technologies
- The model for each transparent channel is AWGN nonlinear channel affected by
  - Gaussian ASE noise from amplifiers
  - Gaussian NLI from nonlinear crosstalk in fiber propagation
  - Filtering penalties

TRX MODEL

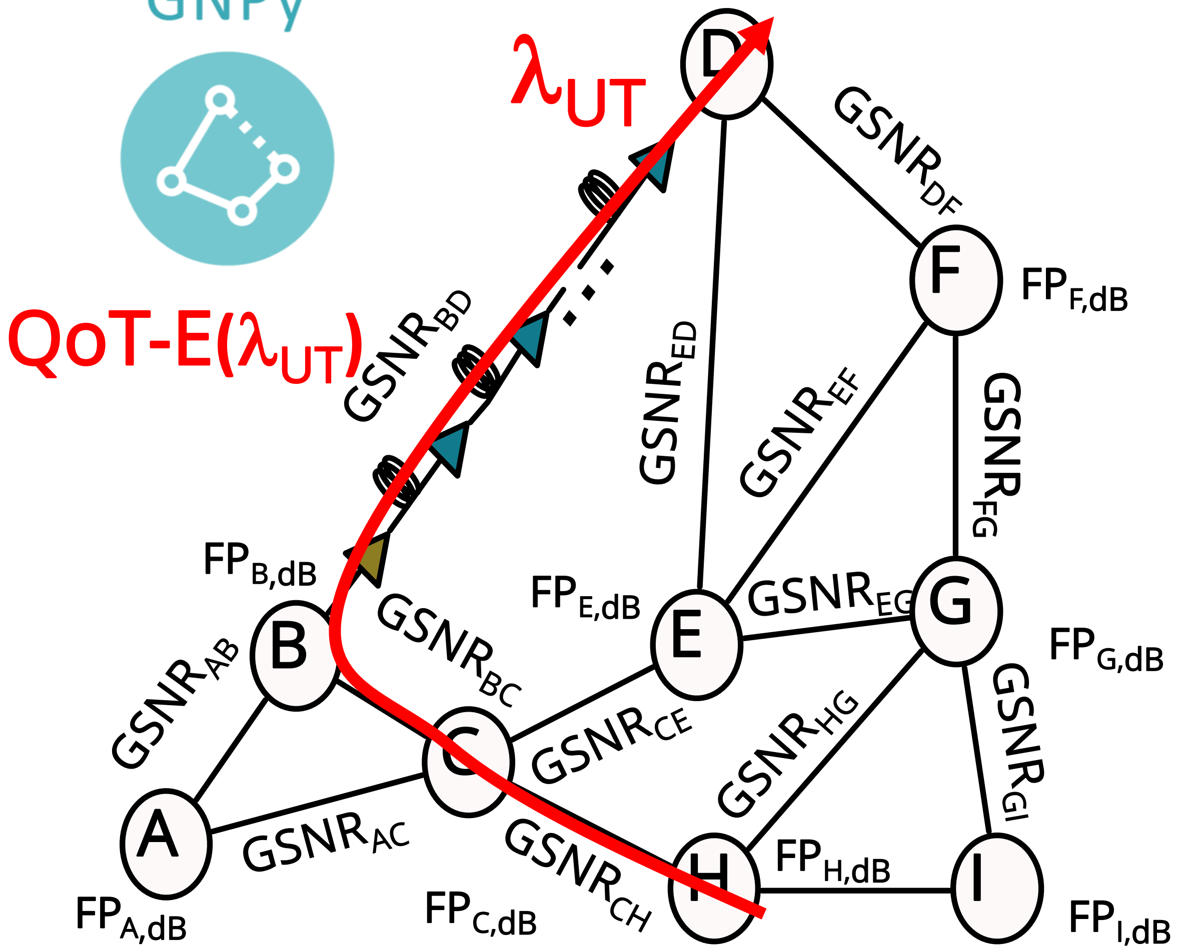
- TRX are typically flexible supporting multiple modulation formats
- The exploited FEC technology defines the maximum tolerable $BER=BER_{max}$
- From b2b characterization we obtain a full model for transceiver



G. Borraccini et al, Using QoT-E for open line controlling and modulation format deployment: an experimental proof of concept , ECOC, 2020

DIGITAL TWIN OF THE OPTICAL TRANSPORT

GNPy



$$GSNR(\lambda_{UT}) = 10\log_{10}\left(\frac{1}{\frac{1}{GSNR_{CH}}+\frac{1}{GSNR_{BC}}+\frac{1}{GSNR_{BD}}}\right) + $$

$$-\begin{pmatrix} FP_{H,dB}+FP_{C,dB}+ \\ FP_{B,dB}+FP_{V,dB} \end{pmatrix} \quad [\mathrm{dB}]$$

$$\Delta\tau(\lambda_{UT}) = \Delta\tau_{CH} + \Delta\tau_{BC} + \Delta\tau_{BD} \quad [\mathrm{ms}]$$

$$D_{acc}(\lambda_{UT}) = D_{acc,CH} + D_{acc,BC} + D_{acc,BD} \quad \left[\frac{\mathrm{ps}}{\mathrm{nm}}\right]$$

V. Curri, Software-defined WDM optical transport in disaggregated open optical networks, ICTON, 2020

SOFTWARE DEFINED OPTICAL NETWORKING

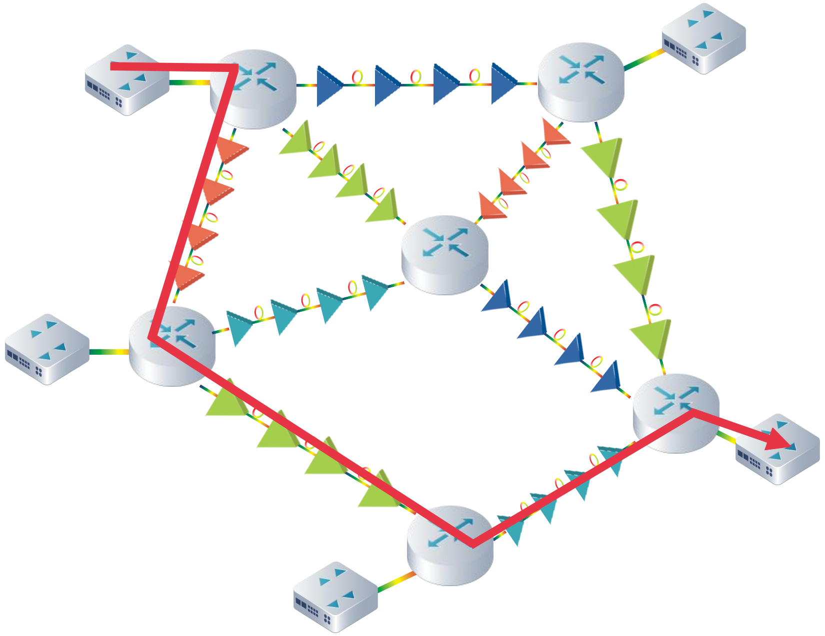
HIERARCHICAL CONTROLLER

OPTICAL CONTROLLER

GNPy

Optical circuits controller

- Centralized
- Global vision
- Find a transparent source-to destination lightpath
- Set swithching matrices
- Evaluate the LP QoT
- Set the modulation format in TRX

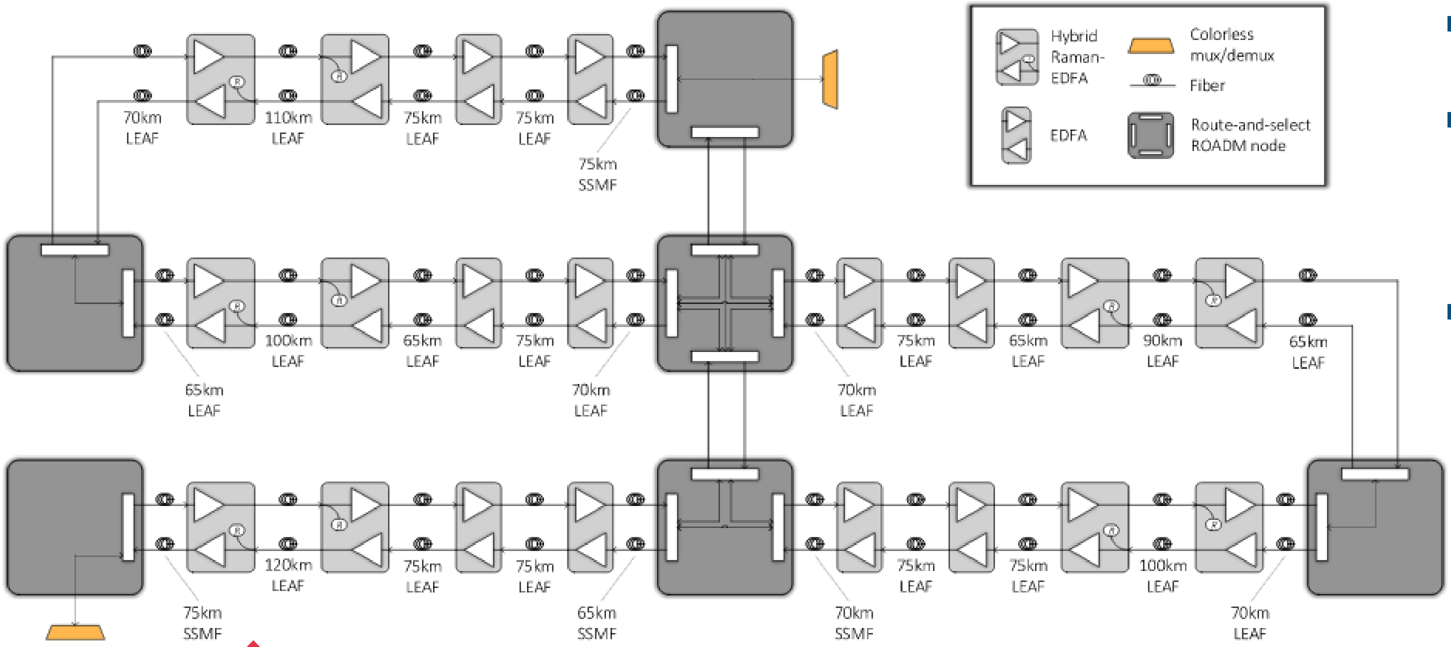


Optical power controllers

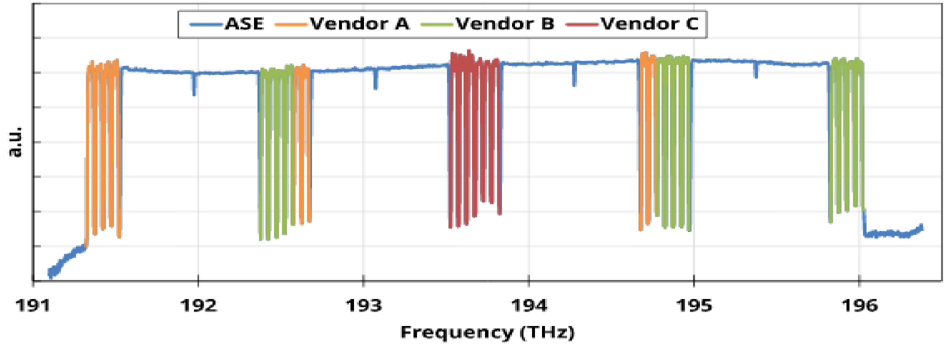
- Distributed
- Local on each OLS
- ROADM-ROADM vision
- Define the optimal power spectral density at fibers input
- Set amplifiers

USING MACHINE LEARNING IN THE DIGITAL TWIN

THE MSFT EST-BED



- 6 ROADMS
- Mixed fiber OLS 400 km up to 2000 km
- Multivendor/multirate/multiformat transceivers on full C-band
- 500+ tested cases



Microsoft SDN Controller

Datasheets

JSON models
- Topology
- HW
- Services

Network Description

GNPy

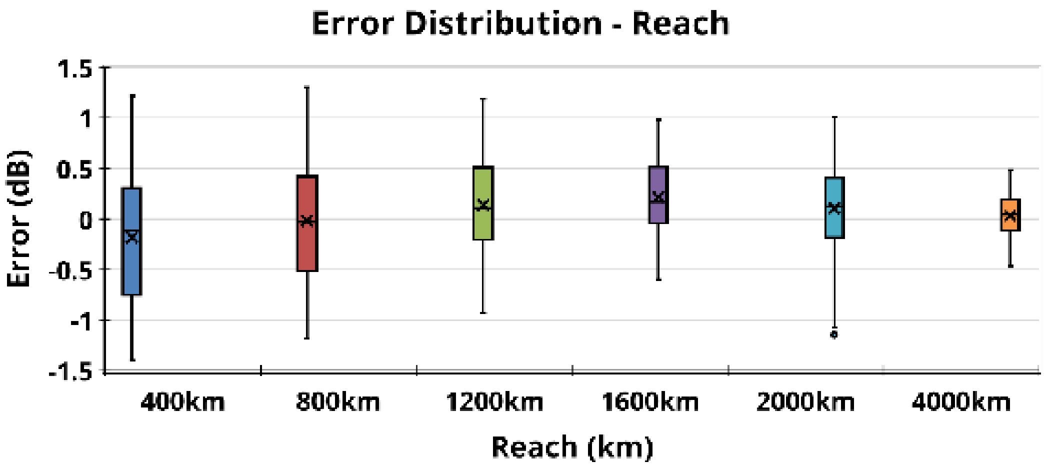
Estimated GSNR

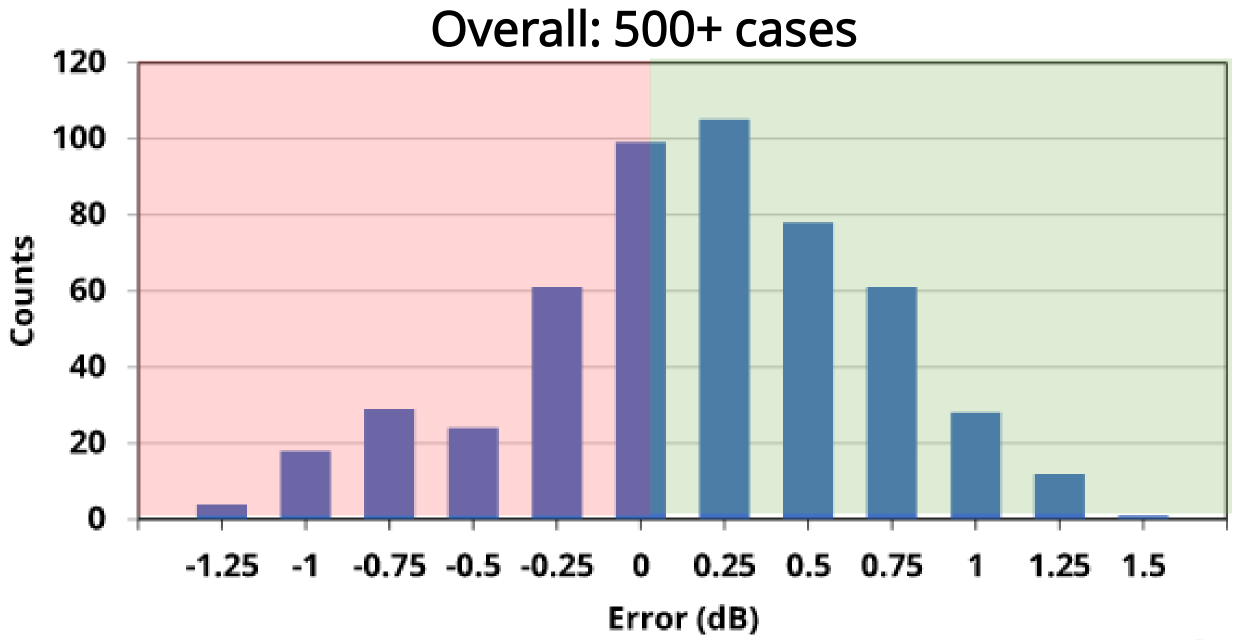
?

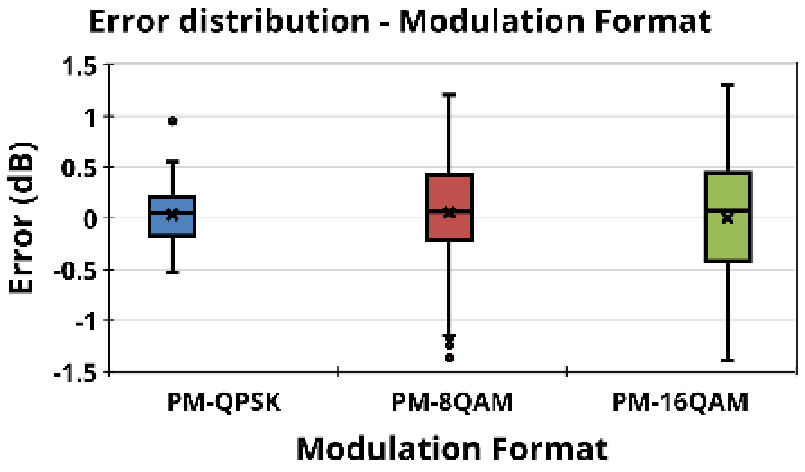
Measured GSNR

GNPy QoT-E ACCURACY

Error = Measured GSNR – GNPy GSNR







- Inaccuracy mainly due to lack of exact knowledge of models for network elements: Machine learning may help
- **Need for dataset!**

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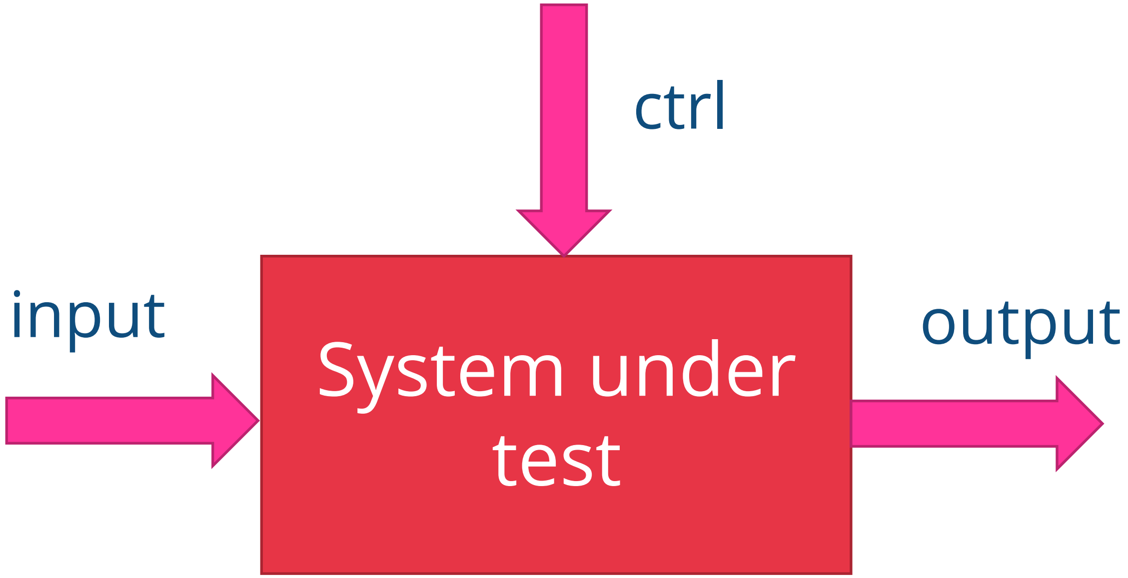
DIRECT AND INVERSE ML MODEL



- Direct ML model: the ML agent is trained in order to predict the I/O behavior given the ctrl
- Inverse ML model: the ML agent is trained to predict the needed ctrl to obtain a wanted I/O behavior

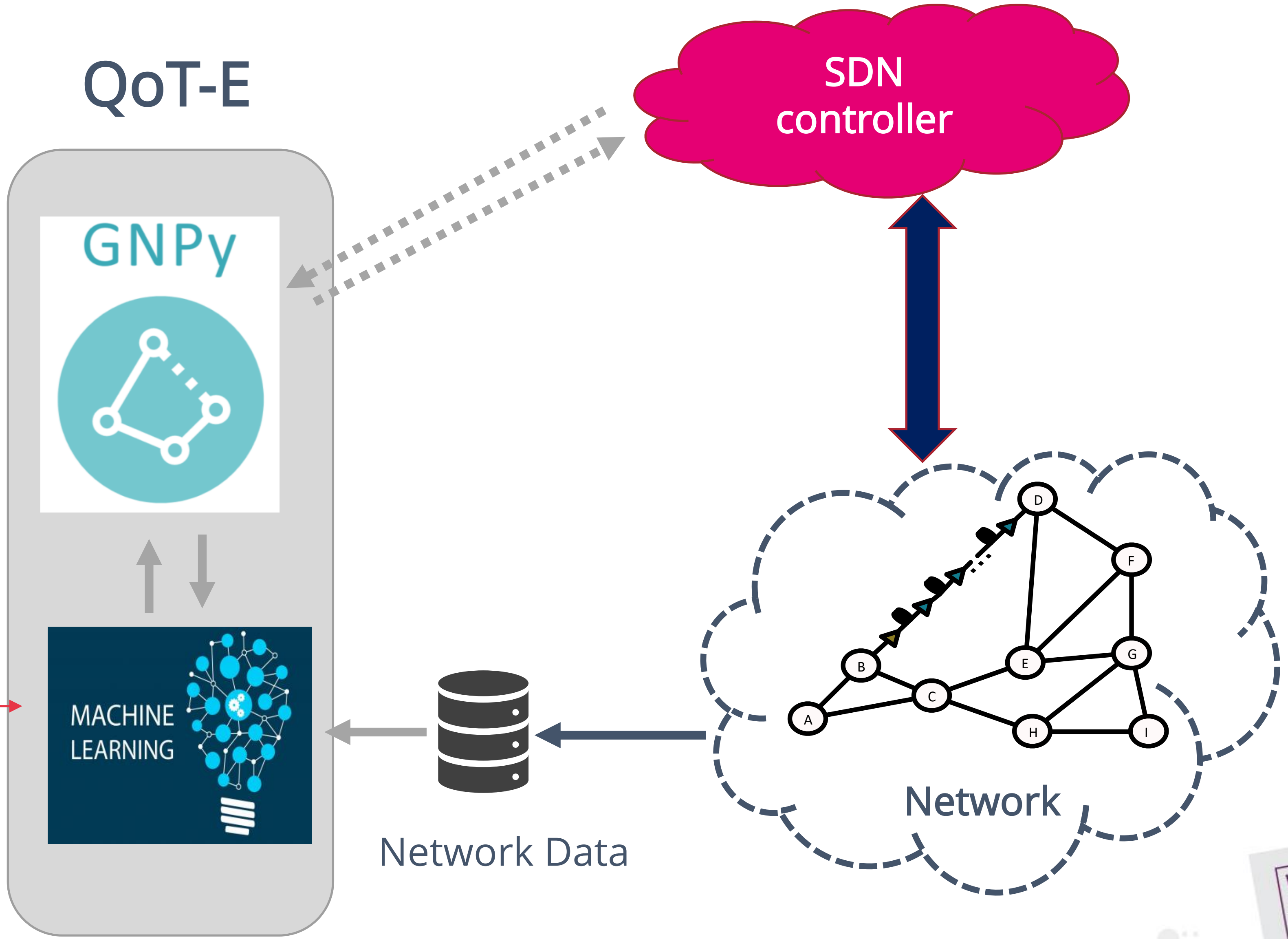
SELF- AND TRANSFER-LEARNING

- The ML agent is trained on the system under test and it is used on that specific systems
- The ML agent is trained on a system, then it is applied to a “sister system”
  - As “sister system” we consider a system we suppose is sharing with the training system most of the fundamental mechanism defining system performance
  - In optical networking, a sister system can be a network using the same HW on a different geographical topology

MACHINE-LEARNING BASED HW MODEL

- A ML model can replace a mathematical model of network elements
- Both inverse and direct ML models are useful to define the needed control (inverse) or the GSNR impairment (direct) of a component
- It can be useful for all NE for which a dataset can be easily obtained before installing the HW as for instance EDFA, switches
- It is more difficult to be applied when we need a dataset from the field

MACHINE LEARNING ASSISTED L-PCE

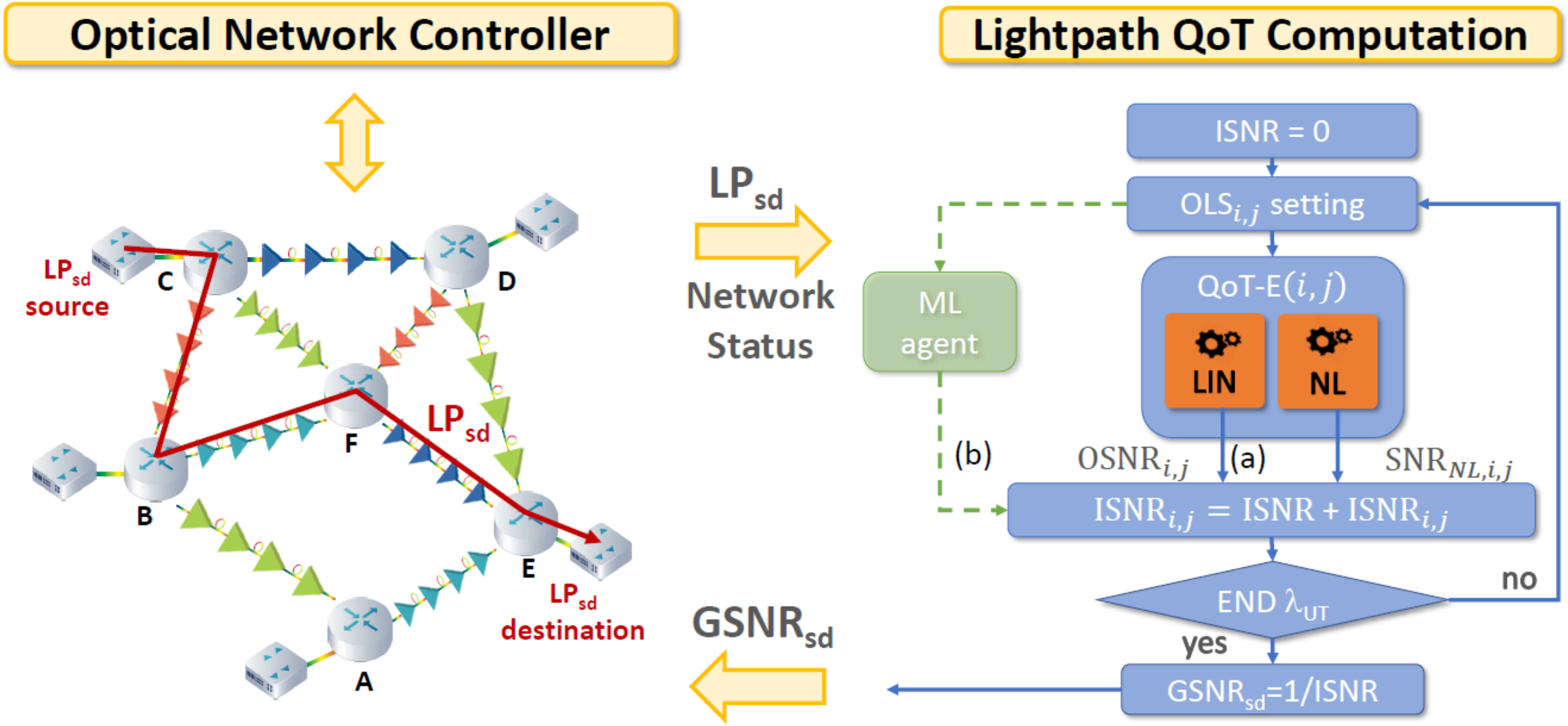


Both self- and cross-training options for training dataset

USING ML TO PREDICT THE OSNR COMPONENT OF THE GSNR: EXPERIMENTAL PoC

ENHANCING GNPy WITH MACHINE LEARNING

ML agent trained by ASE shaped noise do predict the OSNR



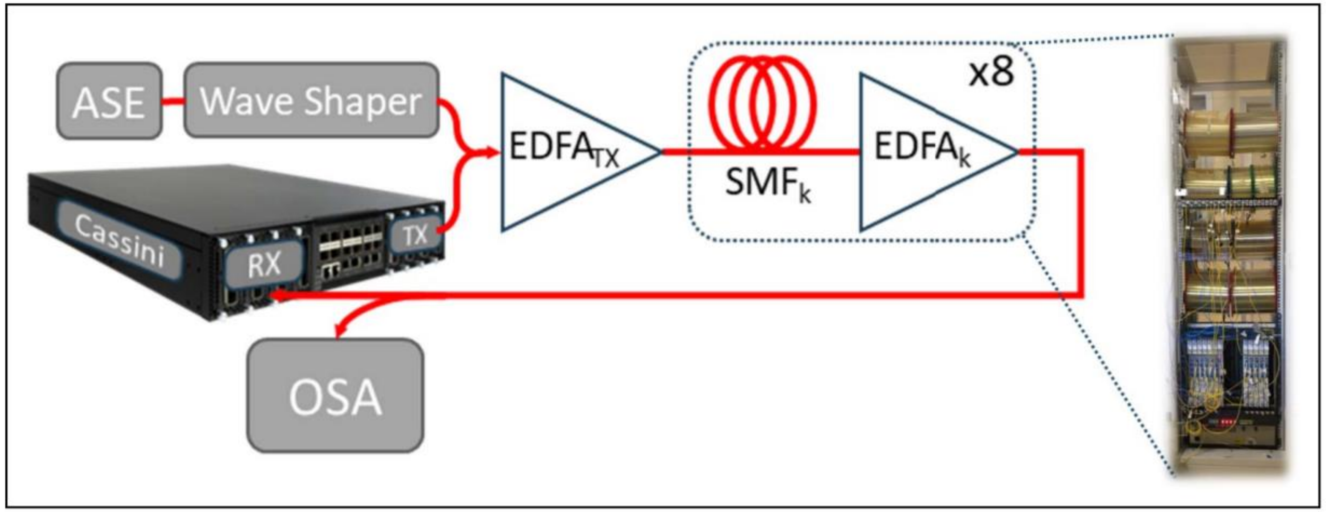
A. D'Amico et al, Enhancing Lightpath QoT Computation With Machine Learning in Partially Disaggregated Optical Networks, IEEE OJCS, 2021

APPLICATION SCENARIO

- Reliable QoT computation with different spectral load
- Optical amplifiers may strongly vary their performance with the spectral load given the control
- We suppose that amplifier are not reachable individually
- We suppose to be able to collect a data set with different input spectral loads obtained by ASE shaping
- We suppose to rely on optical channel monitors at the input and output OLS ROADMs
- We target to train a ML agent that replaces the evaluation of the OSNR component of QoT by GNPy

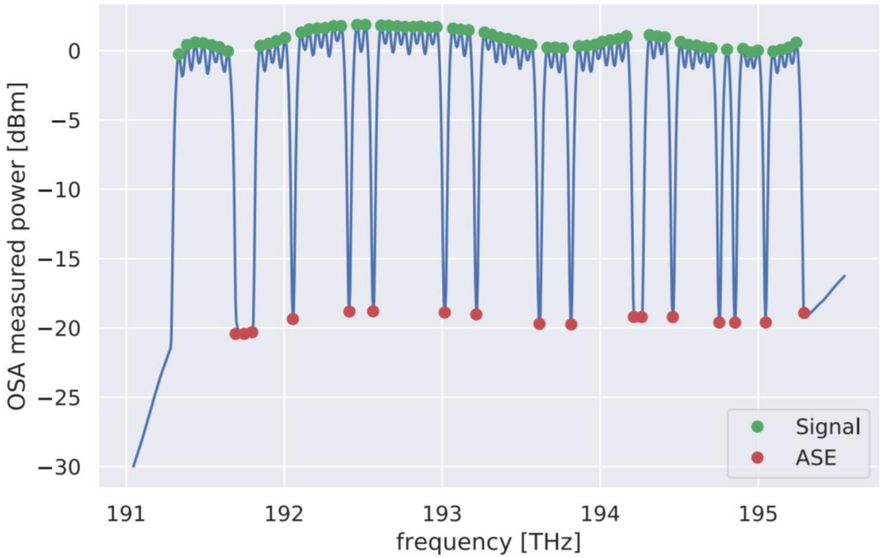
EXPERIMENTAL SET-UP AND DATASET

EXPERIMENTAL SETUP



- 8 span line
- Commercial amplifiers set to the optimal working point according to nominal values
- Waveshaper micking ROADM in generating shaped noise
- OSA at the receiver mimicking the OCM
- Two pluggable DCO to test the effectiveness on the method

DATASET



- Waweshaper to generate different spectral loads (96 ch in the C-band)
- 2520 spectral load configurations
- For each we collect
  - the amount ASE noise for the OFF channels
  - the overall gain for ON channels

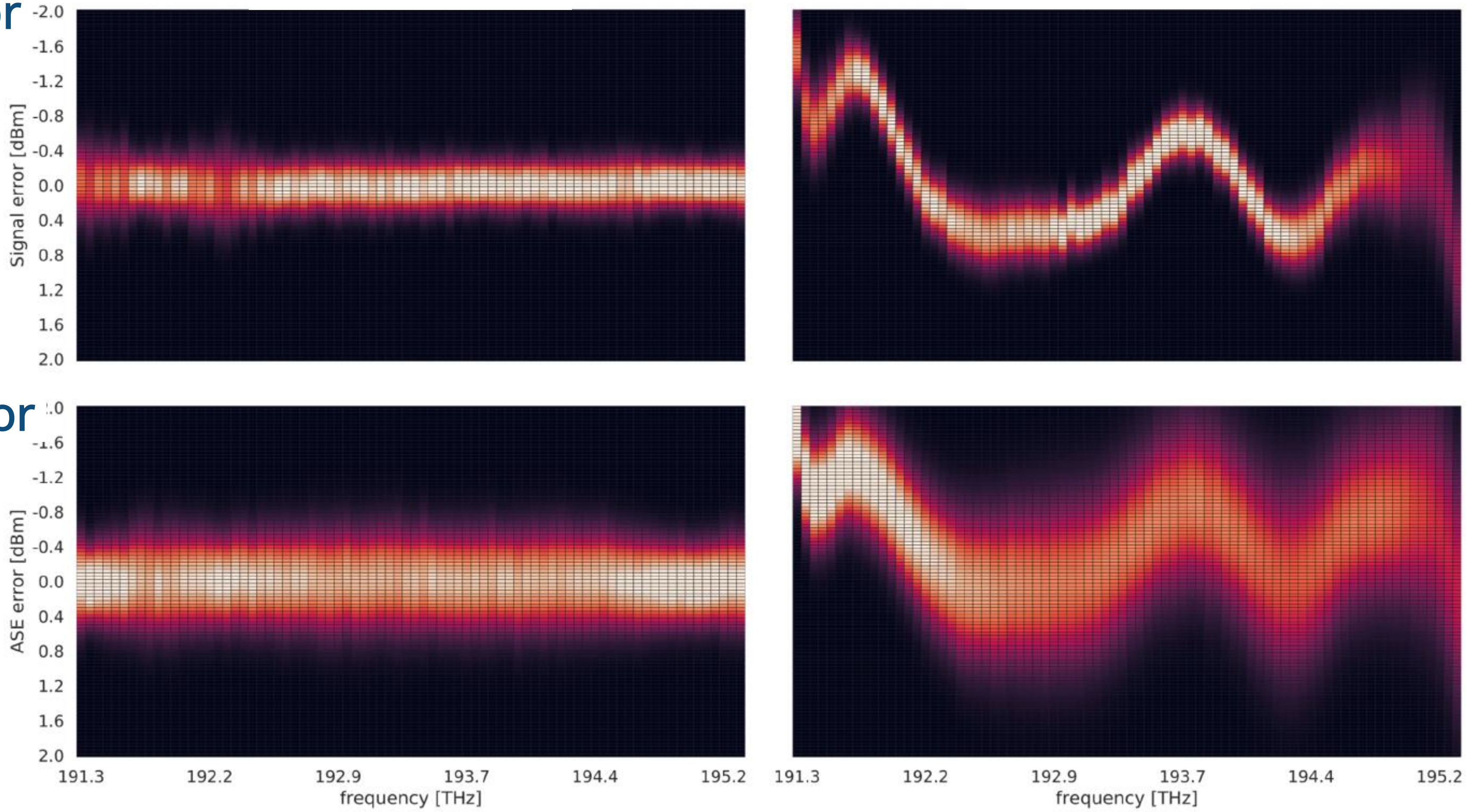
PERFOMANCE OF TRAINED MACHINE LEARNING AGENT FOR OSNR PREDICTION

PREDICTIONS BY THE ML AGENT

PREDICTIONS USING NOMINAL G AND NF FOR EDFA MODEL

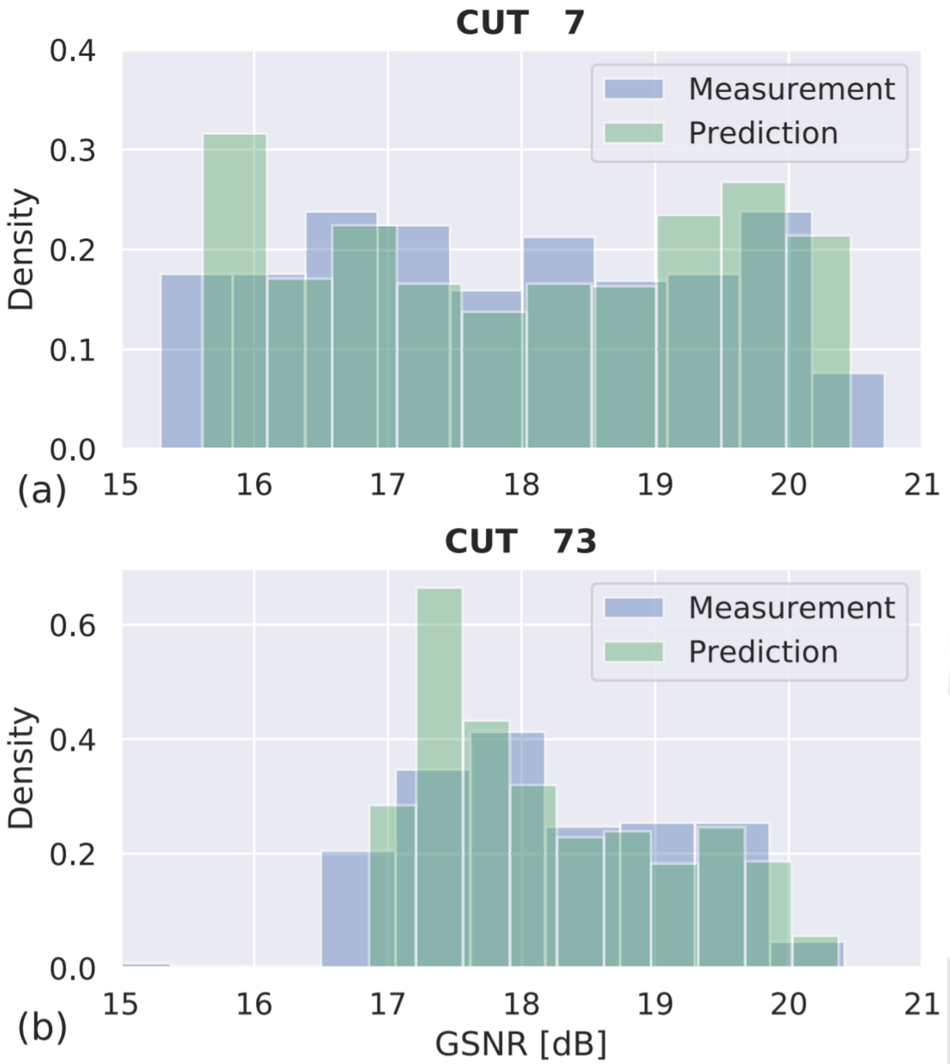
Signal level error [dB]

Noise level error [dB]



GSNR COMPUTATION: GNPy + ML AGENT

- The ML agent to predict the OSNR is used within GNPy to predict the overall GSNR
- Prediction results are compared to measurements obtained by testing two modulated channels on two channels: 7^{th} and 73rd
- GSNR is obtained from pre FEC BER measurement converted to GSNR by b2b characterization
- Large set of spectral load is tested



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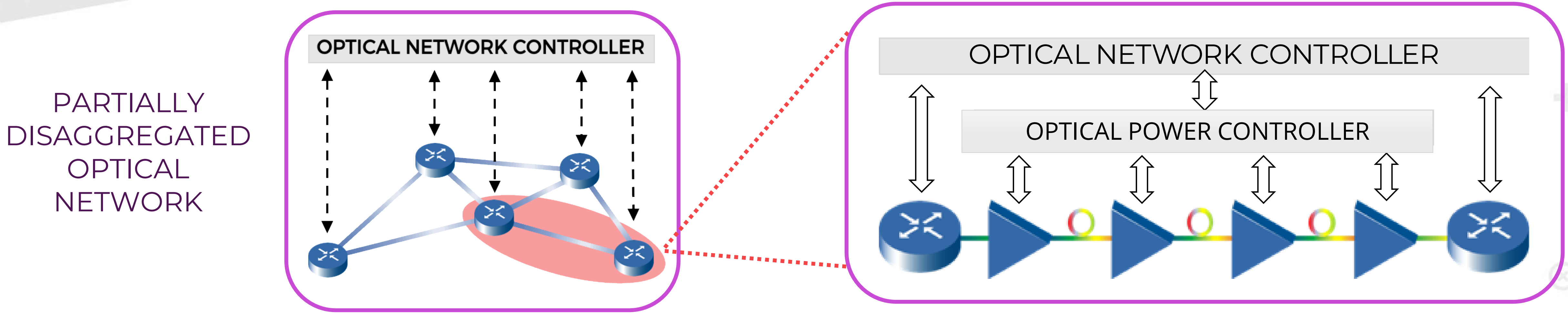
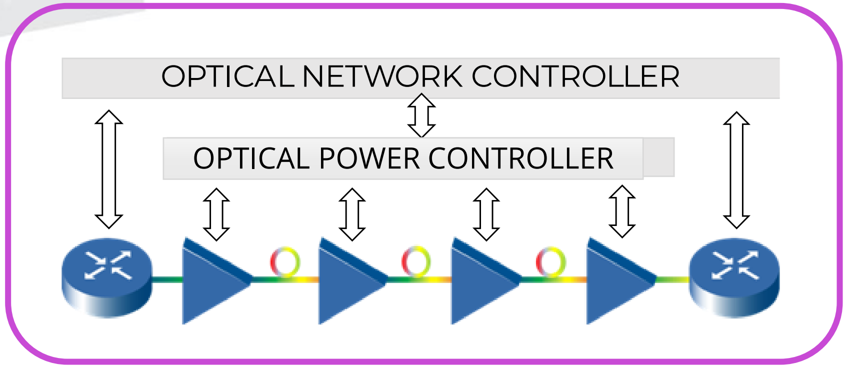
NON DATA-DRIVEN COGNITIVE AND AUTONOMOUS OPTICAL POWER CONTROLLER

OPTICAL POWER CONTROLLER



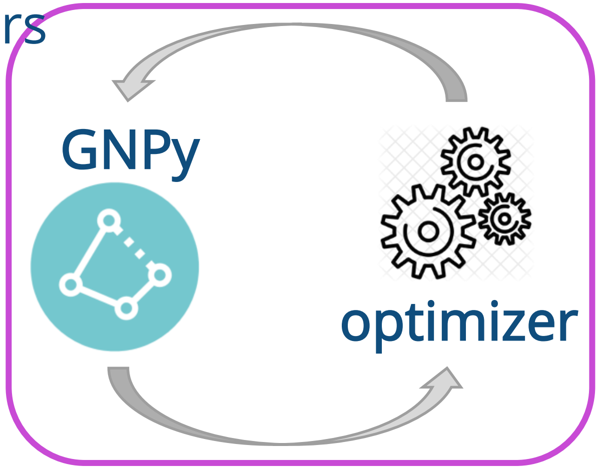
- The OPC sets the working point (e.g, gain and tilt) of OAs in the OLS
- In partially disaggregated network, independent OOPC for each ROADM-to-ROADM OLS
- The purpose is to minimize the propagation impairment on any LP propagating on the OLS
- The OPC is typically static and traffic agnostic

OPC BASED ON GNPy



- Line model
- OA model
- Data from monitors

Optimal OA settings



- Feeding GNPy with OA models and possible data from monitors
- Possible training or probing phase
- GNPy computes the GSNR for every frequency varying the OA setting
- An optimizer engine drives the process to the optimal setting given the target
- Typical targets
  - Maximizing GSNR: Max{<GSNR(f)>}
  - Flattening GSNR: Min{<|GSNR(f)-<GSNR>|>^{2}}

QoT-E FOR OPC: INPUT DATA

INPUT → GNPy →

$$GSNR(f) = \frac{1}{\frac{1}{OSNR(f)} + \frac{1}{SNR_{NL}(f)}}$$

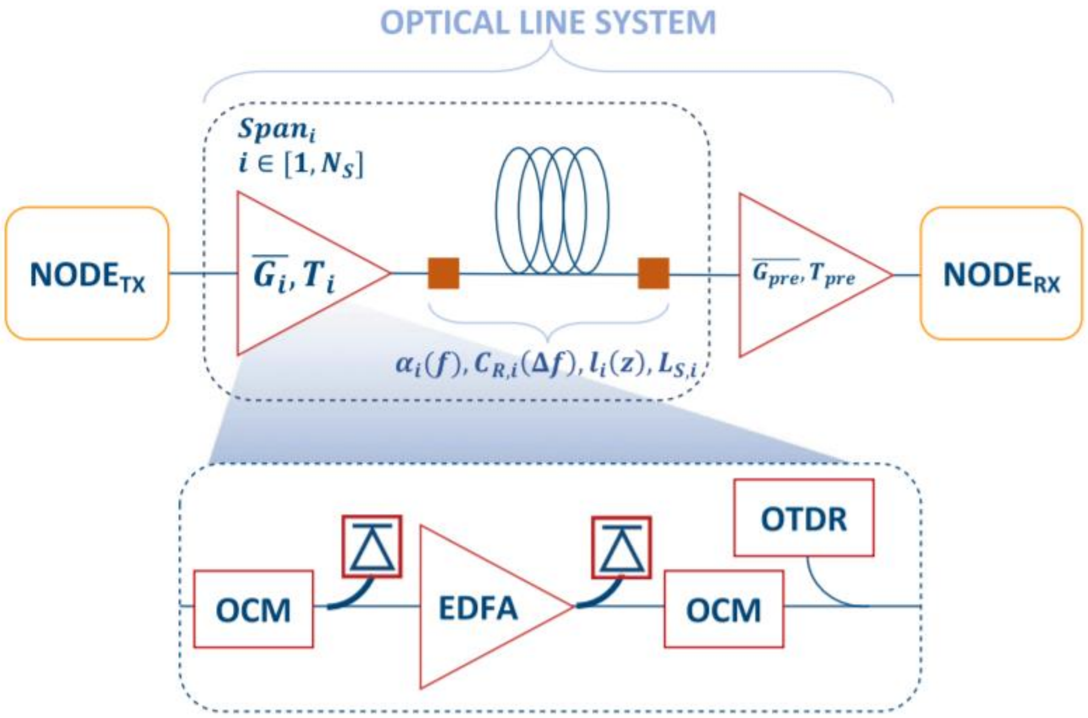
- OSNR(f)← OA model
    - Gain(f) and NF(f) for every power level and gain and tilt setting
    - OA model
        - from accurate characterization (look-up table
        - from trained ML agent
- $SNR_{NL}(f)$
    - Need accurate line description
    - Fiber type (α(f), D(f) A_{eff}) and length
    - Connector losses
    - IMPOSSIBLE TO GET A DATASET FOR DATA DRIVEN APPROACH BECAUSE IT NEEDS DEPLOYED CHANNELS

AUTONOMOUS LINE CHARACTERIZATION

JOURNAL OF
Optical Communications
and Networking

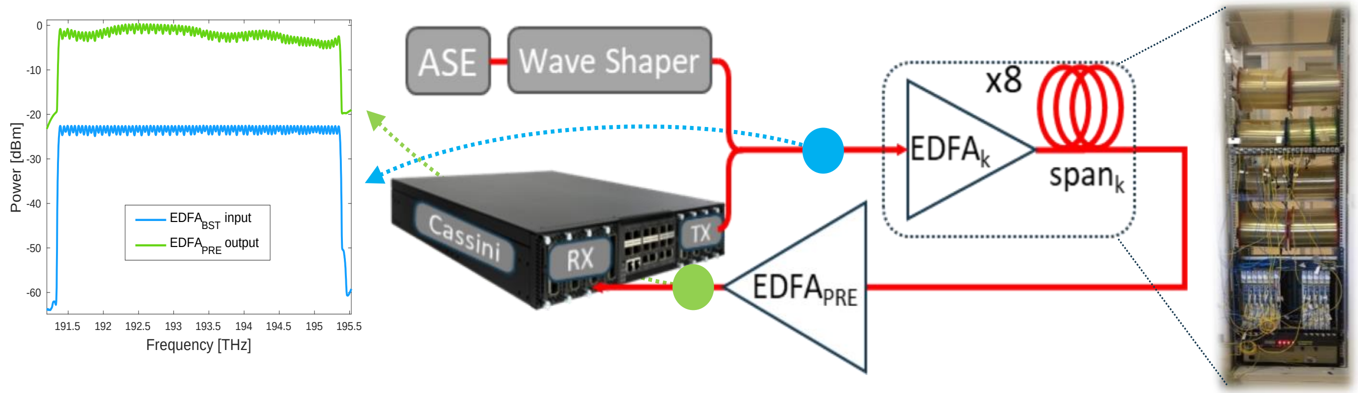
Cognitive and autonomous QoT-driven optical line controller

Giacomo Borraccini,[1,*] Andrea D'Amico,[1] Stefano Straullu,[2] Antonino Nespola,[2] Stefano Piciaccia,[3] Alberto Tanzi,[3] Gabriele Galimberti,[3] Stefano Bottacchi,[4] Scott Swail,[4] and Vittorio Curri[1]



- Suppose to rely on OCM and OTDR
- Need for a single probing action
- Evolutionary algorithm to classify each fiber span to obtain $\alpha(f)$, D(f) A_{eff}, Lspan
- NOTE: probing can be done after every fiber cut

EXPERIMENTAL PoC



- Amplifiers → *commercial EDFAs*
  - Lab characterized
- Fibers → *8 spans of roughly 80 km*
  - Physical characteristics:
    - Attenuation profile
    - Chromatic dispersion
    - Kerr effect
    - Stimulated Raman scattering

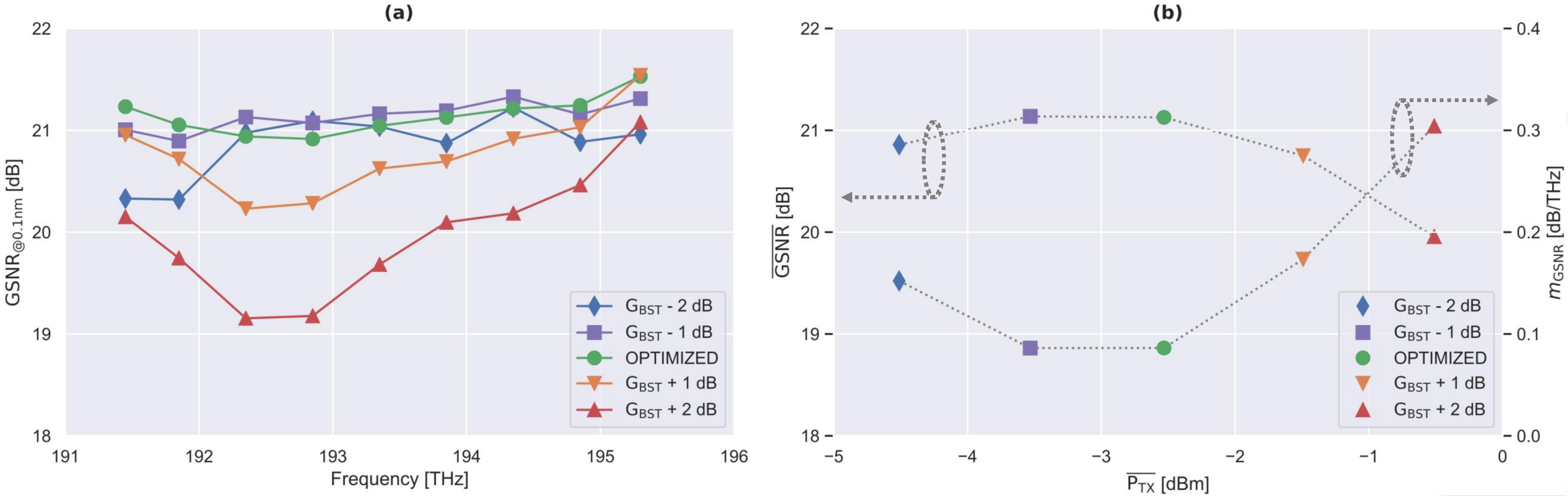
- Input WDM Spectrum → ***80 ASE-shaped channels*** through a ***commercial wave shaper filter*** (1000S, Fisinar)
- *Modulated channels* → generated by flexible **CFP2-DCO coherent modules** from Lumentum plugged in the Edgecore Cassini AS7716-24SC

AUTONOMOUS CHARACTERIZATION RESULTS

Span	L_S [km]	C_R [(W · km)$^{-1}$]	D [ps/(nm·km)]	$\alpha(f_{OTDR})$ [dB/km]	$l(z=0)$ [dB]	$l(z=L_S)$ [dB]
#1	80.4	0.42	16.7	0.191	0.9	0.1
#2	80.4	0.54	3.8	0.194	2.0	1.0
#3	80.6	0.60	8.0	0.188	0.6	0.3
#4	79.9	0.73	4.4	0.196	0.1	3.6
#5	79.8	0.60	8.0	0.199	0.1	2.3
#6	75.8	0.73	4.4	0.210	1.7	0.4
#7	64.7	0.44	16.7	0.189	0.2	3.0
#8	78.6	0.54	3.8	0.187	0.3	0.1

EXPERIMENTAL PoC: RESULTS

- Using autonomous line characterization Gain and tilt of each amplifier are jointly optimized
- Results are tested using modulated channels generated by pluggable DCO tuned on 9 different wavelength in the C-band



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CONCLUSION

- Coherent optical technologies enable Software-Defined Optical Networking
- Abstraction and virtualization of WDM optical transport is based on accurate QoT-E
- Lacking knowledge of exact models for physical layer: mainly, amplifiers and fiber span
- If dataset are available or can be obtained, ML mdels of NE or subsystem is extremely effective
- If dataset are difficult to get or scenario varies with time, autonomous technics are needed and proven effective

THANK YOU FOR YOUR ATTENTION

CONTACTS

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