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U.S. DEPARTMENT OF ENERGY | Office of Science

# Anomaly Detection in Accelerator Facilities Using Machine Learning

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SLAC NATIONAL ACCELERATOR LABORATORY | Argonne NATIONAL LABORATORY | BROOKHAVEN NATIONAL LABORATORY

# Background

- APS, LCLS and NSLS-II are light sources under BES, to operate >5000s hrs for user experiments

- Machine reliability: a key parameter of the machine performance
  - Achieved >95% reliability
  - Downtime will affect individual scheduled user experiments
  - Waste of operation cost

- Strategics for high reliability: heavily rely on experts
  - Preventive maintenance on subsystems
  - Quick diagnose and recover machine from downtime

- Funded by DOE BES, three labs collaborated to develop machine learning based approaches aiming to solve both situations, hardware failure prediction and machine failure diagnosis to find fault sources

# Goals

- Accelerator facilities experience
  - Partial beam loss or complete beam dumps (i.e., downtimes)
  - Example: NSLS II in 2018 → 1.5 hours MTTR (mean time to recover)
  - Triggered by various subsystem faults; water system defects, power supply faults, RF system trips etc.
  - Goal → improve machine operation reliability and performance
    - Preventive maintenance to reduce hardware failure and machine beam down time to detect hardware performance degrading
    - Reducing diagnosis during machine downtime
    - Monitor machine performance trend, such as beam stability
- Identify faulty subsystems
  - Analyze signals from healthy + unhealthy times
  - Examine subsystem correlation with beam performance (e.g., beam current)
  - Formulate prototypes to detect faults to reduce downtimes
  - Help operators with automated diagnosis

***Requirement: Subsystem fault identification to reduce beam downtimes through spatio-temporal signal correlations !!***

# Challenges

RF System → Which of these signals show faulty trends?

Water System → Are faulty trends distinguishable from patterns of non-fault times?

Power Supply → How much of the faults correlate with beam quality?

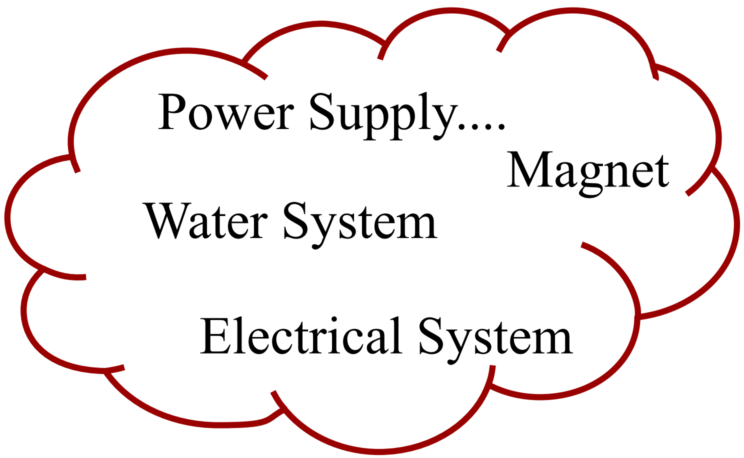
**Light Sources**

- Signals → Irregular time-series (Process Variables)
- Diverse subsystems
- No labeled data
- Limited ground truth
- Scalability with high dimensions (e.g., $10^3$)

***Identify unsupervised efficient methods for signal selection and fault detection !!***

# Problem

- How to detect a faulty subsystem using the available archived signals?




**Accelerator Facility**

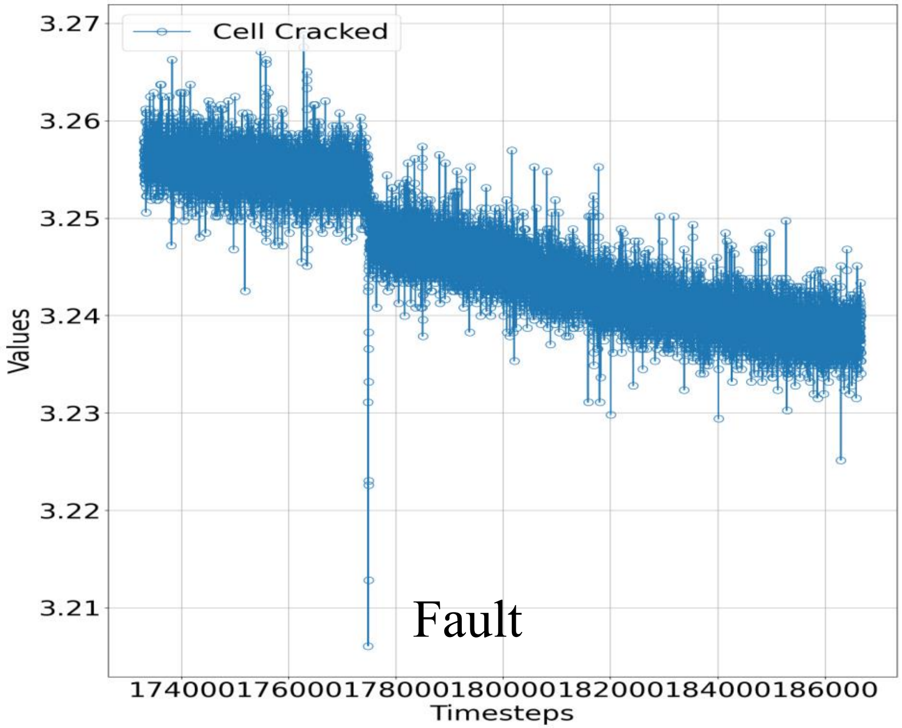
**Explore**

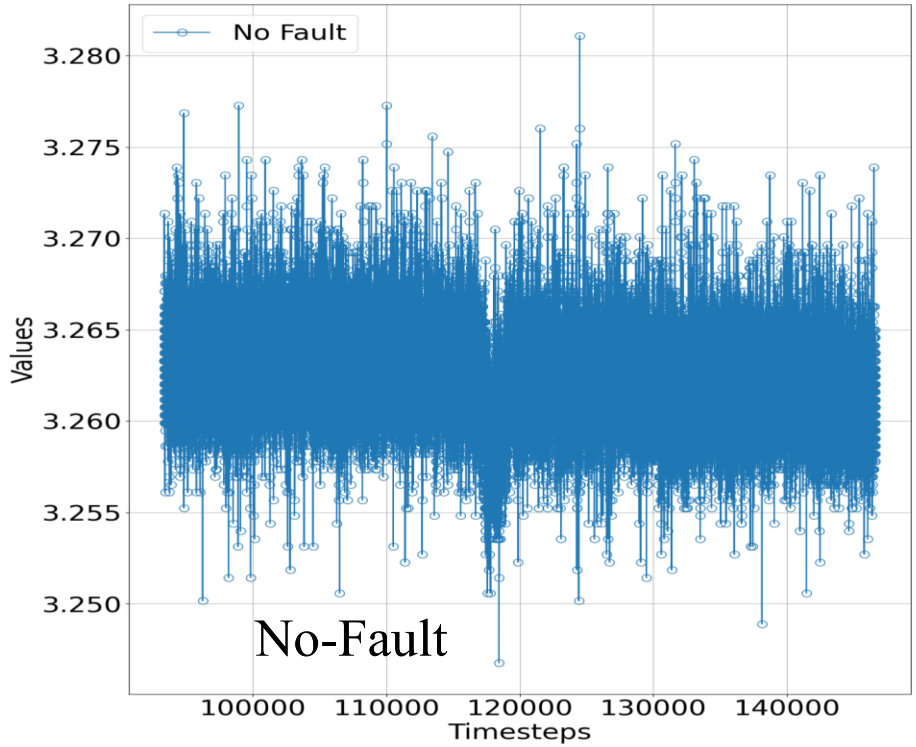
- Statistical models related to time-series distribution and entropy
- Deep learning for training and inference
- Multiple univariate correlations

- **Solution Approach**: Machine Learning guided algorithm design for time-series analysis and fault detection
  - Signal selection or combination from each subsystem
  - Correlation of subsystem with beam performance
  - Distinction of faulty times from healthy times

# Findings

➢ We analyze different signals corresponding to diverse subsystems during healthy and faulty times



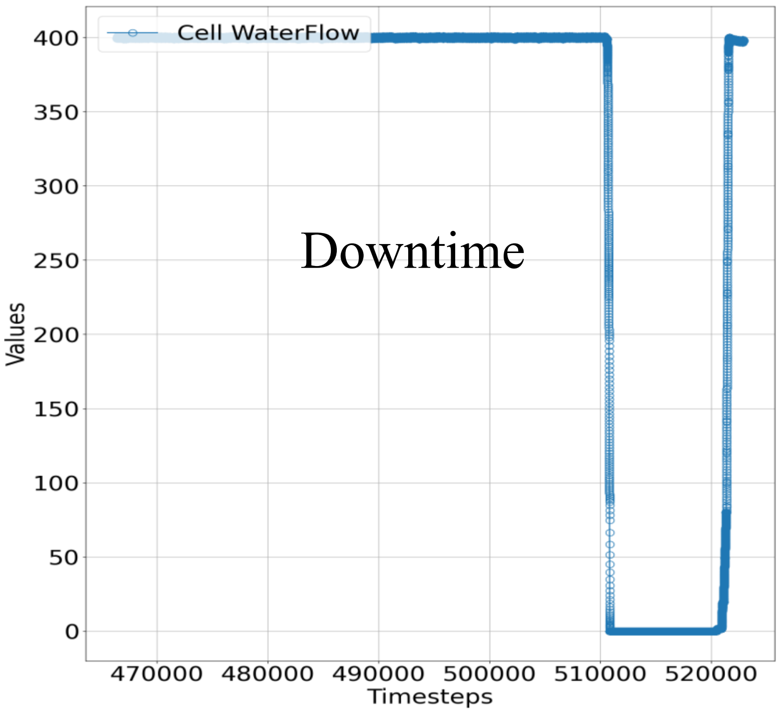



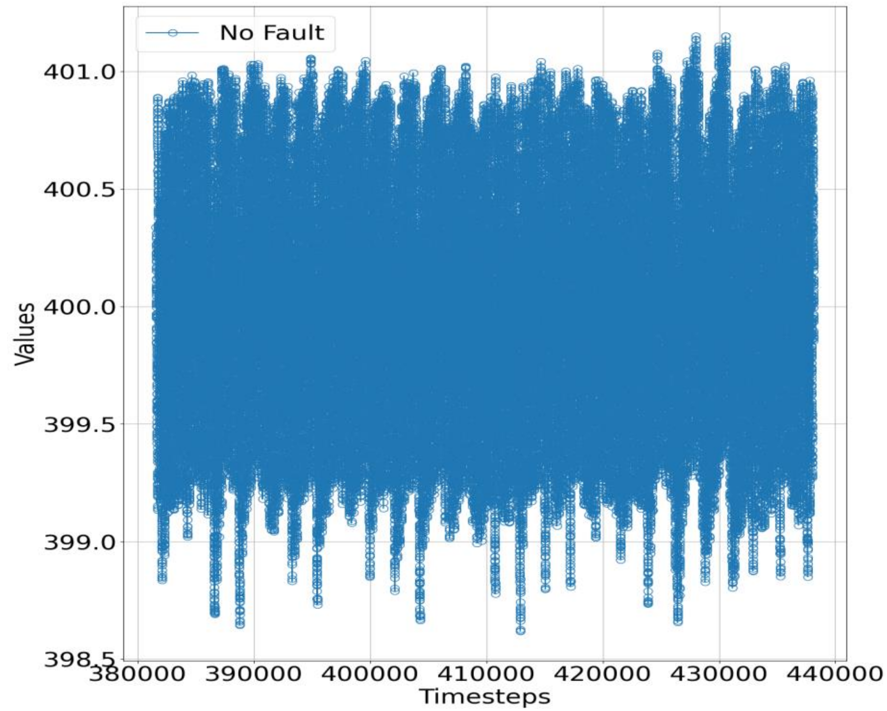

Case-1: Water cell leak: 1 of the signals of the related water system

***Gradual dip in the signal discernible during fault as opposed to healthy time !!***

# Findings

- Case-2: Water system fault: Beam current (indicates beam performance)



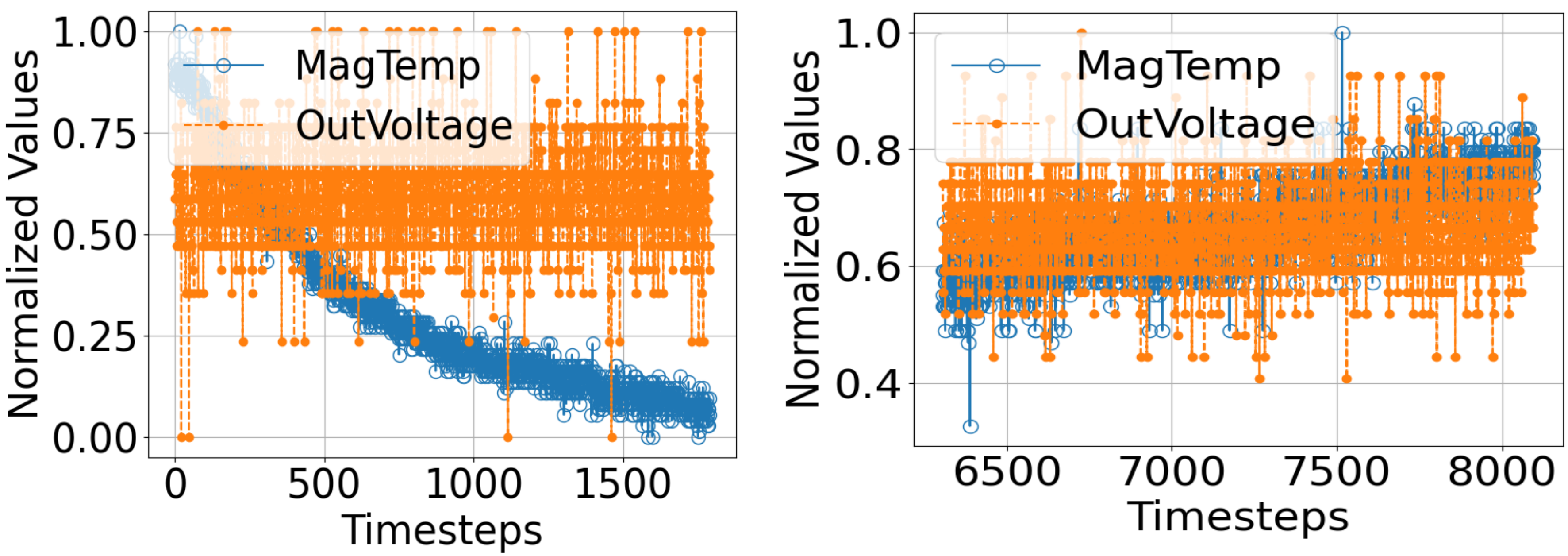

No-Downtime

- ***Clearly there is a drop in the beam current during faulty time***
- ***We find faults with no tangible impact on the beam current as well***

# Findings

- Case-3: Two signals of a specific power supply

Fault　　　　　　　　　　No-Fault

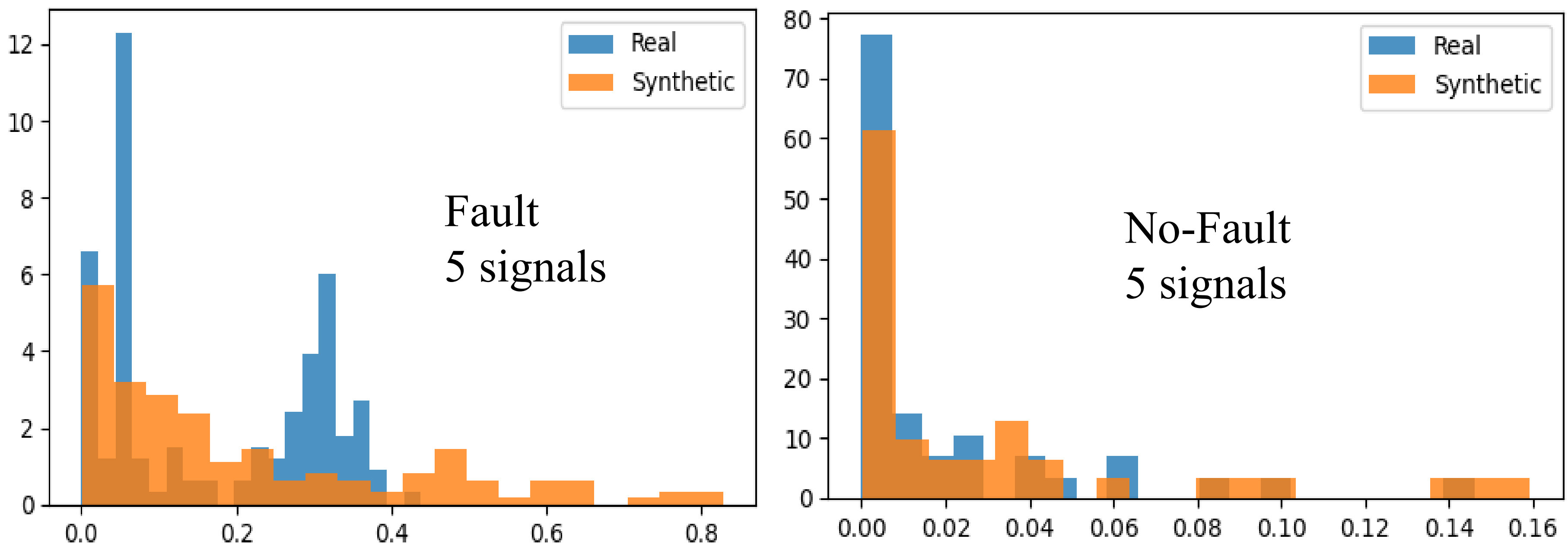



→ ***Not all signals of a subsystem may exhibit helpful trends (here temperature has better trends than voltage)***

→ ***ML-based design needs those signals that are less prone to false positives***

# Findings

- Combine signals through Gaussian copula (multivariate joint distribution)
- RF system trip: Consider 5 signals from the faulty RF system



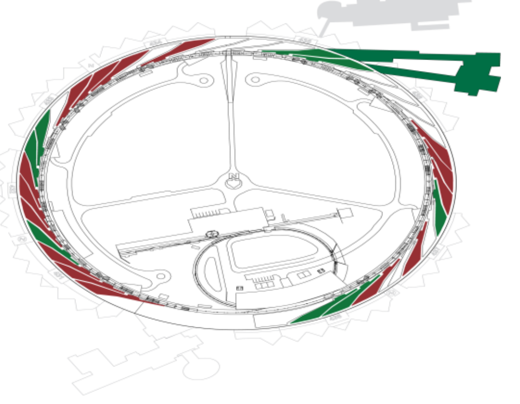

***→ Lower magnitude of combined signal during fault (left), higher values obtained during normal times (right)***

***→ Univariate signal analysis can be helpful over multi-signal combination → reduce per signal information loss***

# Conclusions

- We analyze signals of subsystems during healthy and faulty times
  - Signal variations similar to faulty times → observed during healthy times
  - Distinction between faulty and non-faulty times → non-trivial
  - Relevant signals from the faulty subsystem needs to be identified
    - For accurate fault detection via deep learning models
  - Faults may or may not lead to beam downtime or degraded beam
    - Diverse light source facilities differ in intricate signal correlations
    - Generic design → intend to account for this diversity

Storage Rings



# Future Work

- Design univariate time-series model with minimal information loss
  - Choose signals indicative of faults from the available parameter space
- Design a detector to distinguish faulty times from no-fault times
  - Is prediction possible? Depends on the nature of the subsystem faults
    - Power supply trips lead to instant beam dumps → prediction difficult, RF systems show signal drifts before downtime → prediction feasible
  - Model applicable to multiple light source facilities?

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*Thank you*