

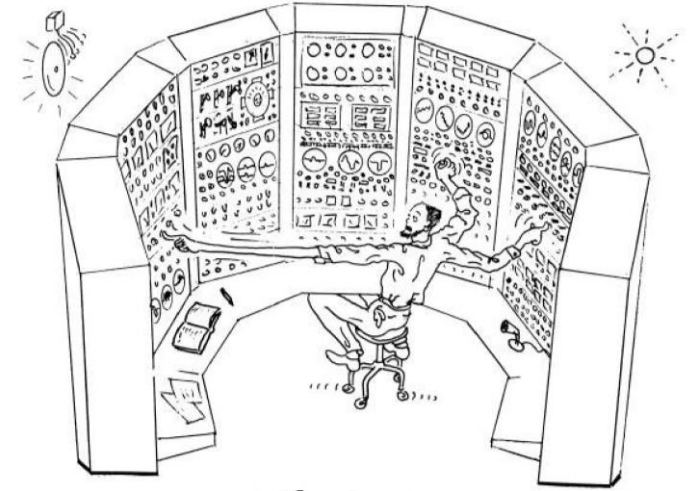


BE-CSS and SY-ABT activities

A. Huschauer, V. Kain, M. Schenk, F. Velotti
on behalf of the extended EPA & accelerator communities

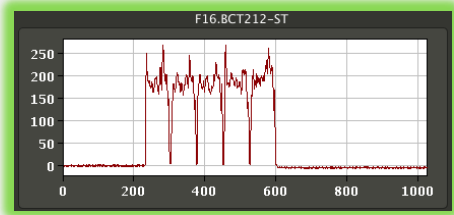
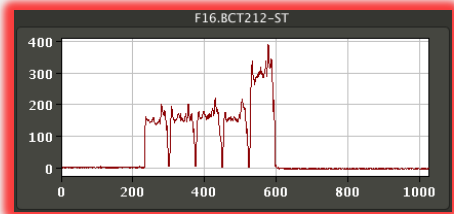
Intro

- **ML & NNs** for applications in **beam operations** and **beam transfer**
- **Dealing with a very diverse landscape of problems & data**
 - **Controllers:** parameter optimisation & drift compensation (on-demand or continuous), feed-backs / feed-forward corrections, scheduling
 - **Monitoring:** forecasting, virtual / enhanced diagnostics, anomaly detection
 - **Other:** project on LLMs (knowledge retrieval)
- **No “one size fits all”**
 - (Meta-)RL, BO, model-predictive control (GP-MPC), physics-informed methods, transformers, numerical optimisers (gradient free) & classical control
often in combination with simulations or surrogate models
 - **Anomaly detection:** typically auto-encoders, but also SVMs, isolation forests, ...
 - **Challenges:** no online training (sample efficiency) → sim2real gap, exploitation vs exploration / continual learning, **running safely & reliably 24/7**, lack of beam observation / diagnostics, ...
- **Remarks on safety**
 - Above everything, we have an **independent machine protection system**^(*)
 - Controllers typically work in **bounded parameter space**
 - Can still have **undesirable consequences** if controllers unsafe: **degraded beam quality, increased particle loss and radio-activation, machine downtime**



^(*)ML-free

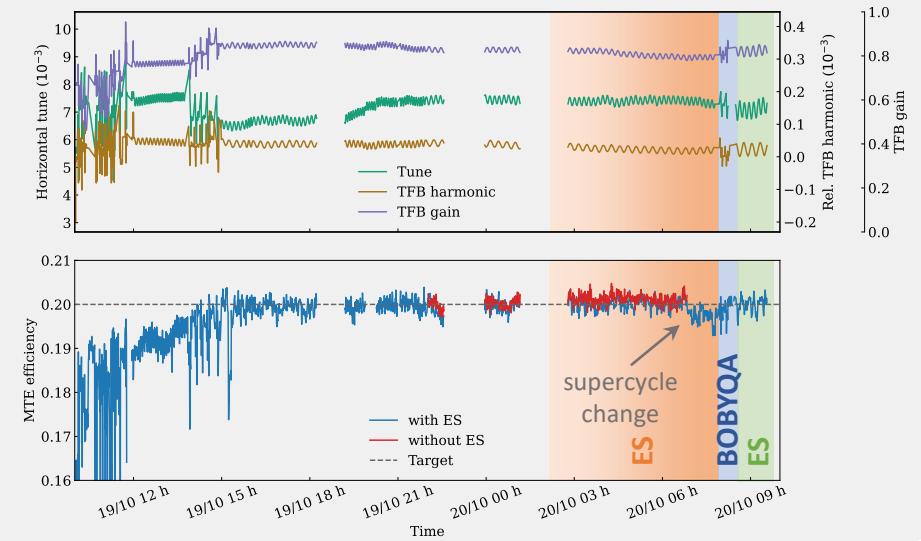
Examples using classical control



PS Multi-Turn Extraction

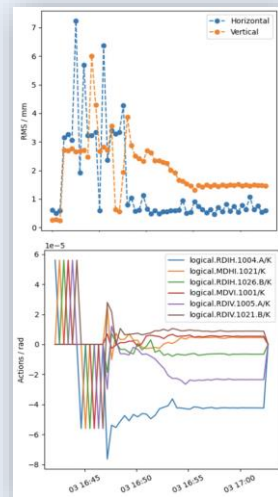
- **Automatic drift compensation**
- **Successfully tested and tuned in MDs**
- **Hybrid agent:** continuous controller interleaved with optimizer when far off

A. Huschauer, M. Schenk, C. Uden



Trajectory steering framework using *acc-geoff4ucap*

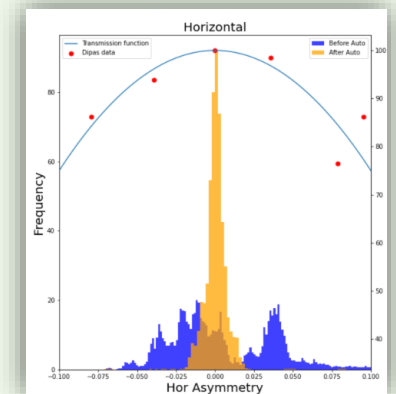
- **Versatile objective**
Beam position, beam loss, ...
- **Various algorithms**
incl. Micado / SVD, numerical opt.
- **In 2024:** PS2SPS, SPS2LHC



G. Trad, F. Velotti

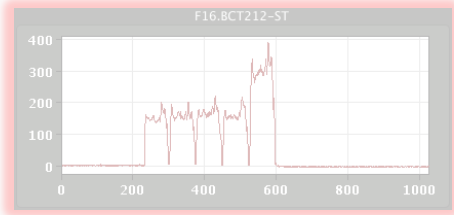
PS EAST: fixed target beam steering

- **PID regulator on UCAP**
- **Simple & effective**
- **Similar controller for TL** towards AD



J. McCarthy

Examples using classical control



PS Multi-Turn Extraction

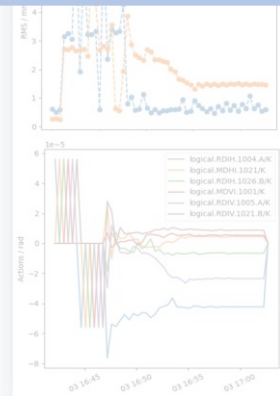
- Automatic drift compensation
- Successfully tested and tuned in MDs

- **Generally easier to validate than ML-based methods**
 - Bounded parameter spaces
 - Predictable / deterministic behaviour
 - Can still run into unforeseen situations over longer time scales



Trajectory steering from using *acc-geoff4ucap*

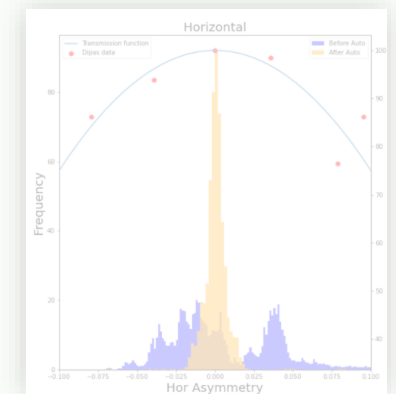
- Versatile objective
Beam position, beam loss, ...
- Various algorithms
incl. Micado / SVD, numerical opt.
- In 2024: PS2SPS, SPS2LHC



G. Trad, F. Velotti

- PID regulator on UCAP
- Simple & effective
- Similar controller for TL towards AD

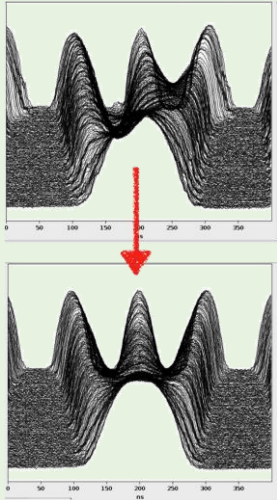
steering



J. McCarthy

Examples using RL

PS



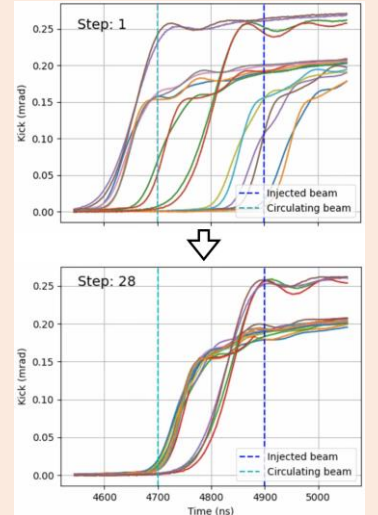
- Correct RF **phase & voltage** for **uniform bunch splitting** (LHC beams)
- **Multi-agent (SAC) & CNN** for initial guess
- Successful **sim2real** transfer
- **If things go wrong**: degraded beam

A. Lasheen, J. Wulff

PS to SPS

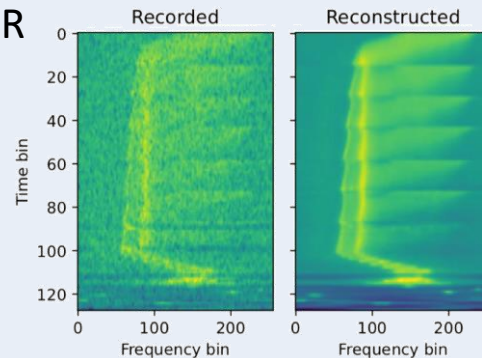
- Adjust **fine delays** of SPS **injection kicker**
- RL agent (PPO) trained on **data-driven dynamics model**
- **If things go wrong**: beam loss, activation

M. Remta, F. Velotti



LINAC3 / LEIR

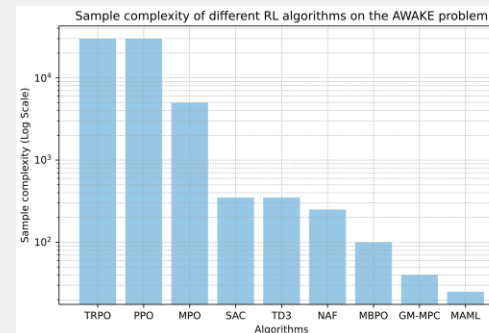
- Achieve **optimal injection** into LEIR
- RL state based on **β -VAE-encoded Schottky spectra**
- Agent trained on **data-driven dynamics model**
- **If things go wrong**: beam loss, activation, equipment trips



V. Kain, N. Madysa, B. Rodriguez

AWAKE

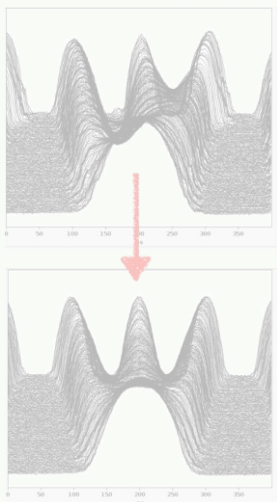
- **Steer electron beam** in AWAKE line
- **Test-bed** for different RL algorithms & sim2real transfer
- Large improvements in **sample efficiency** (Meta RL)
- **If things go wrong**: not critical



S. Hirlander, V. Kain

Examples using RL

PS



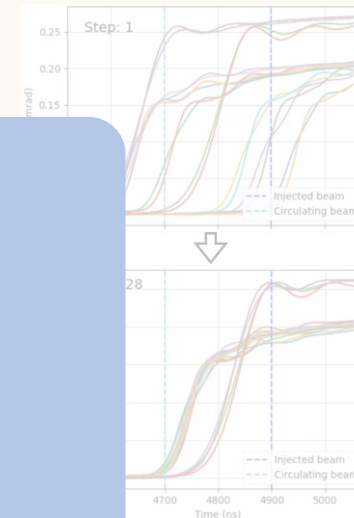
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A. L.

- **RL training “by definition” unsafe** (trial and error learning)
there are some ways to add safety to RL ...
- **RL policies typically hard to validate:** true for all NNs, even if RL policy networks are typically small
are all actions safe for all possible states?
- **For us**

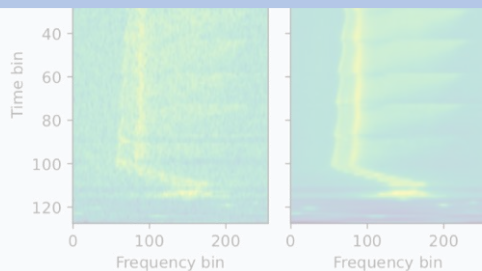
- Usually **no online training** possible (safer)
- Instead **sim2real transfer** either using simulation or data-driven dynamics model (might be safety issue, depending on sim2real gap)
- **Continuous state-action spaces**

PS to SPS

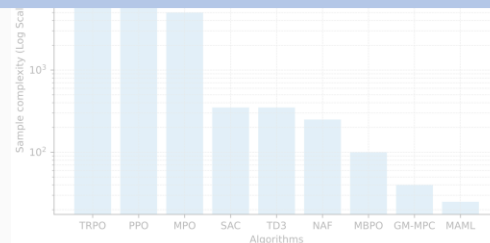


LINAC3 / LEIR

- Achieve **optimal**
- RL state based on **p-VALE-encoded Schottky spectra**
- Agent trained on **data-driven dynamics model**
- **If things go wrong:** beam loss, activation, equipment trips



V. Kain, N. Madysa, B. Rodriguez



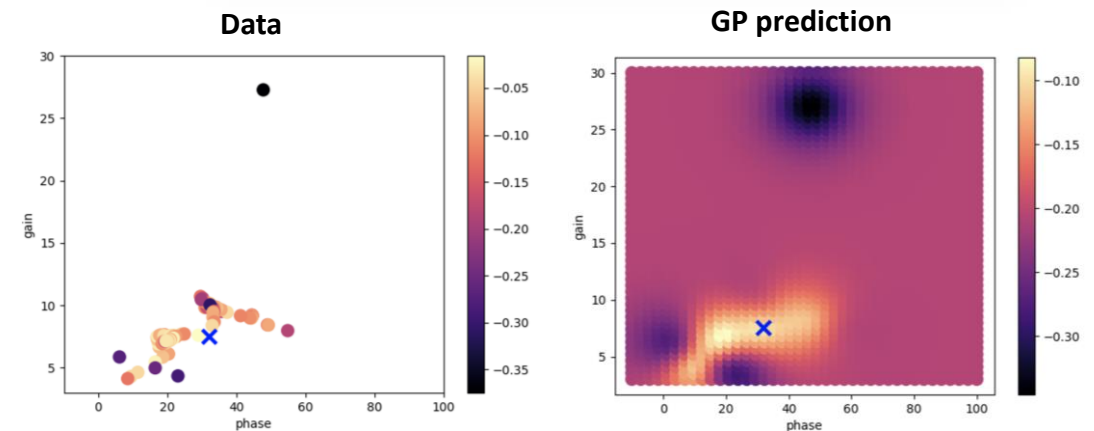
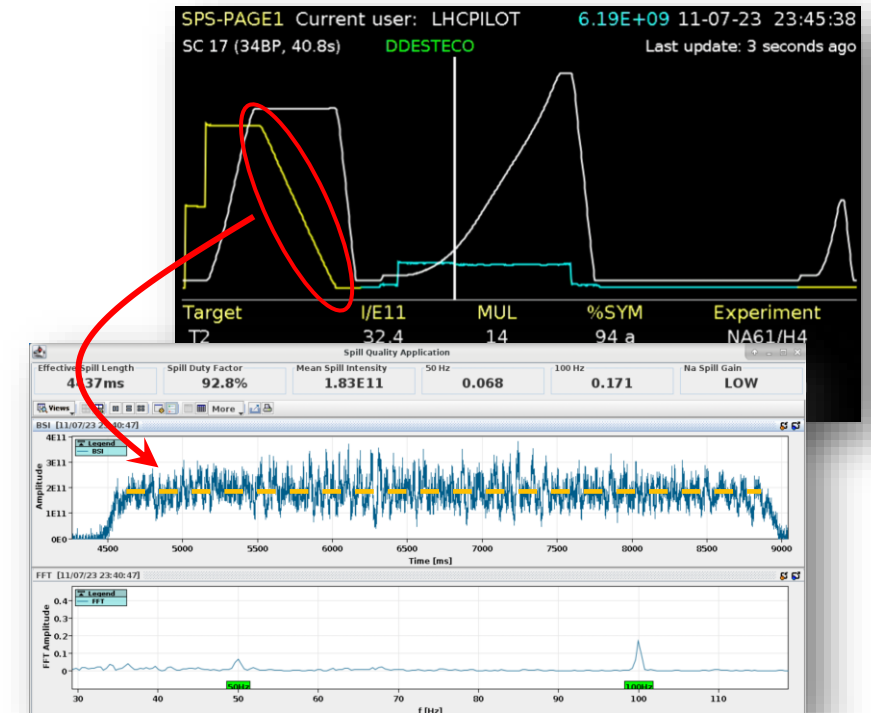
S. Hirlander, V. Kain

- **Test-bed** for different RL algorithms & sim2real transfer
- Large improvements in **sample efficiency** (Meta RL)
- **If things go wrong:** not critical

Example using BO

Spill noise cancellation

- **SPS** slow-extracted beam has **50 Hz & 100 Hz noise** originating from **quadrupole** power converter **ripple**
- **Continuous controller for active noise cancellation**
 - Adaptive Bayesian optimisation
 - Spatio-temporal Gaussian Process model
 - Low dimensional: two spatial parameters + time
- **Challenges**
 - Exploration vs exploitation
 - Jumping to bounds occasionally *under control with proximal biasing*
 - Time dependence: model updates on-the-fly, has sometimes ended up in “degenerate state”, but does usually recover
- **If things go wrong:** degraded beam and potentially time lost for physics experiments
- **N.B.:** there is SafeOpt for safety-critical BO



Example using PhyLSTM / transformers

Hysteresis & eddy-current compensation

- **Context**

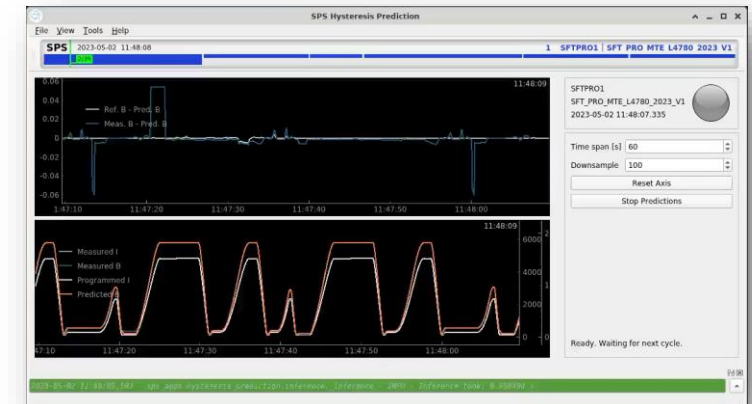
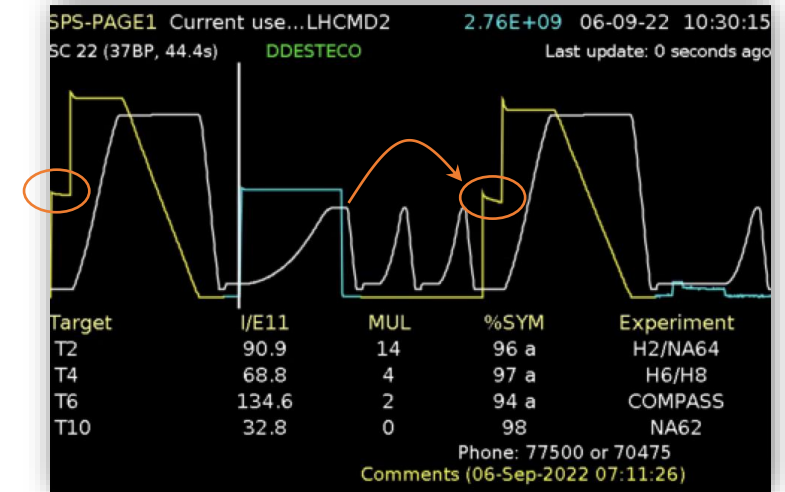
- **Multipole magnets** define beam trajectory, size, oscillation, and some aspects of collective beam behaviour
- Many CERN accelerators are **multi-user machines** each with a **different magnetic cycle**
- **Magnetic hysteresis** introduces **change in beam dynamics** for identical cycles which is problematic in many ways

- **Method & challenges**

- **Feed-forward correction on magnetic strength** to provide reproducible fields
- **PhyLSTM & Transformer models** trained on dipole data
- **Generalisability & accuracy** of model

- **Safety aspect**

- **PhyLSTM**: typically well behaved, even when extrapolating
- **Transformer-based models**: hard to validate "for all possible inputs" / to some degree unpredictable
- Add **safeguard at model output** to limit allowed change of magnetic field



A. Lu, V. Kain, V. Di Capua

Equipment-related ML

- Define new paradigm of **smart and agile equipment**
e.g. adding context-awareness: beam parameters, machine state, etc.
 - ➔ automate **setup, fault analysis, and recovery**
- **Ongoing pilot studies**
 - **Potentially safety-critical:** mix-in ML models to decide whether equipment can be **reset automatically**
e.g. anomaly detection for vacuum interlock spikes on kicker magnet using VAE
 - **Adding safety:** e.g. Conv AE for SPS beam dump anomaly detection, kicker magnet temperature forecasting
- **Systematic studies in that direction have started relatively recently**
 - Validation / safety could become more relevant in the coming years

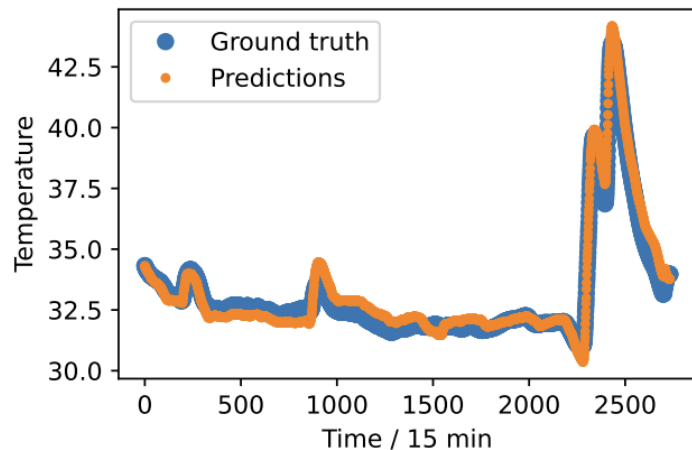
Equipment-related ML

Temperature forecasting & pressure anomalies

• Example 1

Kicker magnet temperature forecasting

- **Kicker temperatures limit SPS high-intensity operation** (beam-induced heating)
- **Goal:** create **temperature forecast** using online measurement, current machine operation and future planning
- **Method:** Light Gradient Boosting Machine and using beam-induced heating equation

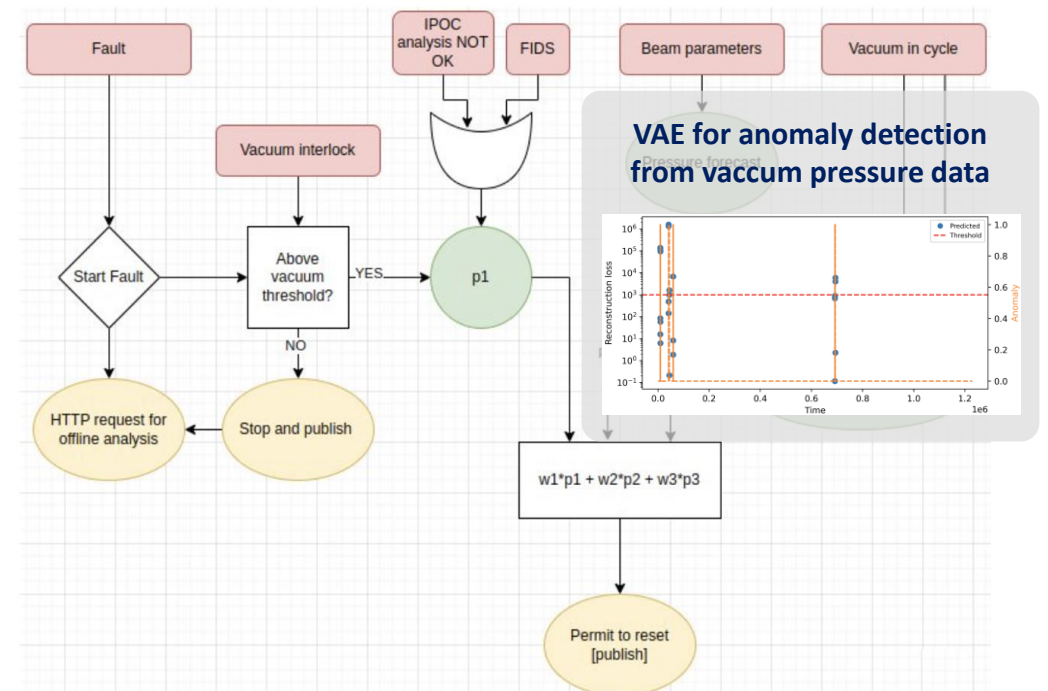


F.M. Velotti et al.

• Example 2

Auto-reset of SPS kicker following vacuum interlock

- **Goal:** correctly classify vacuum “spikes” to avoid unnecessary downtime
- **Method:** VAE trained on historical time-series data
- **Auto-reset and automatic e-mail** with diagnostics plots to experts



Equipment-related ML

Beam dump system failure

F. Huhn, F.M. Velotti, B. Goddard

- **SPS beam dump system (SBDS)**
 - **Machine-safety critical**
 - Malfunctioning may result in **unwanted activation or damage**
- **Goal:** detect anomalous beam dump patterns from BTV images
 - **Challenges:** unlabelled data, be robust to both seen and unseen anomalies, high variability due to other effects, ...
 - **Heavily biased towards “normal” images:** train **convolutional AE** and use **reconstruction loss** to identify anomalies
- **Results**
 - Anomalous SBDS behaviour: **~5 - 20 x higher reconstruction error**
 - Additional info on **localisation of error** (helpful to diagnose)
 - Deployed and **running operationally**
- **Safety aspect**
 - Adds **additional diagnostic and safety check** for the beam dump kickers
 - At the moment **just monitoring**

