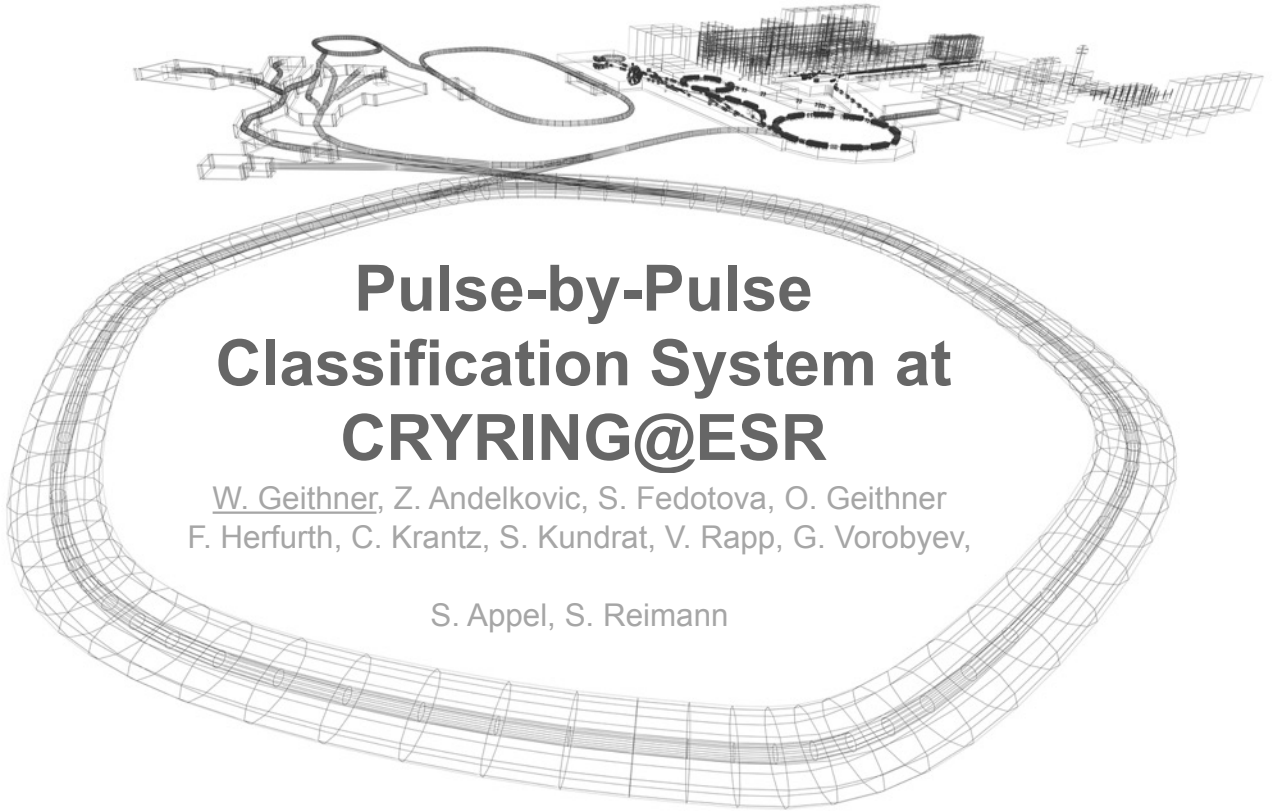
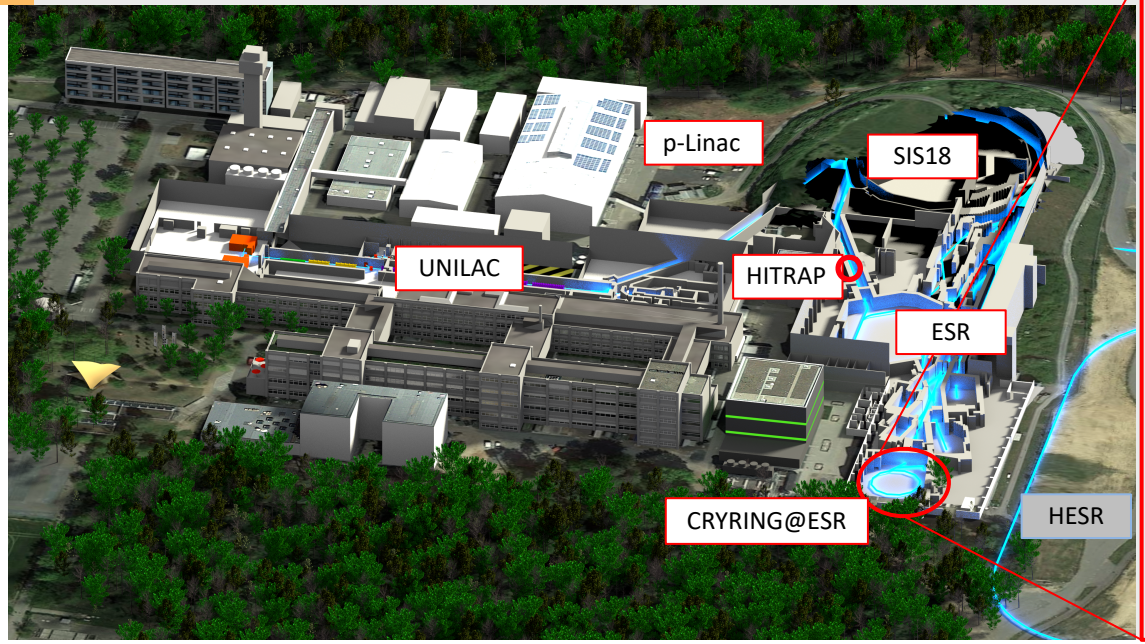


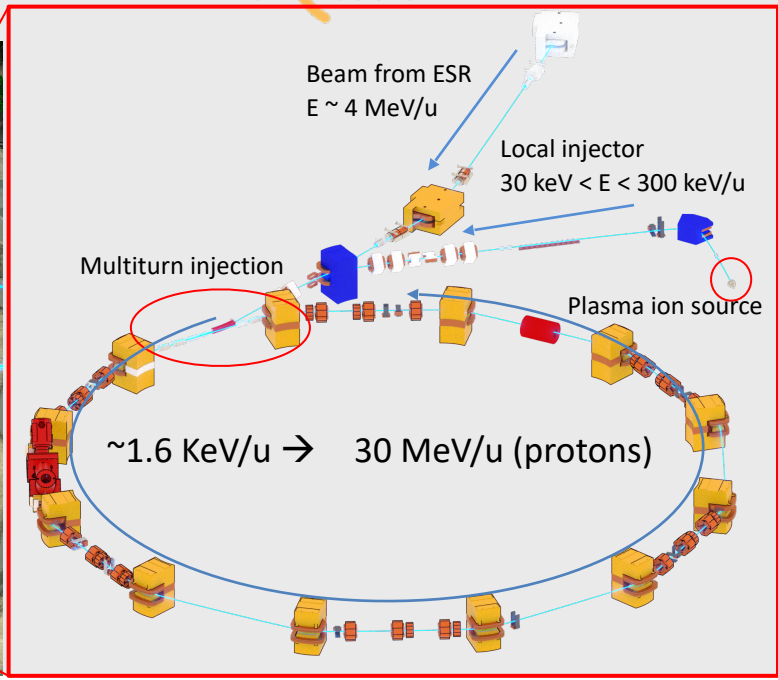
Pulse-by-Pulse Classification System at CRYRING@ESR

W. Geithner, Z. Andelkovic, S. Fedotova, O. Geithner
F. Herfurth, C. Krantz, S. Kundrat, V. Rapp, G. Vorobyev,

S. Appel, S. Reimann

„Decelerators at GSI: CRYRING@ESR & HITRAP





CRYRING

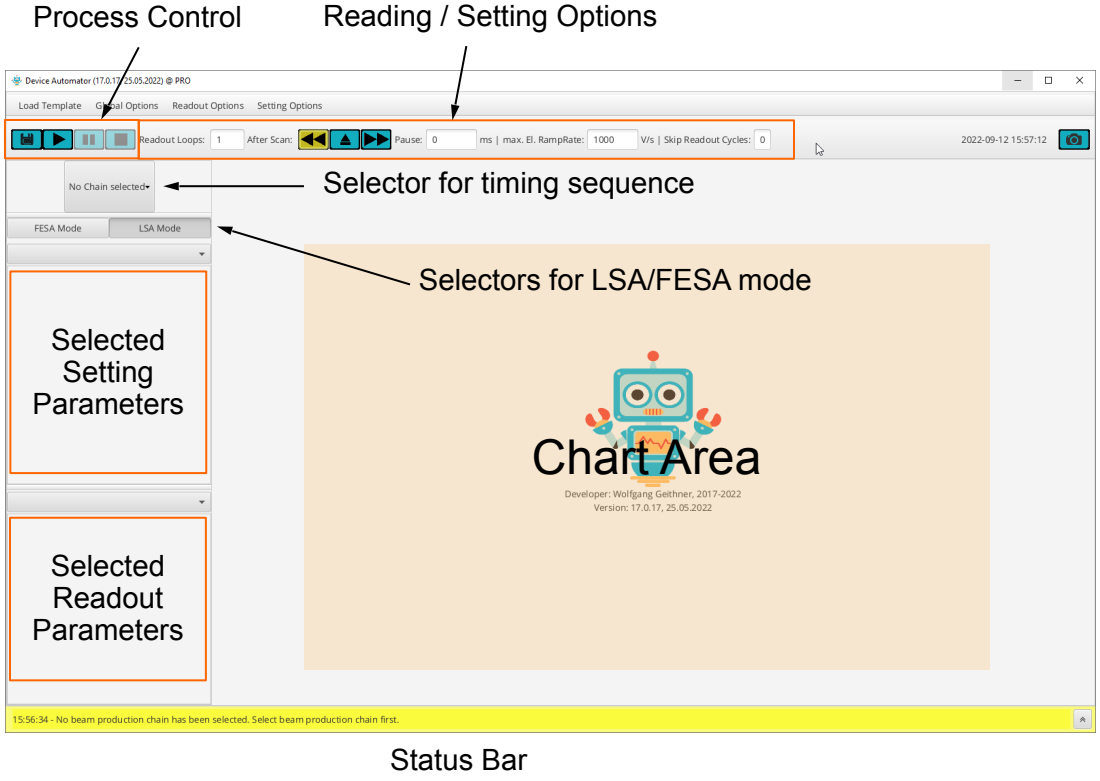
- Atomic & nuclear physics experiments
- Test bench for FAIR concepts
- Ahead-development of FAIR prototypes

HITRAP

- Precision experiments, QED testing
- Studies of ions at rest energy

Motivation for Classification:
Task Automation and Beam Optimization

Operator-User Application “Device Automator”



Project started in 2017

JAVA based application available in operator software toolbox

Able to drive “any” parameter of “any” FAIR accelerator

Able to drive “any” number of parameters

Machine subsystem templates

“Brute Force” scanner or genetic optimizer

Many ideas, no time ;)

Machine Automation:
Measurement of CRYRING@ESR Tune Diagram

- Tune diagram was measured via “device automator” driving LSA tune parameters
- Large parameter ranges were covered
- approx. 9000 steps, step width 0.04
- Measurement took about 2 days

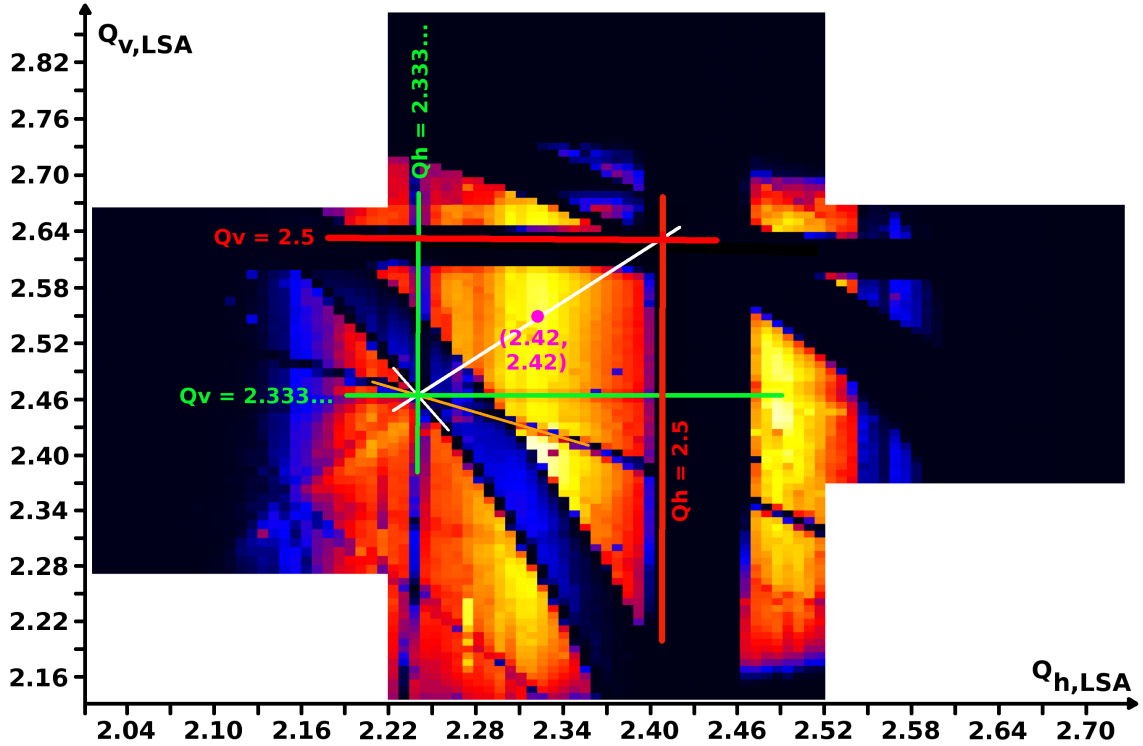
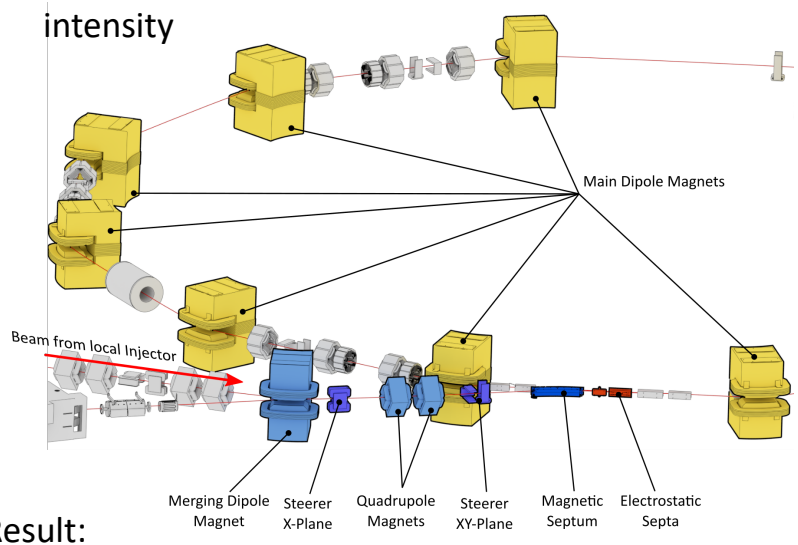
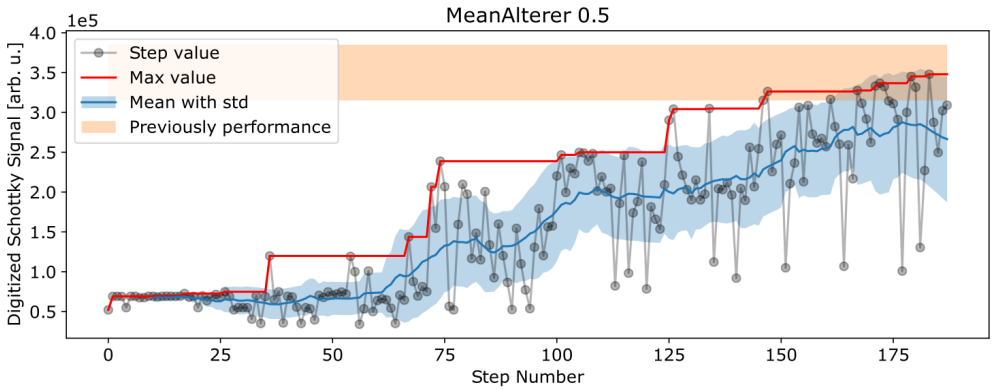


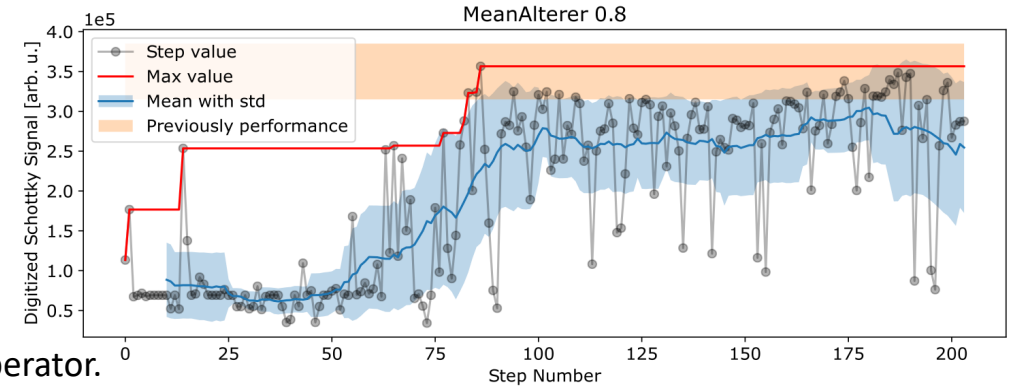
image: courtesy of C. Krantz

Applying Genetic Algorithms: Injection Optimization[1]

- Genetic algorithm controls 10 parameters
- Goal parameter: beam intensity measured by Schottky signal normalized to ion source intensity







Result:

- Genetic algorithm is capable to optimize injection
- Optimization Performance comparable to human operator.

[1] S. Appel, W. Geithner, et al.: “Optimization of heavy-ion synchrotrons using nature-inspired algorithms and machine learning”, 13th Int. Computational Accelerator Physics Conf., doi:10.18429/JACoW-ICAP2018-SAPAF02

Issue: Beam Fluctuations

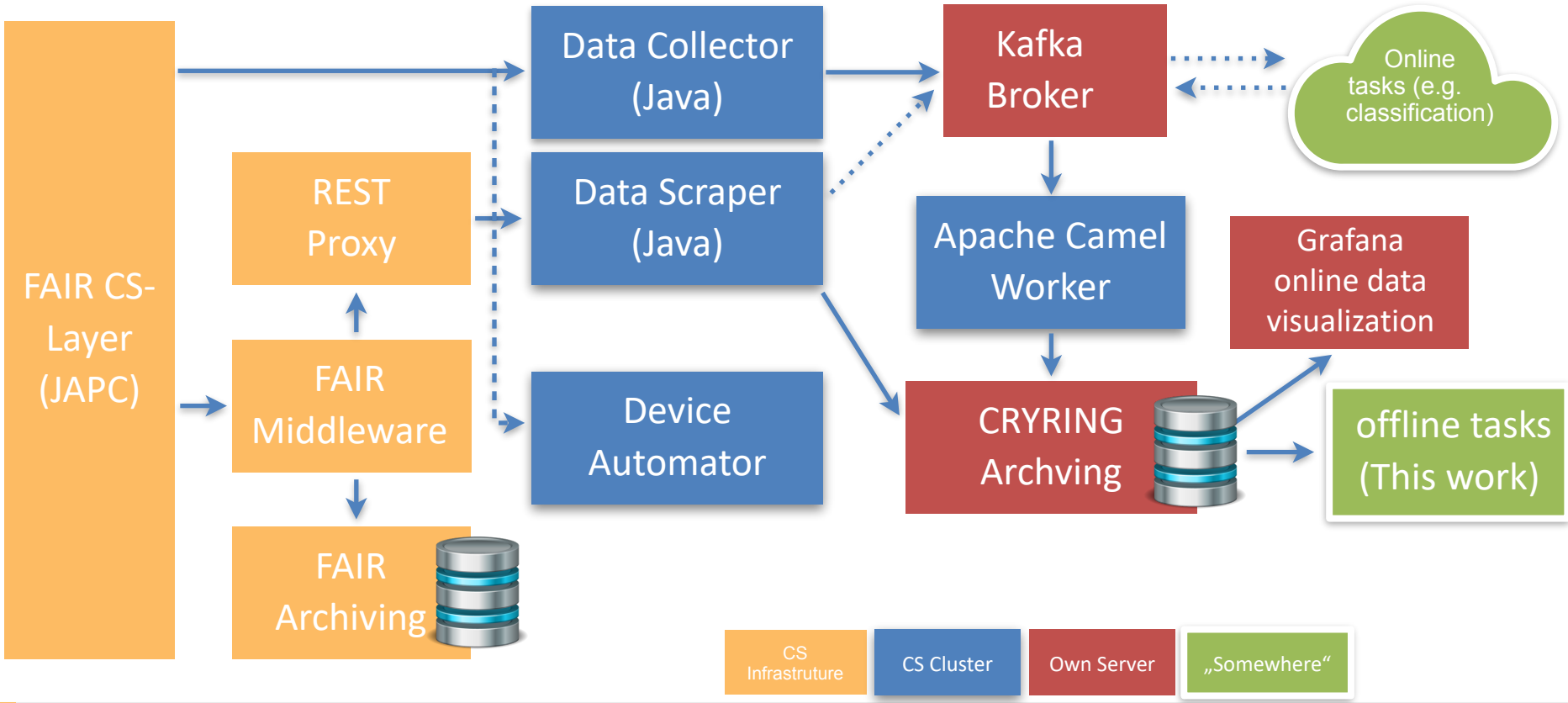
- Beams from local ion source and from ESR show significant intensity variations down to “no beam”
- Affects effectivity of optimizer(s) and other applications/experiments where stability of intensity plays a role
- Non-destructive intensity detector before injection subsystem not feasible due to strong electrical noise from injection kicker

- Approaches to improve the beam fluctuation issue:
  - Average over multiple pulses (slow)
  - Normalize measurement to incoming intensity (“difficult” without detector before injection)
  - Discrimination of pulses on basis of good/bad (“lot of work”, knowhow needed (to be built))

“Lightweight” Technology Stack for Pulse-by-Pulse Classification

Wolfgang Geithner

IT Infrastructure for CRYRING@ESR Datalogging



Data Logging Key Achievements

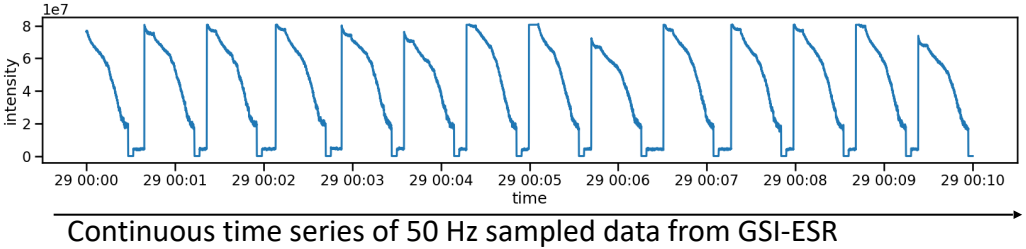
- Online monitoring capability was major breakthrough for getting operation of CRYRING cry-system under control
- Slow monitoring of whole machine
- Online view on key machine data in range of minutes to weeks possible
- Dashboards with multiple charts and indicators allow quick overview
- Partner project with UNILAC ion sources enabled on-line monitoring of these devices too

Pulse-by-Pulse Classification System

Wolfgang Geithner

Basic Idea

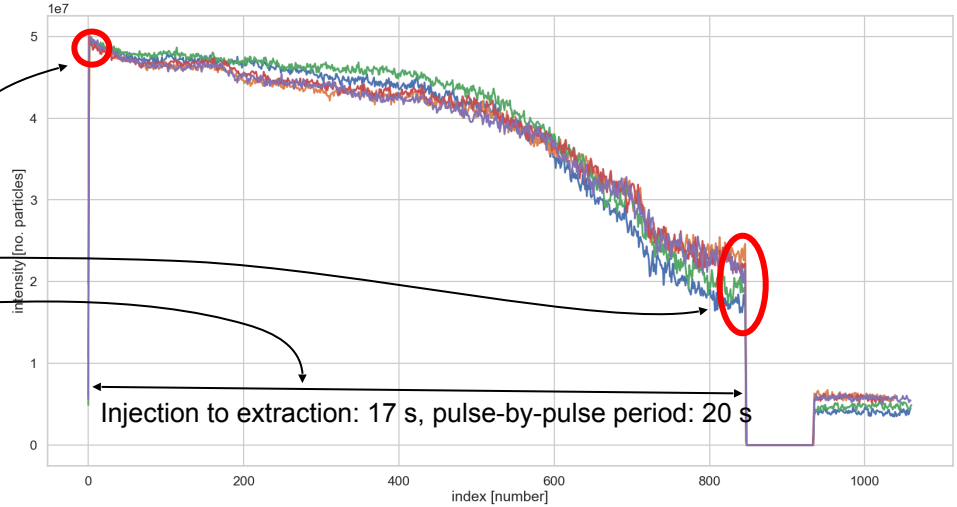
Convert time-series problem to classification problem



Continuous time series of 50 Hz sampled data from GSI-ESR

- Slice time series by “last injection” timestamps into pulses

- Characterize each pulse by metrics:
  - injection maximum
  - extracted particles
  - pulse length
  - integral under curve
  - matrix profile distance (next slide)



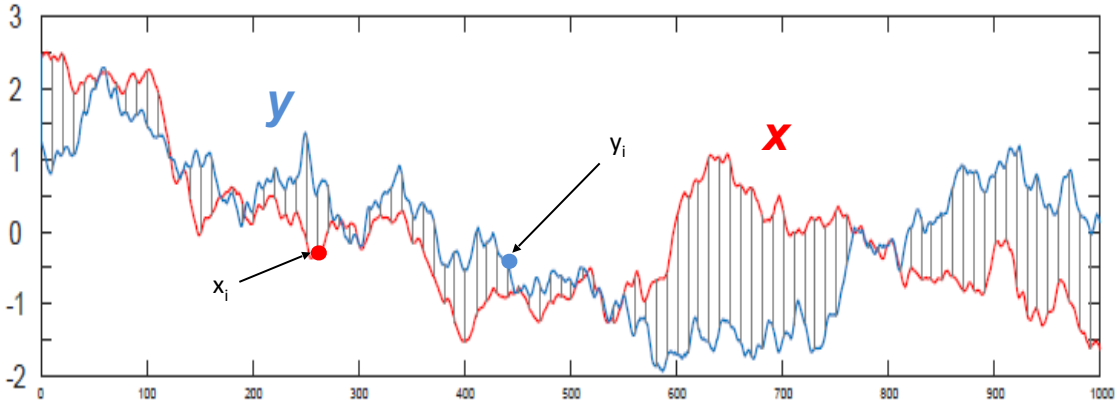
MPdist: Normalized Matrix Profile Distance[1]

Simple measure for similarity of two time series

Compare two arrays of beam transformer readout values → compare “shape” of signal

z-normalized Euclidean distance:

$$d(\hat{\mathbf{x}}, \hat{\mathbf{y}}) = \sqrt{2m\left(1 - \frac{\sum_{i=1}^{m} x_i y_i - m\mu_x\mu_y}{m\sigma_x\sigma_y}\right)}$$



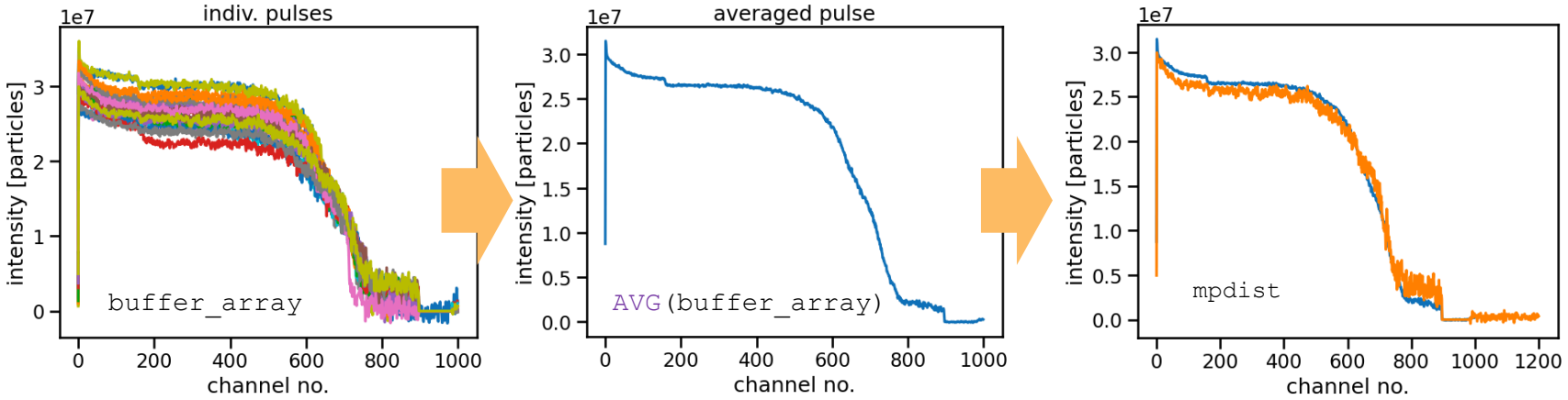
➔ smaller values —> series are similar

Here, series were normalized to maximum value

[1] Shaghayegh G., et al: Matrix Profile XII: MPdist: A Novel Time Series Distance Measure to Allow Data Mining in More Challenging Scenarios, 2018 IEEE International Conference on Data Mining (ICDM). IEEE, 2018.
mpdist code & documentation: https://sites.google.com/site/mpdistinfo/

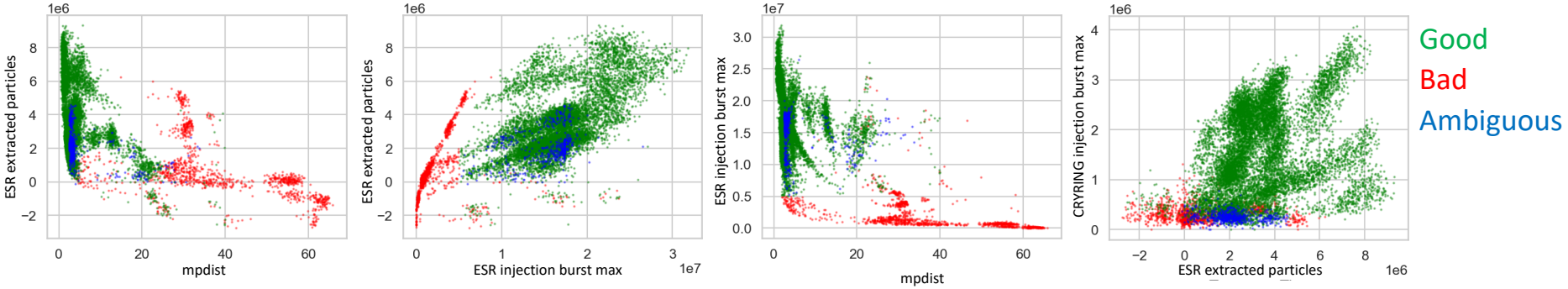
Logic for Pulse Metrics Determination

- Injection burst = Maximum of first 10 channels
- Extracted particles = mean of last 5 channels before extraction timestamp
- Integral = sum of values between injection and extraction
- Calculate MPdist between average of last N pulses and present pulse
- Add pulse array to buffer of size N if pulse fulfills „OK“ criteria



Generation of Reference Data Set:

CMAT experiment ESR to CRYRING - Au^{78+}

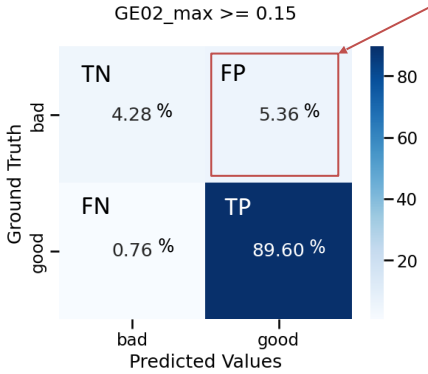


- ~13.000 Pulses labeled by hand
- Good pulses:
  - Injection burst over limit
  - extraction over limit
  - injection into CRYRING visible
- Bad pulses:
  - extraction below limit
- Ambiguous pulses:
  - fulfill “good” criteria
  - not visible in CRYRING

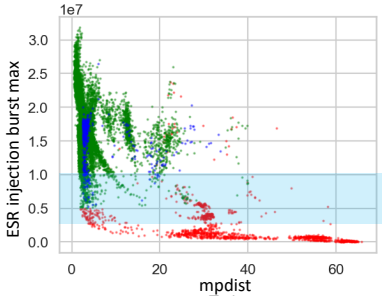
Naïve Discrimination: Thresholding 1

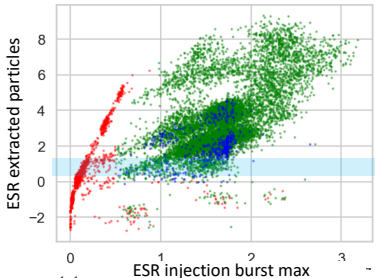
confusion matrix
for each value:

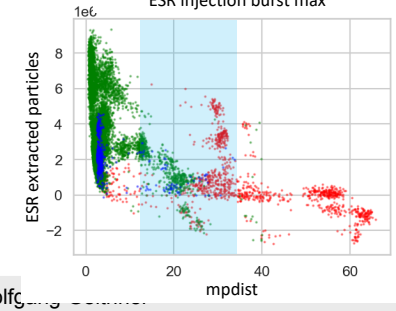
most critical for optimization

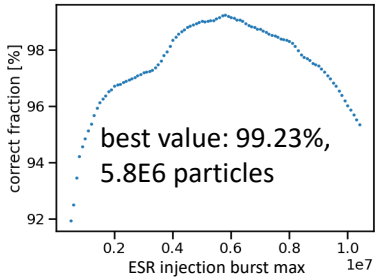


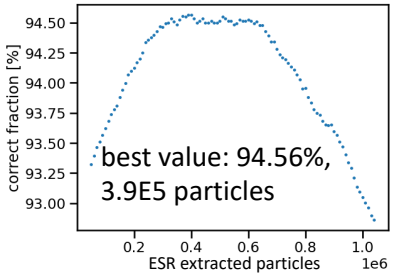
$$\text{Accuracy} = \frac{TN + TP}{TP + TN + FP + FN}$$

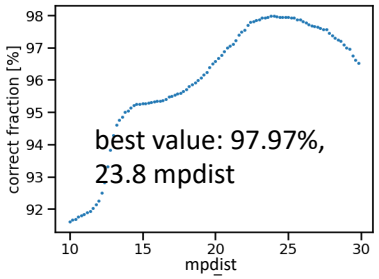




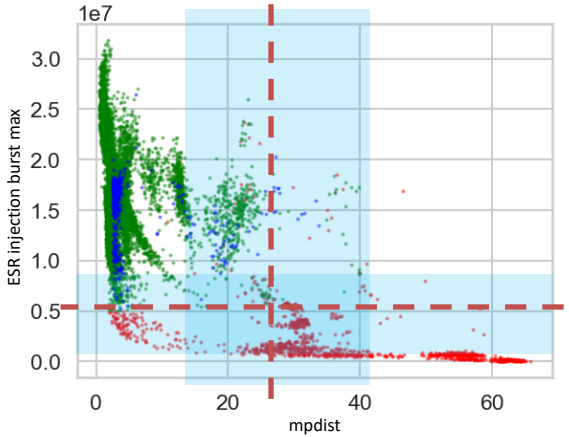




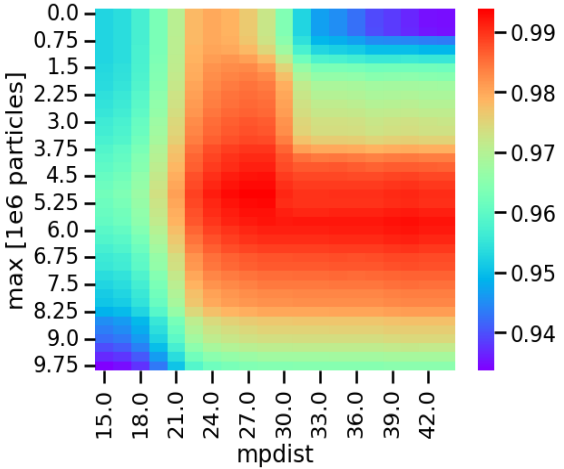




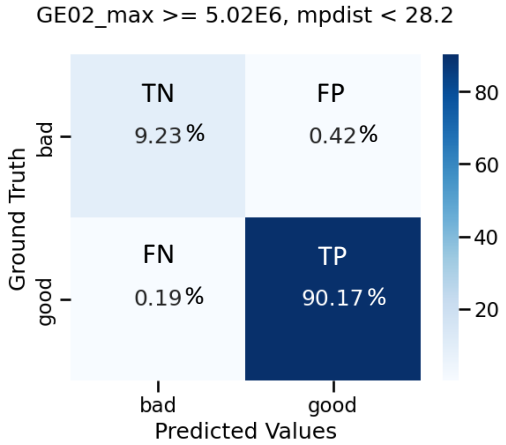
Naïve Discrimination:
2 Parameter Thresholding



confusion matrix
for each values tuple:
Accuracy



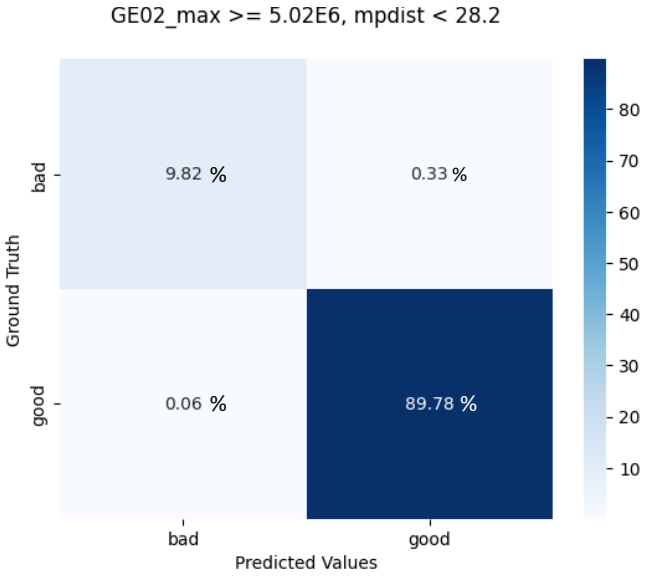
Best values:
Accuracy = 99.4 %

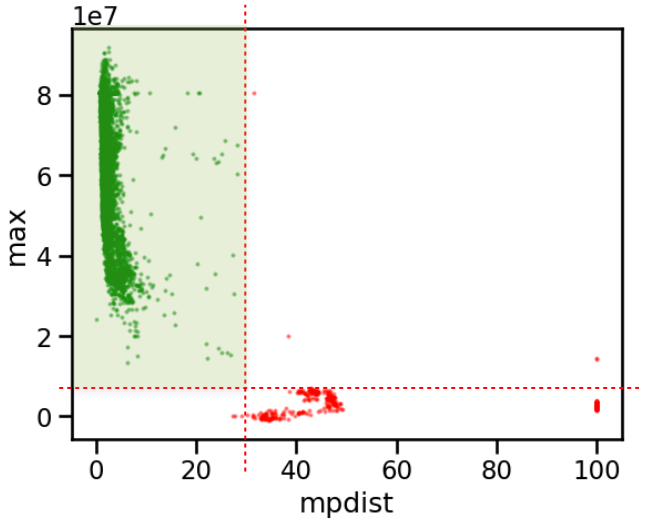


Application to Test Data:

HITRAP, 2nd week - Ni^{28+}

- Approx. 7900 pulses in data set
- ESR cycle comparable to CRYRING cycle
- 10/90 bad/good ratio, same as for CRYRING training data
- Unfortunately, no HITRAP injection data —> labeling only by „eye“



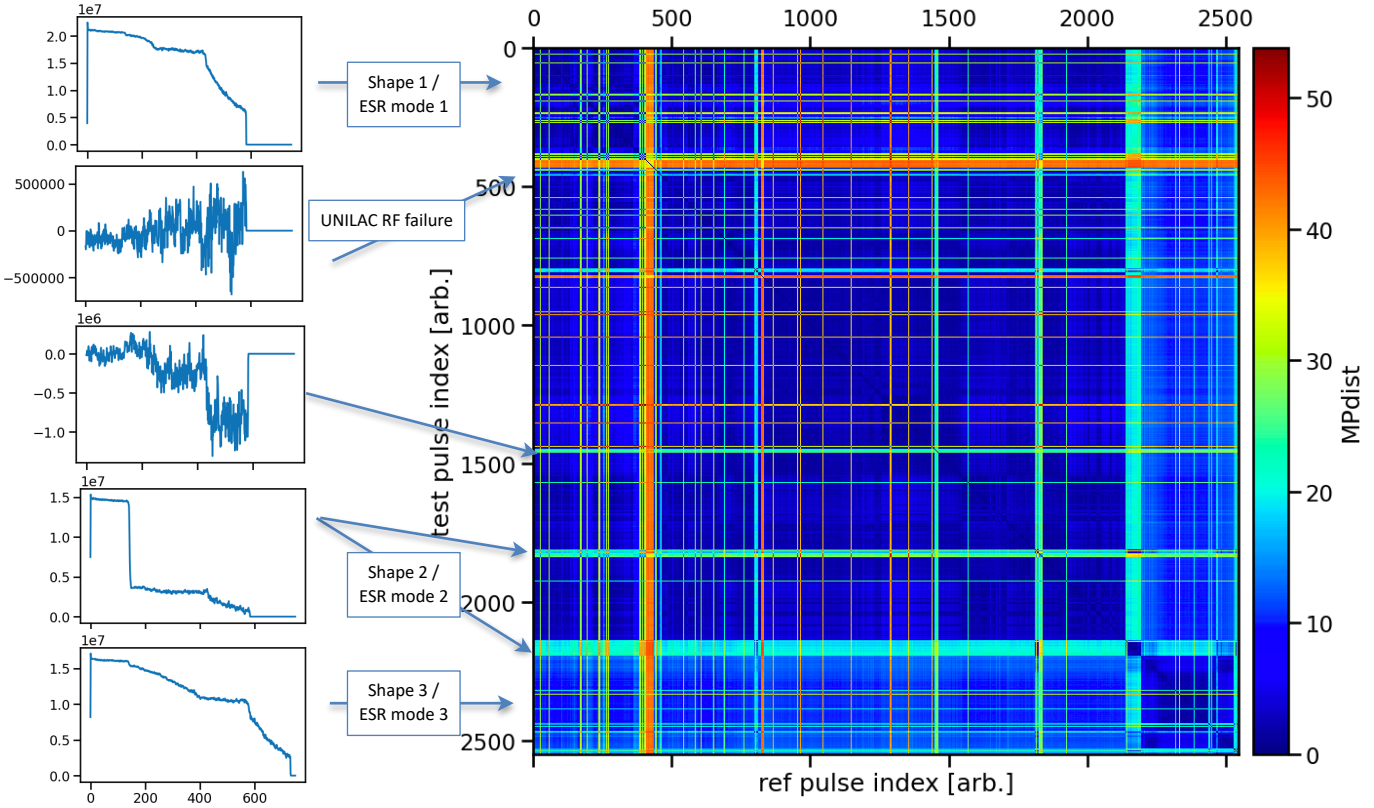


Naive thresholding works surprisingly well

Pulse Shape / Machine Mode Analysis via MPdist

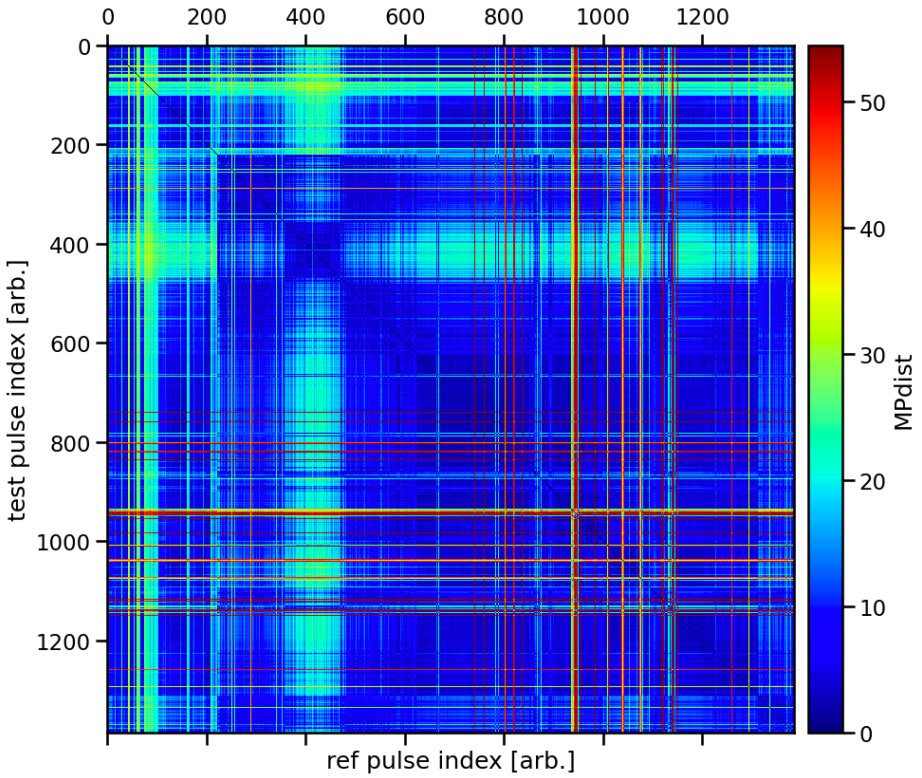
ESR/CRYRING: Au^{78+}

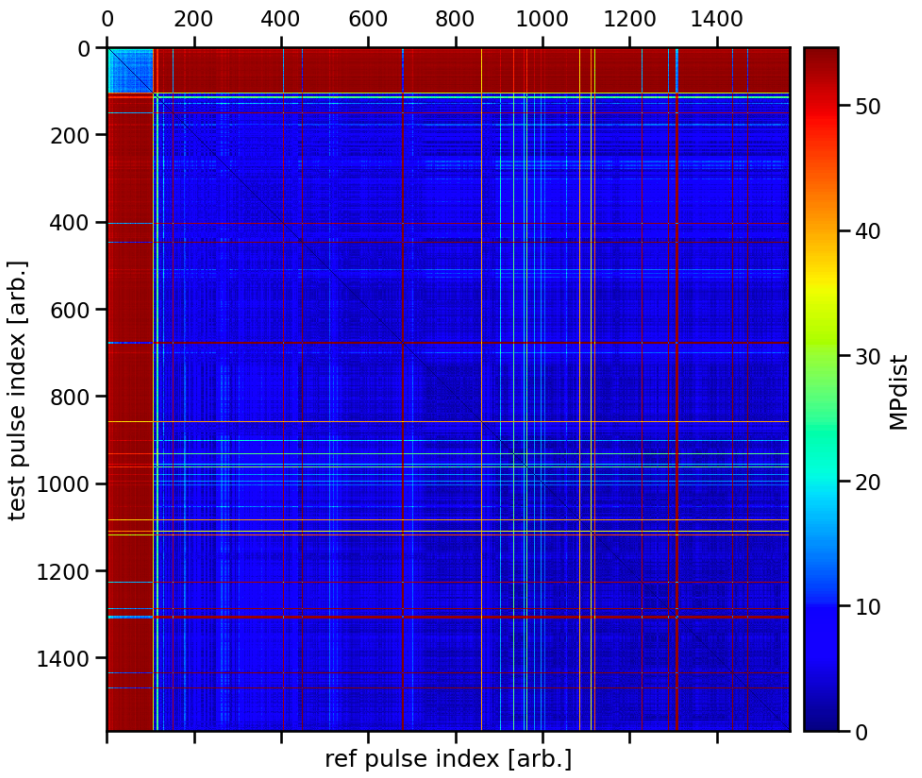
- Calculate MPdist of every pulse and all other pulses
- Blue: shapes are similar
- Red: shapes differ



MPdist Matrix for HITRAP1, HITRAP2:

Ni^{28+} 400 —> 4 MeV/u



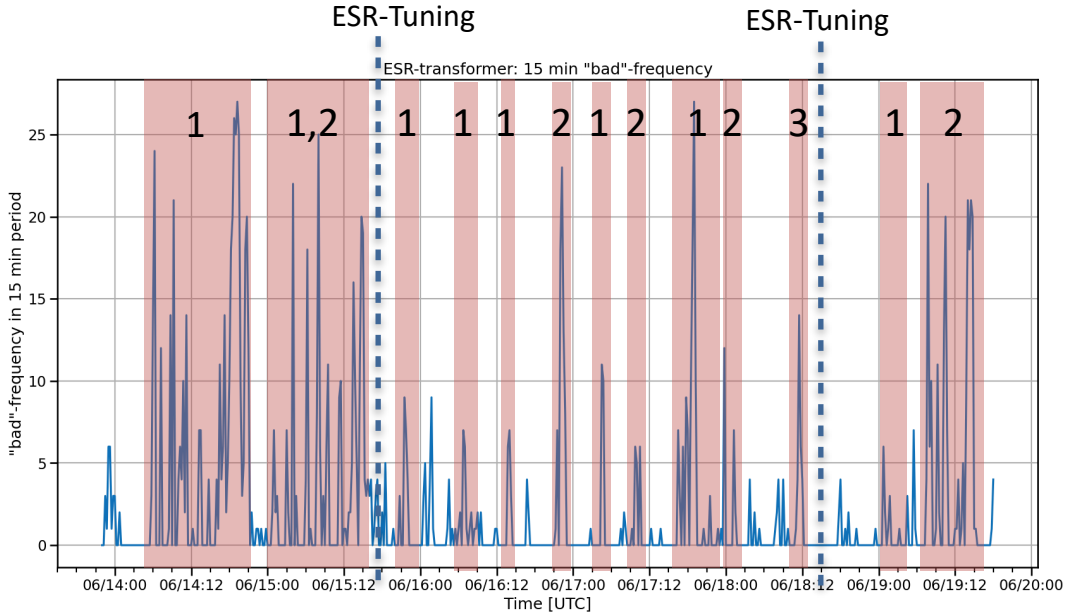


Machine Availability and Error Frequency

- Pulse classification can be used for availability accounting
- Online pulse classification can be used for machine monitoring

OPS reports:

1. injector-RF problems, ion source maintenance
2. Magnet-power problems
3. ESR failure



Lessons Learned, some Pros and Cons

- ✓ Using group-owned system: features can quickly be implemented
- ✓ Data contains valuable insight into machine availability, performance
- ✓ Clear objectives help to develop data workflows
- ✓ Data science projects challenge existing infrastructure for data archiving, etc.
- ✓ Automation has potential to operate machines more efficiently
- ✓ Establishing machine learning skills in organization is value by itself
- ✓ Establishing machine learning skills gives rise to new ideas for improvement
- ✓ Machine learning projects give rise to machinery for data extraction and analysis which were not developed without —> useful by-products can be expected

- ➡ Broad skillset software/IT system maintenance & development needed
- ➡ Development of „parallel structure“, redundancy, technological island
- ➡ Large invest of time required

Summary & Outlook

- Operator-grade application for automation tasks has been developed
- Beam intensity fluctuations impact results of automation and (more severely) optimization
- Data aggregation in parallel to FAIR stack has been developed
- Collected data gives rise to new applications
- Beam classification via simple thresholding is feasible

- Consolidation of python mingle-mangle for classification into an ordered tool
- Started Masters thesis on the topic of classification together with University of Applied Sciences DA
- Transfer offline code to online-code
- Make classification result available to other applications
- Use pulse classification result in device automator and other tools

Questions?

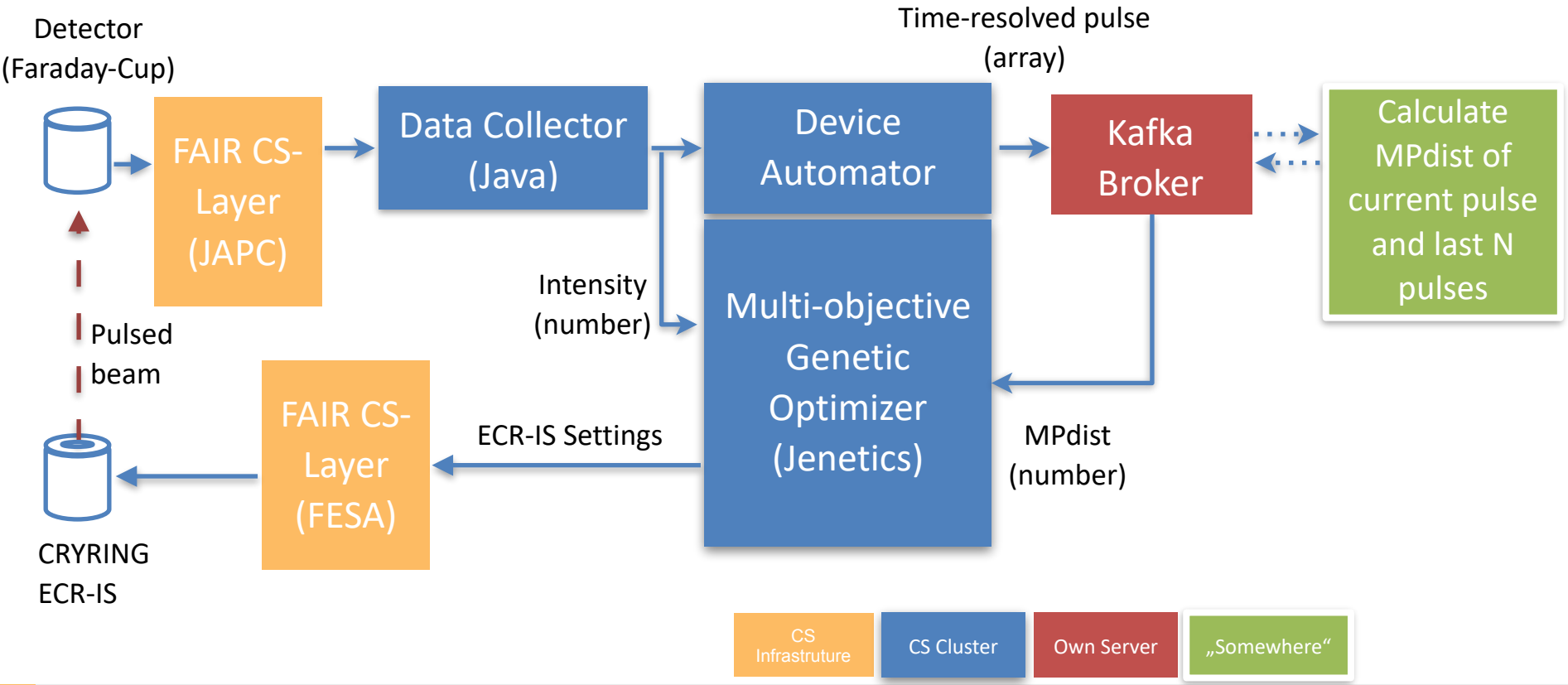
Questions?

I have some…

- Do you have advice on the choice of database for time series data? InfluxDB faces resistance by our IT department?
- Does anyone of you employ SAP HANA as database? What are your experiences?
- What approaches do you use to tackle problems involving time series?
- What would you see as the main obstacles (and maybe solutions) for adopting machine automation/machine learning

More applications of MPdist

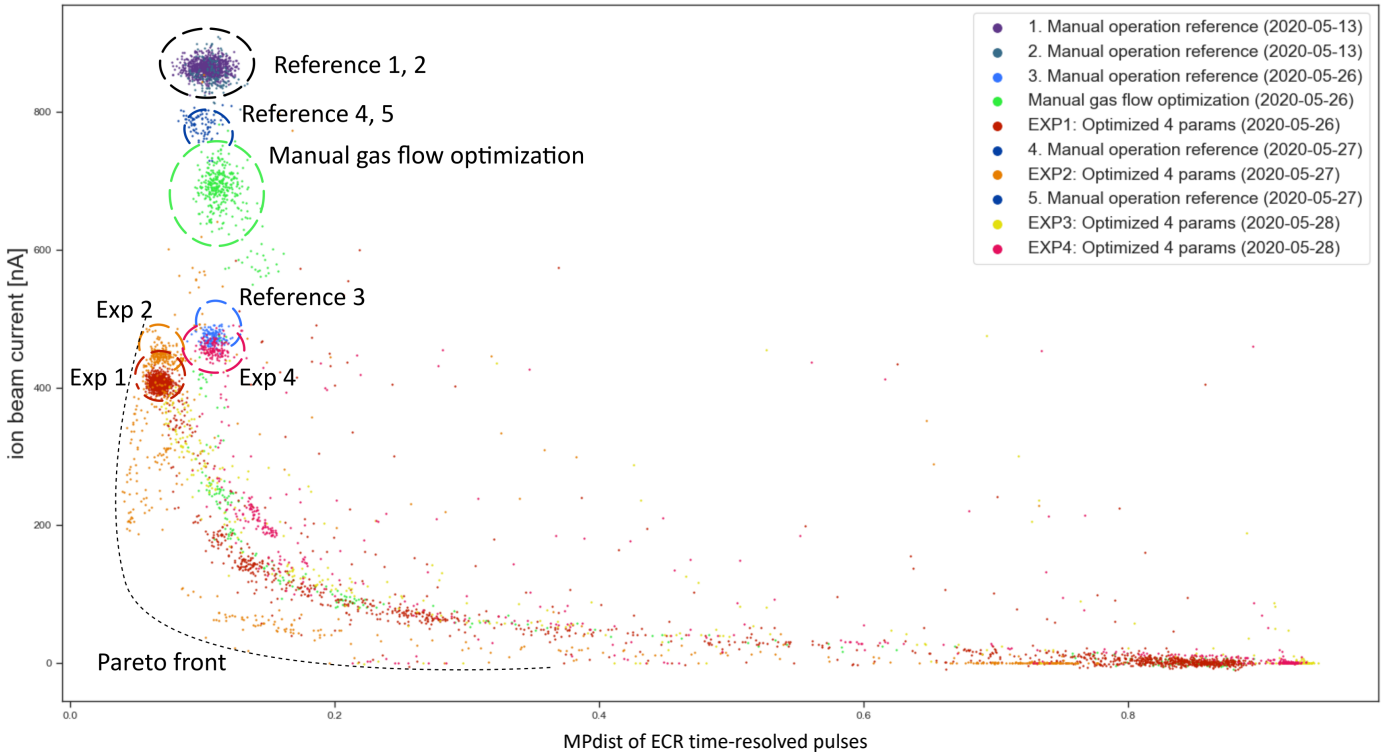
More MPdist-Application:
Bi-Objective Genetic ECR Ion Source Optimization



Bi-Objective Genetic local ECR Ion Source Optimization: Experimental Results

- Series of experiments performed at the end of regular beam time
- NE^{7+} at 28.6 keV
- Technique seems to be feasible
- Results were impacted by depleted ECRIS gas reservoir

- Useful where trade-off between beam intensity and stability is the goal



W. Geithner, et al.: Ion Source Optimization Using Bi-Objective Genetic and Matrix-Profile Algorithm, IPAC2021, https://jacow.org/ipac2021/papers/tupab300.pdf