Data-Driven Diagnosis at EuXFEL

Antonin Sulc

Hamburg, April 27, 2022

CDCS
CENTER FOR DATA AND COMPUTING
IN NATURAL SCIENCES

DESY.

TUHH
Technische Universität Hamburg

Universität Hamburg
DER FORSCHUNG | DER LEHRE | DER BILDUNG

Overview

> What's European XFEL.

Overview

- What's European XFEL.
- Diagnosis and predictive maintenance tasks on accelerator controls.

Overview

- What's European XFEL.
- Diagnosis and predictive maintenance tasks on accelerator controls.
- **Example:** Quench detection with a purely data-driven model.

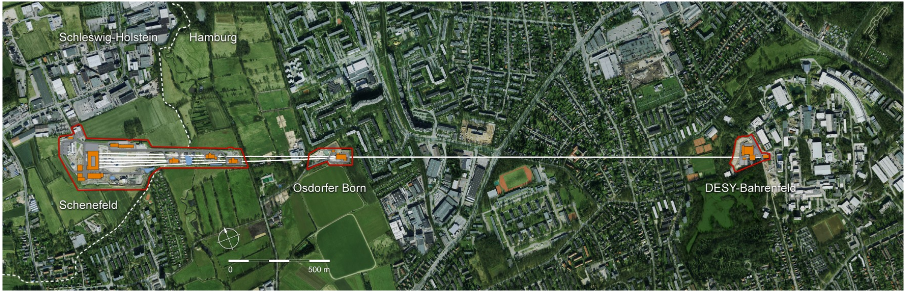
Overview

> What's European XFEL.
> Diagnosis and predictive maintenance tasks on accelerator controls.
> **Example:** Quench detection with a purely data-driven model.
> **Example:** Anomaly detection on beam position monitors.

European XFEL - Overview

The European XFEL:

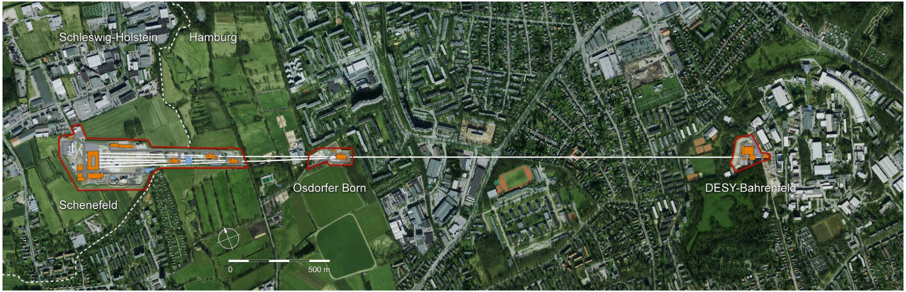
- Consists of a superconducting cavities that boosts electrons.



European XFEL - Overview

The European XFEL:

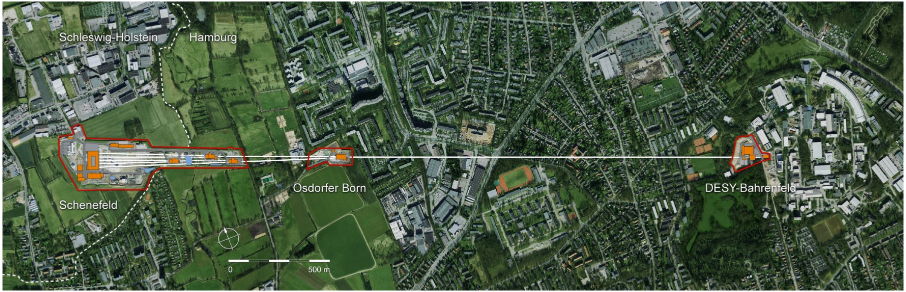
- Consists of a superconducting cavities that boosts electrons.
- The electrons are then directed through specially arranged magnets (undulators).



European XFEL - Overview

The European XFEL:

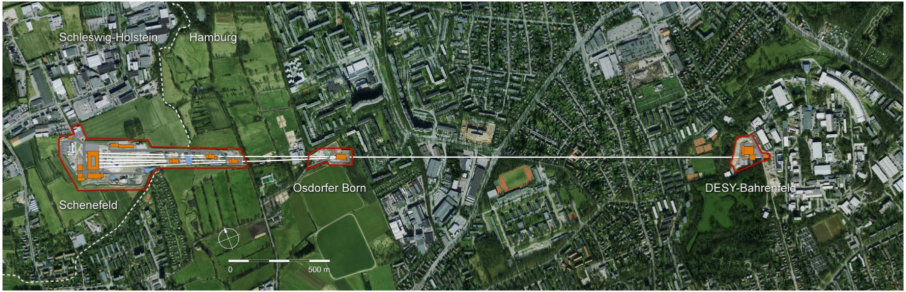
- Consists of a superconducting cavities that boosts electrons.
- The electrons are then directed through specially arranged magnets (undulators).
- Then they emit extremely short and intense X-ray flashes.



European XFEL - Overview

The European XFEL:

- Consists of a superconducting cavities that boosts electrons.
- The electrons are then directed through specially arranged magnets (undulators).
- Then they emit extremely short and intense X-ray flashes.
- These X-ray flashes are then distributed to three beamlines (SASE).



Data-Driven Predictive Maintenance on European XFEL

- Thousands of devices are involved in EuXFEL.

Data-Driven Predictive Maintenance on European XFEL

- Thousands of devices are involved in EuXFEL.
- Many components are operating in **extreme conditions** (radiation, heat...).

Data-Driven Predictive Maintenance on European XFEL

> Thousands of devices are involved in EuXFEL.
> Many components are operating in **extreme conditions** (radiation, heat...).
> At any moment, any component can **fail**.

Data-Driven Predictive Maintenance on European XFEL

- Thousands of devices are involved in EuXFEL.
- Many components are operating in **extreme conditions** (radiation, heat...).
- At any moment, any component can **fail**.
- When a component fails, it can lead to undesired **downtime**.

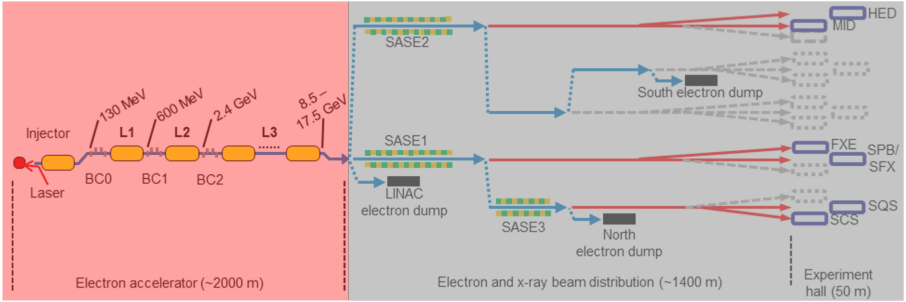
Examples

(1) LLRF Cavities

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

(2) Orbit Monitoring

- Analyzing electron orbits in SASEs.
- Various types of problems are indicated by variations on orbits.



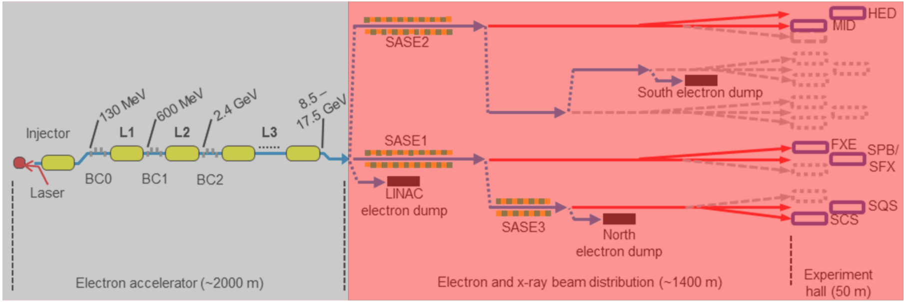
Examples

(1) LLRF Cavities

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

(2) Orbit Monitoring

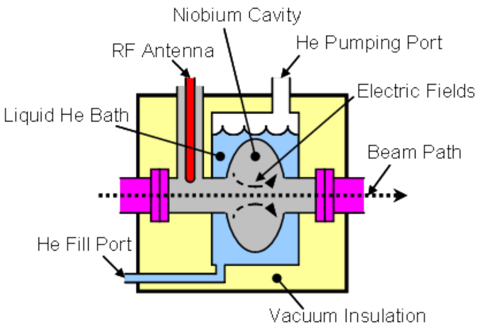
- Analyzing electron orbits in SASEs.
- Various types of problems are indicated by variations on orbits.



(1) Superconducting Low-Level Radio Freq. Cavities

Cavities

- The superconducting LLRF cavities accelerate electron bunches.

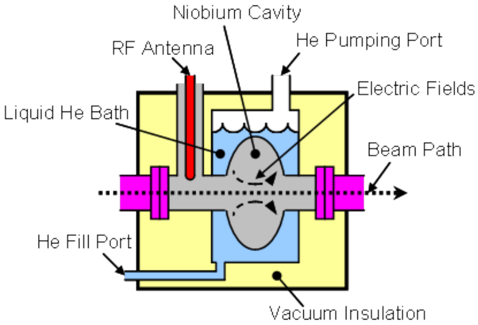


[Wikipedia]

(1) Superconducting Low-Level Radio Freq. Cavities

Cavities

- The superconducting LLRF cavities accelerate electron bunches.
- The electrons are accelerated by alternating electric fields.

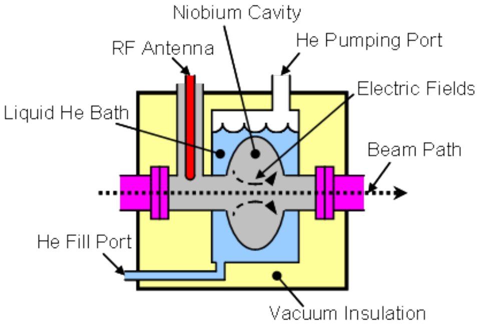


[Wikipedia]

(1) Superconducting Low-Level Radio Freq. Cavities

Cavities

- The superconducting LLRF cavities accelerate electron bunches.
- The electrons are accelerated by alternating electric fields.
- Trajectory is manipulated via a magnetic field.

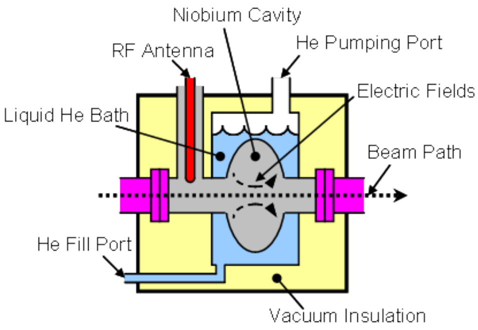


[Wikipedia]

(1) Superconducting Low-Level Radio Freq. Cavities

Cavities

- The superconducting LLRF cavities accelerate electron bunches.
- The electrons are accelerated by alternating electric fields.
- Trajectory is manipulated via a magnetic field.
- Superconductivity is important to maintain the efficiency.

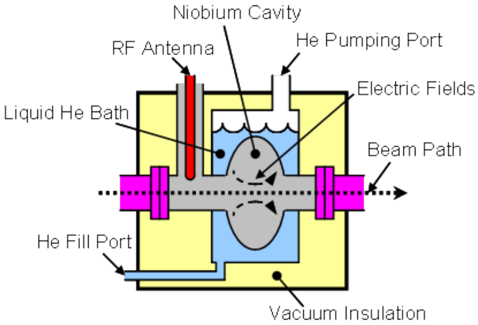


[Wikipedia]

(1) Superconducting Low-Level Radio Freq. Cavities

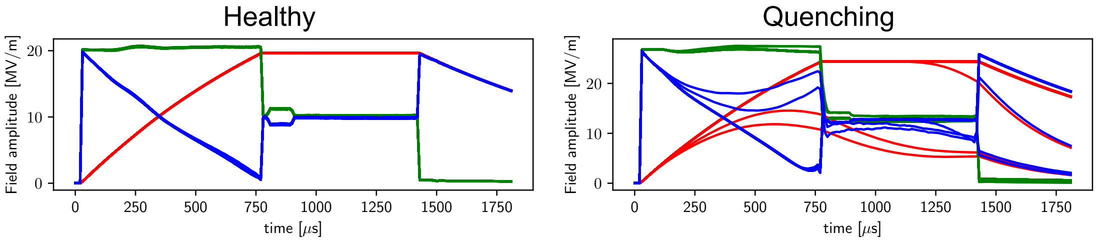
Cavities

- The superconducting LLRF cavities accelerate electron bunches.
- The electrons are accelerated by alternating electric fields.
- Trajectory is manipulated via a magnetic field.
- Superconductivity is important to maintain the efficiency.
- Very low temperatures (near absolute zero) are needed for superconductivity.



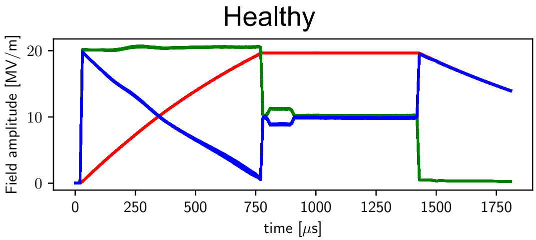
[Wikipedia]

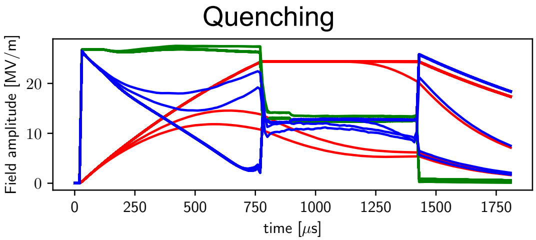
(1) Monitoring Superconducting LLRF Cavities



- We record an envelope (phase, amplitude) of three signals - probe, forward and reflected signals.

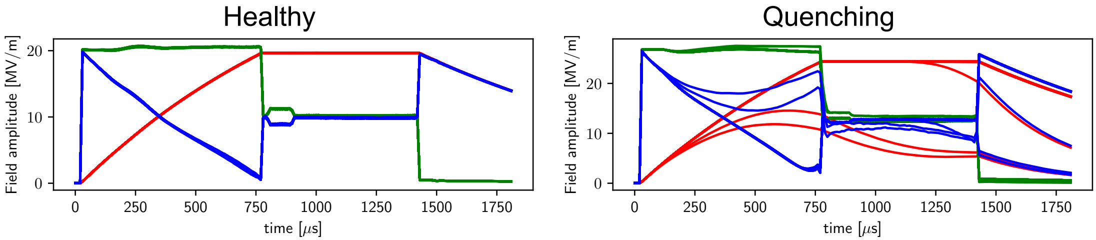
(1) Monitoring Superconducting LLRF Cavities





- We record an envelope (phase, amplitude) of three signals - probe, forward and reflected signals.
- Each signal consists of a pair of 1820 values (amplitude, phase) per pulse.

(1) Monitoring Superconducting LLRF Cavities



- We record an envelope (phase, amplitude) of three signals - probe, forward and reflected signals.
- Each signal consists of a pair of 1820 values (amplitude, phase) per pulse.
- Quench (right) means a loss of superconductivity in a cavity, which has a significant effect on the quality factor.

(1) Data-Driven Monitoring of Superconducting LLRF Cavities

$$\underbrace{\mathbf{h}_1{=}\mathrm{LSTM}(\mathbf{x}) \xrightarrow{} \mathbf{h}_2{=}\mathrm{LSTM}(\mathbf{h}_1) \xrightarrow{} \phi{=}\mathrm{Linear}(\mathbf{h}_2)}_{f_\theta(\mathbf{x})} \xrightarrow{} s = \|\phi\left(\mathbf{h}_2\right) - \mathbf{c}\|_2^2 \xrightarrow{}$$

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

> A RNN is assigning a score to series of cavity pulses.

(1) Data-Driven Monitoring of Superconducting LLRF Cavities

$$\underbrace{\underset{\text{input=1092, output=256}}{\mathbf{h}_1=\mathrm{LSTM}(\mathbf{x})} \longrightarrow \underset{\text{input=256, output=256}}{\mathbf{h}_2=\mathrm{LSTM}(\mathbf{h}_1)} \longrightarrow \underset{\text{input=256, output=64}}{\phi=\mathrm{Linear}(\mathbf{h}_2)}}_{f_\theta(\mathbf{x})} \longrightarrow \underset{\text{input=64, output=1}}{s=\left\|\phi\left(\mathbf{h}_2\right)-\mathbf{c}\right\|_2^2} \longrightarrow$$

- A RNN is assigning a score to series of cavity pulses.
- Each datum **x** (pulse) consist of (probe, forward and reflected signals).

(1) Data-Driven Monitoring of Superconducting LLRF Cavities

$$\underbrace{\mathbf{h}_1{=}\mathrm{LSTM}(\mathbf{x}) \xrightarrow[\text{input=1092, output=256}]{} \mathbf{h}_2{=}\mathrm{LSTM}(\mathbf{h}_1) \xrightarrow[\text{input=256, output=256}]{} \phi{=}\mathrm{Linear}(\mathbf{h}_2)}_{f_\theta(\mathbf{x})} \xrightarrow[\text{input=256, output=64}]{} s=\left\|\phi\left(\mathbf{h}_2\right)-\mathbf{c}\right\|_2^2 \xrightarrow[\text{input=64, output=1}]{}$$

- A RNN is assigning a score to series of cavity pulses.
- Each datum **x** (pulse) consist of (probe, forward and reflected signals).
- We have a disproportionately smaller dataset with faults (1300 faults) and (almost) unlimited access to healthy data.

(1) Data-Driven Monitoring of Superconducting LLRF Cavities

$$\underbrace{\mathbf{h}_1 = \mathrm{LSTM}(\mathbf{x}) \xrightarrow[\text{input=1092, output=256}]{} \mathbf{h}_2 = \mathrm{LSTM}(\mathbf{h}_1) \xrightarrow[\text{input=256, output=256}]{} \phi = \mathrm{Linear}(\mathbf{h}_2) \xrightarrow[\text{input=256, output=64}]{}}_{f_\theta(\mathbf{x})} s = \|\phi(\mathbf{h}_2) - \mathbf{c}\|_2^2 \xrightarrow[\text{input=64, output=1}]{}$$

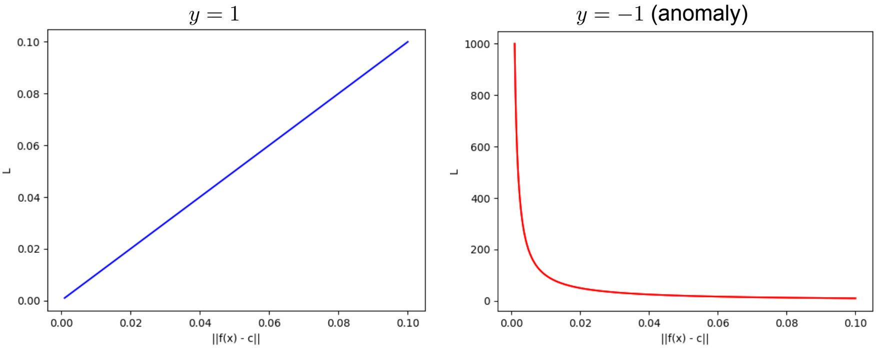
- A RNN is assigning a score to series of cavity pulses.
- Each datum **x** (pulse) consist of (probe, forward and reflected signals).
- We have a disproportionately smaller dataset with faults (1300 faults) and (almost) unlimited access to healthy data.
- Semi-supervised anomaly loss [Ruff(2019)]

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

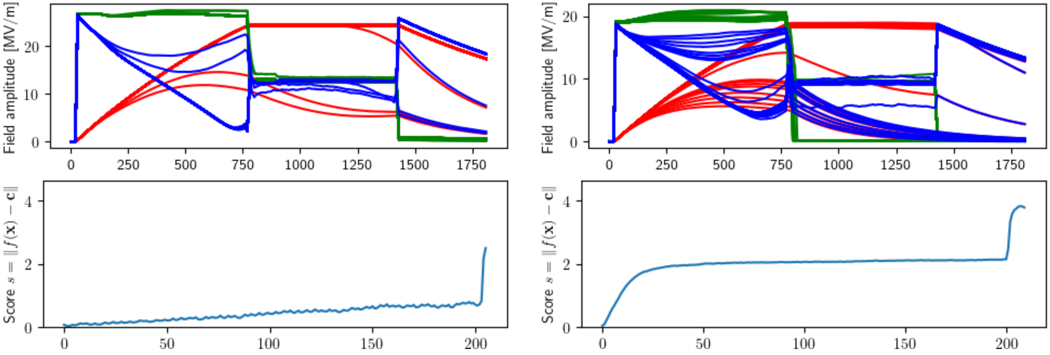
Semi-Supervised Anomaly Loss

Semi-supervised anomaly loss [Ruff(2019)]

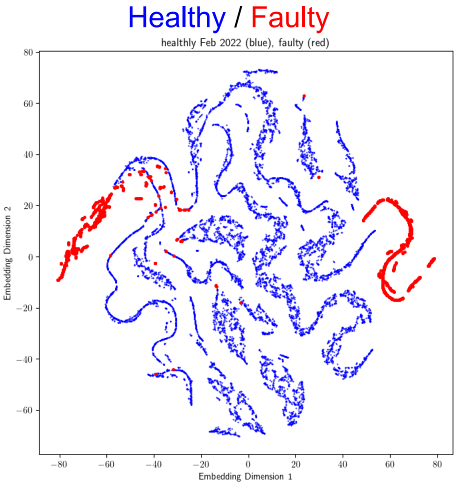
$$L(\theta) = \|f_\theta(\mathbf{x}) - \mathbf{c}\|_2^y + \|f_\theta(\mathbf{x}) - \mathbf{c}\|_2 \text{ where } y \in \{-1, 1\}.$$

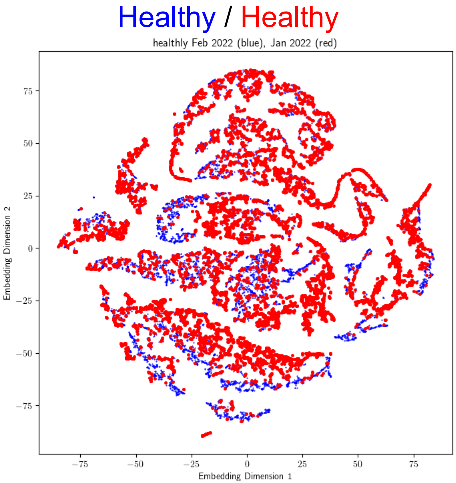


(1) Results - Quenches



(1) Feature Space - TSNE of $f_\theta(\mathbf{x})$

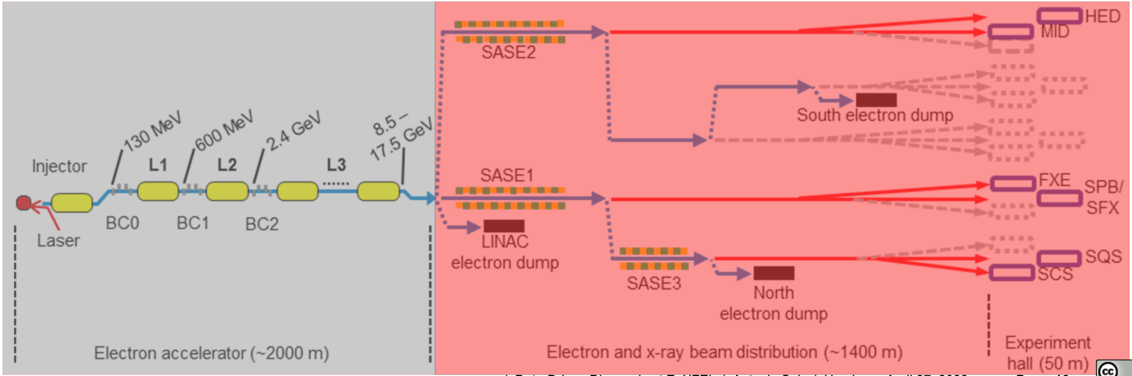




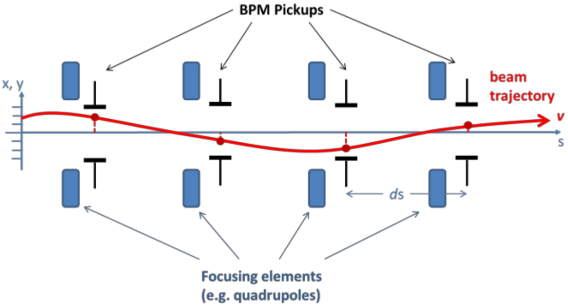
(2) Orbit Monitoring

Assumption

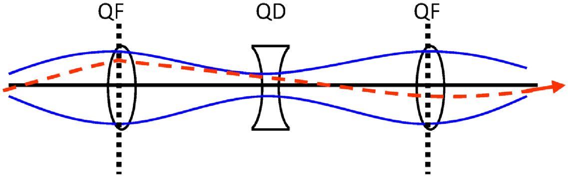
There is a systematic pattern shown in orbits given by the physical construction of EuXFEL.



Orbit Monitoring - FODO Lattice

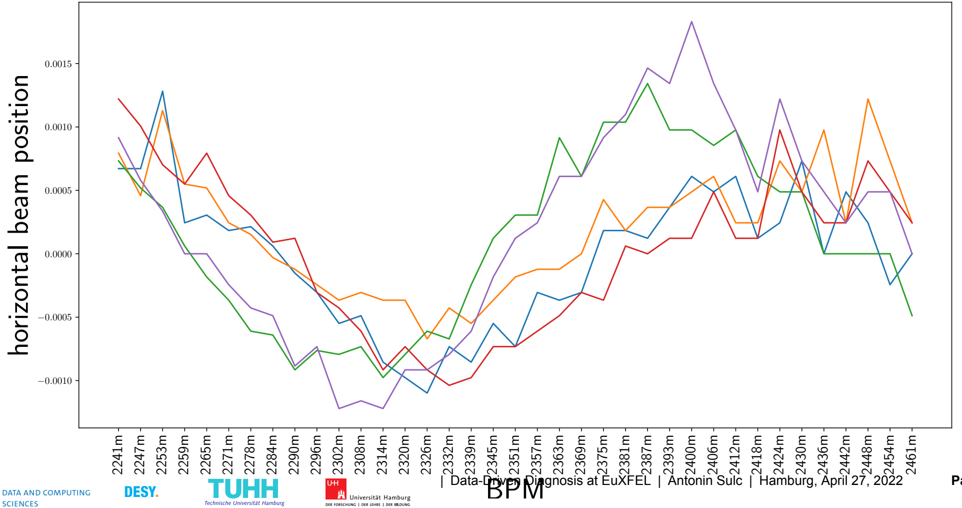


[Wendt(2011)]

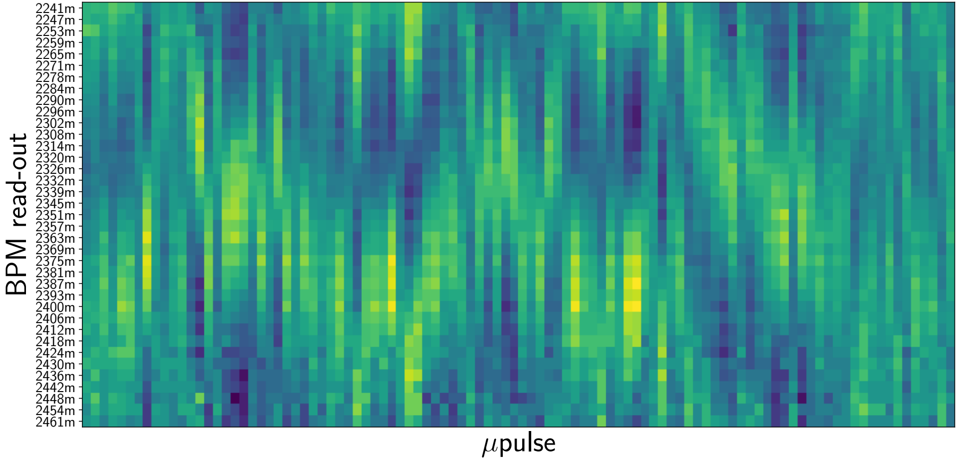


[Holzer(2006)]

(2) Orbit Monitoring

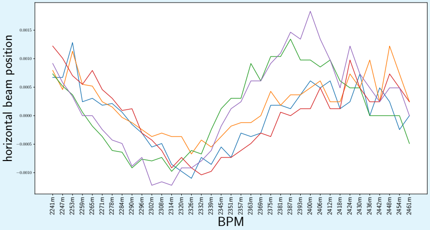


(2) Orbit Monitoring



(2) Data-Driven Orbit Monitoring

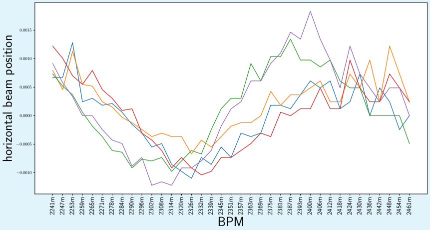
Model-Based Orbit Monitoring



- Credits to **R. Kammering**.
- Fit a sine and measure residual.
- **Pros** It is **fast** and **intuitive**.
- **Cons** No intra-bunching instabilities.

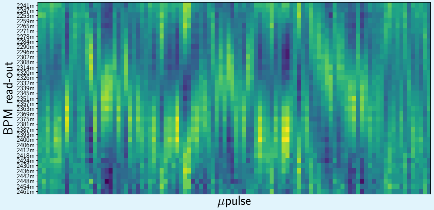
(2) Data-Driven Orbit Monitoring

Model-Based Orbit Monitoring



- Credits to **R. Kammering**.
- Fit a sine and measure residual.
- **Pros** It is **fast** and **intuitive**.
- **Cons** No intra-bunching instabilities.

Model-Free Orbit Monitoring



- Series of BPM read-outs.
- Train a model with the anomaly loss.
- **Pros** Takes into consideration intra-bunching instabilities.

(2) Model-Free Data-Driven Orbit Monitoring

$$\underbrace{\mathbf{h}_1 = \text{Transformer}(\mathbf{x}) \rightarrow \mathbf{h}_2 = \text{Transformer}(\mathbf{h}_1) \rightarrow \phi = \text{Linear}(\mathbf{h}_2)}_{f_\theta(\mathbf{x})} \rightarrow s(\phi) := \|\phi - \mathbf{c}\|_2^2$$

input=206, output=512 | input=512, output=512 | **input=512, output=64** | input=64, output=1

> Stacked transformers that are scoring series of BPM read-outs

(2) Model-Free Data-Driven Orbit Monitoring

$$\underbrace{\underset{\text{input=206, output=512}}{\mathbf{h}_1 = \mathrm{Transformer}(\mathbf{x})} \longrightarrow \underset{\text{input=512, output=512}}{\mathbf{h}_2 = \mathrm{Transformer}(\mathbf{h}_1)} \longrightarrow \underset{\textbf{input=512, output=64}}{\phi = \mathrm{Linear}(\mathbf{h}_2)}}_{f_\theta(\mathbf{x})} \longrightarrow \underset{\text{input=64, output=1}}{s(\phi) := \|\phi - \mathbf{c}\|_2^2}$$

- Stacked transformers that are scoring series of BPM read-outs
- Each input are stacked horizontal and vertical positions from all beamlines.

(2) Model-Free Data-Driven Orbit Monitoring

$$\underbrace{\mathbf{h}_1 = \mathrm{Transformer}(\mathbf{x}) \longrightarrow \mathbf{h}_2 = \mathrm{Transformer}(\mathbf{h}_1) \longrightarrow \phi = \mathrm{Linear}(\mathbf{h}_2)}_{f_\theta(\mathbf{x})} \longrightarrow s(\phi) := \|\phi - \mathbf{c}\|_2^2$$

input=206, output=512 | input=512, output=512 | input=512, output=64 | input=64, output=1

- Stacked transformers that are scoring series of BPM read-outs
- Each input are stacked horizontal and vertical positions from all beamlines.
- We **do not** have any **faulty labels**.

(2) Model-Free Data-Driven Orbit Monitoring

$$\underbrace{\mathbf{h}_1 = \text{Transformer}(\mathbf{x}) \longrightarrow \mathbf{h}_2 = \text{Transformer}(\mathbf{h}_1) \longrightarrow \phi = \text{Linear}(\mathbf{h}_2)}_{f_\theta(\mathbf{x})} \longrightarrow s(\phi) := \|\phi - \mathbf{c}\|_2^2$$

input=206, output=512 | input=512, output=512 | **input=512, output=64** | input=64, output=1

> Stacked transformers that are scoring series of BPM read-outs

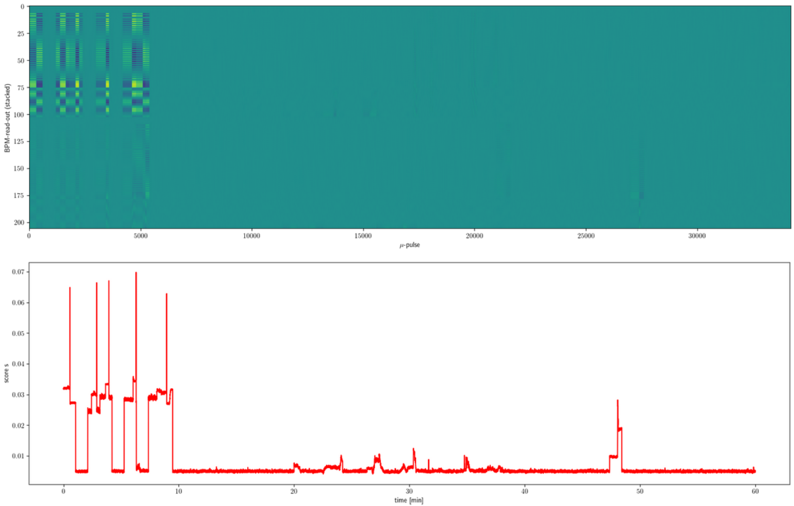
> Each input are stacked horizontal and vertical positions from all beamlines.

> We **do not** have any **faulty labels**.

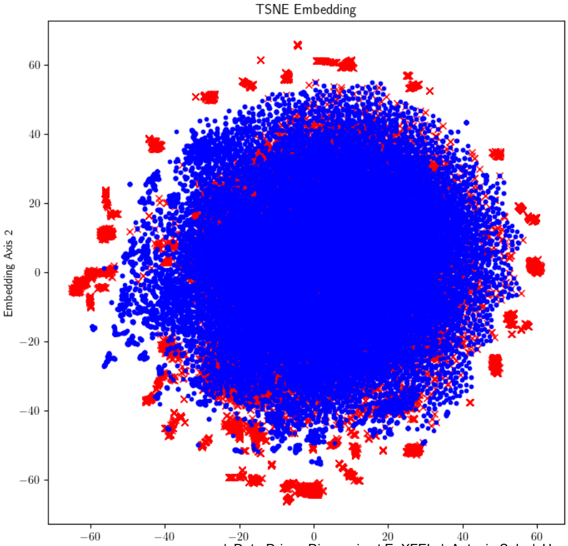
> **Unsupervised anomaly** loss

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

(2) Model-Free Data-Driven Orbit Monitoring



(2) Feature Space - TNSE of $f(\mathbf{x};\theta)$



Thank you!

This is the joint work of A. Eichler and Raimund Kammering!

Contact

DESY. Deutsches
Elektronen-Synchrotron

www.desy.de

Antonin Sulc
0000-0001-7767-778X
MCS DESY
antonin.sulc@desy.de

Bibliography

BJ Holzer.
Lattice design in high-energy particle accelerators.
2006.

L Ruff.
Deep semi-supervised anomaly detection.
arXiv preprint arXiv:1906.02694, 2019.

Manfred Wendt.
Overview of recent trends and developments for bpm systems.
Technical report, Fermi National Accelerator Lab.(FNAL), Batavia, IL (United States), 2011.