CERN

Application of Machine Learning to Breakdown Prediction in CERN's High-Gradient Test Stands[1]

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[1]Accepted for publication at PRAB, available: https://arxiv.org/pdf/2202.05610.pdf

Outline

1. Introduction

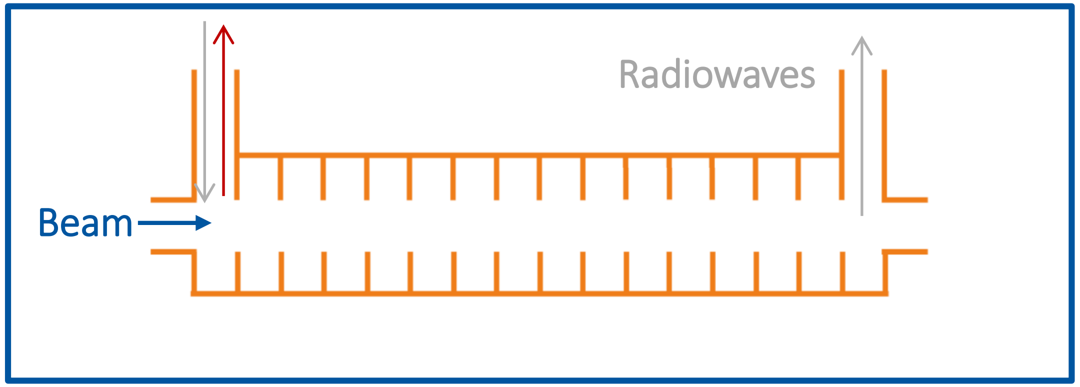
a. RF Cavities
b. RF Cavity breakdowns
c. XBOX 2 Test Stand

1.a. RF Cavities

Radiofrequency (RF) cavities: To accelerate particles, the accelerators are fitted with metallic chambers containing an electromagnetic field known as radiofrequency (RF) cavities. Charged particles injected into this field receive an electrical impulse that accelerates them.

- In linear accelerators the peak gradient determines the maximum achievable energy
- We analyze the very high gradient (100MV/m) cavities for the Compact Linear Collider (CLIC) *
- CLIC RF cavities are tested in the XBOX test stands at CERN
- Several aplications beyond accelerators (e.g. cancer treatment)

RF cavity



CLIC concept image

* https://home.cern/science/accelerators/compact-linear-collider

1.b. RF Cavity Breakdowns

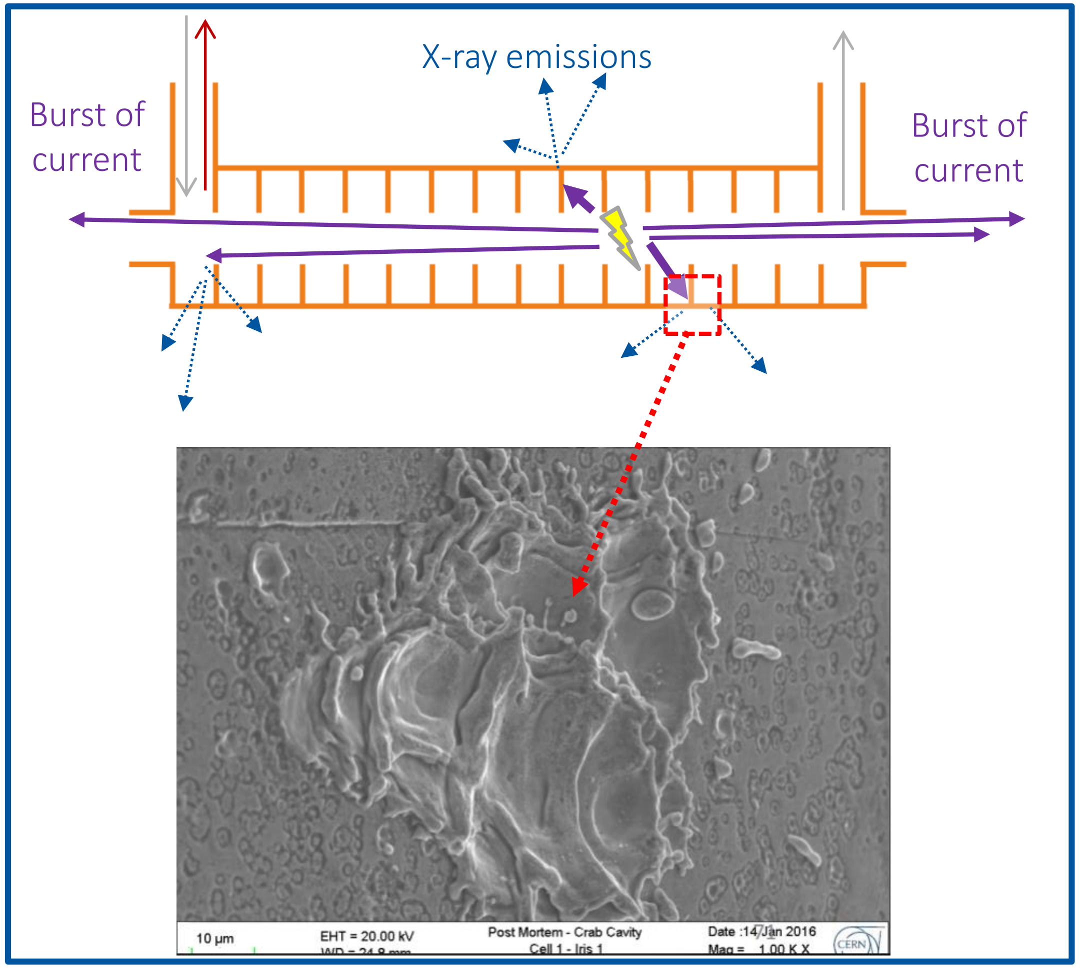
RF cavity breakdown: Small deformities cause field enhancement on surface which can lead to plasma formation (arc) and surface damage.

- Main limitation of high field in the CLIC RF cavities
- Conditioning necessary to minimize breakdown rate
- They mainly occur in groups. The first breakdown in each group is called **primary breakdown**, the others are **follow-up breakdowns**.

Goals:

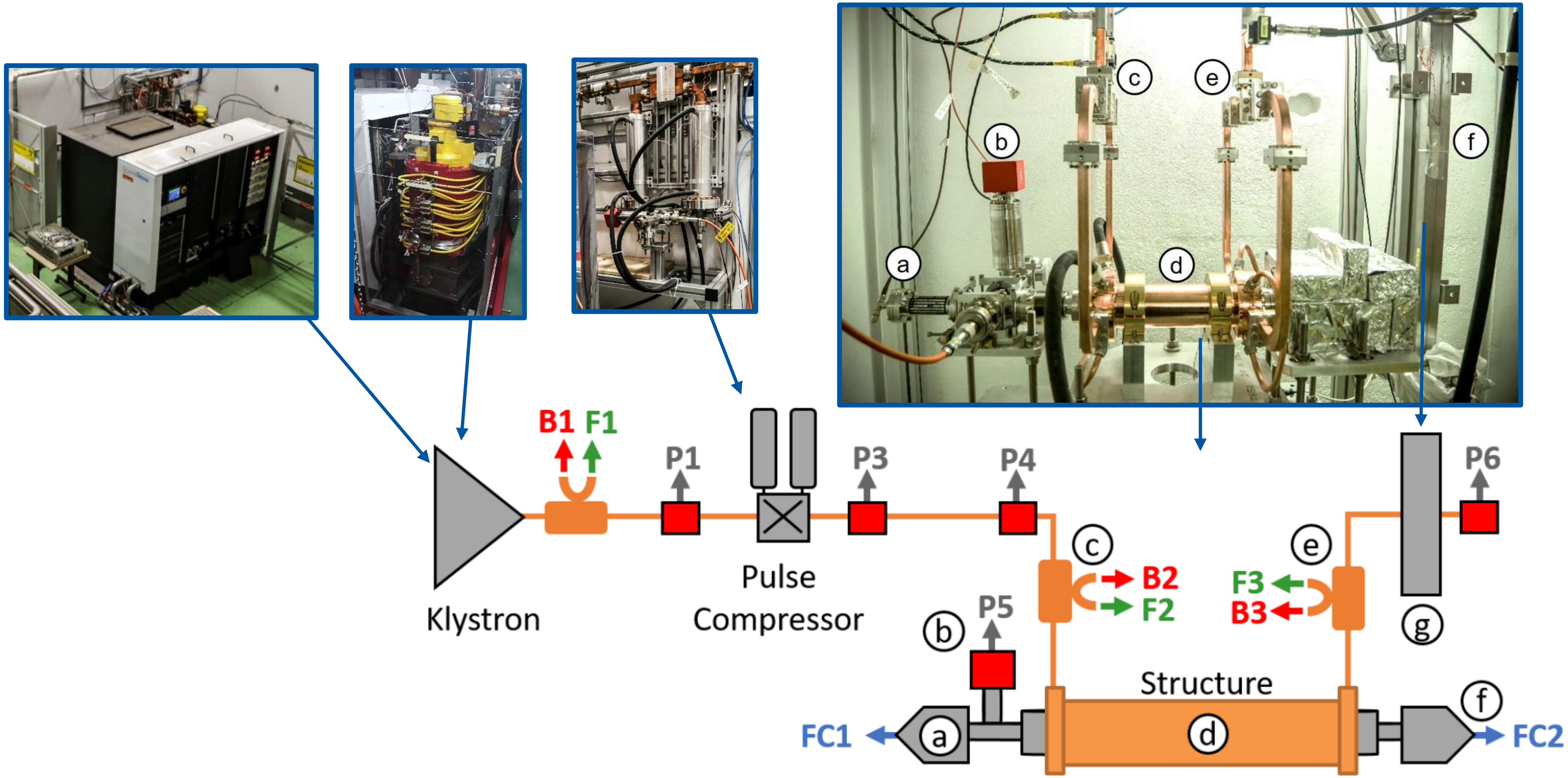
1. Investigate **breakdown precursors** in CLIC RF structures
2. **Operational tool** for breakdown reduction, in order to avoid their occurrence by suitable adjustment of the power in the cavity

RF cavity breakdown



Content provided by Lee Millar

1.c. XBOX 2 Test Stand



Legend:

B ... Backward reflected traveling wave

F ... Forward travelling wave

FC ... Faraday cups

P ... Pressure

a ... Faraday

b ... Ion pump

c ... RF input

d ... RF cavity

e ... RF output

f ... Shielded lead enclosure

g ... High-power RF load

2. Methodology

a. Data Overview
b. Transformation
c. Exploration
d. Modeling

2.a. Data Overview

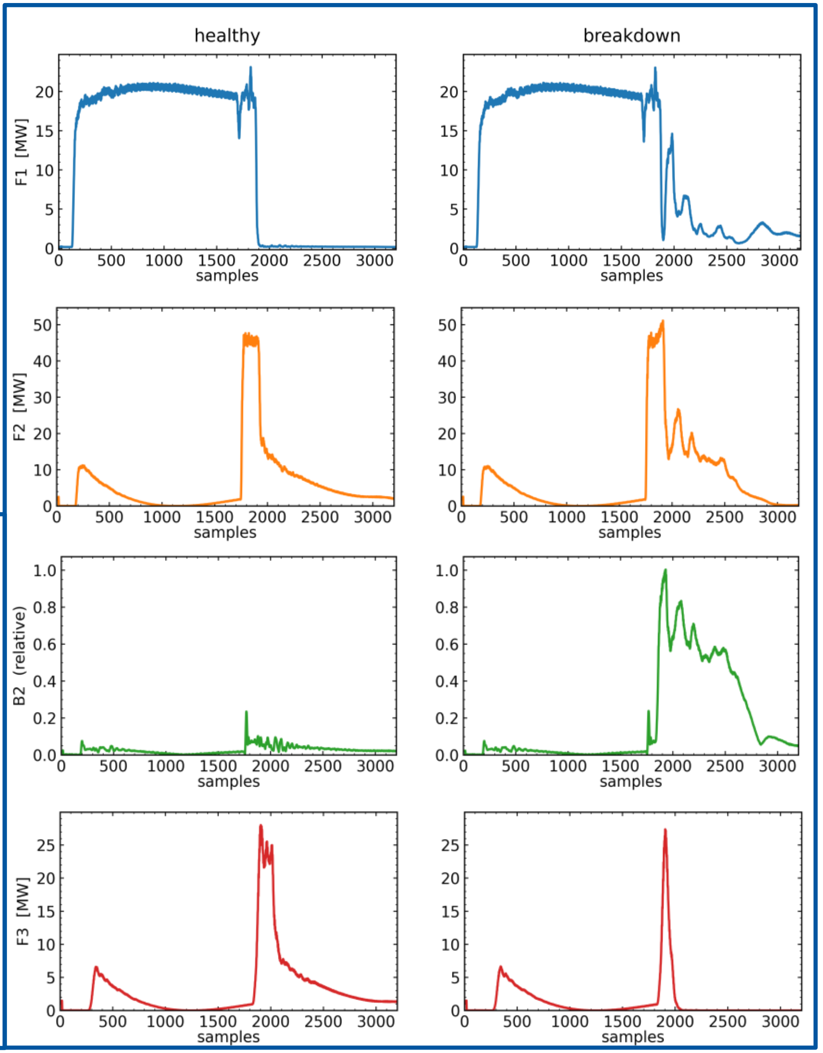
Data available: 90 GB of Data from 2018 (6months of data)

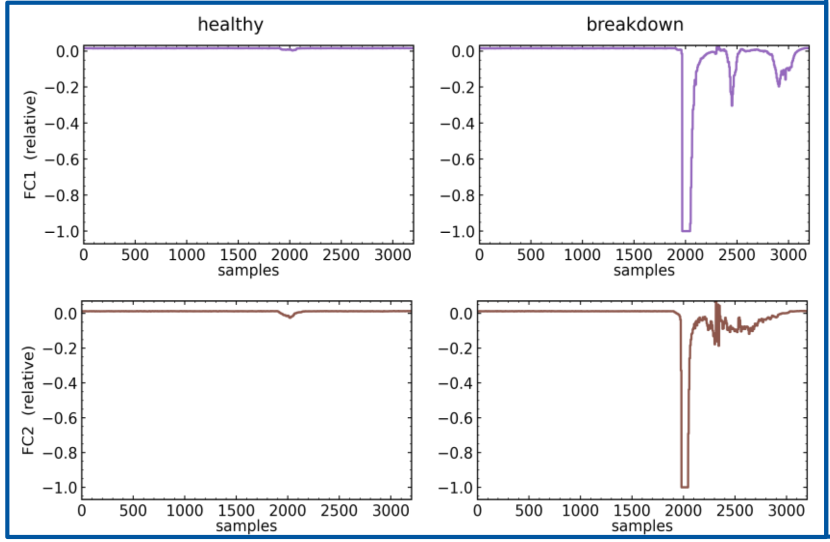
a.) Trend data:

- Context data about other machine parameters: i.e. Temperature, pressure (~1Hz sample rate)

b.) Event data:

- Data from test stand sensors: 6 Channels with up to 3200 sample points (1.6 GHz sample rate) RF signal is 12 GHz



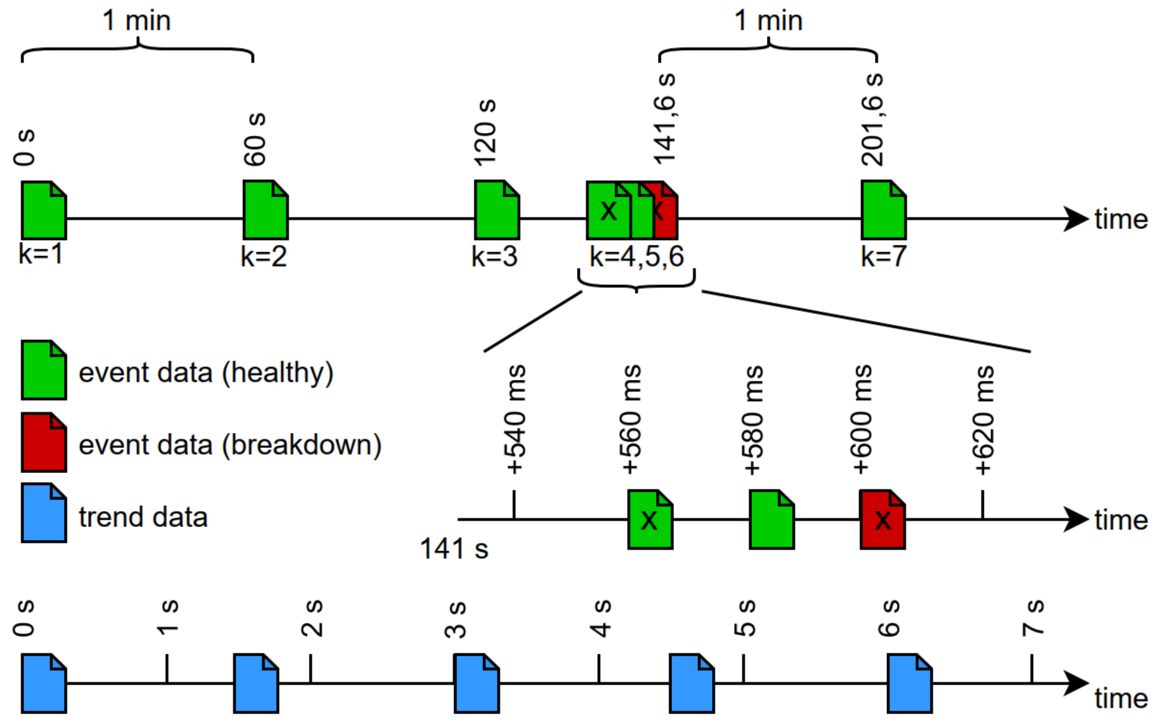


	Bunker_WG_Temp	Klystron_Flange_Temp	Load_Temp	PC_Left_Cavity_Temp
0	24.134285	24.116962	27.955711	30.285633
1	24.082500	24.145723	27.876066	30.277182
2	23.241980	24.400513	27.502401	30.253901
3	18.783634	19.573864	27.900787	30.100540

2.b. Transformation: Merging

Input data:

- Different sampling time of event data (~20ms/1min) and trend data (~1s)
- Clean the data such that we do not give the answer ("high contrast")

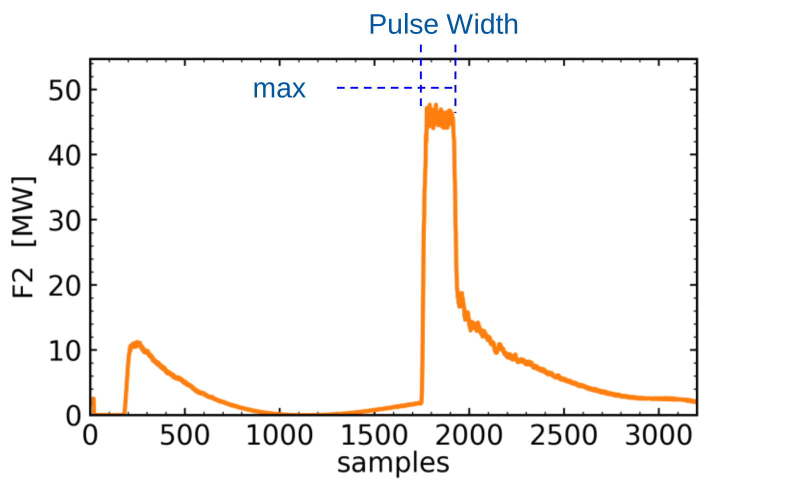


2.b. Transformation: Filtering

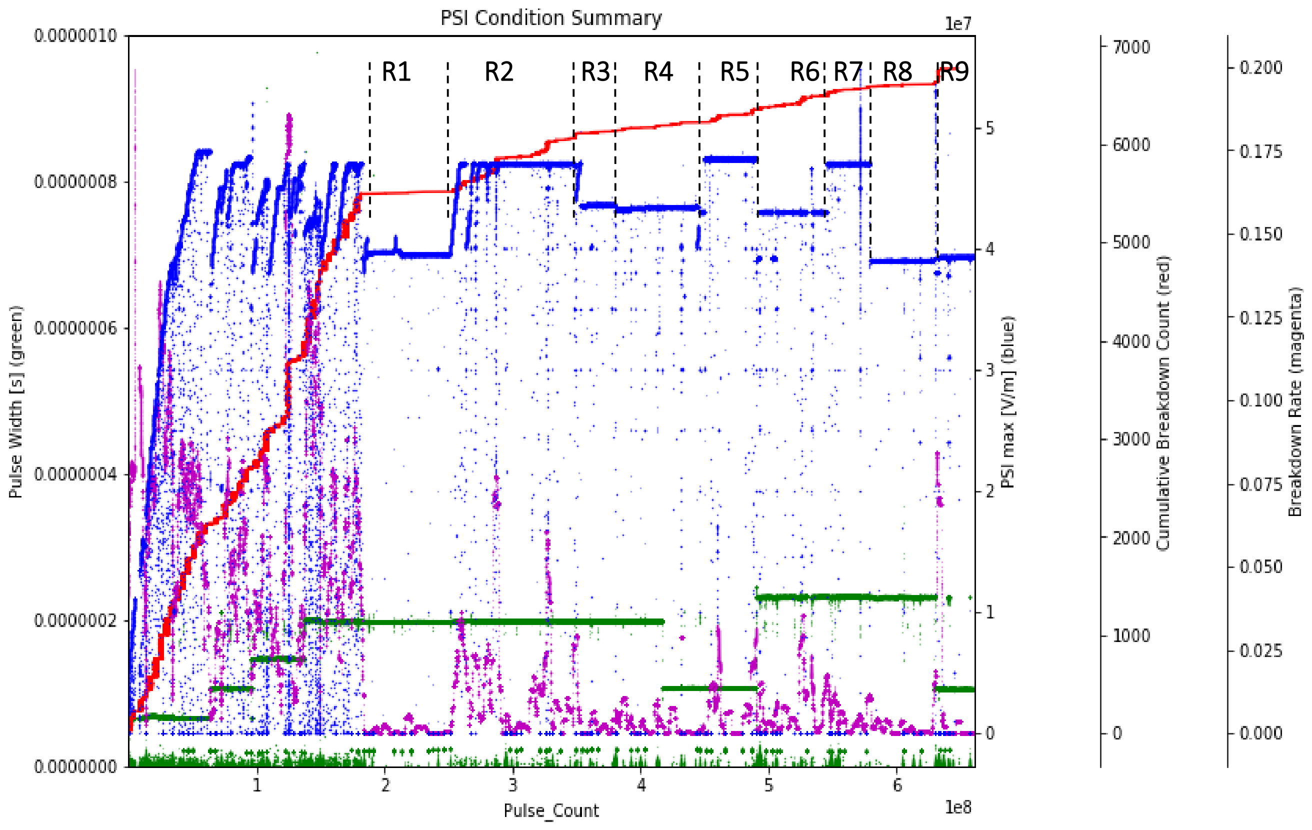
Goal: Clean data, fast queries, memory efficient storage

- Adding of extra features (e.g. pulse width, max, run 1-9)
- Transformation of data into .hdf5 (24 GB)

Extracted Features



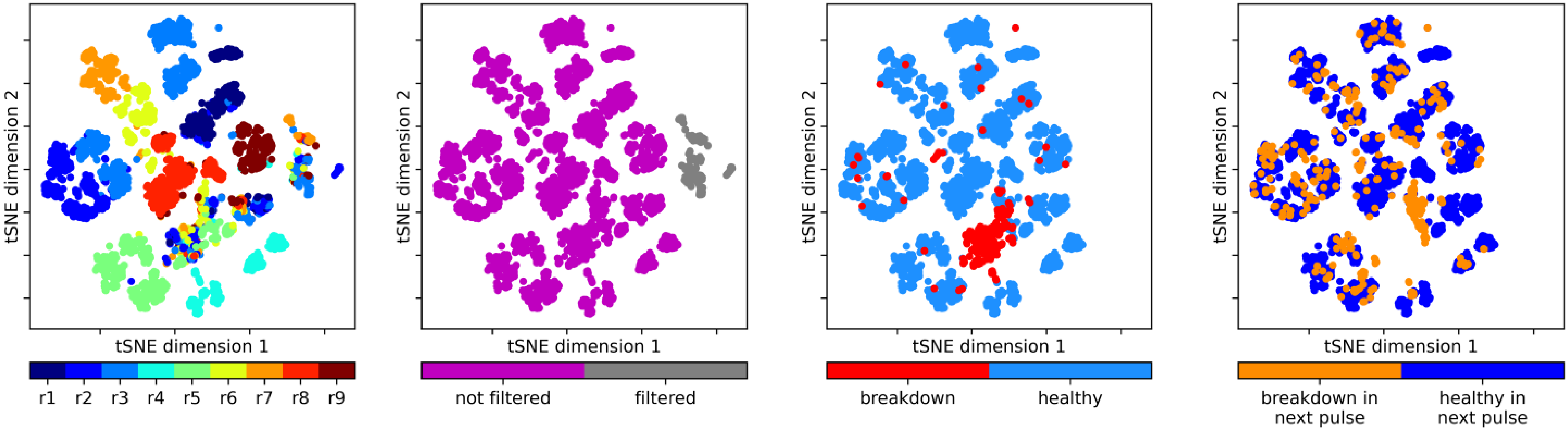
2018 Trend Data



2.c. Exploration

Goal: General method to explore multidimensional dataset.

Method: 2D-tSNE to reduce dimension, different coloring to understand clusters

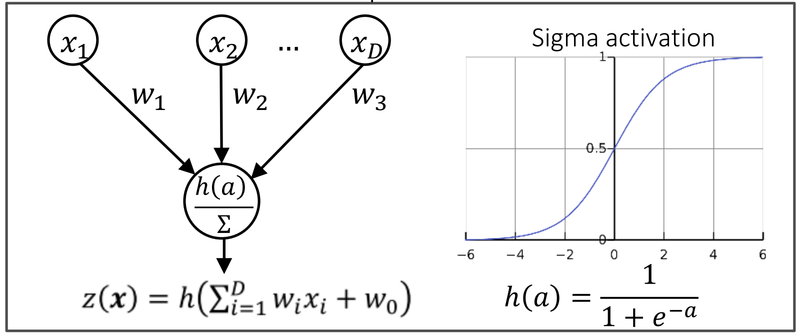


2.d. Modeling

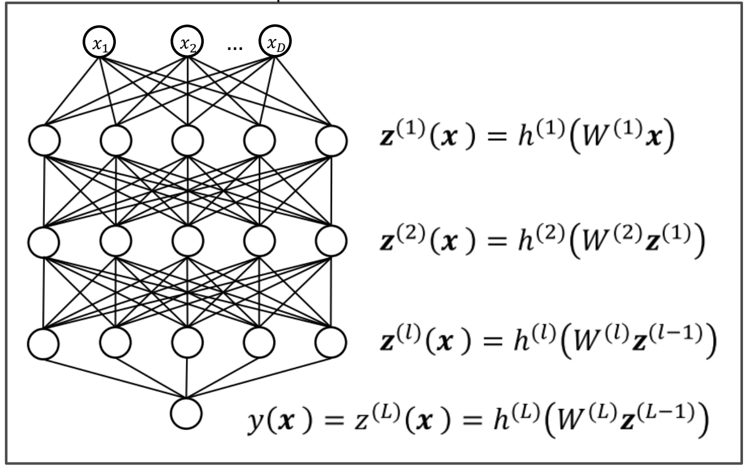
Neuron:

Main component of neural network
x … input samples
w … neuron weights

Example Neuron



Example Neural Network



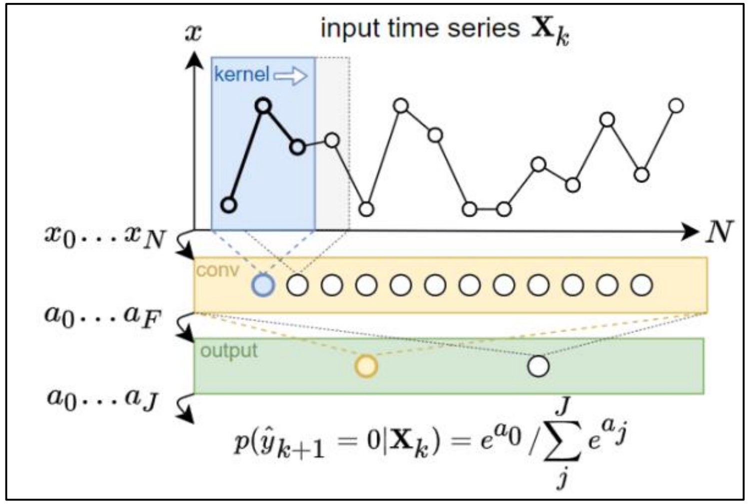
Neural networks:

Many layers of neurons makes it possible to find nonlinear properties (deep learning)

Convolutional neural networks:

A neuron is not connected to every single neuron in the next layer,
but only to neighbouring neurons (convolution).*

Example CNN for Time Series Classification



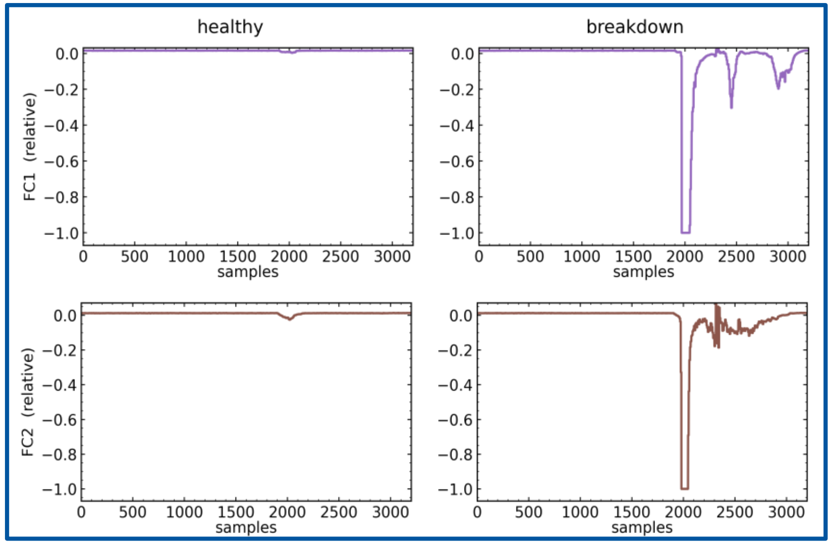
Explainable AI

Analyze w_i to reverse engineer which sample was important for classification.
"SHAP values"** are calculated and state the importance of each input x_D.

*H. Fawaz et al., „Deep learning for time series classification", 2019
**Lundberg, Scott M., and Su-In Lee. "A unified approach to interpreting model predictions." NeurIPS. 2017.

2.d. Modeling

	Bunker_WG_Temp	Klystron_Flange_Temp	Load_Temp	PC_Left_Cavity_Temp	PC_Right_Cavity_Temp
0	24.134285	24.116962	27.955711	30.285633	30.187632



Two modeling stages:

a. Train on trend data + extracted features (scalars)

b. Train on event data (time series signals)

Class imbalance (within runs):

“healthy”: 124448, “faulty”: 479 (250 are follow-up breakdowns)

→ 2.5% of “healthy” signals taken + weight for “faulty”

Classification:

Assumption from trend data analysis: Precursor occurs only in the previous pulse

- Classification problem: calculate probability of a **breakdown in next pulse** → **used label**

Computation time:

- a. Computiation time on HTCondor with GPU: 1min, locally with only CPU: 10 min
- b. Computiation time on HTCondor with GPU: 1h, locally with only CPU: 24h

3. Results trend data analysis

a. Exploration
b. Modeling
c. Explainable AI
d. Experimental validation

	Bunker_WG_Temp	Klystron_Flange_Temp	Load_Temp	PC_Left_Cavity_Temp	PC_Right_Cavity_Temp
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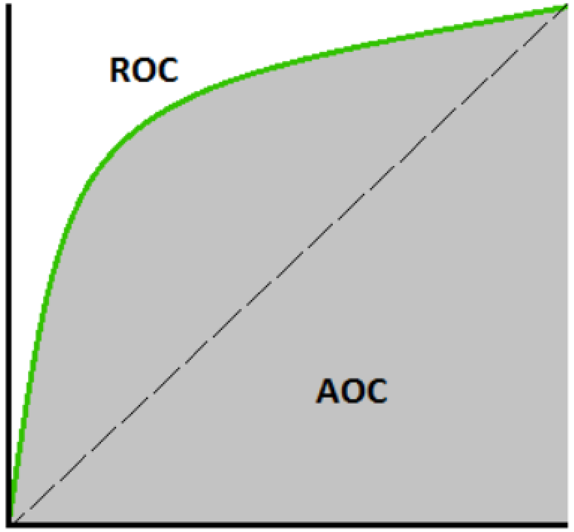
3.a. Modeling

Used Performance Measure:

AUC ROC Score: **A**rea **U**nder **C**urve of **R**eceiver **O**perating **C**haracteristic curve

Model	(1) Primary Breakdowns AR_μ	AR_σ	AR_t	(2) Follow-up Breakdowns AR_μ	AR_σ	AR_t	(3) All Breakdowns AR_μ	AR_σ	AR_t
k-NN	61.0%	7.4%	63.1%	89.8%	8.1%	92.9%	76.7%	8.0%	75.9%
SVM	68.8%	10.0%	73.8%	93.6%	5.7%	97.0%	84.2%	9.8%	87.8%
Random Forest	81.0%	16.7%	82.5%	96.9%	3.5%	96.5%	87.9%	13.3%	90.0%
time-CNN	55.2%	11.0%	48.1%	92.8%	3.8%	87.6%	67.7%	6.3%	66.0%
FCN	86.1%	8.7%	81.0%	98.2%	1.0%	97.8%	**93.8%**	**4.2%**	**90.6%**
FCN-dropout	84.9%	9.0%	81.7%	95.6%	3.0%	97.3%	92.7%	4.6%	90.6%
Inception	85.4%	8.5%	82.9%	**98.7%**	**1.6%**	**98.6%**	92.3%	4.8%	90.9%
ResNet	**87.9%**	**7.2%**	**80.4%**	98.7%	1.4%	98.0%	93.1%	4.6%	90.1%

$$\mathbf{TPR} = \frac{\mathbf{TP}}{\mathbf{TP}+\mathbf{FN}}$$



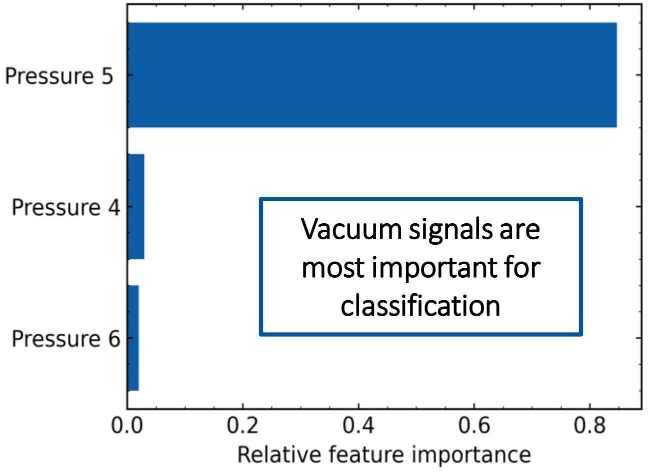
$$\mathbf{FPR} = \frac{\mathbf{FP}}{\mathbf{TN}+\mathbf{FP}}$$

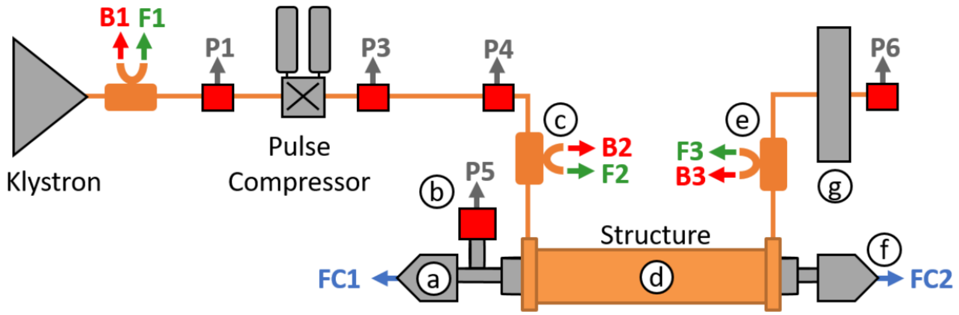
Why do we reach such high AUC ROC score?

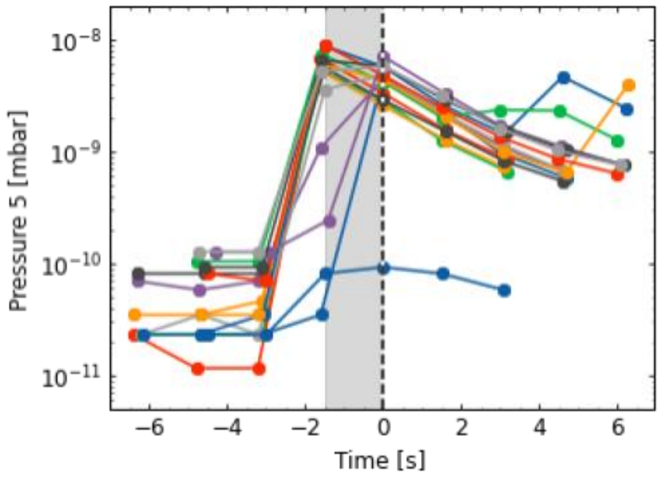
→ **Explainable AI**

3.b. Explanation

Why do we reach such high AUC ROC score?
Spike in pressure before breakdown, **not after** as generally assumed







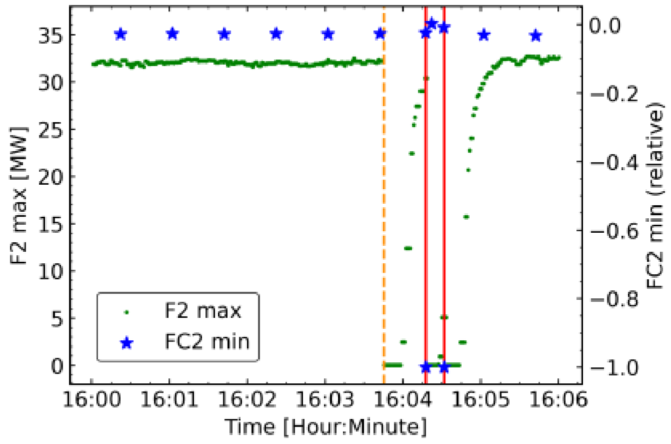
3.c. Experimental validation

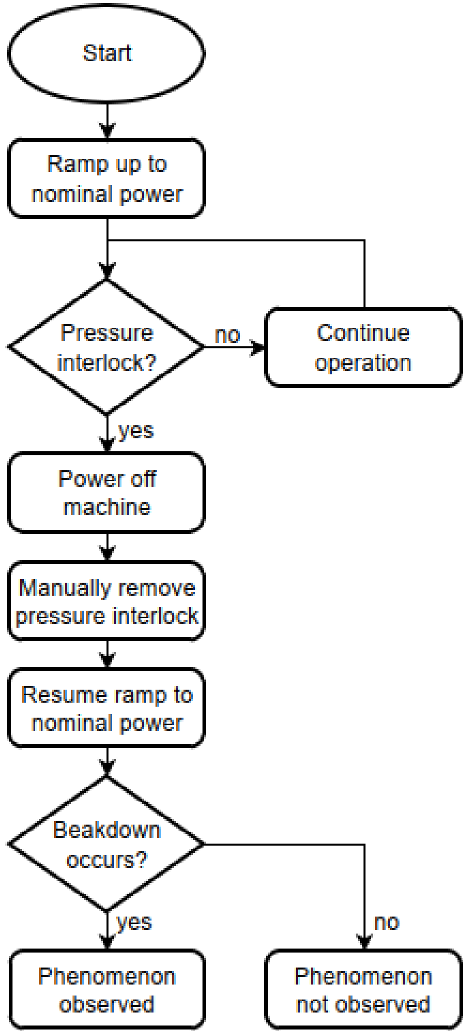
Idea:

- Turn off RF power if vacuum signal exceeds threshold
- Surface imperfections leading local field enhancement in RF cavities remain
- Breakdown should directly occur after turning on power again.

Details:

- The RF was pulsed at 50Hz, the vacuum levels are checked at 600Hz
- 3h of measurement, 15 breakdowns occurred in total (5 groups with 4, 1, 4, 2 and 4 breakdowns).
- In **two** breakdown groups, the vacuum precursors were **observed**.
- Other groups could have occurred due to change of settings during the test



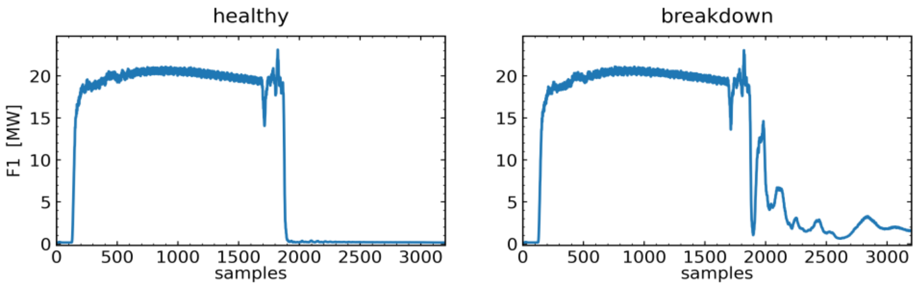


Further experiments are mandatory to draw final conclusion!

4. Results event data analysis

a. Modeling

b. Explainable AI



4.a. Modeling

Used Performance Measure:

AUC ROC Score: **A**rea **U**nder **C**urve of **R**eceiver **O**perating **C**haracteristic curve

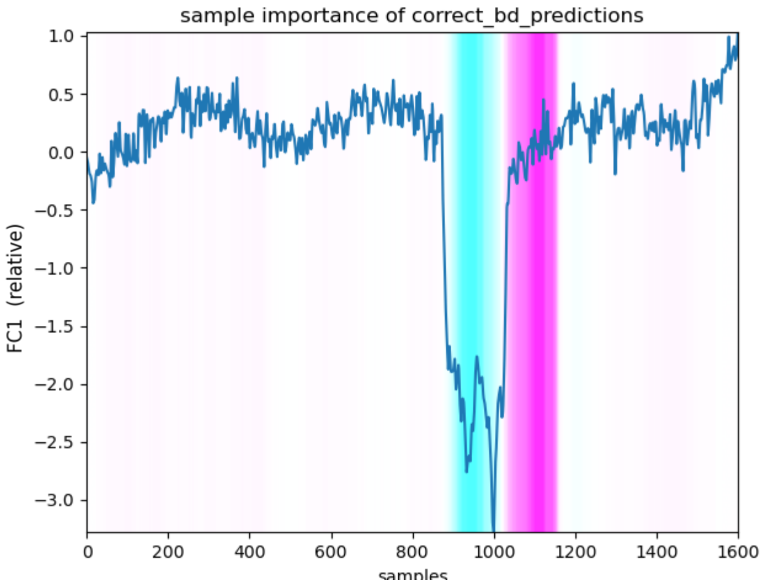
	(4) Primary Breakdowns			(5) Follow-up Breakdowns			(6) All Breakdowns		
Model	AR_μ	AR_σ	AR_t	AR_μ	AR_σ	AR_t	AR_μ	AR_σ	AR_t
k-NN	49.6%	1.2%	48.4%	61.4%	10.1%	58.7%	57.2%	10.0%	54.9%
SVM	50.0%	0.0%	50.0%	63.0%	7.8%	62.5%	57.3%	3.6%	56.3%
Random Forest	48.2%	3.4%	50.0%	66.9%	9.2%	73.0%	58.4%	6.9%	59.7%
time-CNN	52.7%	3.4%	51.9%	79.2%	12.8%	82.1%	59.8%	7.7%	66.6%
FCN	54.7%	9.8%	52.8%	**89.7%**	**8.1%**	**91.1%**	66.8%	12.5%	68.7%
FCN-dropout	**56.6%**	**8.3%**	**54.0%**	89.1%	5.3%	83.7%	**65.2%**	**7.3%**	**67.3%**
Inception	52.6%	3.6%	49.9%	87.9%	8.4%	90.5%	65.9%	13.6%	67.1%
ResNet	51.9%	7.0%	53.5%	88.7%	7.7%	89.9%	67.2%	14.3%	68.5%

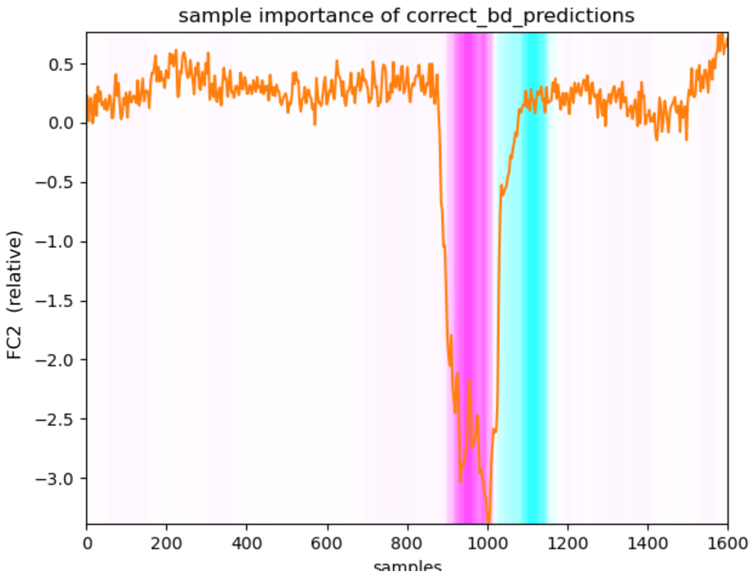
Why do we reach such high AUC ROC score on predicting follow-up breakdowns?

→ **Explainable AI**

4.b. Explanation

Why do we reach such high AUC ROC score for follow-up breakdowns?:





Red: information indicates bd in the next pulse
Blue: information indicates no bd in the next pulse

- DC signals are most important for model (91% with all signals, 87% accuracy with only DC signals)
- The signal sporadically changes following breakdowns → **high importance region** often temporally located **at the end** of the compressed RF pulse.

4.b. Explanation

Better results in the frequency domain?

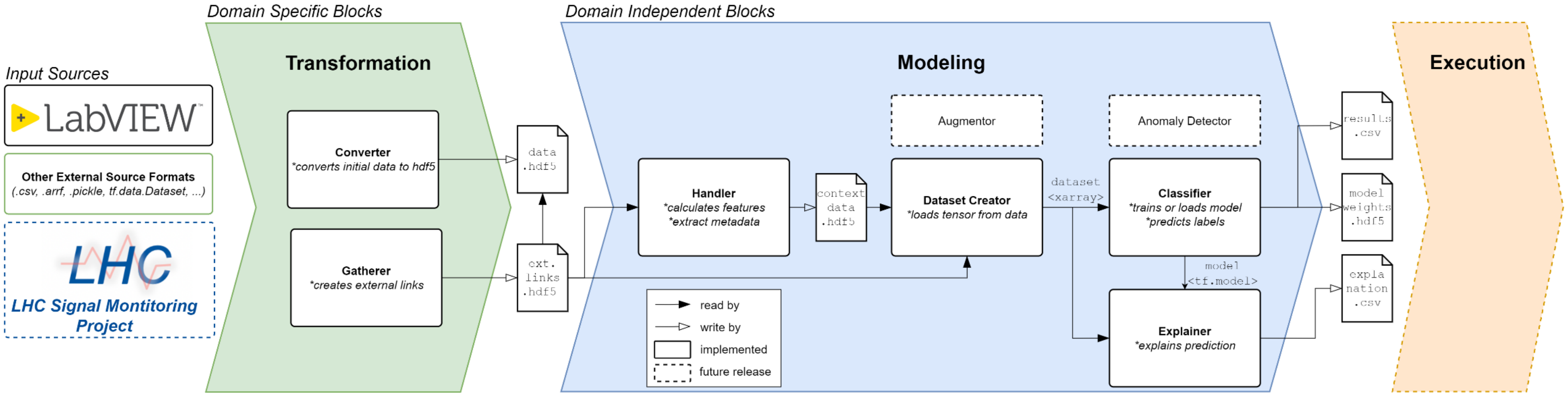
Input	$\mathbf{AR_t}$
All Signals	91%
Both FC signals	87%
Only FC1	84%
Only FC2	83%
Both FC signals – FFT Amplitude	71%
Only FC signals – FFT Amplitude + Phase	75%
Only FC signals – Spectrogram	72%

- Main information is stored in the time domain, not in the frequency domain.

5. ML Framework: Overview

We work on a generic framework (Gitlab CI/CD + code reviews), which can be applied to:

- Similar use-cases at CERN, LHC RB circuit analysis
- Similar use-cases from Institutions interested in our work: Consorzio RFX (ITER), Melbox (Melbourne University)
- Similar use-cases from Institutions who work on the same topic: Daresbury Laboratory, DESY



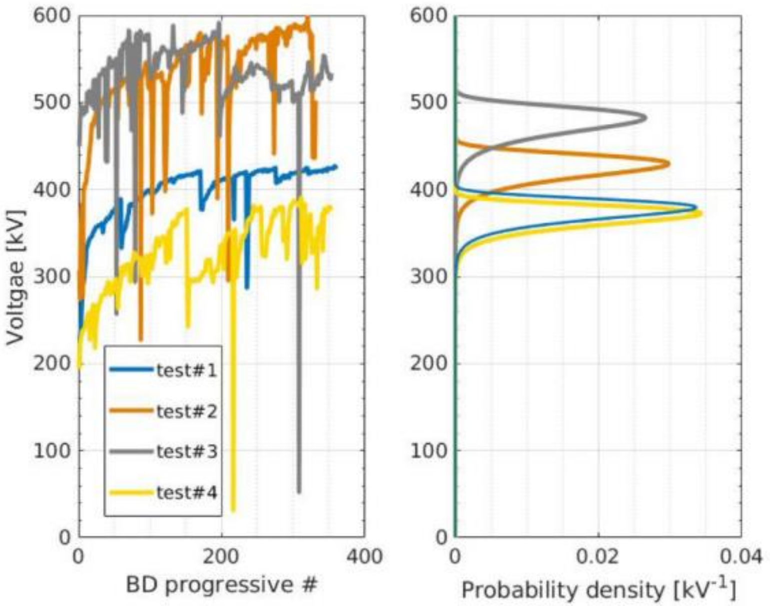
[1]https://github.com/cobermai/rfstudies

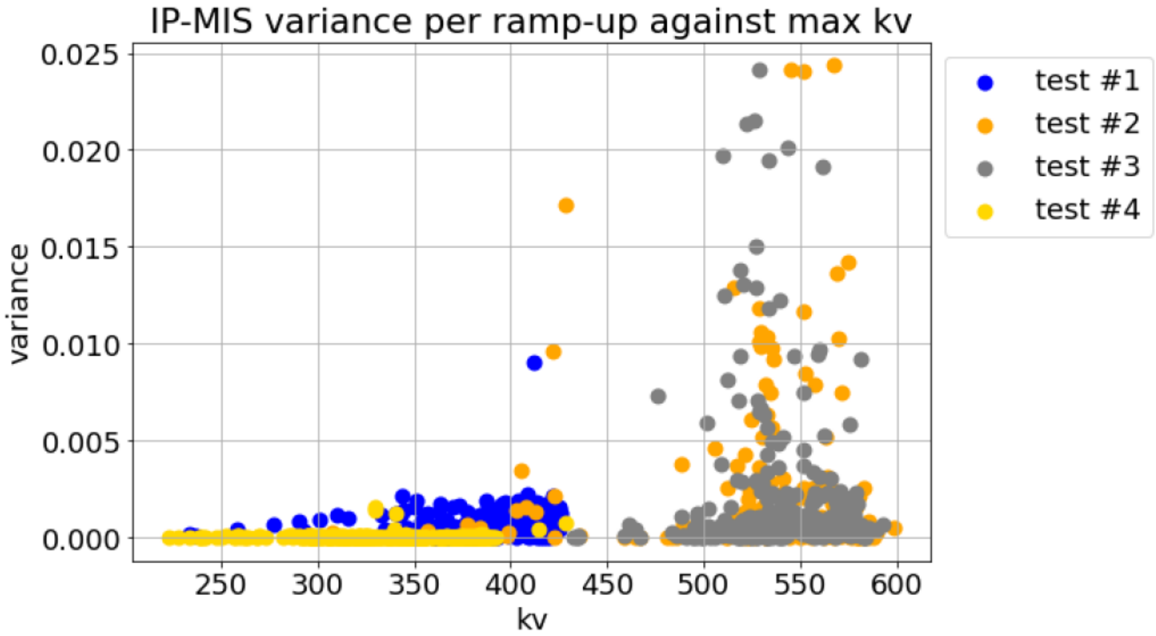
5. ML Framework: Anomaly Detection @ Consorzio RFX

Past measurements showed deviation from existing model[1] to estimate probability density distribution of the DC breakdown voltage

Goal: Find anomalies in data, which could explain the deviation

Summary: Most of the anomalies we analyzed were found in the current of the experimental setup





[1]https://iopscience.iop.org/article/10.1088/1741-4326/ab8d03

6. Conclusion

Trend data:

- Prediction of primary breakdowns with **87.9%** AR, prediction of follow-up breakdowns with **98.7%** AR
- **Vacuum spike** prior to breakdown was observed with explainable AI

Event data:

- Prediction of primary breakdowns with **56.6%** AR, prediction of follow-up breakdowns with **89.7%** AR
- Explainable AI showed that the **amplitude of FC signals** is essential for model prediction

CLIC ML framework for transformation, exploration, modeling is available and is already applied on additional use cases at Consorzio RFX (ITER) and Melbox (Melbourne University)

7. Outlook

Trend data:

- Further experiments to investigate **pressure rise** before breakdown → log pressure with high sampling rate

Event data:

- Further investigate **physics meaning** of good prediction results with DC signals
- Further improve and verify **supervised and unsupervised** modelling techniques (e.g. data augmentation)[1]
- Explore the possibility to **implement** the used ML **methods** in an operational tool for RF accelerating structure conditioning, to smoothen the conditioning process and avoid as much as possible breakdowns by suitable adjustment of the power in the cavity
- Perform more detailed studies by applying the framework to **higher resolution** datasets →Record every pulse when operating a low rep rates (e.g. 5Hz) instead of 1 pulse/minute.

[1]https://accelconf.web.cern.ch/ipac2022/papers/tupoms054.pdf