Current Development of Automated Accelerator Controls

at DESY

Antonin Sulc
Hamburg, 27/09/2022

HELMHOLTZ

DESY accelerators & test benches: birds view …

Challenges

Facilities with many, highly diverse and distributed components

Challenges

- Largely distributed
- Various types of systems
- Strongly coupled subsystems
- Highly nonlinear processes
- High dimensionality
- **High data intensity**
- Hardly any long-term data available

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 14 days
- In total: < 1% sent from front-ends

Courtesy: A. Eichler [A. 22]

Goals

Diverse landscape of accelerators at DESY

Performance

- fs arrival time at km scale
- μm on vert. and horiz. orbits

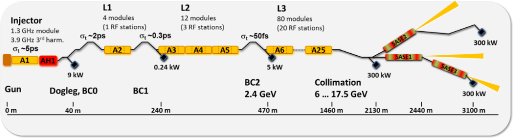
Flexibility

- Switching bunch patterns
- Multi-beam line operation

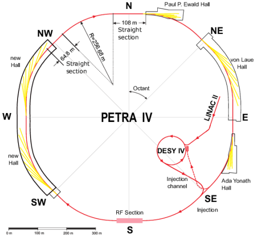
Availability

- Reduce setup times
- Reduce tuning times
- Predict problems

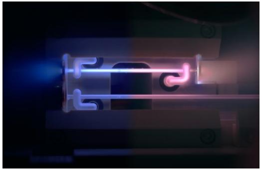
FELs (no equilibrium)



Storage Ring (equilibrium, non-linear)



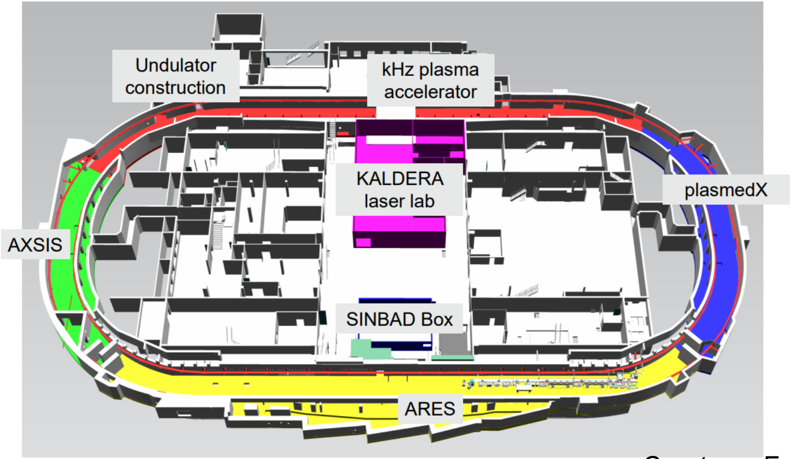
Plasma Accelerators (highly non-linear)



ARES at SINBAD

Accelerator test facility

S-band electron linac for the production of ultra-short bunches.



Courtesy: F. Burkart [F. 20]

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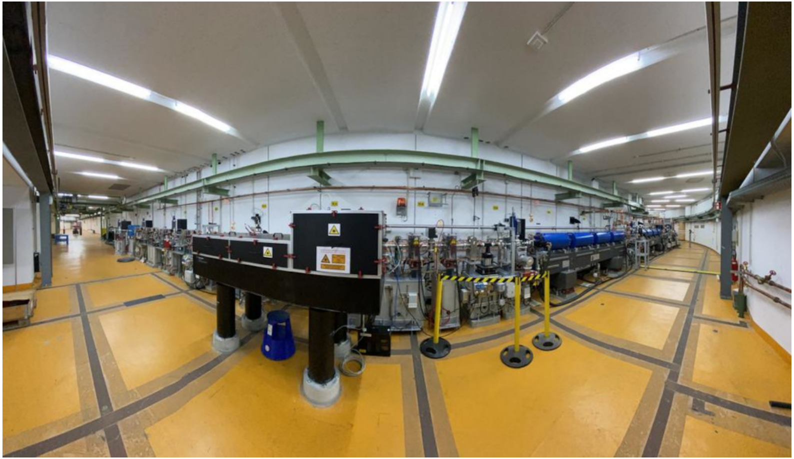
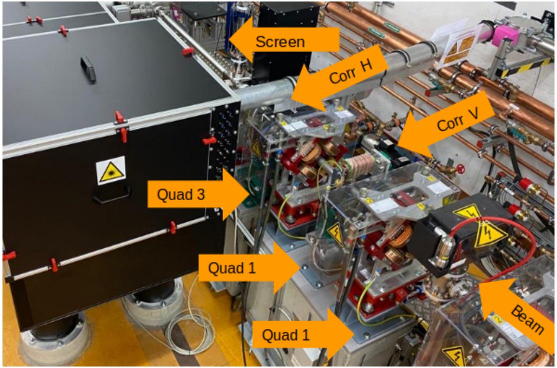


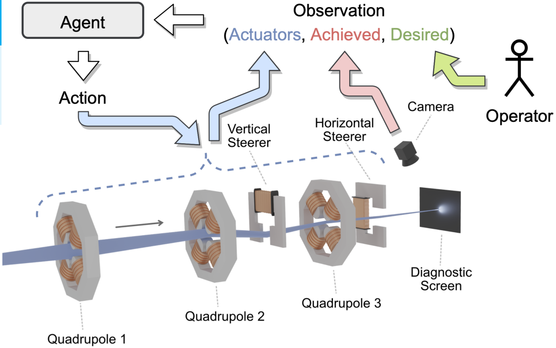
Beam Focusing with Reinforcement Learning

Proof of concept example at ARES

Task

Control a position and focus the beam in the Experimental Area





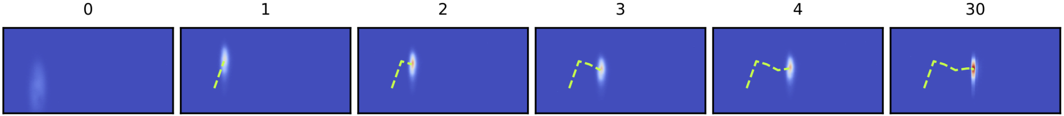
Courtesy: Stein O. and Kaiser J.

[KSE22]

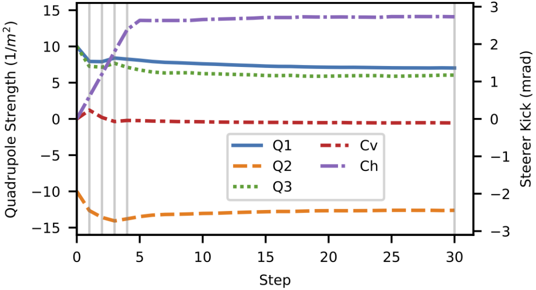
Results

Performance

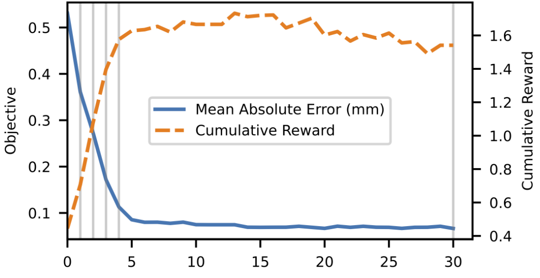
Experimental Area screen figures



Actuator Values



Objective and Cumulative Reward

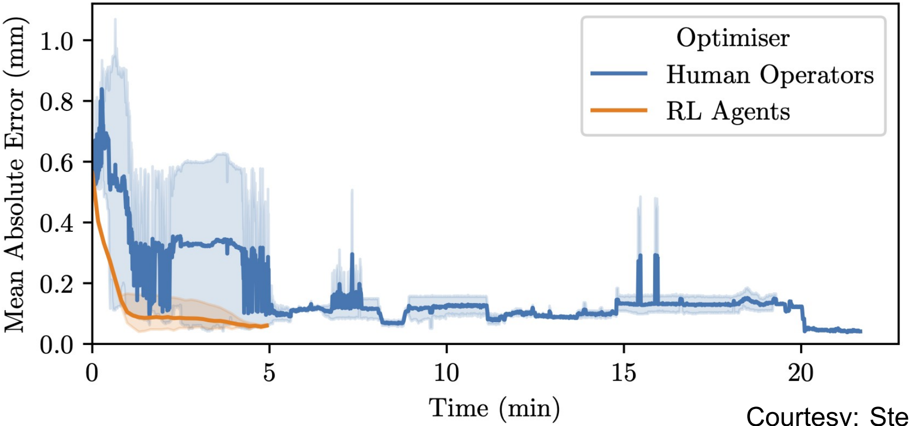


Courtesy: Stein O. and Kaiser J.

[KSE22]

Results

Comparison to the operators



Courtesy: Stein O. and Kaiser J.

[KSE22]

Predictive Maintenance at EuXFEL

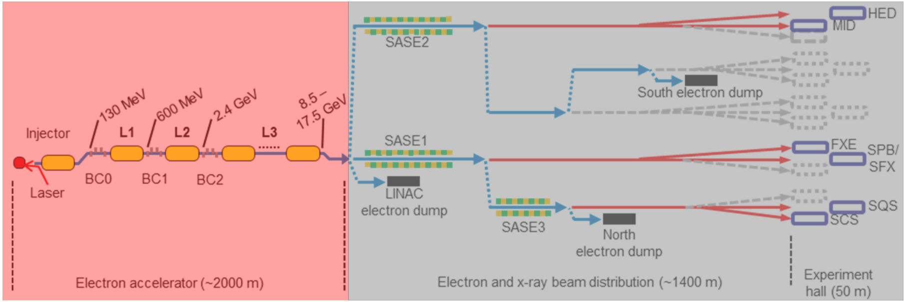
Two use cases of ML applications

LLRF Cavities

- Monitoring signals from cavities.
- Detecting quenches and other faults.

Orbit Monitoring

- Analyzing orbits in SASE beamlines.
- Various types of problems are indicated by variations in orbits.



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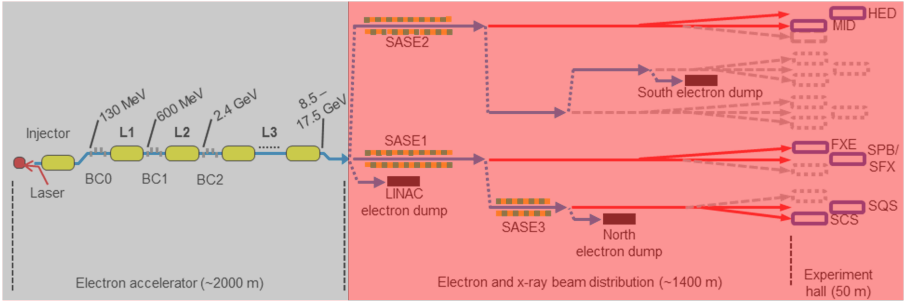


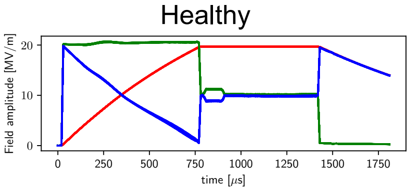
Data-Driven Monitoring of Superconducting LLRF Cavities

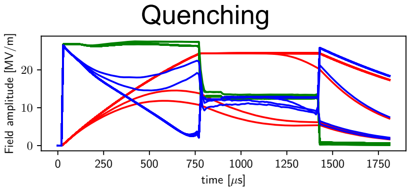
Semi-supervised anomaly detection on cavity data

$\mathbf{h}_1 = \mathrm{LSTM}(\mathbf{x})$ → $\mathbf{h}_2 = \mathrm{LSTM}(\mathbf{h}_1)$ → $\phi = \mathrm{Linear}(\mathbf{h}_2)$ → $s = \|\phi(\mathbf{h}_2) - \mathbf{c}\|_2^2$ →

input=1092, output=256 | input=256, output=256 | input=256, output=64 | input=64, output=1

$\underbrace{\qquad\qquad\qquad\qquad\qquad\qquad}_{f_\theta(\mathbf{x})}$





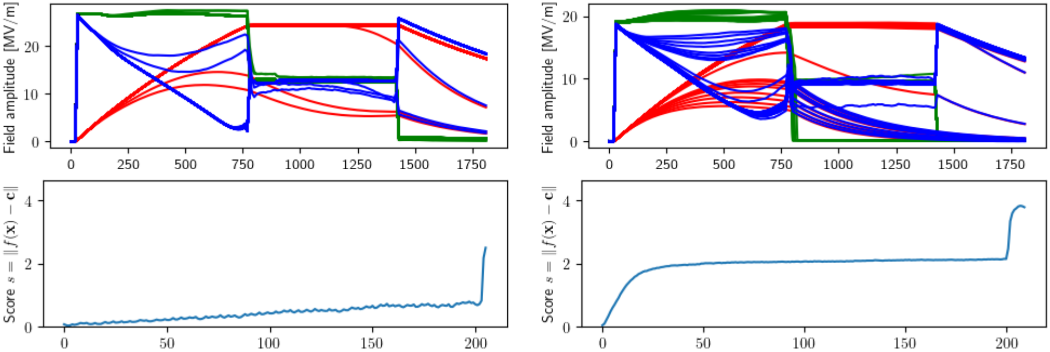
- A RNN is assigning a s to a sequence of cavity pulses.
- Each pulse consists of (probe, forward and reflected signals).
- We have a disproportionately smaller dataset with faults (≈1300 faults) and (almost) unlimited access to non-anomalous data.
- Semi-supervised anomaly loss [RVG+19]

$$L(\theta) = \|f_\theta(\mathbf{x}) - \mathbf{c}\|_2^y + \|f_\theta(\mathbf{x}) - \mathbf{c}\|_2 \text{ where } y \in \{-1, 1\}.$$

[SEW22]

Results - Quenches

Examples of early detection of quenches



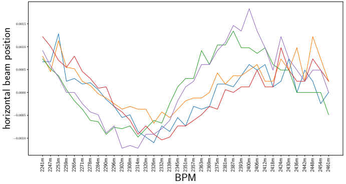
[SEW22]

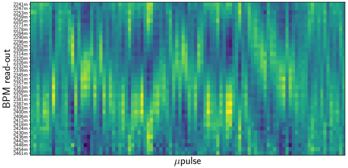
EuXFEL Orbit Monitoring

Unsupervised learning task on BPM data

$\mathbf{h}_1 = \text{Transformer}(\mathbf{x})$ → $\phi = \text{Linear}(\mathbf{h}_2)$ → $s(\phi) := \|\phi - \mathbf{c}\|_2^2$

input=no. of BPMs, output=128 | input=128, output=16 | input=16, output=1





Model-Free Orbit Monitoring

- A transformer that is scoring a set of BPM read-outs.
- Each input is stacked horizontal and vertical positions from selected beamlines.
- We **do not** have any **faulty labels**.
- **Unsupervised one-class anomaly** loss [RVG+18]:

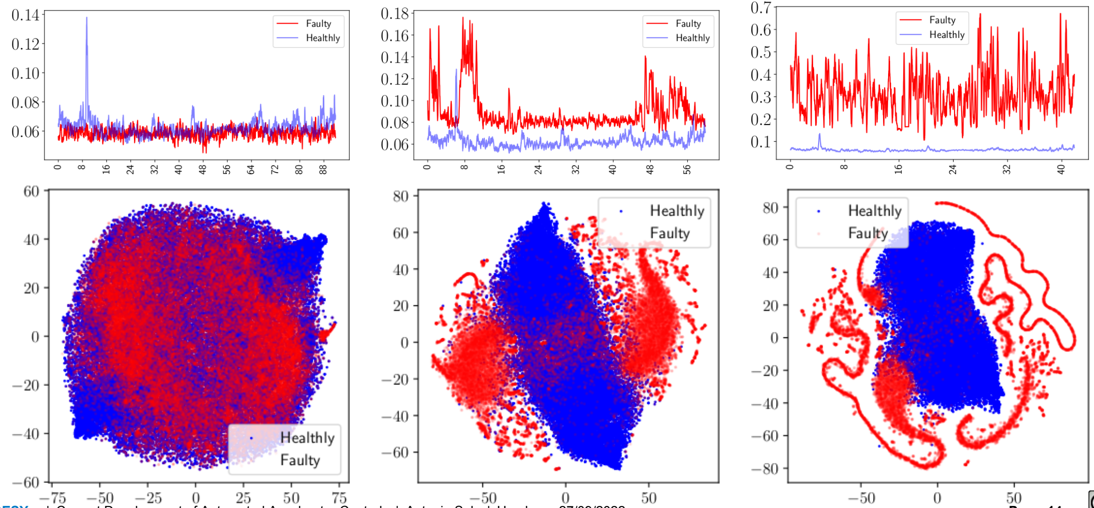
$$L(\theta) = \|f_\theta(\mathbf{x}) - \mathbf{c}\|_2$$

[SKW22]

Orbit Monitoring

Unsupervised learning task from orbit data - ≈ 1 hour before reported fault

Beam is OK | Phase Shifter | Undulator Server

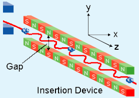


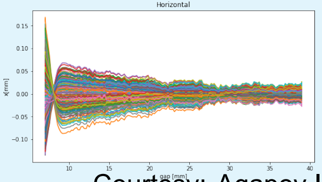
PETRA III Projects

Ongoing AI projects for storage ring

Undulator Gap Compensation

- During operation gaps of insertion devices are varied unpredictably.
- Training NN model to account for orbit disturbance using the model for orbit disturbance correction.

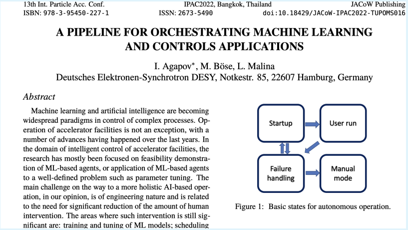




Courtesy: Agapov I.

SW development for automation

Steps toward making the software and hardware data-driven approaches compatible.



13th Int. Particle Acc. Conf. IPAC2022, Bangkok, Thailand JACoW Publishing
ISBN: 978-3-95450-227-1 ISSN: 2673-5490 doi:10.18429/JACoW-IPAC2022-TUPOMS016

A PIPELINE FOR ORCHESTRATING MACHINE LEARNING AND CONTROLS APPLICATIONS

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Abstract

Machine learning and artificial intelligence are becoming widespread paradigms in control of complex processes. Operation of accelerator facilities is not an exception, with a number of advances having happened over the last years. In the domain of intelligent control of accelerator facilities, the research has mostly been focused on feasibility demonstration of ML-based agents, or application of ML-based agents to a well-defined problem such as parameter tuning. The main challenge on the way to a more holistic AI-based operation, in our opinion, is of engineering nature and is related to the need for significant reduction of the amount of human intervention. The areas where such intervention is still significant are: training and tuning of ML models; scheduling

Figure 1: Basic states for autonomous operation.

[ABM22]

Thank you!

This work was only possible thanks to A.Eichler, R.Kammering and T.Wilksen.

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10.3204/PUBDB-20YY-nnnn

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