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Optical Communications Group

How IBN can be Embedded within Optical Transport Networks

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Invited Tutorial

Abstract

❖ Deployment of business intent across the optical network through policies for automated management is introduced through illustrative examples spanning from connection provisioning, dynamic network adaptation, and connection degradation and failure localization.

Motivation

- Operators' network management continuously measure network health by collecting data from the deployed network devices.
  - Data are used mainly for performance **reporting,** diagnosing problems **after failures**, and to **predict future traffic growth** for planning.
- Network management is typically **reactive** and requires significant human effort and skills to operate effectively.
- As optical networks evolve to fulfil highly flexible connectivity and dynamicity requirements, they must also provide **reliable connectivity** and **increased** network resource **efficiency**.
- Future optical networks must support **fully automated management**, providing:
  - **dynamic** resource re-optimization to rapidly adapt network resources based on **predicted** conditions and events
  - identify service **degradation** conditions that will impact connectivity and **highlight** critical devices and links for further inspection
  - **Activate recovery** if a failure is predicted or detected and facilitate **resource optimization after restoration** events.
- IBN is the automation of deploying business intent across a network through policies.

Monitoring and Data Analytics for Optical Networking

L. Velasco et al., "Monitoring and Data Analytics for Optical Networking: Benefits, Architectures, and Use Cases," IEEE Network Magazine, vol. 33, pp. 100-108, 2019.

Illustrative Use Cases

Use Case 1:
Network planning and provisioning
with reduced margins

Use Case 2:
Dynamic Network adaptation

Use Case 3:
Lightpath degradation
and failure localization

Use Case 1: Network planning and provisioning with reduced margins

Use Case 1:
Network planning and provisioning
with reduced margins

Use Case 2:
Dynamic Network adaptation

Use Case 3:
Lightpath degradation
and failure localization

Description	Expected Benefits	Modeling and Parameters involved
Application of **just enough margin** in the network design and in lightpaths provisioning.	**CAPEX saving** opportunity by avoiding or postponing unnecessary investments at a given time.	Attenuation, dispersion and other **fiber parameters**, the **noise figure** of amplifiers, **WSS passband**, the **sensitivity of TPs**, etc. Those parameters can be used together with an **analytical model** to estimate the QoT of lightpaths accurately. ML-based methods to **predict** the **probability** that the **QoT** of a candidate lightpath will not **exceed** a defined **threshold**.

Use Case 2: Dynamic Network adaptation

Use Case 1: Network planning and provisioning with reduced margins

Use Case 3: Lightpath degradation and failure localization

Use Case 2: Dynamic Network adaptation

Description	Expected Benefits	Modeling and Parameters involved
Leveraging on **configurable TPs** the allocation of just enough data rate for any connection at any time to cope with **traffic dynamics** at **minutes** or **hours** scale.	Better exploitation of network resources and potential savings by **reducing** the typical **overprovisioning** of static allocation.	Use of **models** to evaluate the expected **QoT** of a lightpath at any **new TP configuration**. Use of models for **traffic analysis** to evaluate traffic trends and periodicity.

Use Case 3: Lightpath degradation and failure localization

Use Case 1: Network planning and provisioning with reduced margins

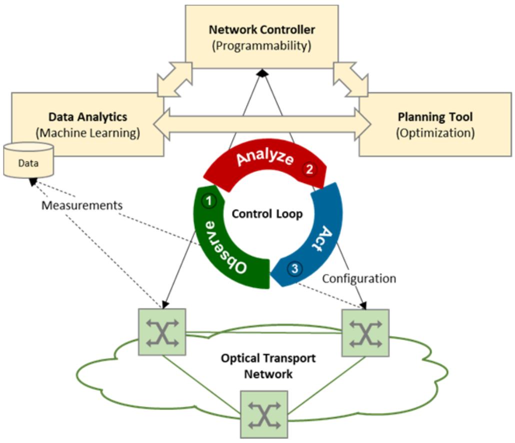
Use Case 3: Lightpath degradation and failure localization

Use Case 2: Dynamic Network adaptation

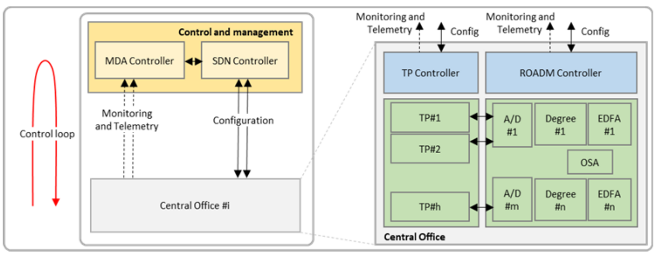
Description	Expected Benefits	Modeling and Parameters involved
QoT reduces over time due to network and device **degradation, ageing**, or **load increasing**.	Degradation **anticipation** allows appropriately **tune systems' parameters** before alarm triggering. **Localizing** the element responsible for a degradation **facilitates** network **maintenance** by planning a human intervention.	**Predictive analysis** based on QoT evolution. **Localization** based on the **per-system analysis**. Algorithms that find the potential cause of the failure.

MDA enables OAA control loop implementation

- The analysis of the collected data can **discover knowledge** and use it to proactively **self-configure and self-tune** the network in a cost-effective (near) real-time manner by adapting resources to future conditions.
- OAA control loops can be enabled, where **outcomes of data analysis** can be used for event notifications together with **recommended actions** to the SDN controller.
- ML models can be estimated from monitoring data to **feed planning tools** to compute optimal solutions for the expected future conditions.



Centralized MDA Architecture



Features	Strengths	Weaknesses
• Includes a **centralized** MDA system with a data repository for monitoring/telemetry data where data analytics can be applied. • Monitoring and telemetry **activation and deactivation** can be managed by an external system, e.g., the NMS.	• Data analytics results can be used for network **self-adaptation** to changing conditions. • **Interfaces** with the SDN controller (and NFVO) can be **easily standardized**.	• Different monitoring / telemetry protocols need to be **available at the MDA controller**. • The **amount of data** to be collated increases exponentially to keep low reaction times against degradations. • **Configuration tuning** through the **SDN controller only**.

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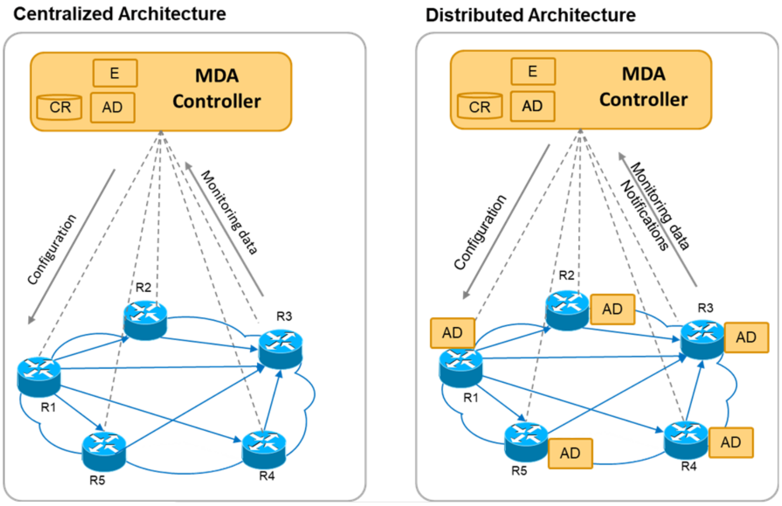
Bringing Data Analytics to the Network Nodes



A. P. Vela et al., "Distributing Data Analytics for Efficient Multiple Traffic Anomalies Detection," Elsevier Computer Communications, vol. 107, pp. 1-12, 2017.

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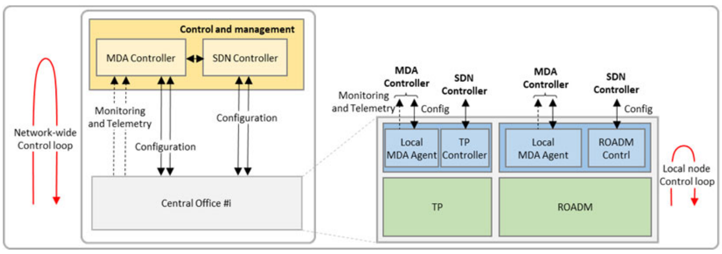
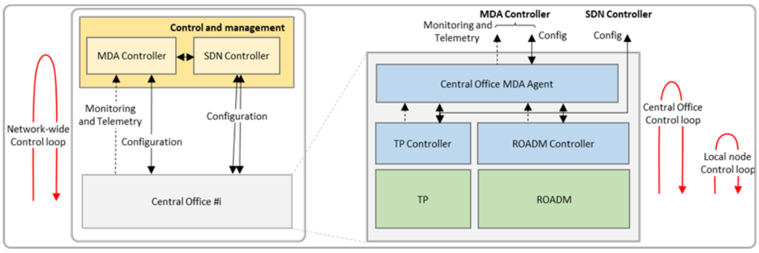
Distributed MDA Architecture



Features	Strengths	Weaknesses
• Allows **data analytics** to be **applied** within the MDA agents, **close to the network nodes**. **Control loops can be implemented locally at the node level**. • Monitoring and telemetry activation / deactivation is **managed by the MDA controller**.	• **Supports configuration tuning**. • It **reduces data to be conveyed** to the MDA controller since pattern recognition can be performed by the MDA agents. • MDA agents expose **one single monitoring and telemetry interface** to the MDA controller.	• A **configuration interface** needs to be defined between the MDA controller and the agents. • **More complex MDA controller** as more features are added, like monitoring/telemetry control, and configuration tuning.

Hierarchical MDA Architecture

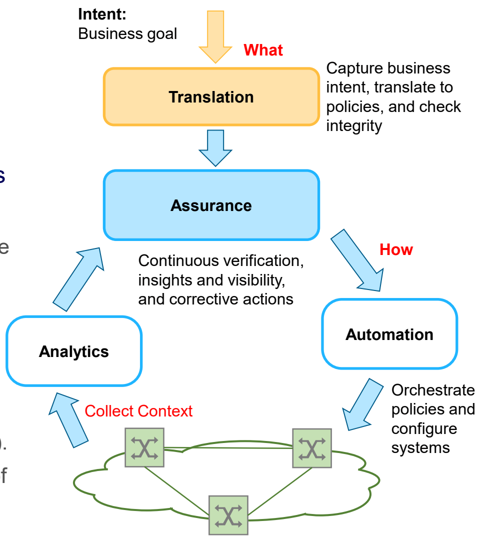


Features	Strengths	Weaknesses
• It includes a **per-CO MDA agent** that connects to all the nodes in the CO.	• **Control loops** can be implemented at the **node**, as well as at the **CO level** involving more than one node. • **Appropriate for node disaggregation scenarios**, where monitoring devices can be installed in one node, but configuration tuning needs to be done in a different node. • It **reduces** the total **number of agents** and the **number of interfaces** toward the MDA controller.	• Requires **more complex MDA agents** to consider complex relations among nodes.

Intent-Based Networking

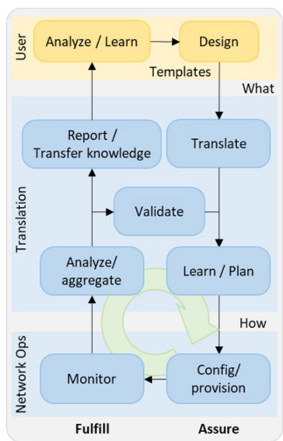
From WHAT to HOW

- IBN abstracts network complexity and improves automation by eliminating manual configurations.
- Administrators state higher-level business policies (**what**), and the intelligence of the system then decides **how** to meet them.
  - A **translation and validation** system take the desired outcome (e.g., service level) (what) as input and converts it to the necessary network configuration (how).
  - Defined policies are **automatically** enforced.
  - Data is gathered to constantly monitor network operations (**awareness of state**).
  - ML **enables** automated implementation of **policies** and **corrective actions**.



Deployment

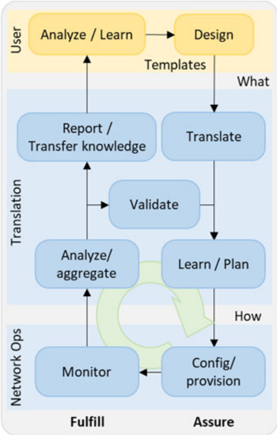
- Service definition uses templates (e.g., TOSCA) to define resources and relationships for the service.
  - The Intent is specified in terms of **policy rules** that guide the service behavior, including the **applications**, **analytics** and closed control loop **events** needed for the **elastic management** of the service.
- The intent is translated into:
  - a **network configuration** and a **set of policies** that the IBN verifies to ensure that such policies can be executed.
  - a **ML pipeline** associated to the service.
    - o The ML pipeline consists of a set of ML nodes (e.g., collectors, pre-processors, models, policies, etc.) that are combined to form an analytics function and are managed by a MLFO and hosted in a variety of NFs.
- Based on AI/ML algorithms, IBN suggests the optimal network configuration for the services and the associated ML pipeline prior to deployment.



Assurance

❖ The service assurance system makes sure that the network **continues to deliver on that intent** with the help of AI/ML algorithms.

- ML training can be carried in an **ML sandbox domain** and be based on data from the network and simulation.
- The target is to deal with scaling or reallocating resources, as well as healing and recovery.
- Reporting generates descriptive outputs, e.g., statistical summaries and knowledge transfer of main service KPIs.



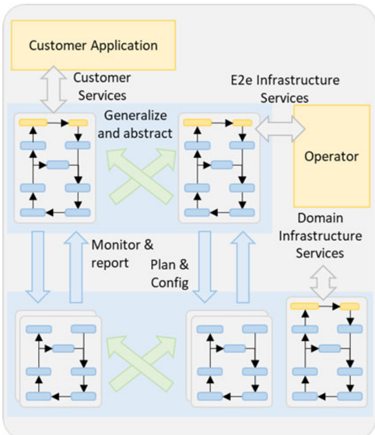
Intent Coordination

❖ **Infrastructure intents** target at providing services that **customer intents** use.

- Customer and infrastructure (N-S) coordination is required.

❖ E-W horizontal coordination is also needed in multi- domain/technology scenarios.

❖ Transfer knowledge/learning techniques can be used.



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MLFO Requirements

- **Multiple sources of data** to take advantage of correlations in data.
- **Multiple technologies and network layers** to achieve e2e user experience
- **Multi-level and distributed** instantiation of the ML pipeline
- ML-pipeline and network service will be as **decoupled** as possible
- Flexible implementation in terms of **splitting** of logical nodes in the ML-pipeline
- Transferring data and trained ML models through **Interface 8**
- **Heterogeneous Interfaces** based on existing or extended interfaces
- ML-ML for **specifying the use case** and translating such specifications into intents
- **Dynamic ML model selection** based on data from the source
- Defining **sandboxes for model training** and host simulators in the sandbox
- Enabling **control loops**
- Using **MLFOs** for monitoring and managing ML-pipelines
- **Plug-in/out data sources** to a running ML-pipeline
- **Sharing data** between nodes in the ML-pipeline.

"Unified architecture for machine learning in 5G and future networks," Focus group on Machine Learning for Future Networks including 5G, ITU-T, 2019.

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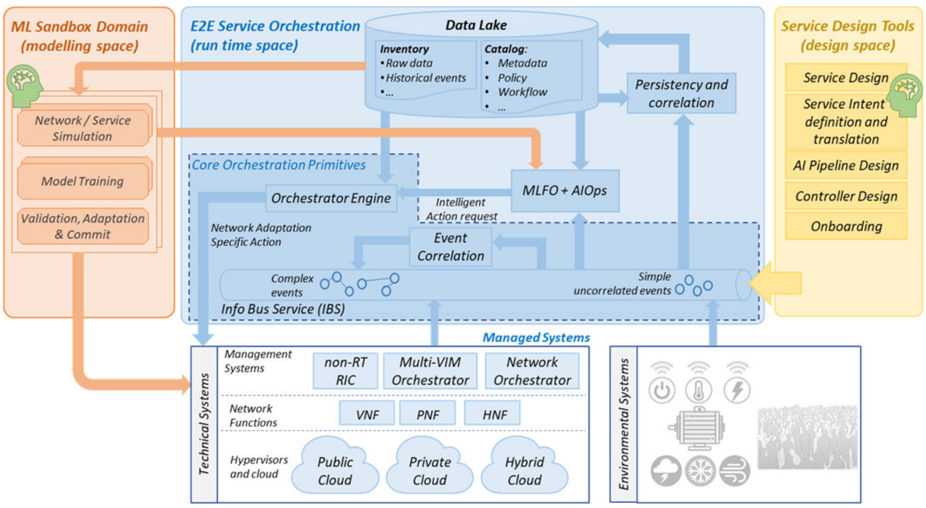
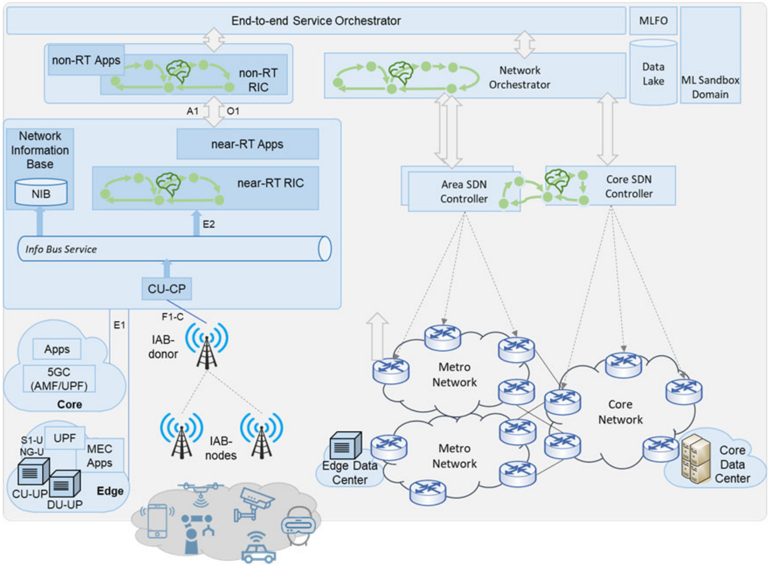
E2E Service Orchestration Architecture



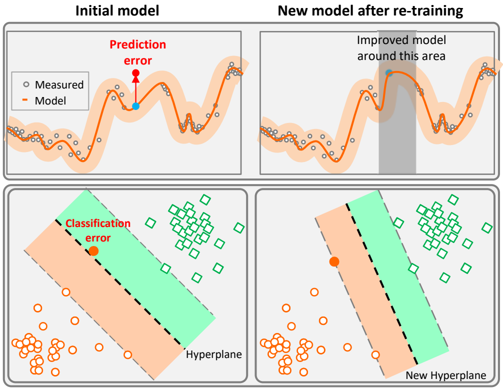
B5G Autonomous e2e Control and Orchestration



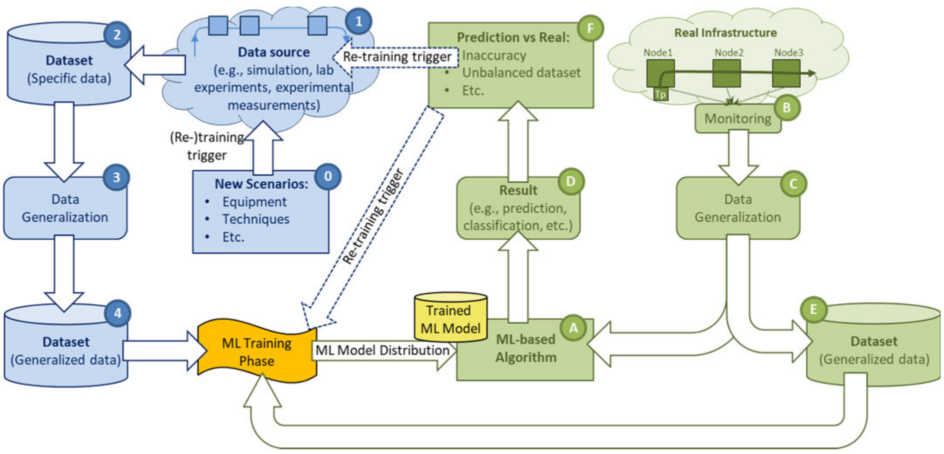
Applications: Collaborative Self-Learning

Motivation

- **Autonomic operation** of optical transmission and networking requires from **ML-based algorithms**.
  - **ML models** require **training** datasets covering the **whole features space** to produce accurate ML models.
  - The **availability** of enough **data** is **rarely ensured**
  - Training datasets **cover just partially the features space**, hence reducing ML models accuracy.
- Datasets can be initially populated for ML training. Once models are generated, **ML re-training** can **improve** their **precision**.

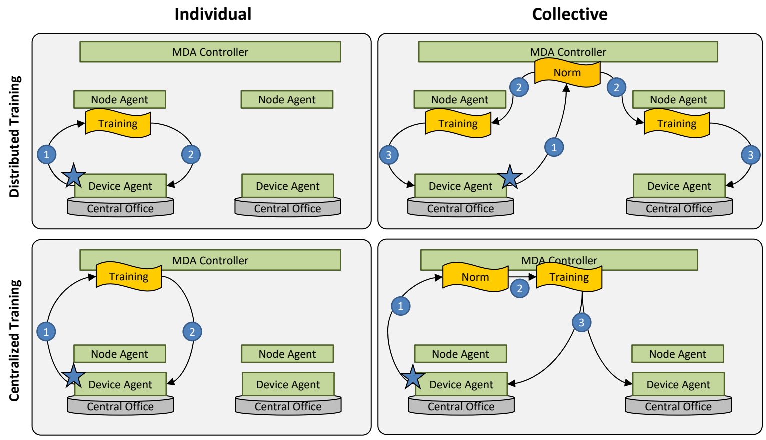


ML-based algorithm life-cycle



L. Velasco *et al.*, “A Learning Life-Cycle to Speed-up Autonomic Optical Transmission and Networking Adoption,” in IEEE/OSA Journal of Optical Communications and Networking, vol. 11, pp. 226-237, 2019.

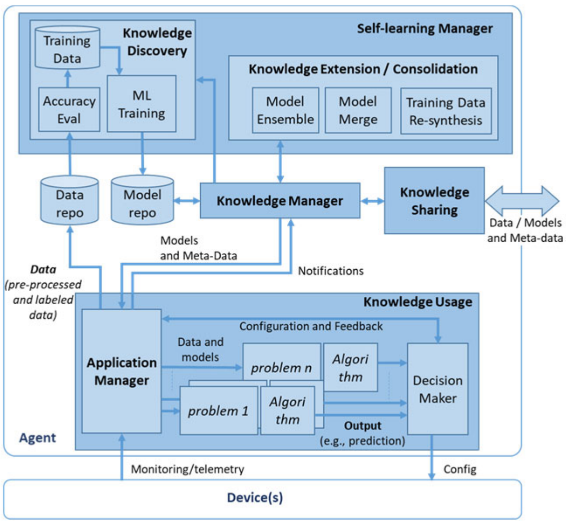
Self-learning



- Collective self-learning outperforms individual strategies…
- …. at the cost of increasing data to be exchanged.

Collective Self-Learning based on Sharing Models

- Collective self-learning based on ML model sharing and combination can **reduce the amount of data** being shared among agents.
- The architecture allows a wide range of ML model combination alternatives
  - **ML training** can be executed either in the **node agent** or in the **controller**
  - **Once trained**, ML models can be **deployed** to the **device agents**.



M. Ruiz et al., "Knowledge Management in Optical Networks: Architecture, Methods and Use Cases [Invited]," IEEE/OSA Journal of Optical Communications and Networking, vol. 12, pp. A70-A81, 2020.

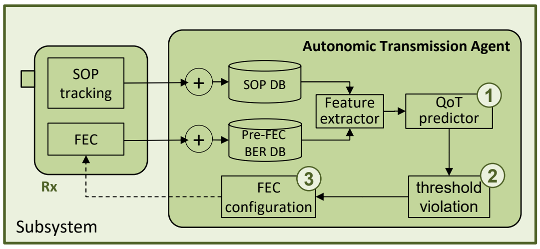
Example: The Autonomic Transmission Use Case

❖ We assume scenarios where **low-resolution ADCs** are used.

- The **evolution** of the **SOP** and the **pre-FEC BER** (last samples in a window) are used for **dynamic receiver configuration** anticipating **BER degradation** (# iterations of FEC algorithm).

❖ Three different ML-based problems need to be continuously solved:

1) a **regression** model that estimates future pre-FEC BER
2) a **probabilistic estimator** of the chance of **violating** a given BER threshold
3) a **classifier** to determine e.g., the number of iterations of soft-decision FEC to run.

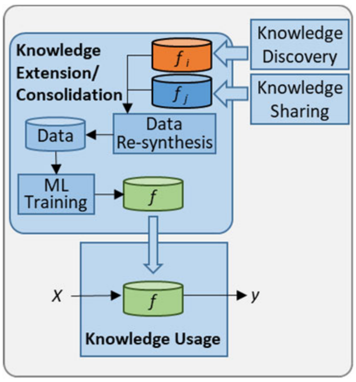


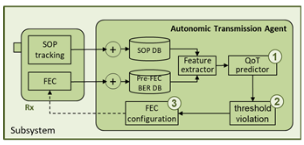
Retraining with data re-synthesis

❖ It consists in generating the response from the shared individual ML models in the given features range to obtain a **synthetic training dataset** from which a new ML model is trained.

❖ The local data re-synthesis from ML models avoids exchanging large amounts of monitored data among nodes and/or to the controller.

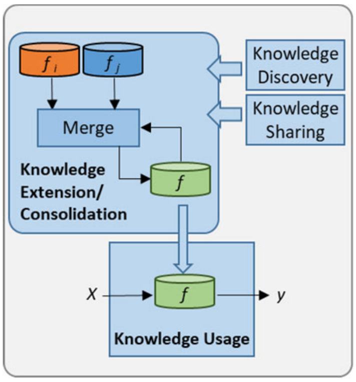
❖ We use re-training with data re-synthesis for the ANN-based pre-FEC BER estimator (1).

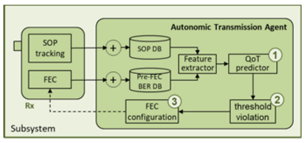




Model Merge

- It merges individual ML models to obtain one single enhanced model.
- It can provide benefits **when model parameters can be partially updated** without affecting the robustness and accuracy of the non-updated part.
- We use model merging in the probabilistic BER threshold violation estimator (2) that it is based on a DT.
  - Model merge can enhance the ML model, e.g., by updating probabilities of leaf nodes and/or extending a new sub-tree (branching) from a leaf node.





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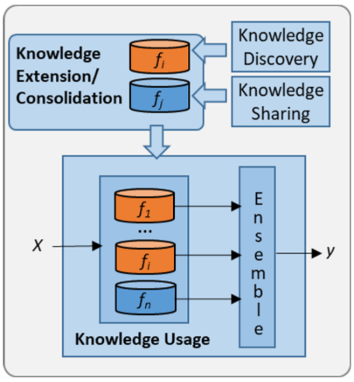
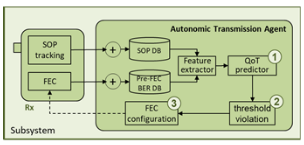
Model Ensemble

- It combines the prediction of several individual ML models and returns one single output.
  - Meta-data can include weights and/or the features range observed during model training.
- It can be applied to any ML technique or a combination of them.
- It requires **low computational effort** to apply collective self-learning, and small additional **storage** for individual ML model's persistency.

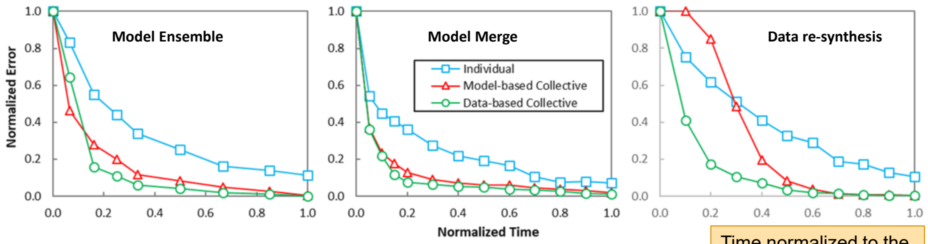


- We apply model ensemble for the local **Rx config. classifier (3)**, implemented as an SVM.
  - the individual ML models can be seen as **weak classifiers** that are combined into a **strong** (accurate) classifier.



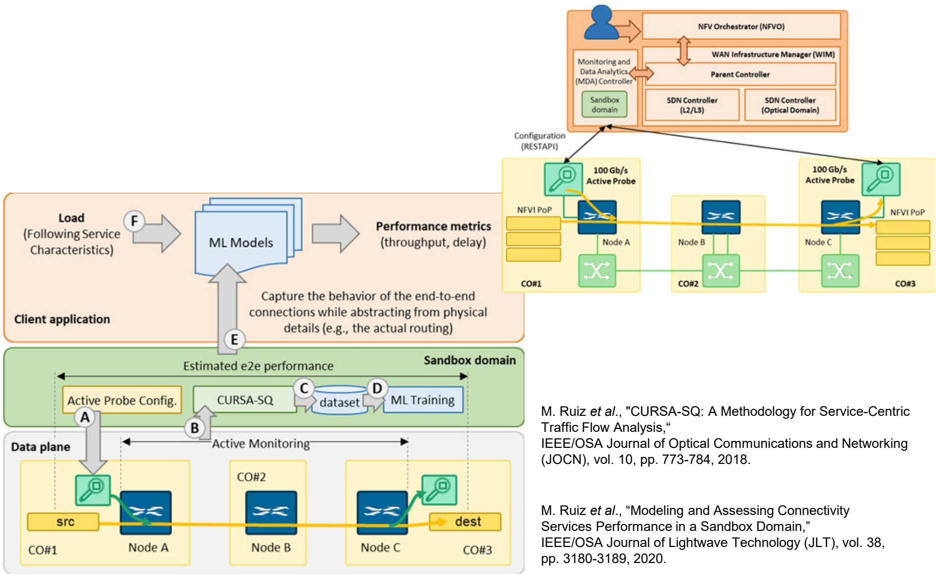
Prediction Error vs Time

Prediction error normalized to the error of the initial trained models.



Time normalized to the time when the most accurate approach reached error <0.5%.

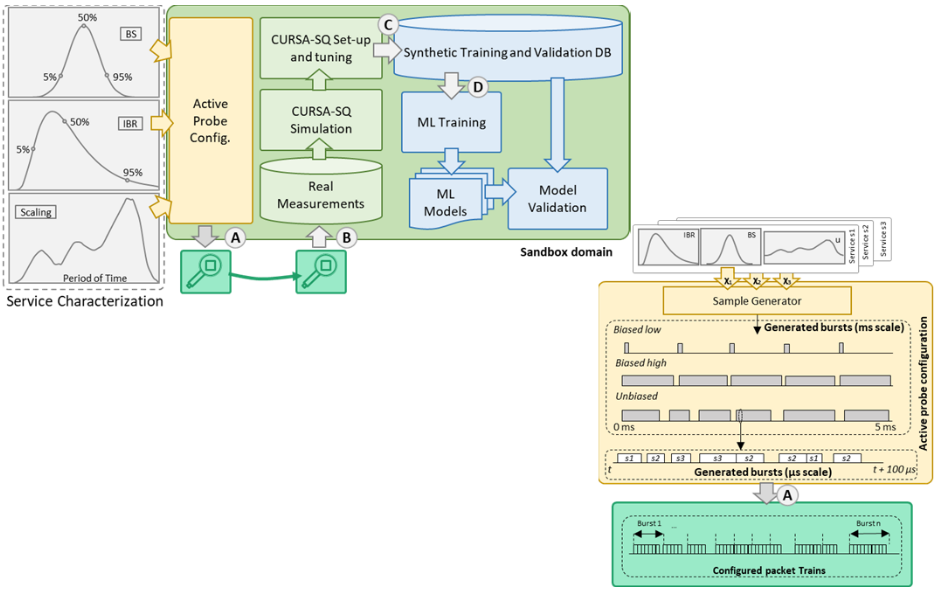
Single Domain Connection Performance



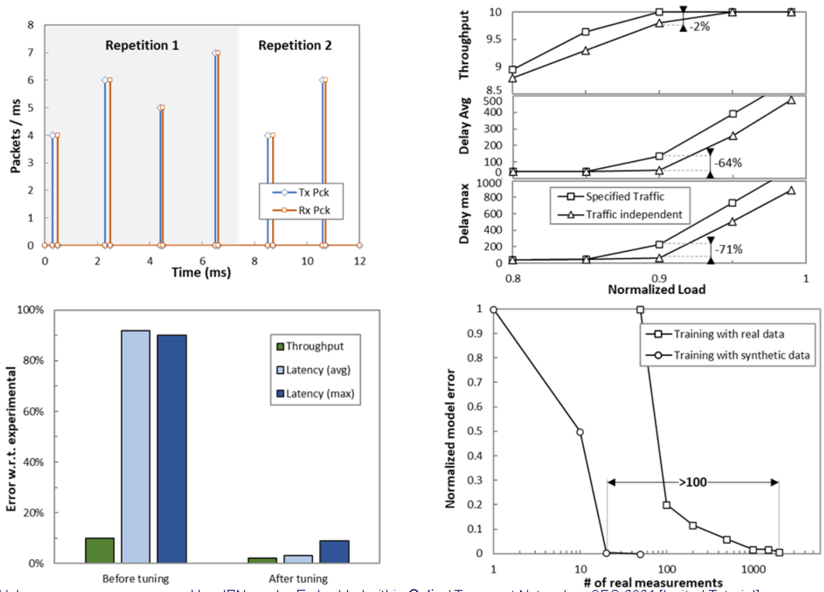
M. Ruiz *et al*., "CURSA-SQ: A Methodology for Service-Centric Traffic Flow Analysis," IEEE/OSA Journal of Optical Communications and Networking (JOCN), vol. 10, pp. 773-784, 2018.

M. Ruiz *et al*., "Modeling and Assessing Connectivity Services Performance in a Sandbox Domain," IEEE/OSA Journal of Lightwave Technology (JLT), vol. 38, pp. 3180-3189, 2020.

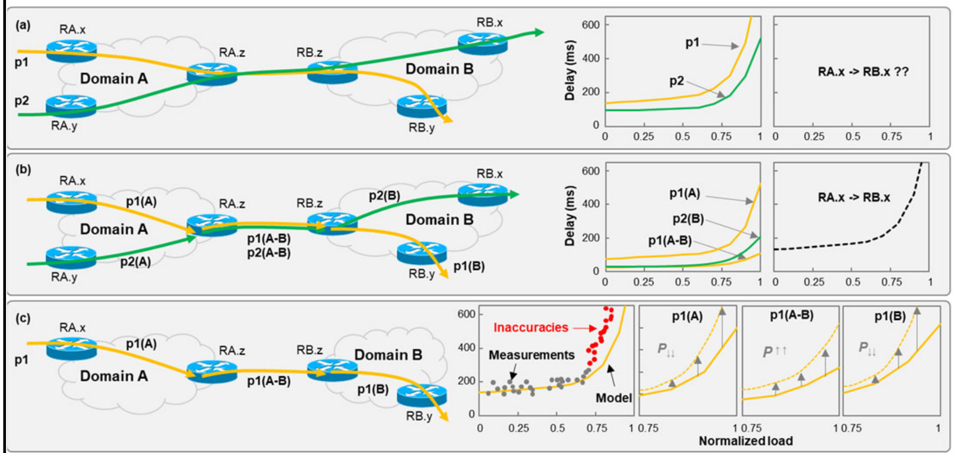
Proposed Methodology



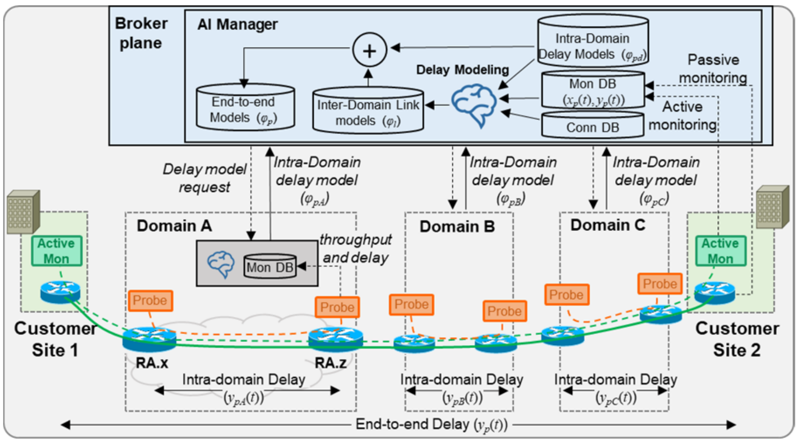
Some Results



Multidomain Connection Performance



Cooperative Learning in Multidomain Networks



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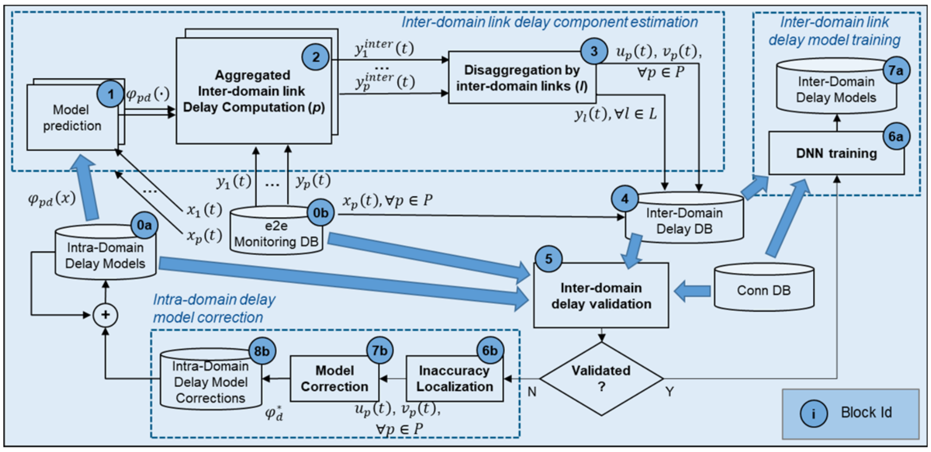
Training and correcting delay models at the broker plane



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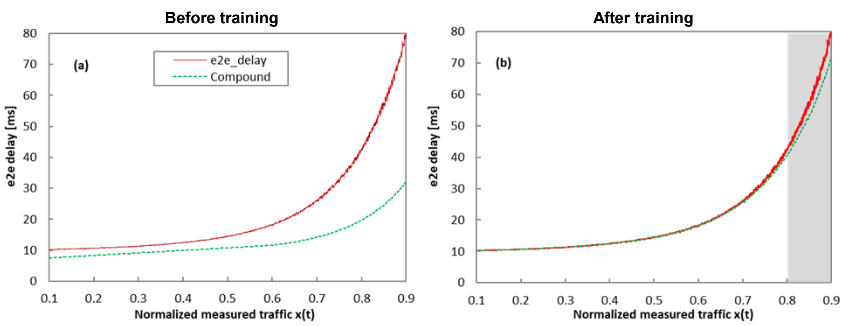
End-to-end delay prediction



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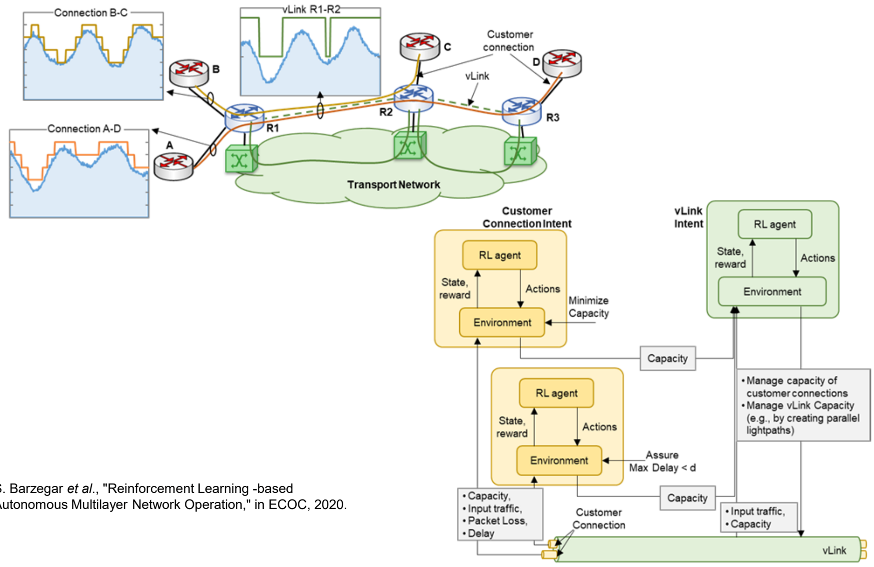
Coordinating AI-based Intent Operation



S. Barzegar *et al.*, "Reinforcement Learning -based Autonomous Multilayer Network Operation," in ECOC, 2020.

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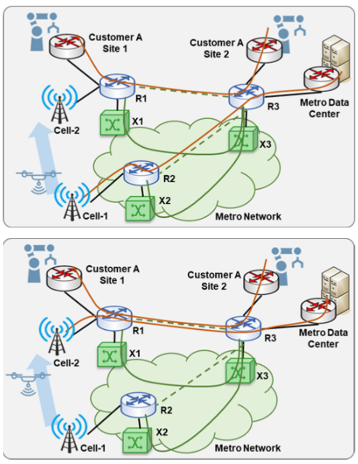
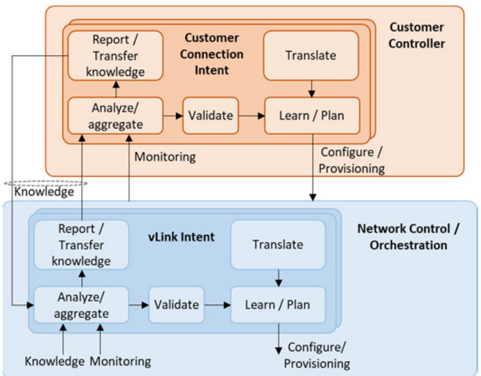
Coordinating AI-based Intent Operation





F. Tabatabaeimehr *et al.* "Supporting Beyond 5G Applications by Coordinating AI-based Intent Operation. An Example for Multilayer Metro Networks," in ECOC, 2020.

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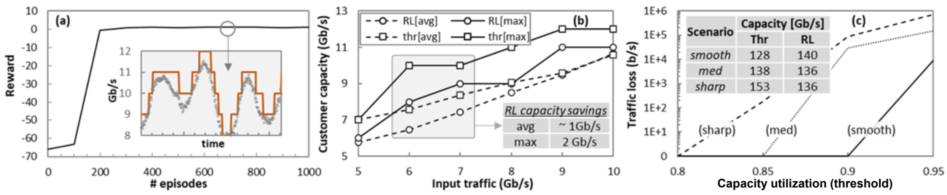
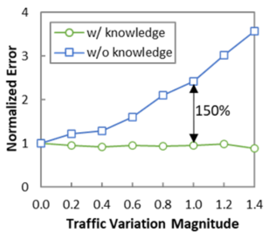
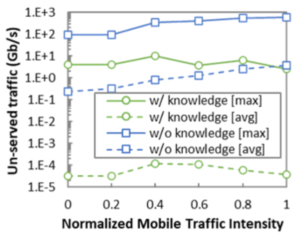
Some results







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Reinforcement Learning (and other techniques)

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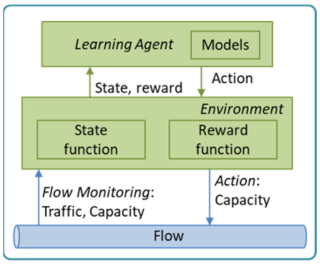
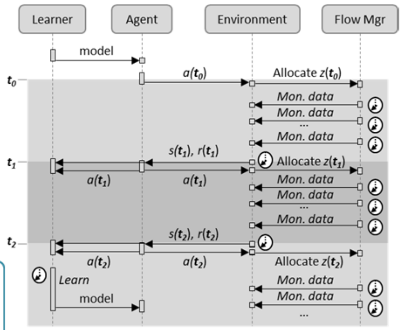
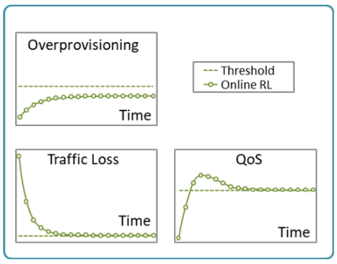
Flow Operation based on RL







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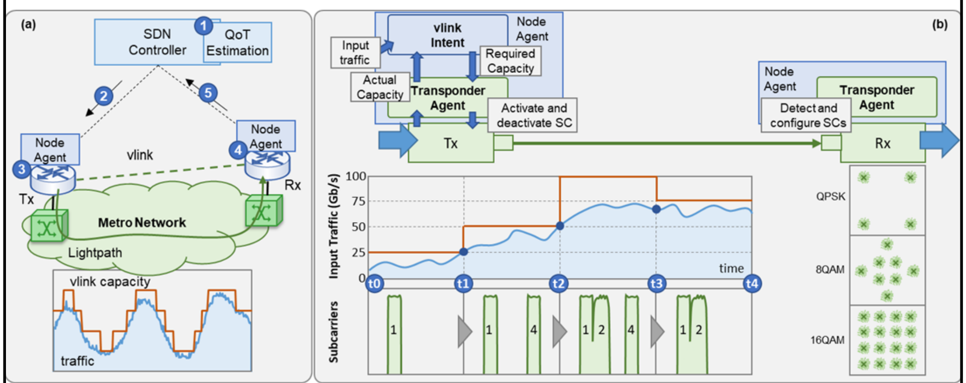
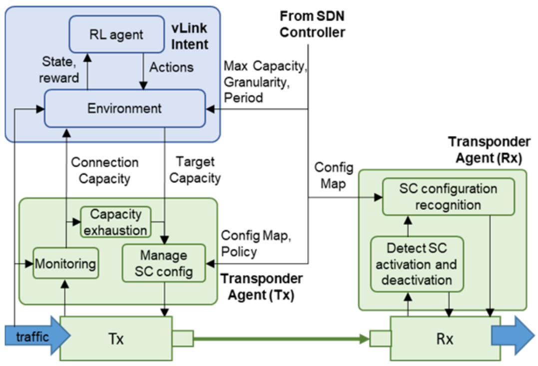
Autonomous Lightpath Operation based on DSCM



L. Velasco *et al.*, "Autonomous and Energy Efficient Lightpath Operation based on Digital Subcarrier Multiplexing," IEEE Journal on Selected Areas in Communications, 2021.

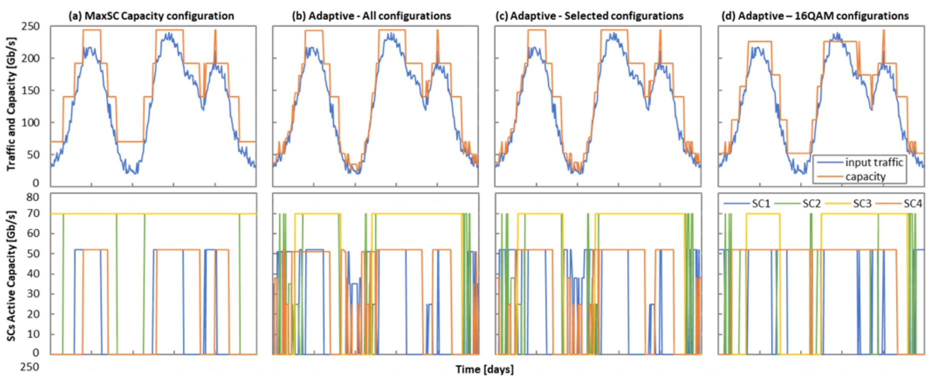
Relationship between vLink Intent and Transponder Agent



Optical Connection Managed by the Transponder Agent

Config. (<MF, SR>)	Capacity [Gb/s]	Config. Set: all	sel	16QAM
QPSK, 8	25.6	x	x	
QPSK, 11	38.4	x		
8QAM, 8	35.2	x	x	
8QAM, 11	51.2	x		
16QAM, 8	52.8	x	x	x
16QAM, 11	70.4	x	x	x

	High Traffic Profile: maxSC	adapt-all	adapt-sel	adapt-16Q
#Changes per day	8.8	51.2	51.2	23.2
Energy savings [%]	28	30	31	32
Packet Loss [MB]	4.8	14.9	11.4	14.9
Queue (max) [MB]	16	16	16	16
Queue (avg) [MB]	0.3	1.4	1.4	1



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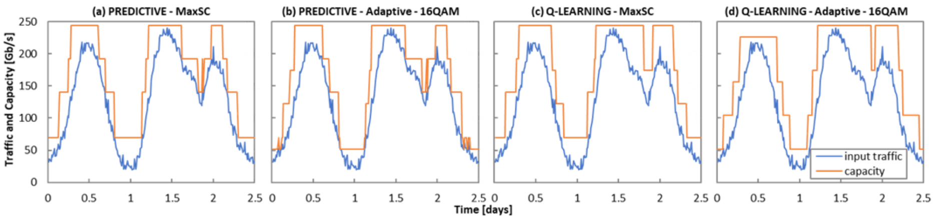
Optical Connection Managed by the vLink Intent



	Predictive		Q-Learning	
	maxSC	adapt-16Q	maxSC	adapt-16Q
#Changes per day	7.2	18.8	7.2	5.6
Energy savings [%]	26	28	31	26
Packet Loss [MB]	0	0	0	0
Queue (max) [MB]	**4.5**	**10.3**	0	0
Queue (avg) [MB]	0	**0.2**	0	0
Cap. Exhaust. per day	1	5	0	0

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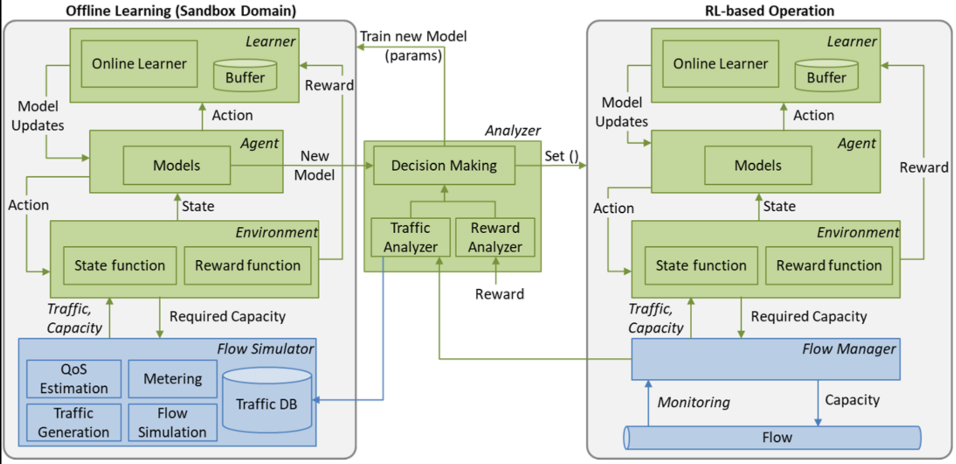
Main Lessons Learnt

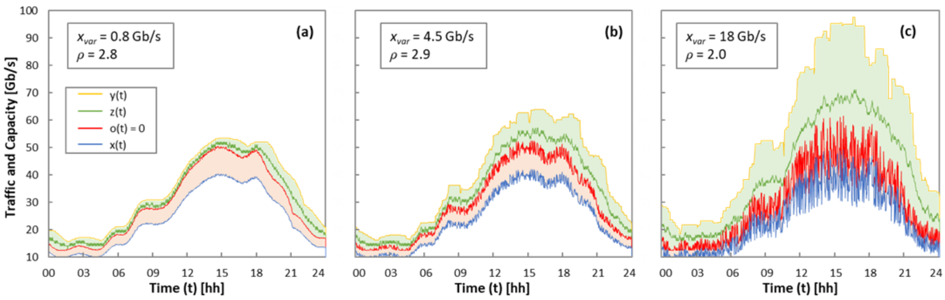
Features	Main observations
per-SC QoT estimation	Penalties are different for the different SC configurations and for the position of the SC in the channel. Therefore, **accurate per-SC QoT estimation** is of paramount importance: • for finding a lightpath and a slot width (l = <p, f, b>) that satisfies the required capacity and minimizes the selected cost function; • for the autonomous SC configuration management at the Tx side by defining the SC configuration map.
Set of supported SC configurations	Having a **large variety of SC configurations** might increase the cost of the transponders unnecessarily, as they do not show additional energy savings and their use might result in variations in the capacity of the vlink, which might add additional complexity at the packet layer.
Capacity management at the Tx side	Algorithms that try to tightly adapt the capacity of the vlink to the current or near future input traffic, did not show large energy savings. Increments in capacity of one SC configured **to the maximum capacity** resulted in effective alternatives, which also simplifies the algorithms. Capacity management **uniquely at the optical layer**, resulted in **poor performance at the packet layer**.
SC Configuration Recognition	Several alternatives might be implemented. Being able to **recognize the right SC** configuration with 100% accuracy allows **bring the intelligence to the data plane** thus, liberating the control plane from collecting monitoring and making configuration decision near real-time.
vlink intent	**Intent-based vlink capacity management** based on RL resulted in a **good solution** for smooth capacity evolution, eliminating completely packet loss and time in vlink queue.

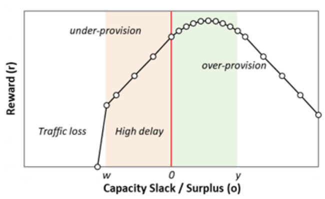
Flow Capacity Operation Based on RL with Online and Offline Learning

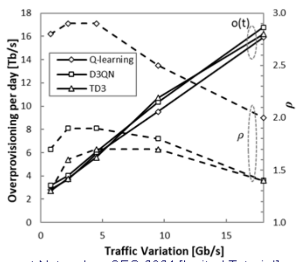


S. Barzegar *et al.*, "Reliable and Accurate Autonomous Flow Operation based on Off-line Trained Reinforcement Learning," in *OFC*, 2021.

Traffic and Allocated Capacity vs Traffic Variation







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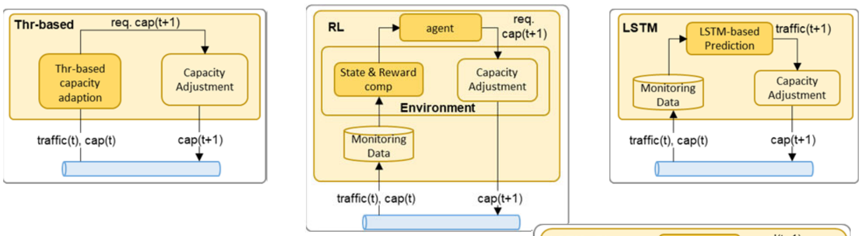
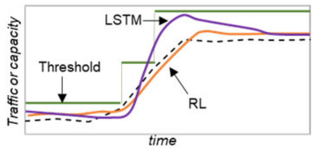
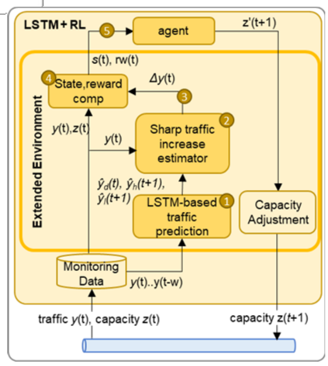
Combining RL and LSTM







F. Tabatabaeimehr *et al.*, "Combining Long-Short Term Memory and Reinforcement Learning for Improved Autonomous Network Operation," *OFC*, 2021.

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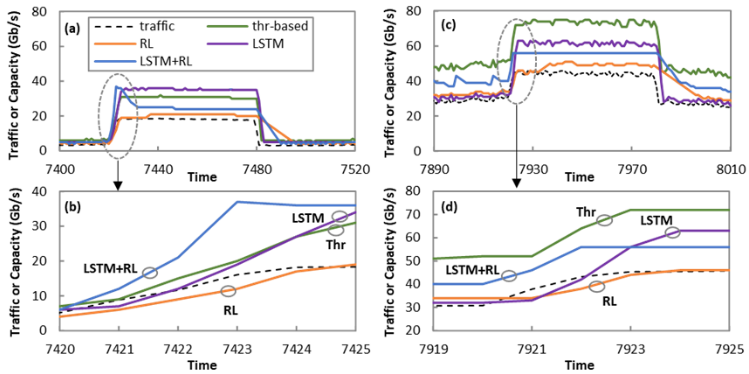
Some results



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Conclusions

- B5G/6G requires radical changes to networks
- **Resilient networking for supporting improved and elastic reliability**
  - **Smart degradation detection**, predicting and resisting negative effects before they happen and/or rapidly recovering if negative effects cannot be avoided
  - **Elastic network technologies**, e.g., support for changing network topologies at runtime.
- **AI/ML-powered adaptative network operations**
  - **Intent-based networking**, monitoring and reacting in real time to changing network conditions.
  - **Closed-loop AI/ML mechanisms** to make automatically actionable decisions.
  - **Proactive** (rather than reactive) resource allocation decisions.
  - **Decision modules** as software control elements realizing an **adaptive control** over the network resources.

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Optical Communications Group

Thank you for your attention!

How IBN can be Embedded within Transport Optical Networks

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OFC-2021 Invited Tutorial