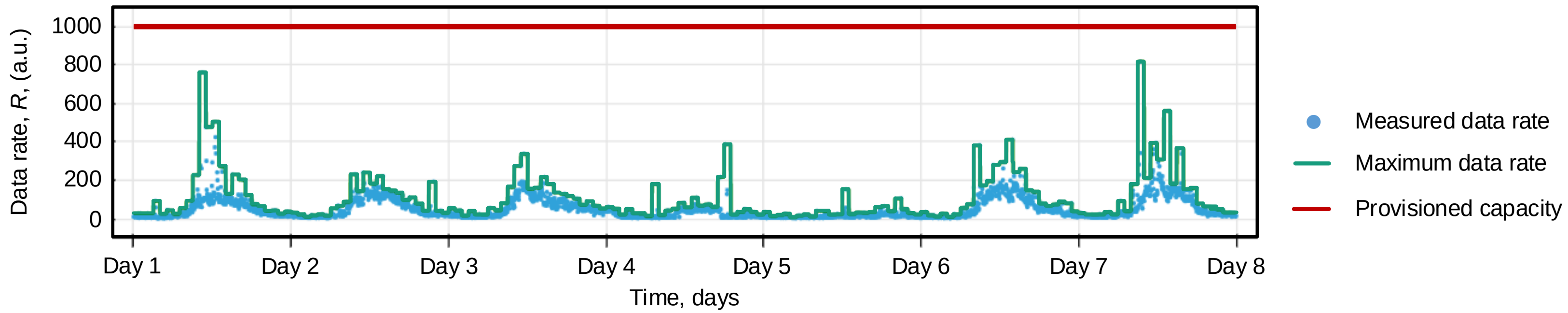

FMD.iDay23
Forschungsfabrik
Mikroelektronik
Deutschland

Dynamic Link-Capacity Adjustment

Motivation

Traditional static link-capacity allocation



Why do networks need dynamic link-capacity adjustment?

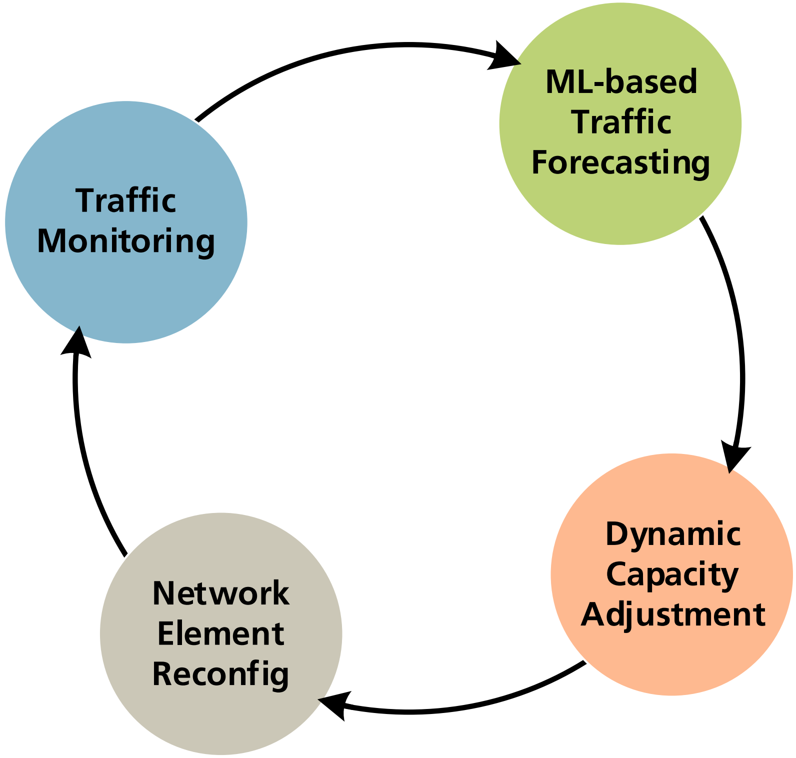
- Reduction of energy consumption and thus carbon footprint*
- Higher flexibility in provisioning of network resources → capacity allocation on demand
- Improved operation efficiency (on network operator side) → enable better utilization of available resources

* A. Lange et al., „Energy Efficiency of Load-Adaptively Operated Telecommunication Networks“, J. Lightwave Technol., vol. 32, no. 4, Feb. 2014.

Dynamic Link-Capacity Adjustment

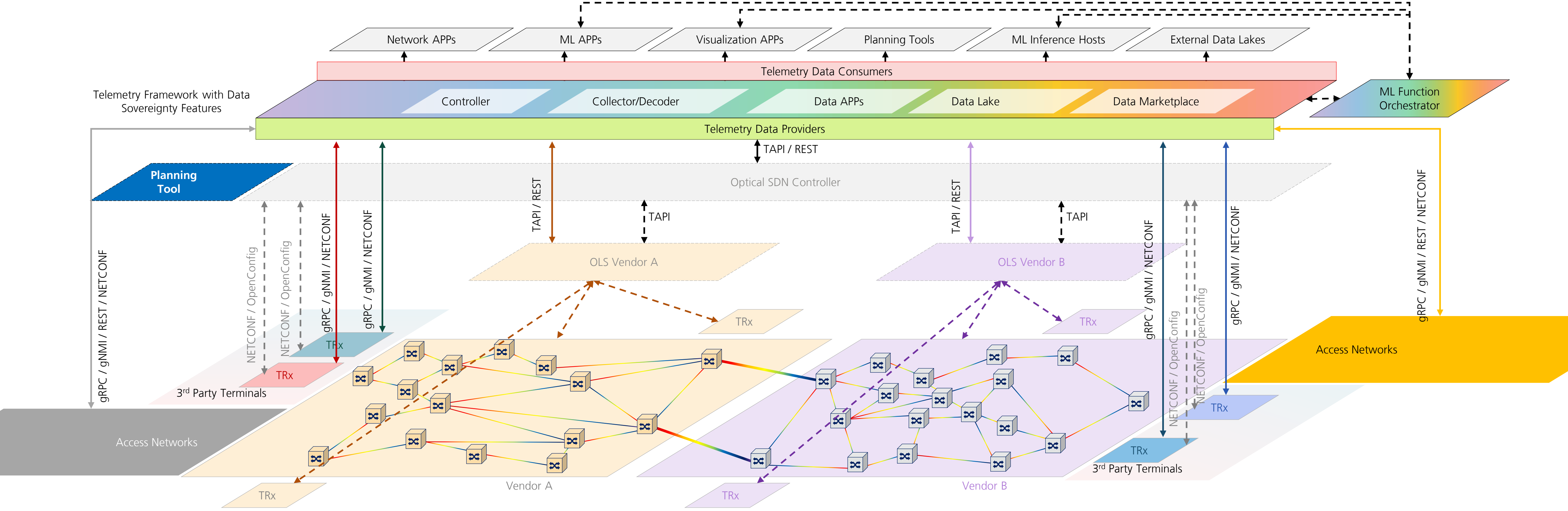
What are the main implementation requirements?

- **Traffic Monitoring:** a suitable telemetry framework supporting a variety of APIs, protocols, etc.
- **ML-based Traffic Forecasting:** an ML pipeline for live traffic prediction, and accurate/reliable traffic forecasting algorithms
- **Dynamic Capacity Adjustment/Network Element Reconfiguration:** suitable network control solutions for dynamic reconfiguration of the NEs



Monitoring of Open and Disaggregated Optical Networks

Telemetry and Machine Learning Framework

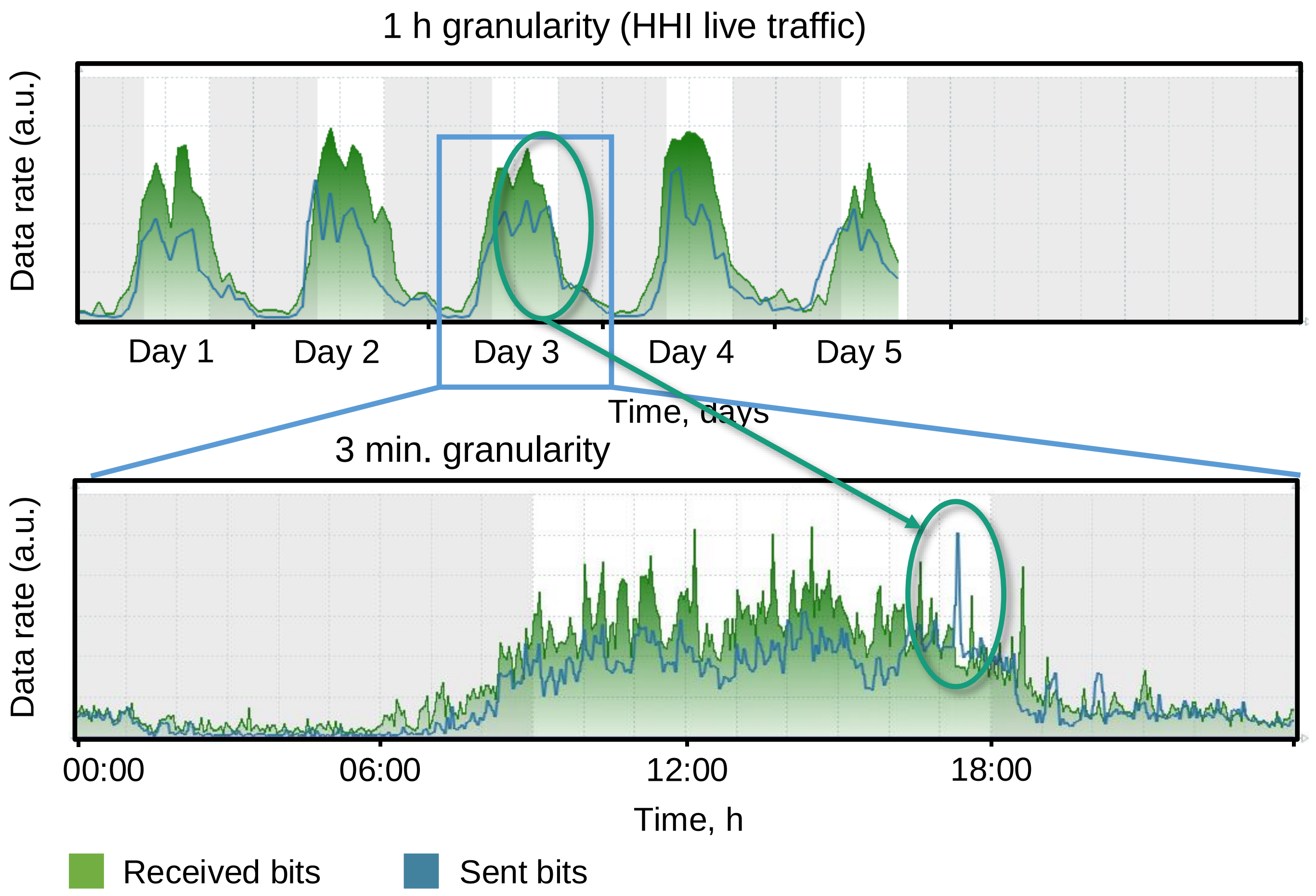


SDN: SDN Controller | TRx: Transponder | OLS: Open Line System | ML: Machine Learning

Traffic Monitoring and Capacity Adjustment

Granularity Considerations

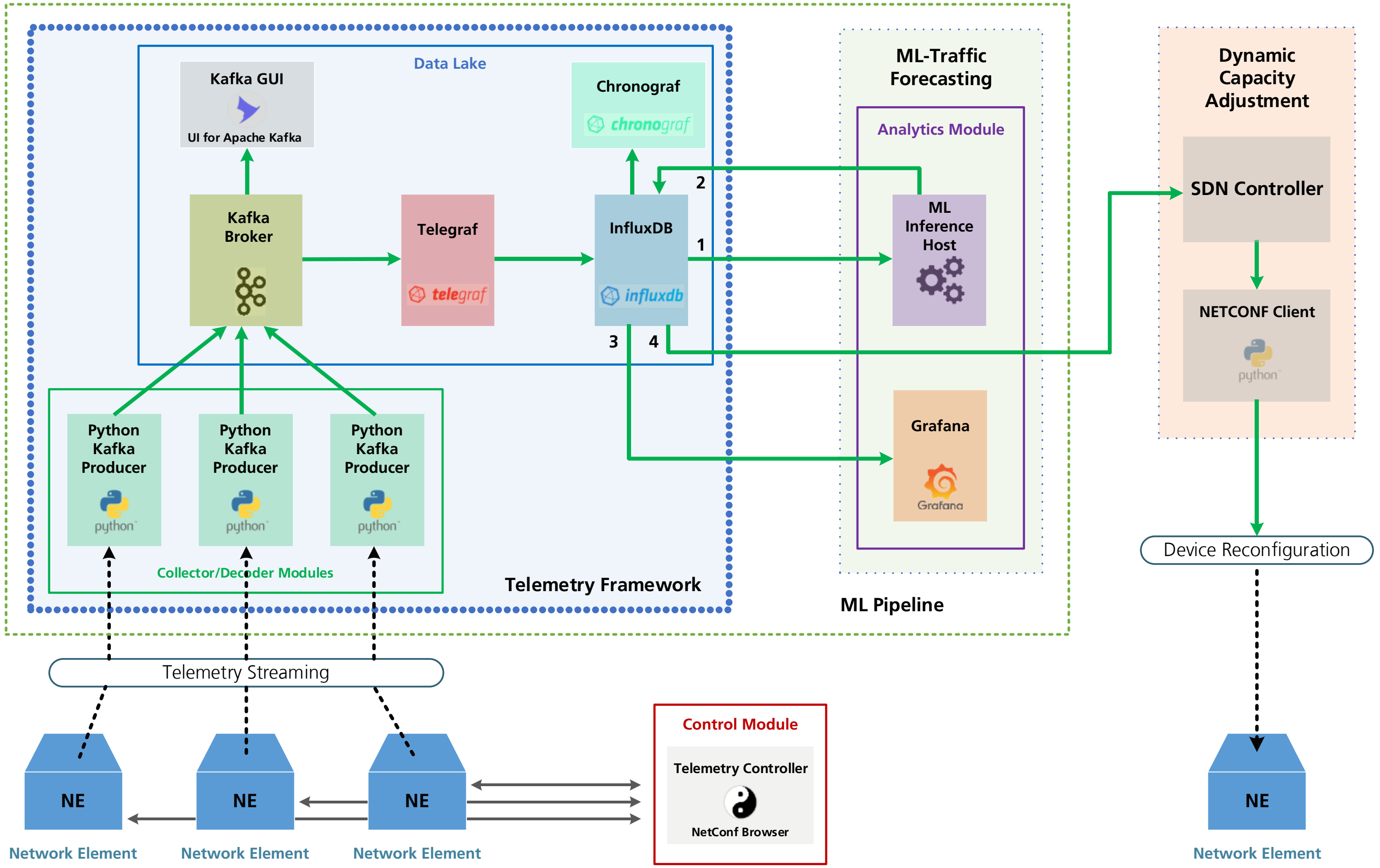
- Traffic monitoring is often performed with a low frequency of measurements (e.g. 1h)
- Fine granular traffic monitoring required to catch short traffic spikes
- Fine granular capacity adjustment steps and periods offer higher capacity and energy resource savings.
- The possible energy savings depend on the granularity of telemetry data and hardware reconfiguration capabilities.



Monitoring of Open and Disaggregated Optical Networks

Telemetry and Machine Learning Pipeline

- Real-time telemetry framework and machine learning (ML) pipeline
- Based on open source components
- Real-time telemetry streaming from network elements to ML inference host and other data consumers on sub-second granularity
- Fundamental tool for generation of training data and real-time inference mode
- Simultaneous monitoring of traffic and energy consumption*



* ITU-T I.1333, Carbon data intensity for network energy performance monitoring

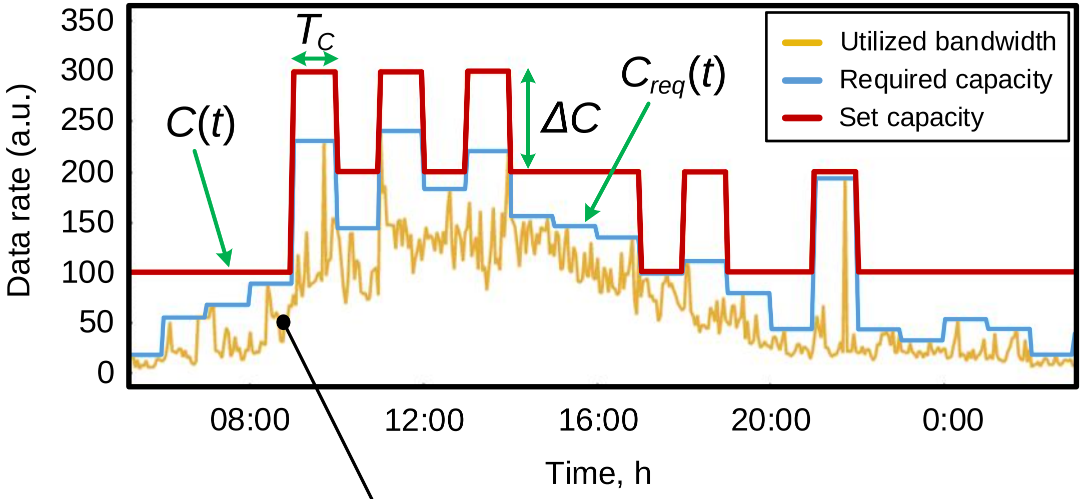
ML-based Traffic Forecasting and Capacity Adjustment

Methodology

FMD.iDay23

Goal: dynamically adjust link-capacity to the changing traffic volume by predicting the future traffic rate

$R(t)$	Data rate
T_c	Capacity cycle interval
$C_{req}(t)$	Required capacity
$C(t)$	Allocated capacity
ΔC	Capacity granularity
M	Capacity provisioning margin



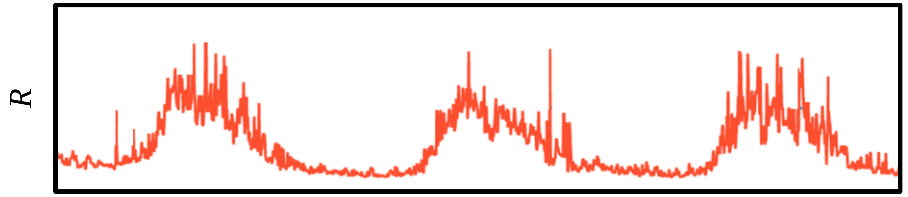
Internal HHI Enterprise traffic flows used for analysis.

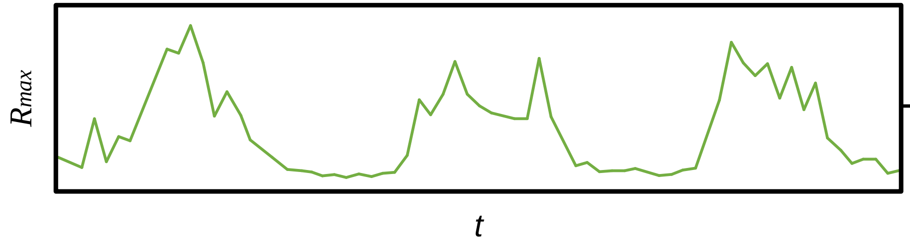
Capacity calculation for the next adjustment cycle:

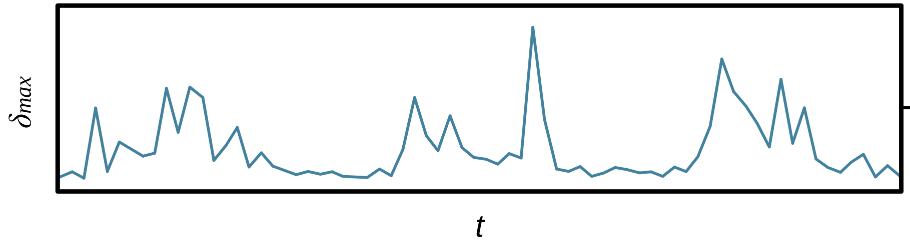
- 1st step: prediction of *max* traffic rate in the next cycle: $\tilde{R}_{max}(t_{i+1}) = f(R_{max}(t_i), R_{max}(t_{i-1}), \dots, R_{max}(t_{i-n}))$
- 2nd step: calculation of the next cycle's allocated capacity: $C(t_{i+1}) = \left\lceil \frac{\tilde{R}_{max}(t_{i+1})+M}{\Delta C} \right\rceil \cdot \Delta C$

Dynamic Capacity Margin Allocation (DCMA)

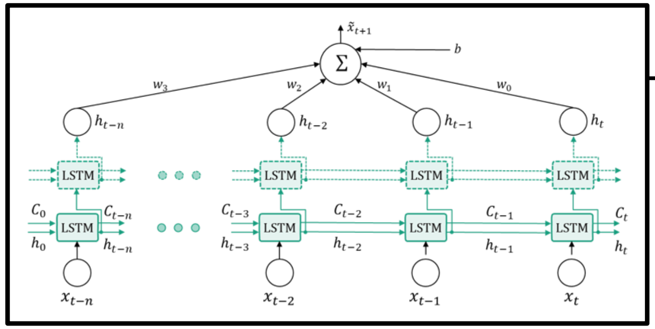
Traffic set decomposition (feature engineering / extraction)



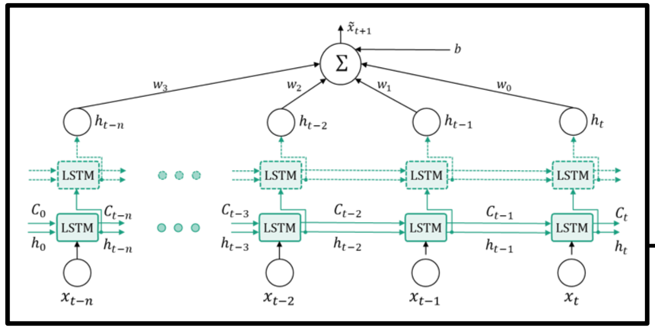




2x long short-term memory (LSTM) neural networks (NN)Ns:



$\tilde{R}_{max}(t_{i+1})$



$\tilde{\delta}_{max}(t_{i+1})$

$$C(t_{i+1}) = \left(\left\lceil \frac{\tilde{R}_{max}(t_{i+1})}{\Delta C} \right\rceil + \left\lceil \frac{\tilde{\delta}_{max}(t_{i+1})}{\Delta C} \right\rceil\right) \cdot \Delta C$$

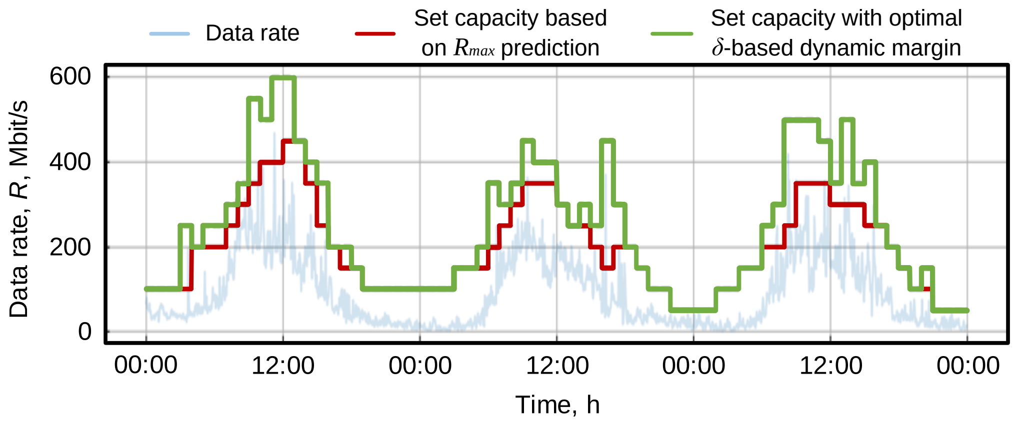
Dynamic Capacity Margin Allocation (DCMA)

Results and Performance

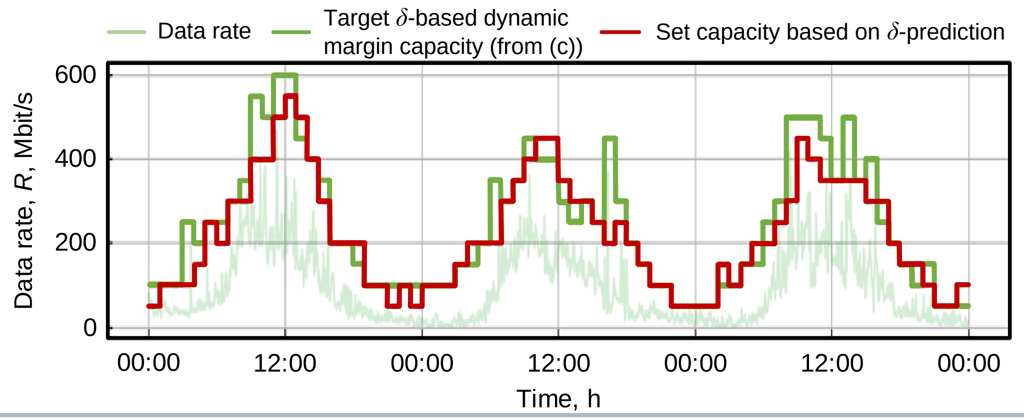
- Test scenario (single switch):
  - $\Delta C = 50\ Mbit/s$
  - Prediction based on last 48 hourly maxima: R_{max} and δ_{max} values
- Performance:

> - **Applied δ_{max}-based DCMA matches the optimal/target capacity in 97% of cases/adjustment intervals.**
> - **Average hourly capacity saving amounts to 77.77%/h.**
> - **An under-provisioning risk of 0.45% is still present, due to „unpredictable“ traffic outliers.**

Set capacity with optimal (theoretical) δ_{max}-based dynamic margin:

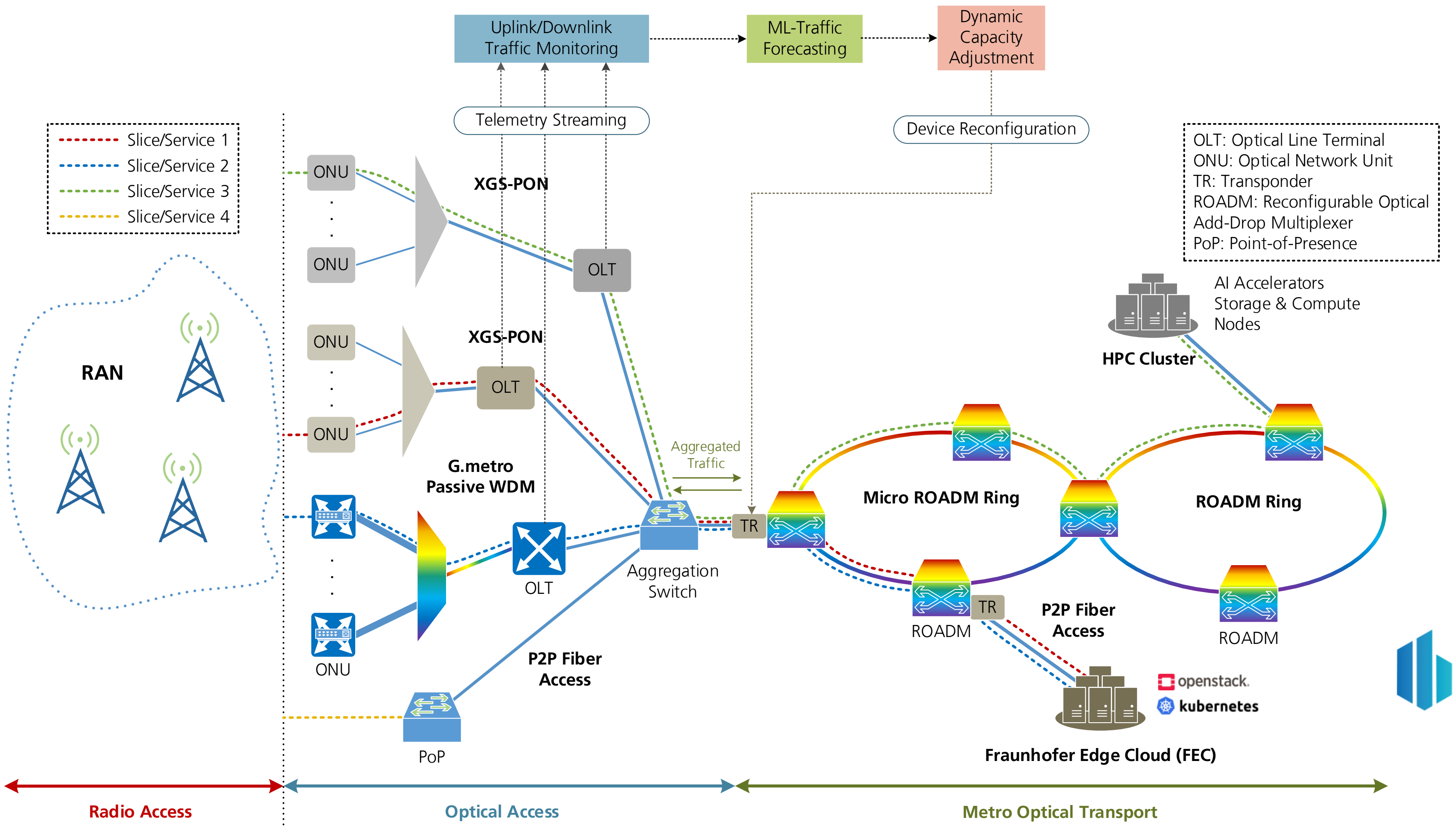


Set capacity after $\tilde{R}_{max}$ and $\tilde{\delta}_{max}$ predictions:



Next Step: Validation in the Field

Large-Scale Testbed @ Fraunhofer HHI



FMD.iDay23

6G-RIC Research and Innovation Cluster

GEFÖRDERT VOM Bundesministerium für Bildung und Forschung

greenict Forschungsfabrik Mikroelektronik Deutschland

Forschungsfabrik Mikroelektronik Deutschland

Eine Kooperation von Fraunhofer MIKROELEKTRONIK

Conclusions
And Outlook

- First results of ML-assisted Dynamic Capacity Margin Allocation show a promising performance of traffic forecasting using real-life traffic flows.
- Parameters such as granularity of telemetry data, provisioning latency, acceptable capacity reconfiguration frequency, available capacity levels, etc. play an important role and need to be considered for optimally tuning the ML-assisted solutions.
- Improved ML solutions to be implemented into a live ML-pipeline for traffic forecasting, followed by an automatic adjustment of link-capacity.
- Testing and PoC demonstration to be carried out on the Fraunhofer HHI large scale photonic testbed in collaboration with the 6G-RIC hub.

GEFÖRDERT VOM
Bundesministerium für Bildung und Forschung

Vielen Dank für Ihre Aufmerksamkeit!