Machine Learning@DESY (M)

ML for operation

LEAPS Integrated Platform Workshop

Annika Eichler, Accelerator Beam Control Group, DESY

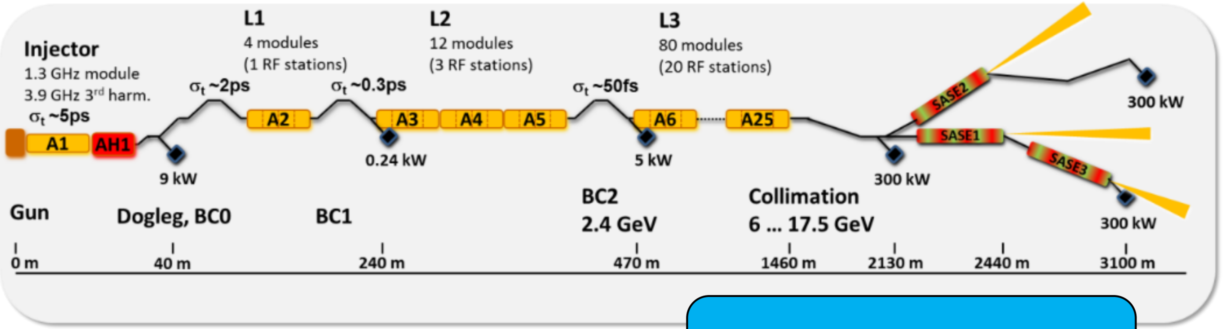
11.05.2021

Courtesy: H. Schlarb

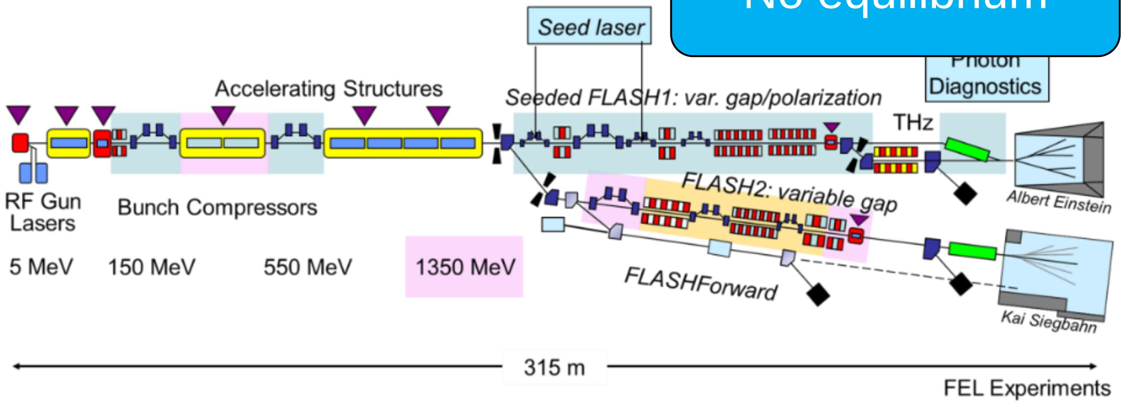
Challenges for the operation

Diverse landscape of accelerators at DESY

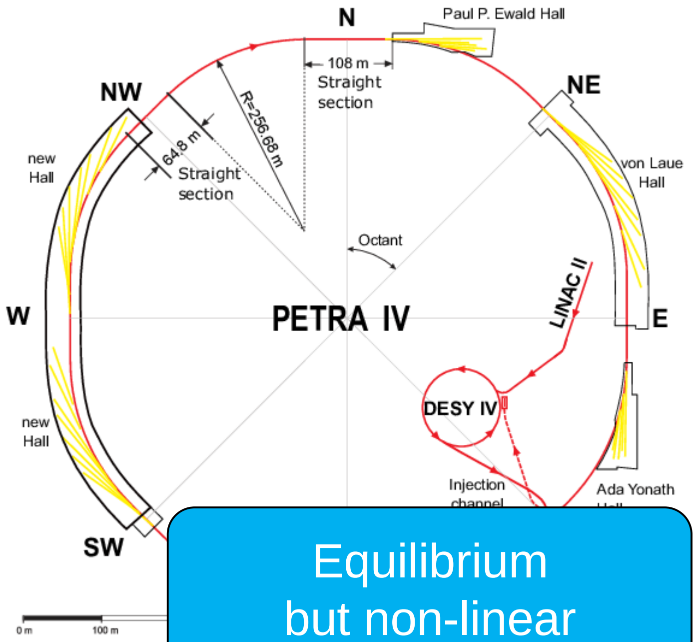
FELs…. (reproducibility / optimization / flexibility / …)



No equilibrium

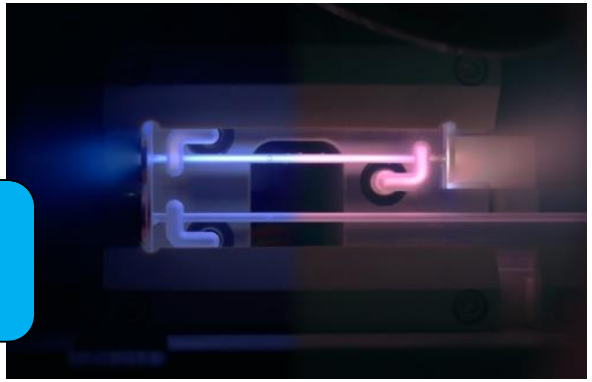


Storage ring
(lattice / beamlin optic &orbit / injection / availability/...)



Equilibrium
but non-linear

Plasma accelerators
(lasers control/ HPC /in-situ FB)



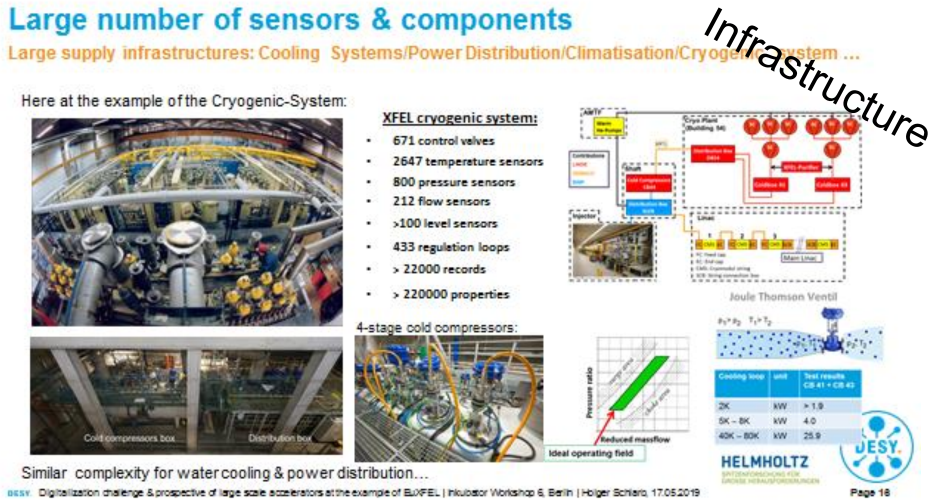
Highly
non-linear

Courtesy: H. Schlarb

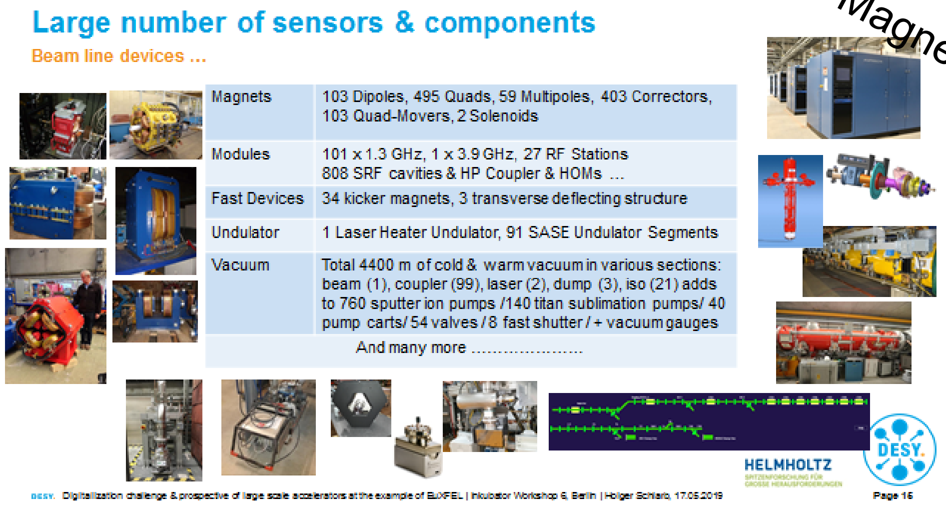
Challenges for the operation

Facilities with many, highly diverse and distributed components

Infrastructure

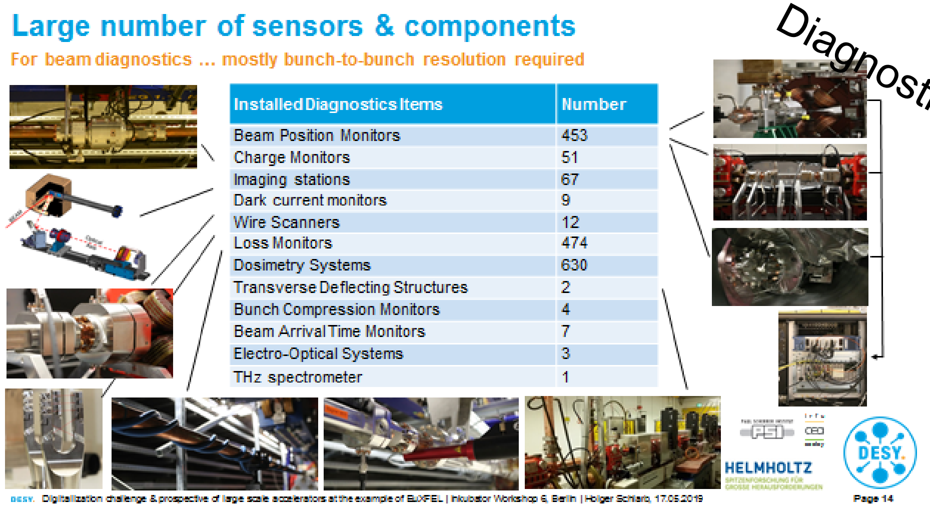


Magnets & RF



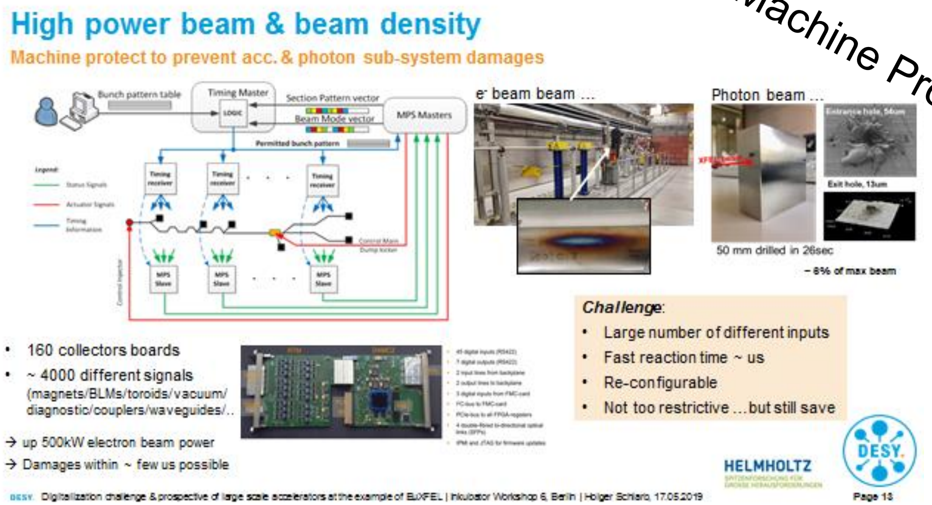
Magnets	103 Dipoles, 495 Quads, 59 Multipoles, 403 Correctors, 103 Quad-Movers, 2 Solenoids
Modules	101 x 1.3 GHz, 1 x 3.9 GHz, 27 RF Stations 808 SRF cavities & HP Coupler & HOMs …
Fast Devices	34 kicker magnets, 3 transverse deflecting structure
Undulator	1 Laser Heater Undulator, 91 SASE Undulator Segments
Vacuum	Total 4400 m of cold & warm vacuum in various sections: beam (1), coupler (99), laser (2), dump (3), iso (21) adds to 760 sputter ion pumps /140 titan sublimation pumps/ 40 pump carts/ 54 valves / 8 fast shutter / + vacuum gauges

Diagnostics



Installed Diagnostics Items	Number
Beam Position Monitors	453
Charge Monitors	51
Imaging stations	67
Dark current monitors	9
Wire Scanners	12
Loss Monitors	474
Dosimetry Systems	630
Transverse Deflecting Structures	2
Bunch Compression Monitors	4
Beam Arrival Time Monitors	7
Electro-Optical Systems	3
THz spectrometer	1

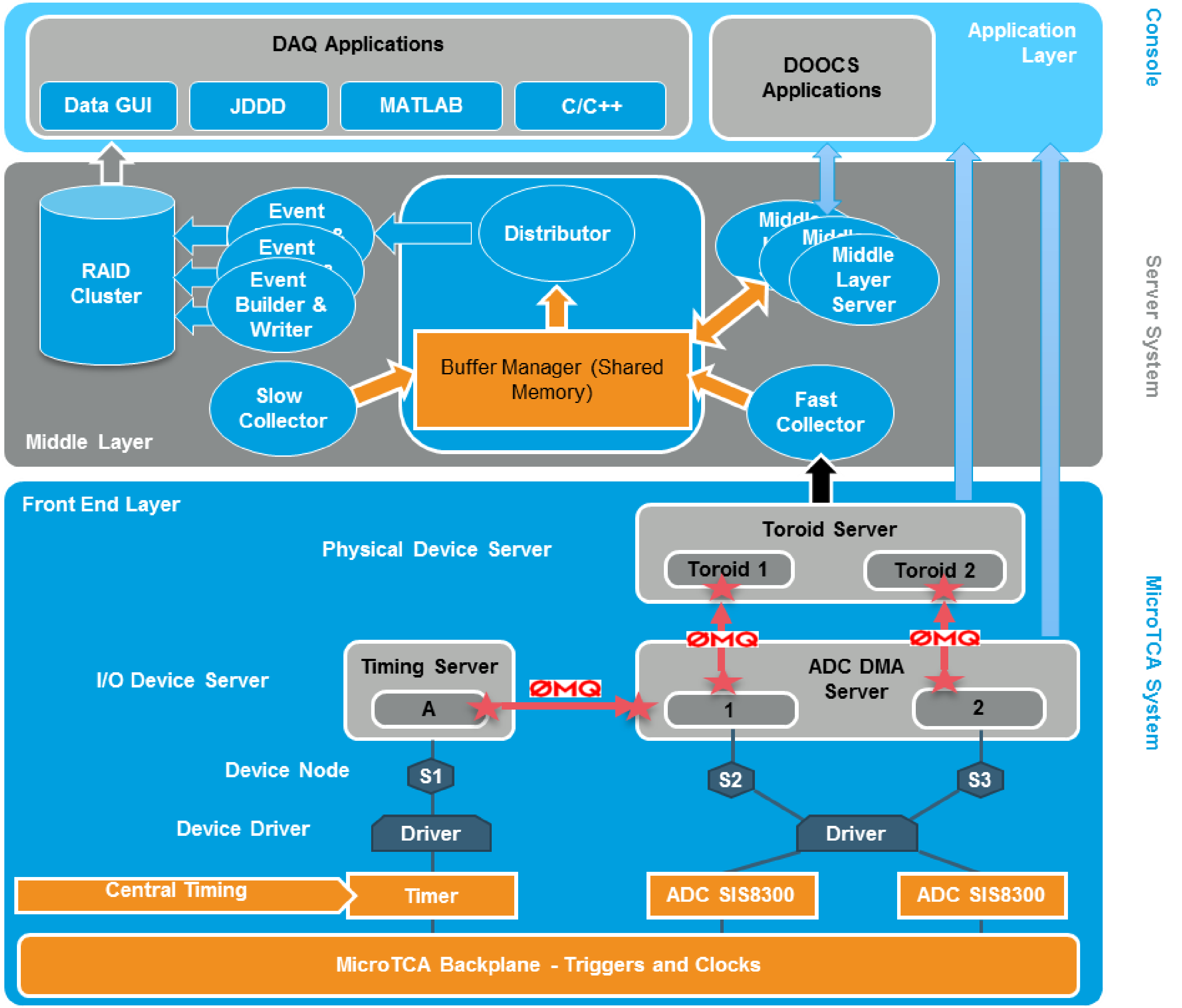
Machine Protection

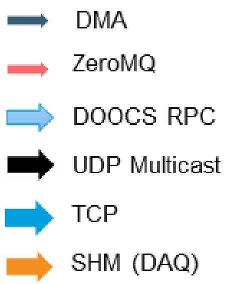


Challenges for operation

High data intensity

- > 10 million control parameters
- > 700.000 local archives
- > 20.000 high data rate channels
- > 30 TB/day written to DAQ (compressed)
- DAQ stores data for ~7 days
- In total: < 1% sent from front-ends





Courtesy: T. Wilksen

Challenges and goals

Challenges

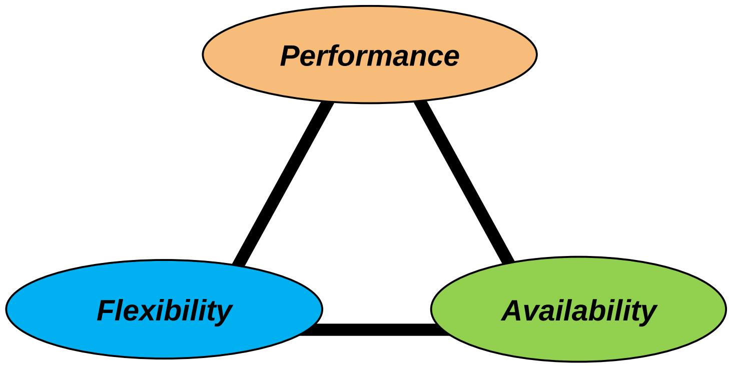
For the operation of particle accelerators (e.g. EuXFEL)

- Largely distributed
- Various types of systems
- Strongly coupled subsystems
- Highly nonlinear processes
- High dimensionality
- High data intensity
- Hardly any long-term data available
- Heterogeneous signals
- Limited access to key observables

Goals

Increasing demand on:

- Performance
  - 0.01% RF phase/ampl.
  - fs arrival time at km scale
  - µm x-y orbits
- Flexibility
  - Switching bunch patterns
  - Multi-beamline operation
- Availability
  - Ideally 99%
  - Reduce setup times
  - Reduce tuning times
  - Predict problems

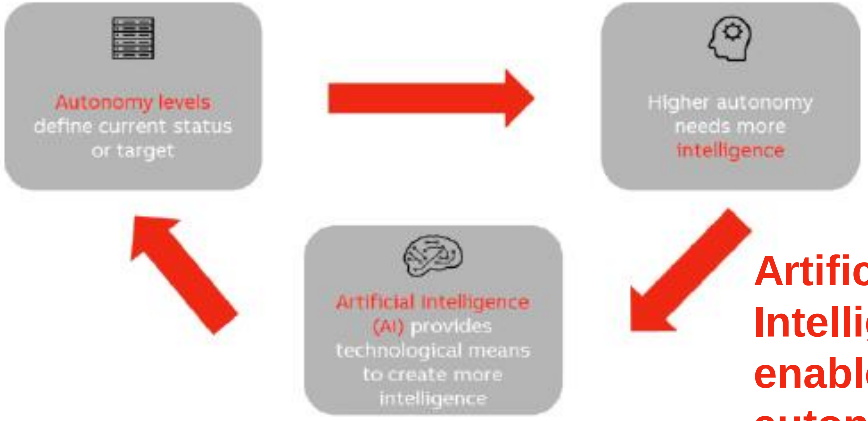


ML as enabler for increased automation to autonomy

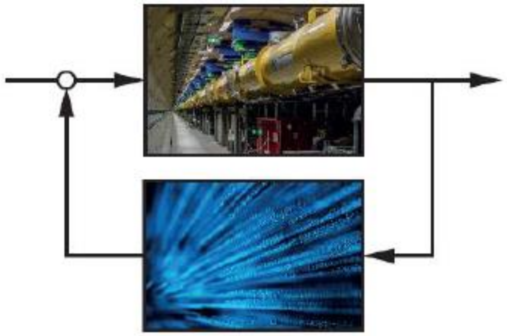
Topics of research

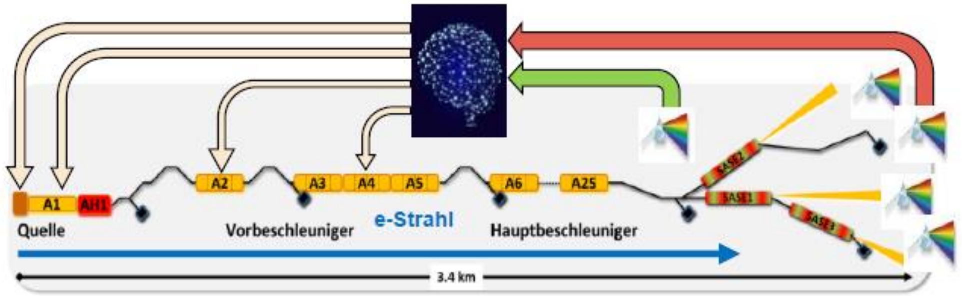
T. Gamer et. al., “The autonomous industrial plant -future ofprocess engineering, operations and maintenance,” 12th IFAC Symposium DYCOPS, vol. 52, no. 1, pp. 454–460, 2019.

- **Data acquisition and data analysis (pipelines)**
  - Get all relevant signals and provide understanding
  - Provide data infrastructure
- **Fault diagnosis and supervisory control**
  - Predict faults, prevent failures
  - Protect the system
- **(Surrogate) modelling, simulations, digital twins**
  - Understanding physics
  - Requirement for predictions, development and control
- **Optimization and feedback control algorithms**
  - Push the way of operation
  - Optimize performance



Artificial Intelligence as enabler for autonomy

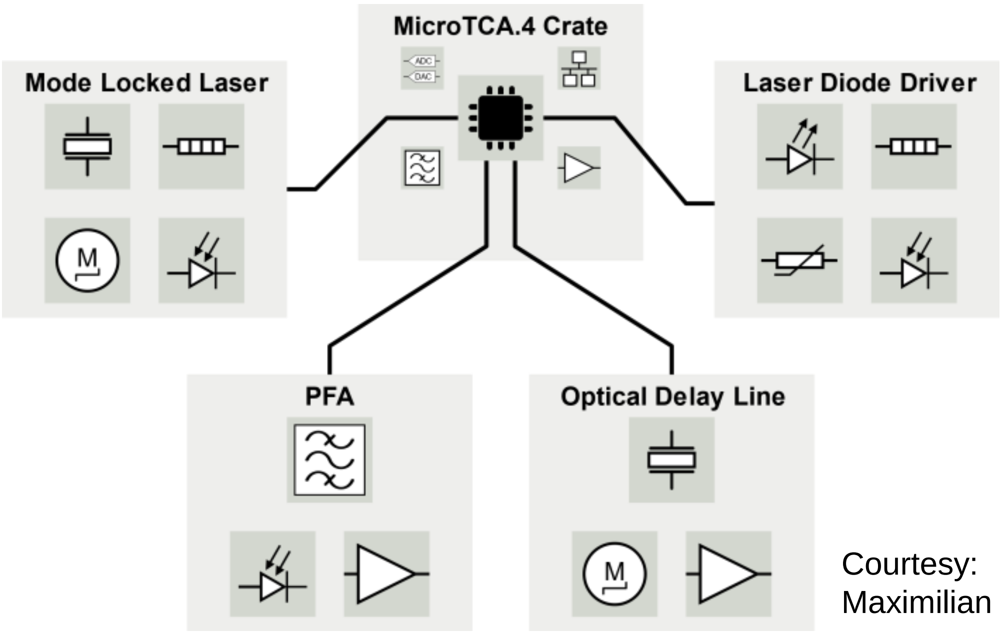




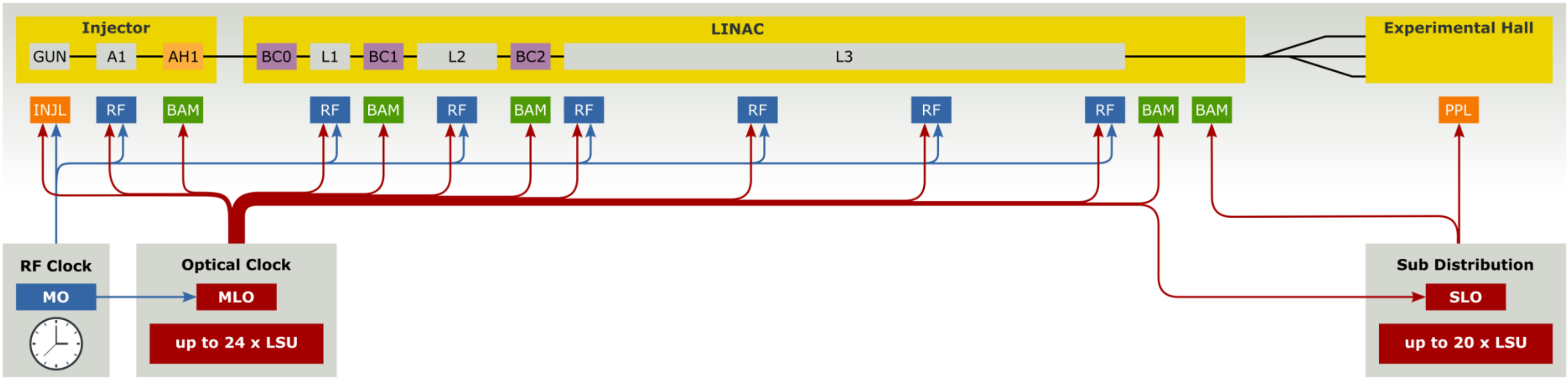
Data acquisition and data analysis (pipelines)

Get all relevant signals and provide understanding

- **Long-term DAQ system for a subsystem:** Build a complete long-term data acquisition system for the optical synchronization system at European XFEL
  - Data scope:
    - 50'000+ data channels (configuration + monitoring),
    - In total > 150 MB/s data to data acquisition system
      → Data reduction necessary (to meet 100 TB/y)
    - ~ 1% of the European XFEL



Courtesy:
Maximilian Schütte

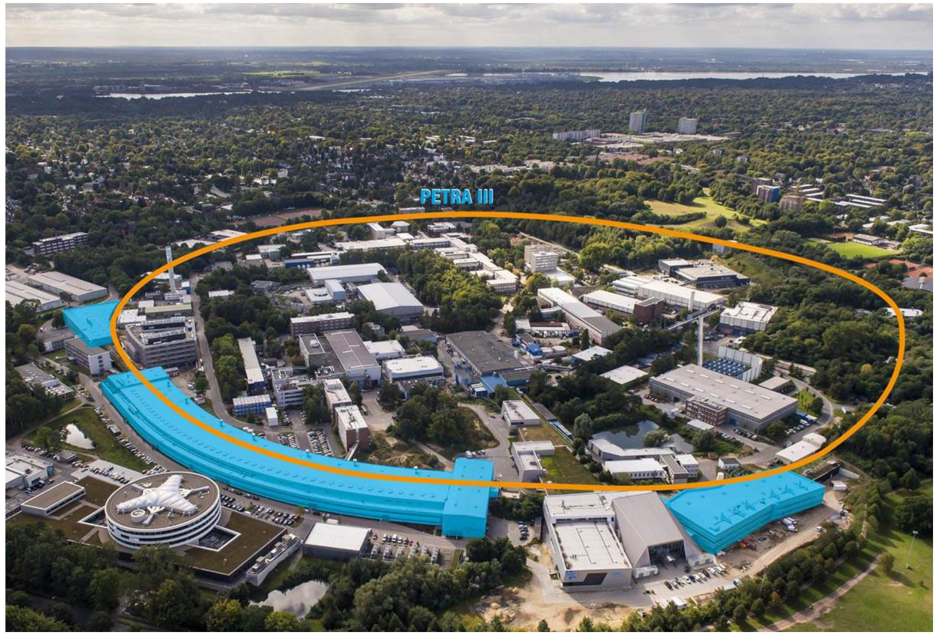


Data acquisition and data analysis (pipelines)

Get all relevant signals and provide understanding

- **Data analysis and control pipeline:** for supporting decision-making and analysis of beam optics, first test at PETRA III based on kafka (M. Boese, I. Agapov)

kafka



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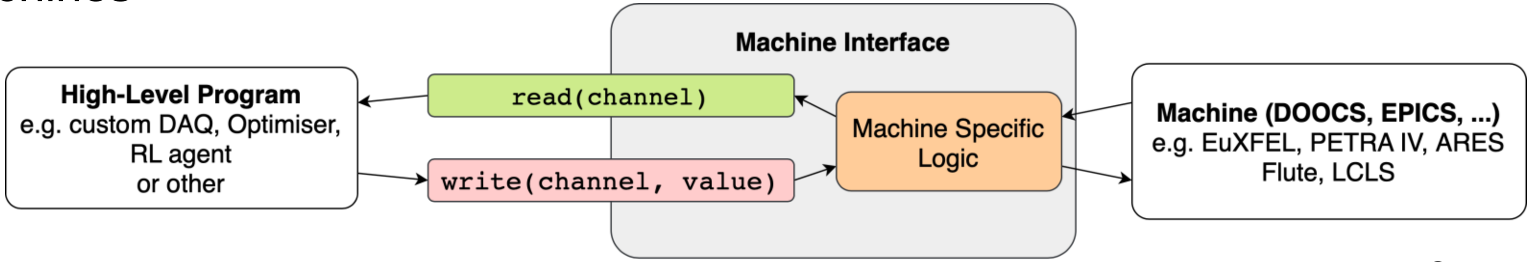
- **Standardize interfaces:** between algorithms and simulations / machines
(J. Kaiser, O. Stein)



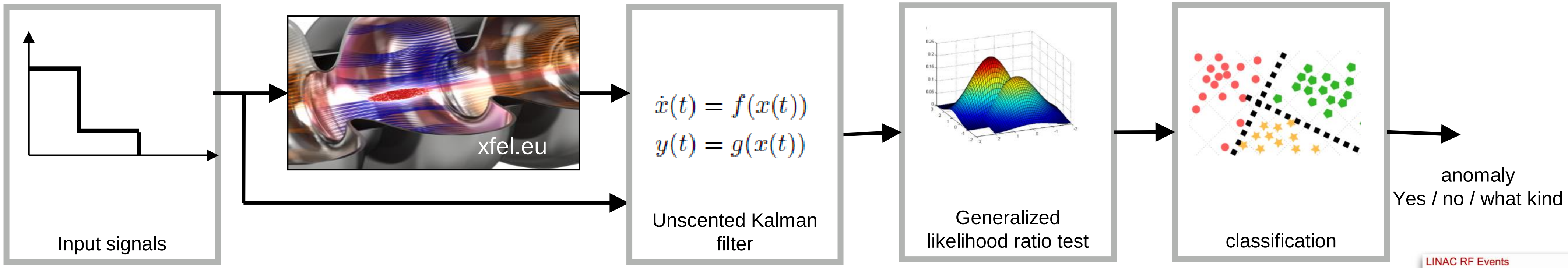
Courtesy Jan Kaiser & Oliver Stein

https://blog.boguszewski.net/root-cause-analysis/

Fault diagnosis and supervisory control

Predict faults and protect the system

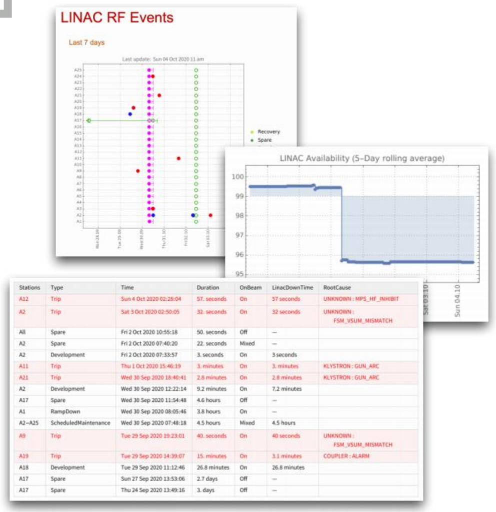
- **Anomaly detection:** for SRF cavities at European XFEL (1.5 GB/s) (Ayla Nawaz)
  - Online implementation of anomaly detection: Trip event logger (Online trip analysis, 18 MHz sampling frequency) (Jan Timm)



Courtesy Ayla Nawaz

- **Root-cause analysis:** (XFEL linac automated trip analysis) (Nicholas Walker)

- **Health Monitoring:** Laser health monitoring with clustering based on abnormal behavior in laser oscillation (H. Hoffmann)

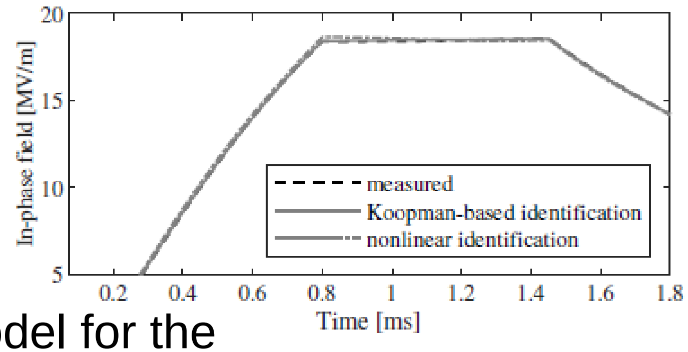


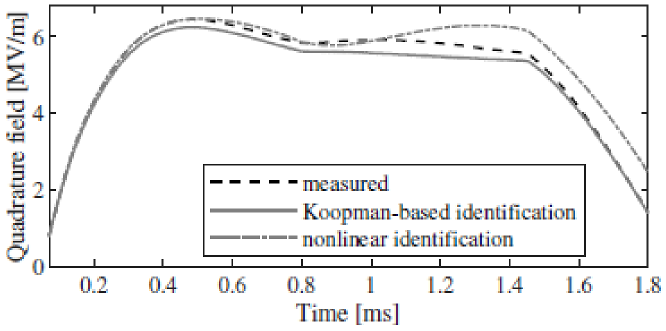
Courtesy Nicolas Walker

(Surrogate) modelling, simulations, digital twins

Understanding physics, requirement for predictions, development and control

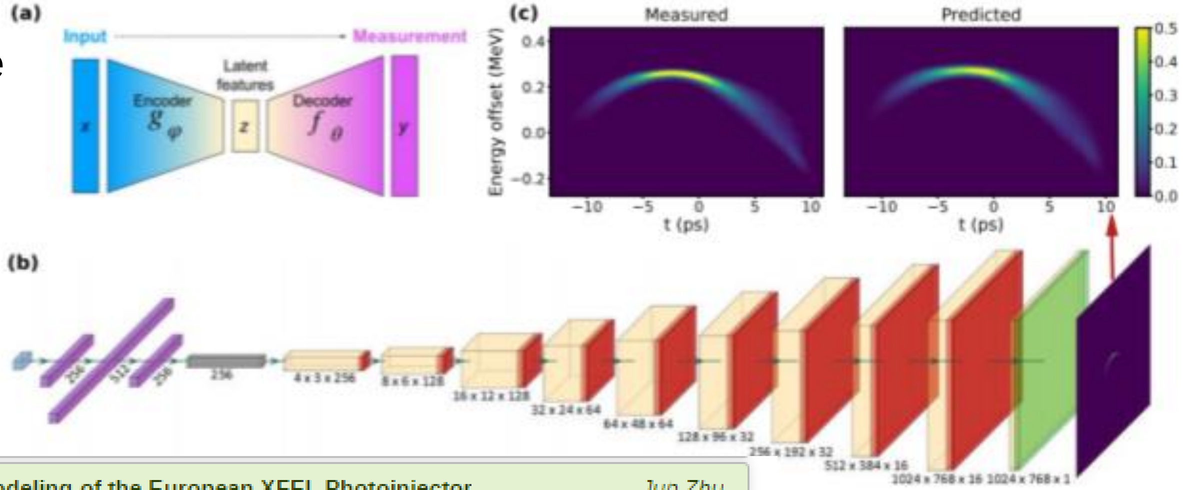
- **Modelling for model-based control / diagnosis:** Data-based nonlinear modeling exploiting physical understanding by Koopman operator theory for SRF cavities at European XFEL (W. Haider, A. Eichler)
  - More precise model as grey-box one
  - 1000 times faster in evaluation for fault detection (Kalman filter)
  - Set-point independent

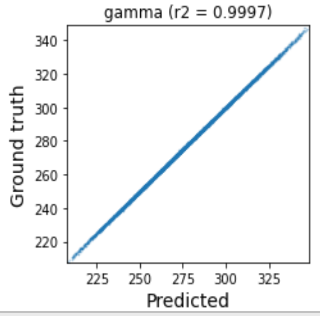




- **Modelling for fast simulations:** Surrogate model for the injector of European XFEL using neural networks (J. Zhu)
  - High-throughput and low-latency applications using hardware acceleration (e.g. Versa ACAP) (with G. Fey, A. A. Zoubi, G. Martino from TUHH)

Experimental demonstration of high-quality mega-pixel image prediction





Prediction result with surrogate model using simulated data

See talk tomorrow:

Deep Learning-Based Autoencoder for Data-Driven Modeling of the European XFEL Photoinjector — *Jun Zhu*
Online, Zoom — 19:05 - 19:15

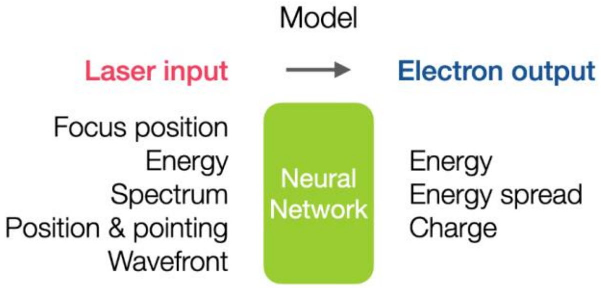
Courtesy Jun Zhu

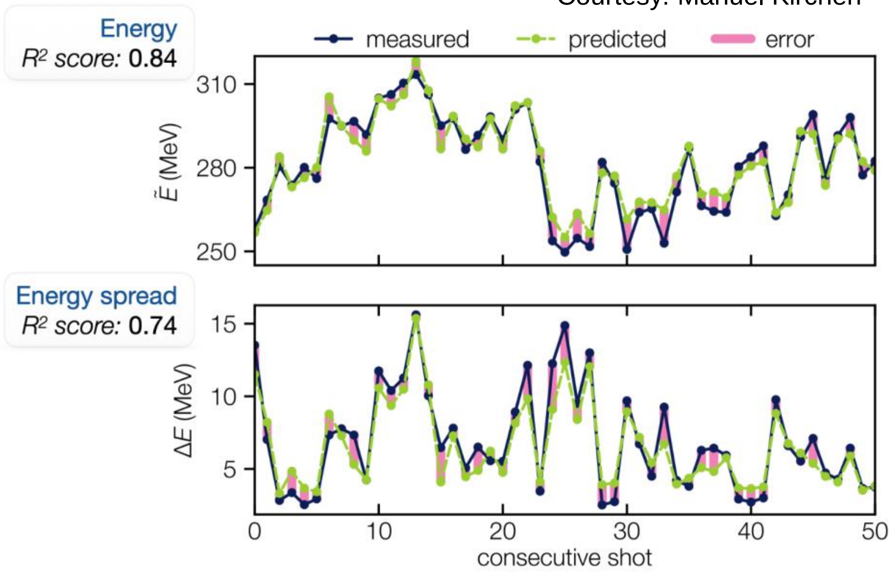
(Surrogate) modelling, simulations, digital twins

Understanding physics, requirement for predictions, development and control

Courtesy: Manuel Kirchen

- **Neural network based surrogate model of LPA experiment**
  - Data from LUX laser-plasma accelerator trains a surrogate model and enables single-shot predictive modeling of the plasma electron properties
  - Paves the way for active feedback + stabilization and virtual diagnostics
  - *M. Kirchen et al., "Optimal beam loading in a laser-plasma accelerator" PRL 126, 174801 (2021)*



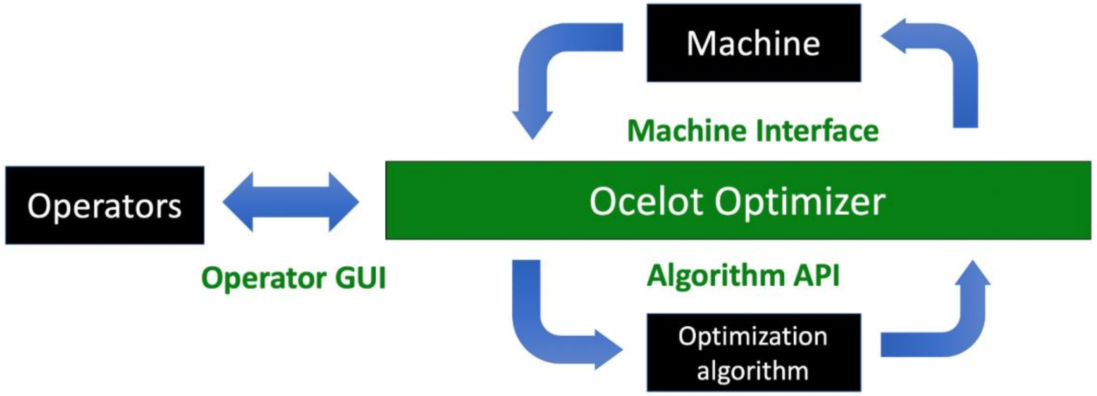


- **OCELOT:** Multiphysics simulation toolkit (already started in 2014) (S. Tomin/ I. Agapov)
  - Charged particle beam dynamics module (CPBD)
  - Native module for spontaneous radiation calculation
  - FEL calculations: interface to GENESIS and pre/post-processing

Optimization and feedback control algorithms

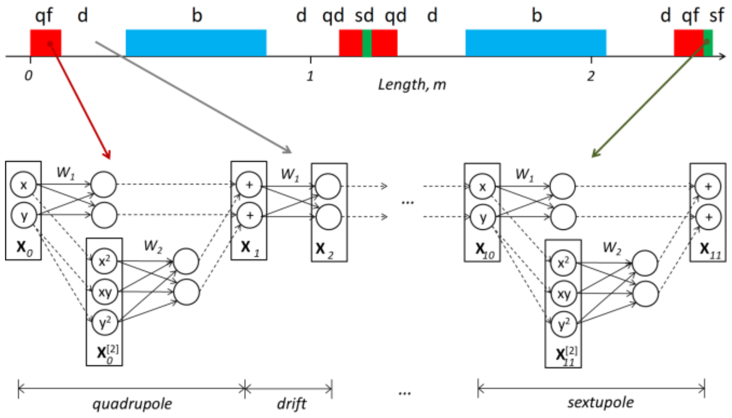
Push the way of operation, optimize performance

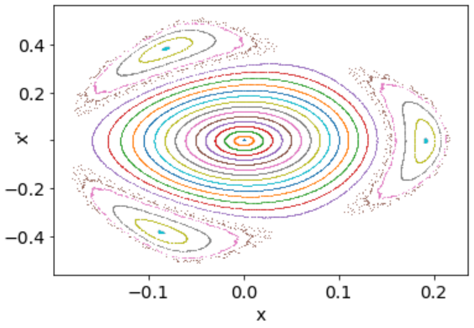
- **OCELOT Optimizer:** Platform for automated optimization of accelerator performance
  (S. Tomin/ I. Agapov)



https://github.com/ocelot-collab/optimizer

- **Physics-based deep neural networks:** NN-based beam adjustable orbit and optics control for storage rings* (A. Ivanov, I.Agapov)





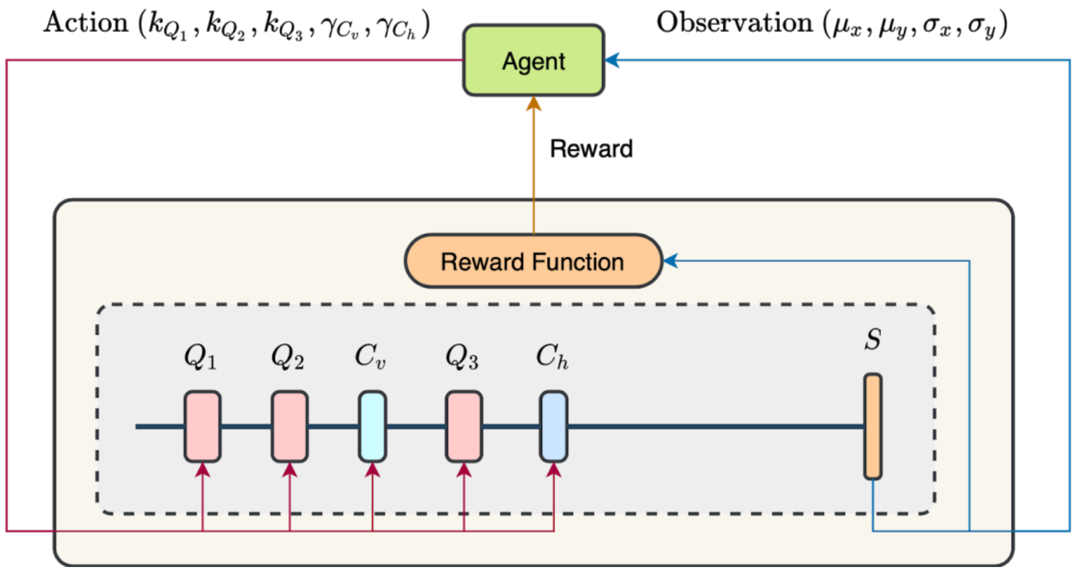
Courtesy Andrei Ivanov

* Andrei Ivanov and Ilya Agapov, “Physics-based deep neural networks for beam dynamics in charged particle accelerators”, Physical Review Accelerators and Beams 23, 07461 (2020)

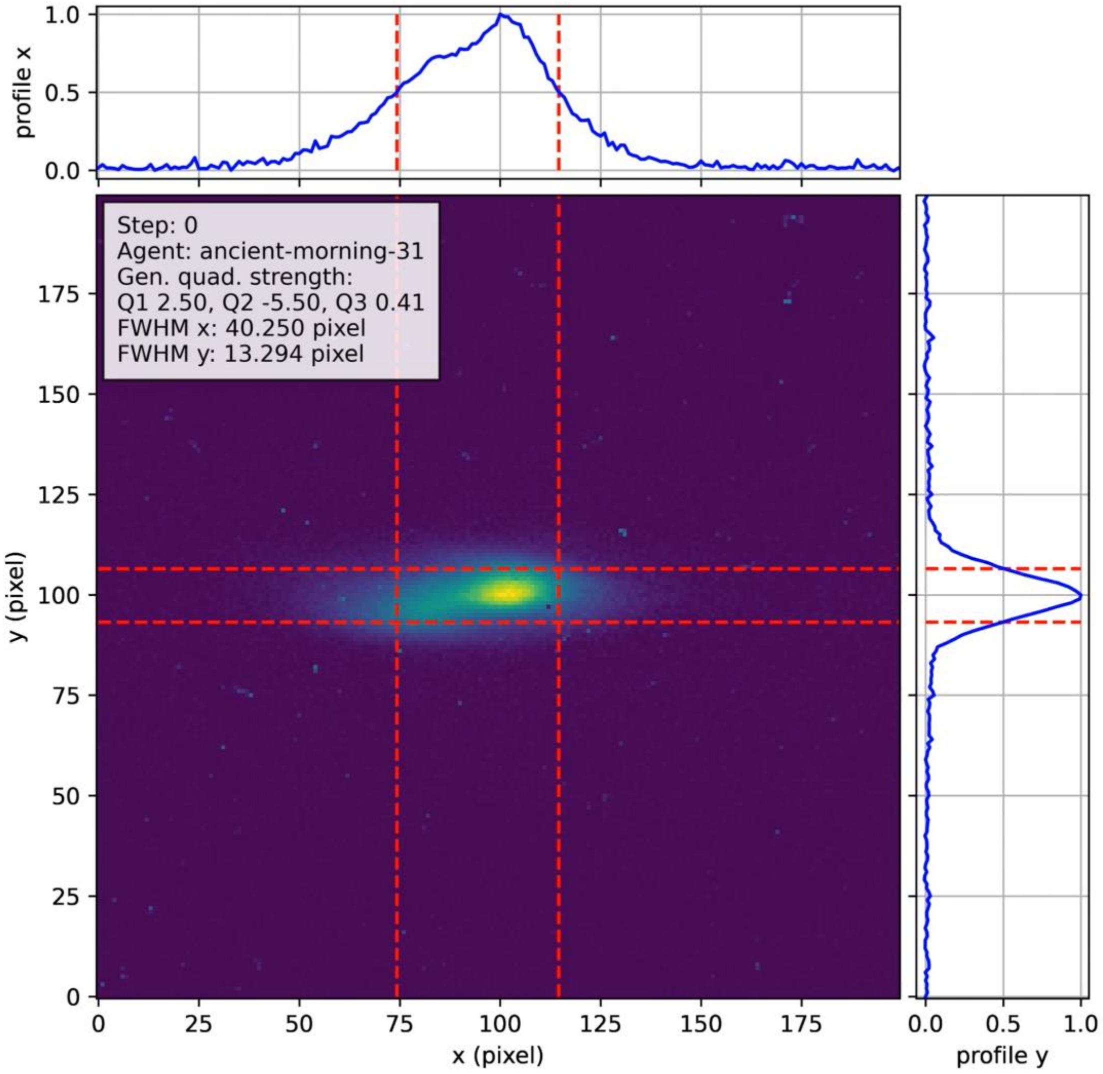
Optimization and feedback control algorithms

Push the way of operation, optimize performance

- **Reinforcement Learning for beam focusing :**
  First steps of applying RL for beam focusing at ARES, collaboration project with KIT (J. Kaiser, O. Stein, A. Eichler)



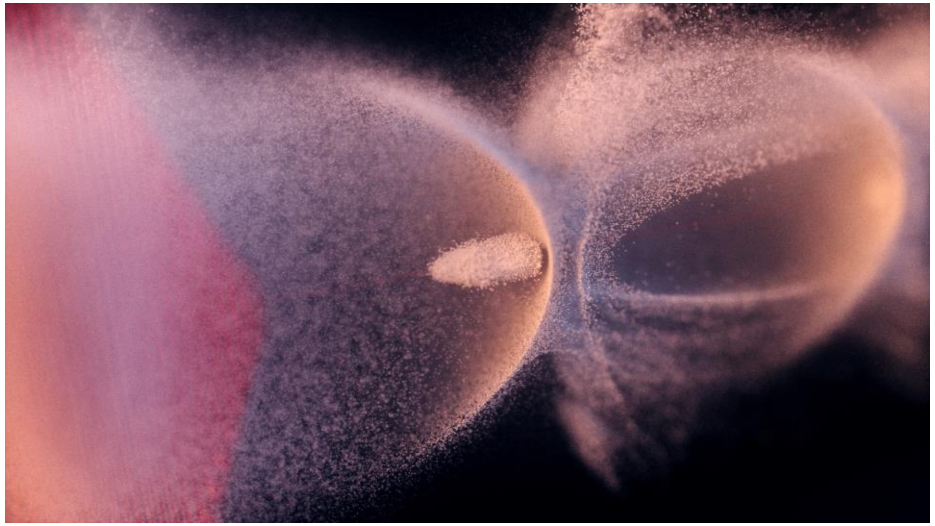
Courtesy Jan Kaiser & Oliver Stein

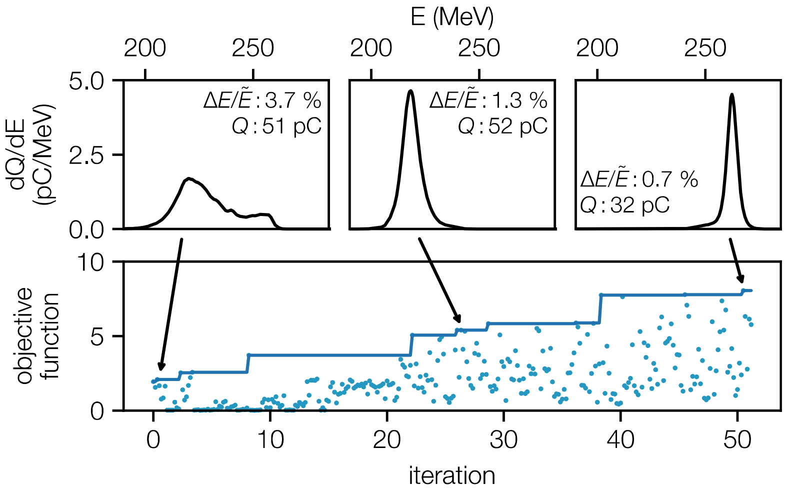


Optimization and feedback control algorithms

Push the way of operation, optimize performance

- **Machine Learning of Laser-Plasma accelerators:**
  Surrogate modeling and Bayesian optimization at LUX
  - **Optimization of electron beam parameters**
    - LUX laser-plasma accelerator tunes to sub-percent energy spread beams using Bayesian optimization
    - *S. Jalas et al. "Bayesian optimization of a laser-plasma accelerator" PRL 126, 104801 (2021)*





Credits:DESY/SciCom Lab
Courtesy: Sören Jalas

See next talk:

Bayesian optimization of a laser-plasma accelerator	*Andreas Maier et al.*
Online, Zoom	19:20 - 19:30

Thank you

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