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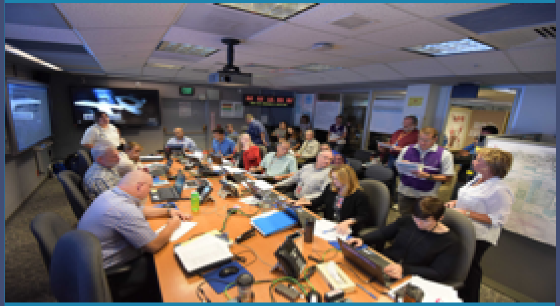
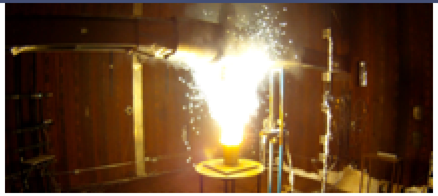
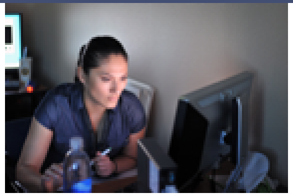
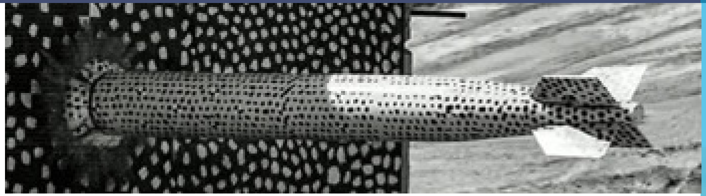


Machine Learning for Unattended Safeguards Monitoring

Nathan Shoman (SNL), Benjamin B. Cipiti (SNL), Thomas Grimes (PNNL), and Ben Wilson (PNNL)

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Outline

- Origins
- Motivation
- Background
- Process model
- Machine Learning Framework
- Current Results
- Future Work

Autonomous Systems, Artificial Intelligence and Safeguards

- Work originated as result of FY18 study by Risa Haddal et al. that examined the use of AI for safeguards purposes
- Three use cases were considered
  - Process monitoring at bulk handling facilities (reprocessing, enrichment)
  - Image recognition for physical inventory verification at fuel fabrication facilities
  - Autonomous robots for geological repository safeguards
- This work focuses on the first use case
- Several potential techniques identified in the original study are utilized or have been evaluated (SVMs, CNNs, DNNs, KNN, Random Forest)

Elimination of on-site laboratories at reprocessing facilities is a long-standing goal of the IAEA

- Currently on-site laboratories are required for large throughput bulk handling facilities under IAEA safeguards, such as PUREX reprocessing facilities
  - Require small measurement uncertainties to have an acceptable sigma MUF value
  - Expensive and time consuming
- Proposed machine learning framework uses non-destructive analysis (NDA) measurements to detect facility anomalies such as diversion or misuse
  - Measurements could be unattended except for required calibration campaigns
- Framework is to aid IAEA safeguards implementation, not to replace inspectors

Hypothesis: bulk handling facilities can represented as learnable functions

Train

- Train an algorithm to predict output of some unit operation given historical data

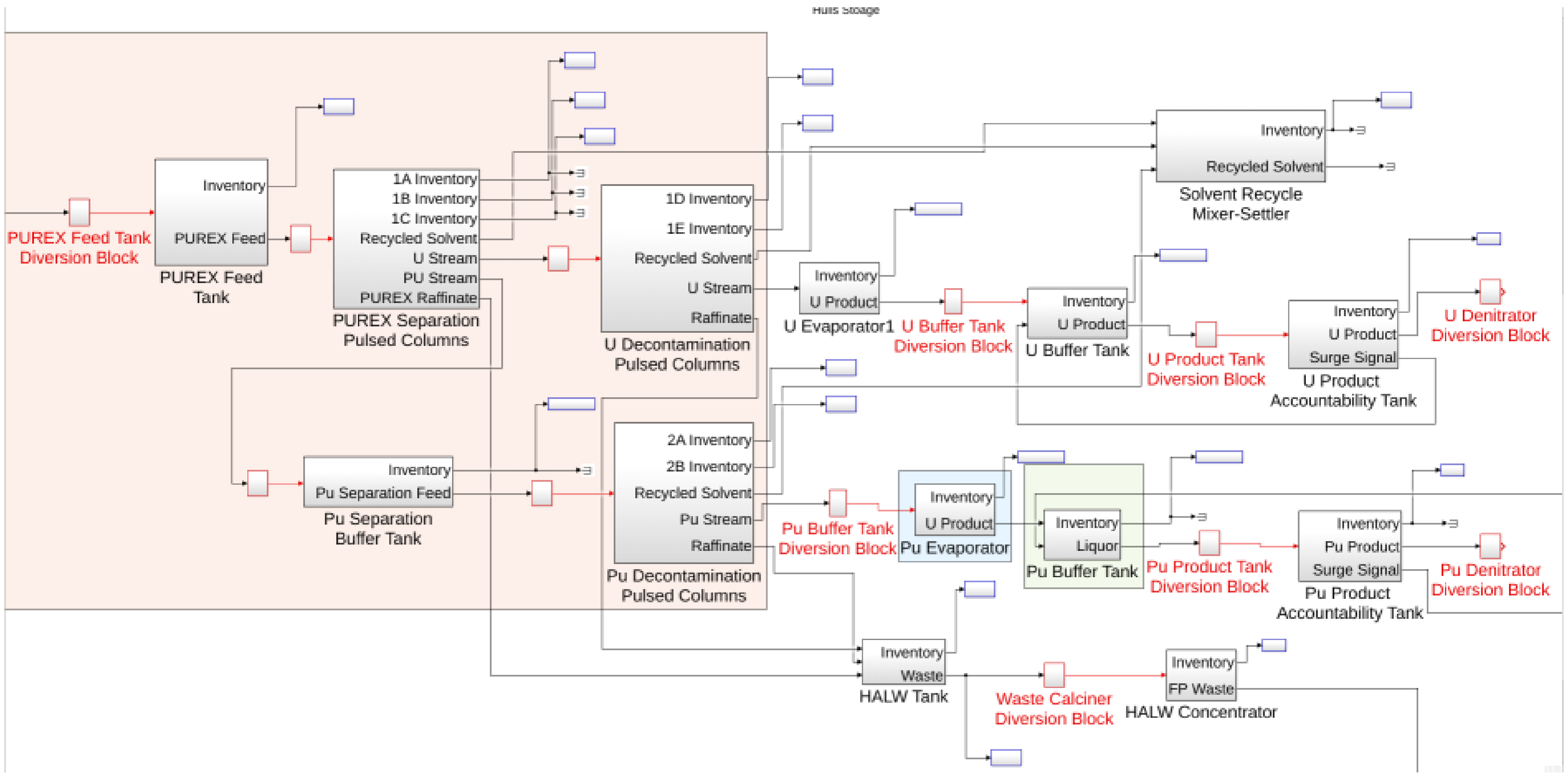
Calculate

- Calculate the difference between the ML prediction and observed values, aka the "residual"

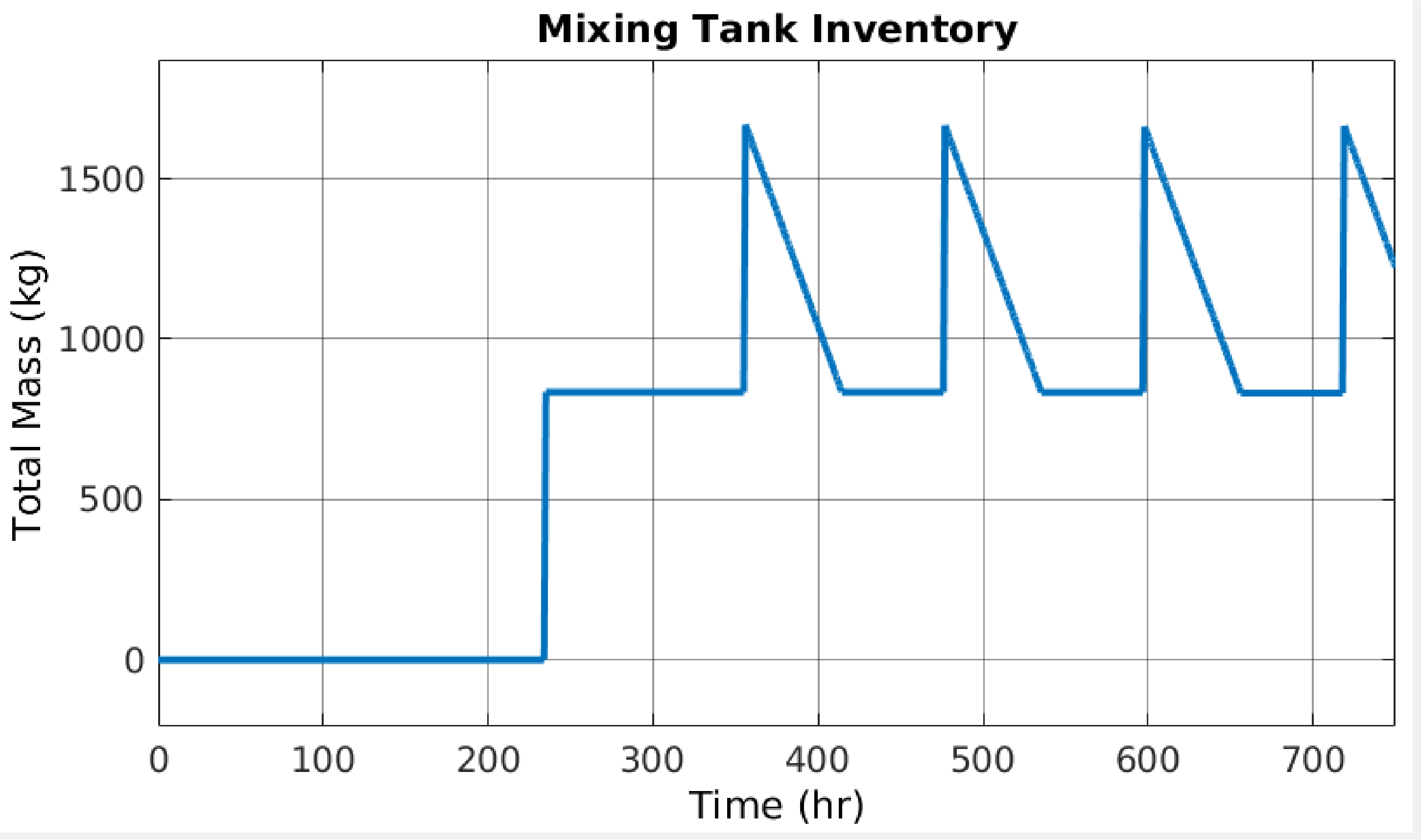
Classify

- Use a second algorithm to determine if residual is normal or off-normal

Alarm



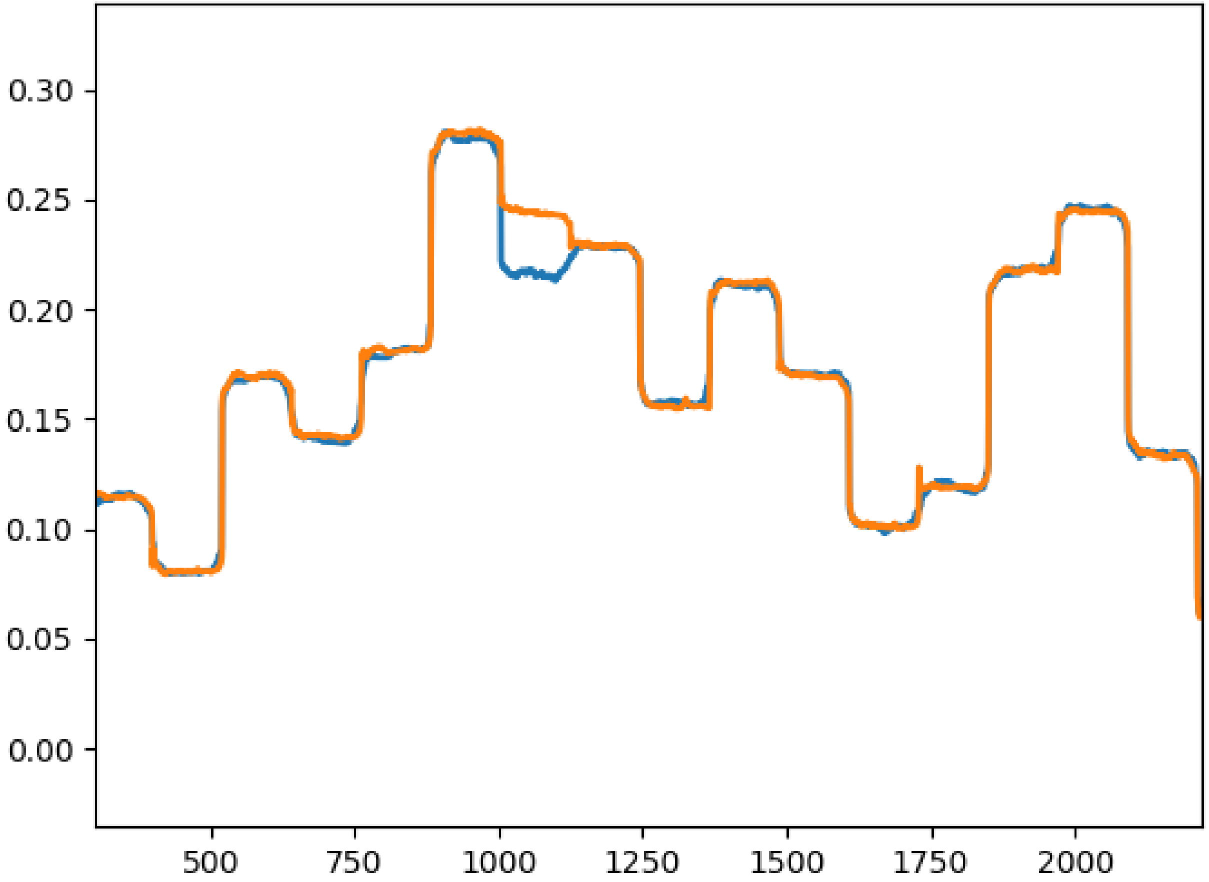
Learning the facility function – ANN/LSTM (1)



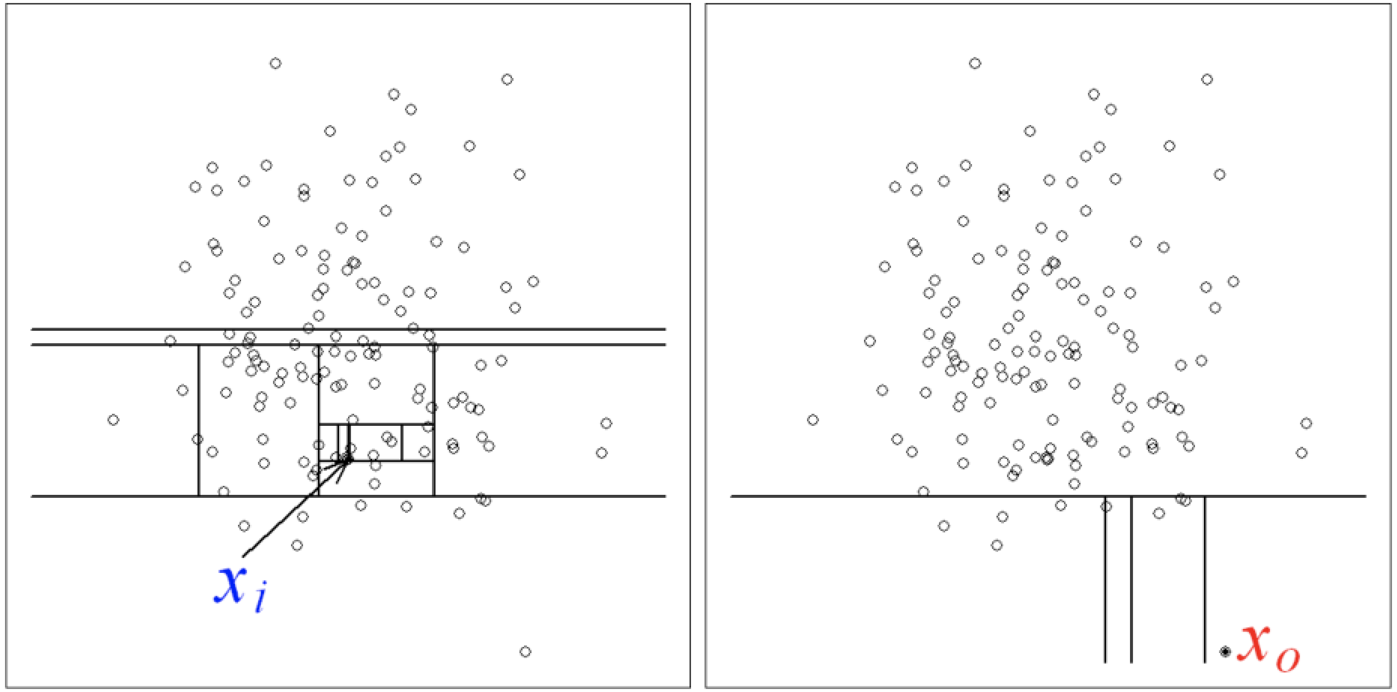
Learning the facility function – unit operations (1)

- Certain areas of the facilities require special consideration
- Mixing/buffer tank outputs are a function of their entire history
- Tank may also have non-uniform output sizes
- Feature representing running average of inventory concentrations required
- Feature representing bulk level measurement required

Calculating the residual (2)

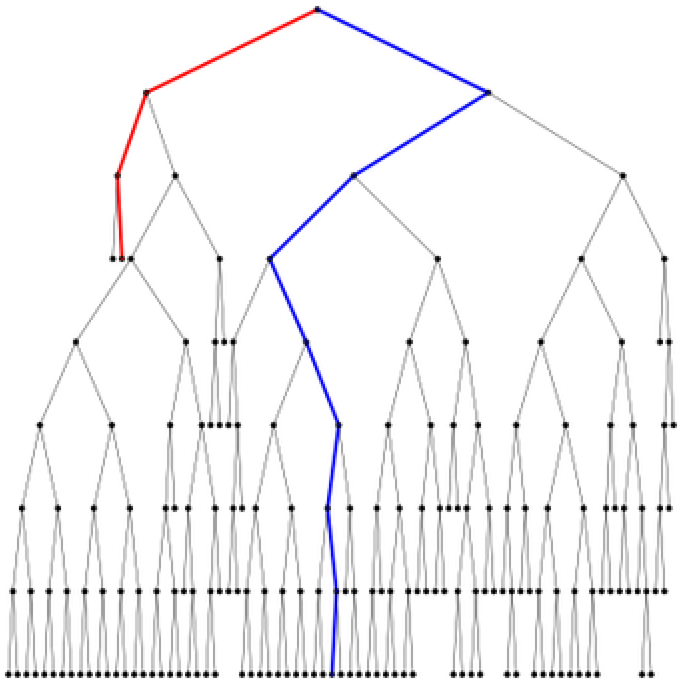


Making sense of residuals – Isolation Forest (3)

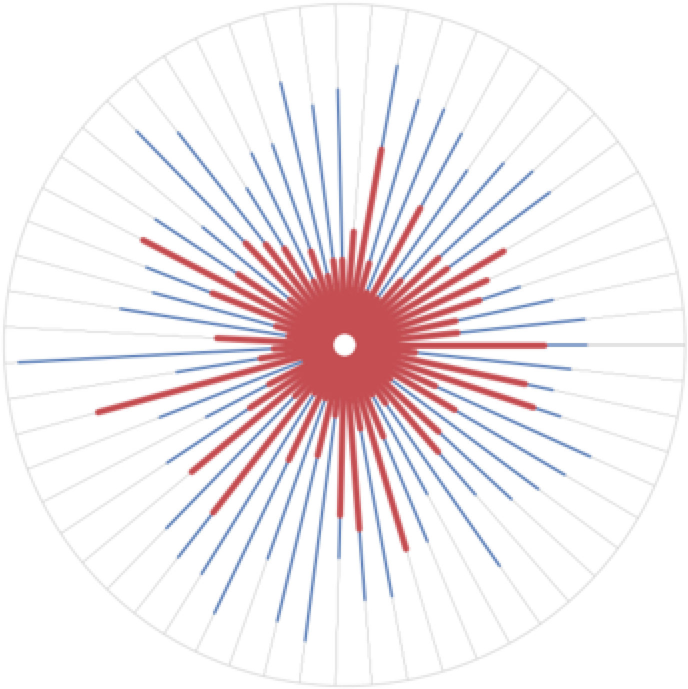


- Randomly select feature and draw a line between and max
- Repeat until point is isolated
- Anomalies/unique points require fewer cuts to isolate

Making sense of residuals – Isolation Forest (3)

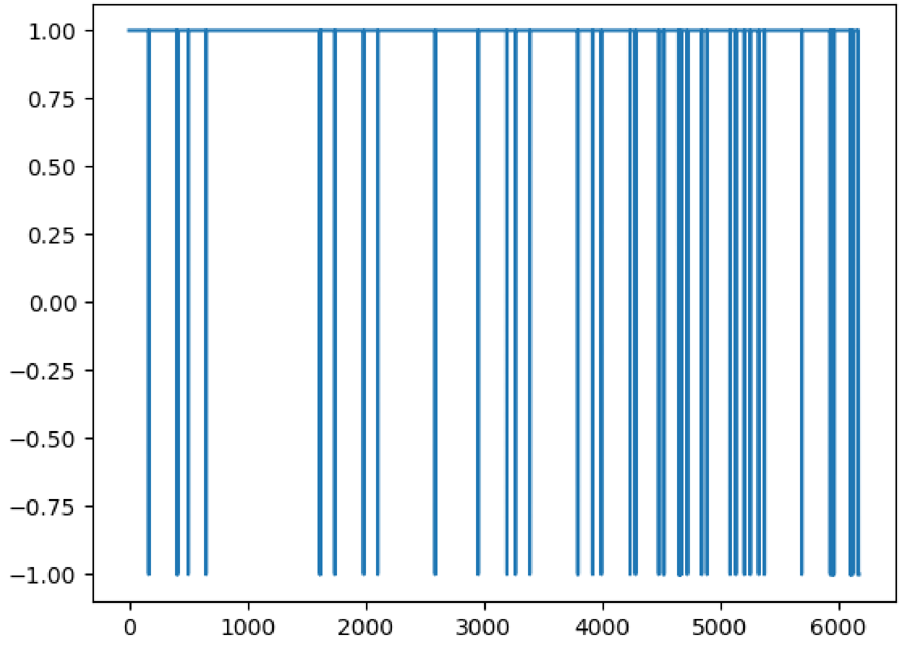


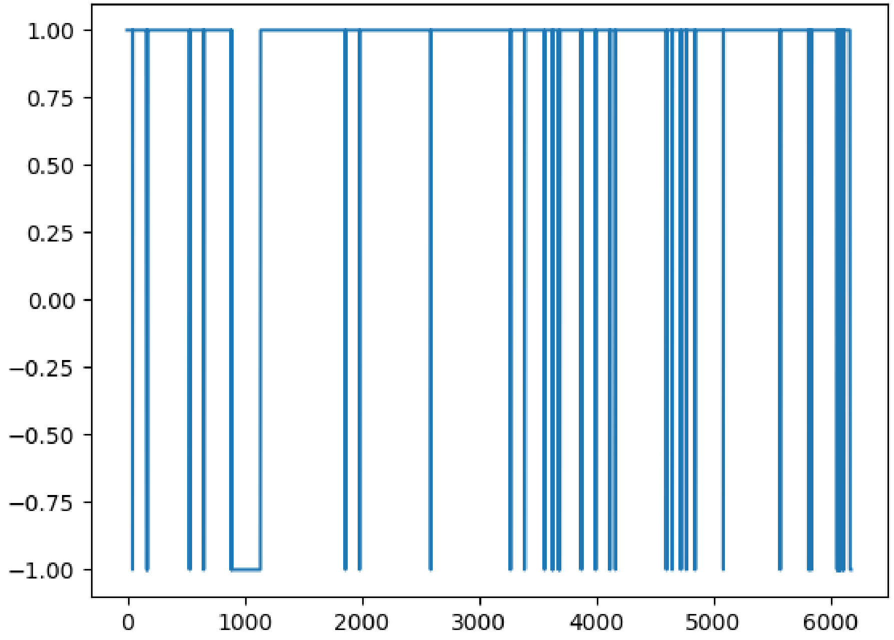
a)



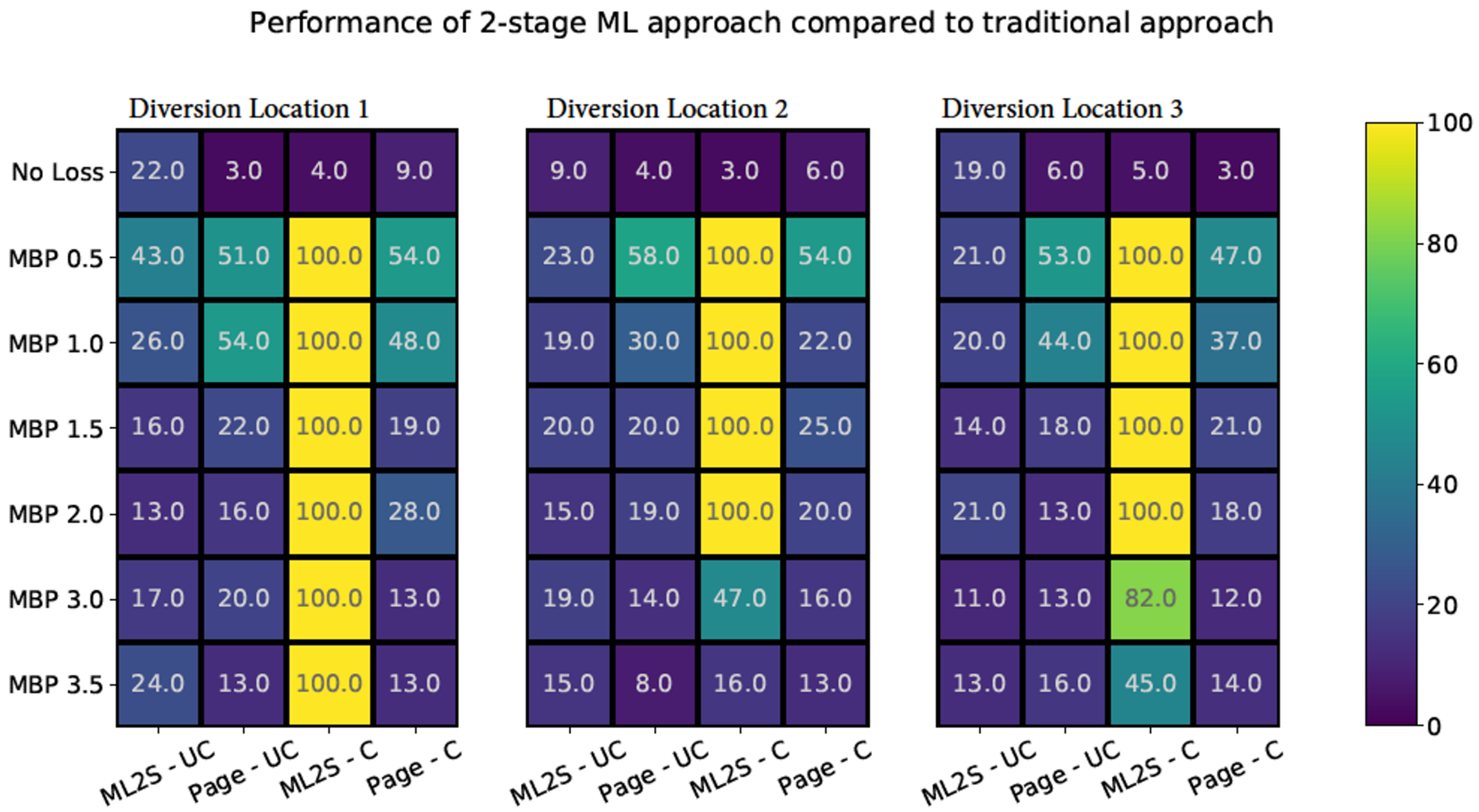
b)

Determining an overall alarm threshold (4)

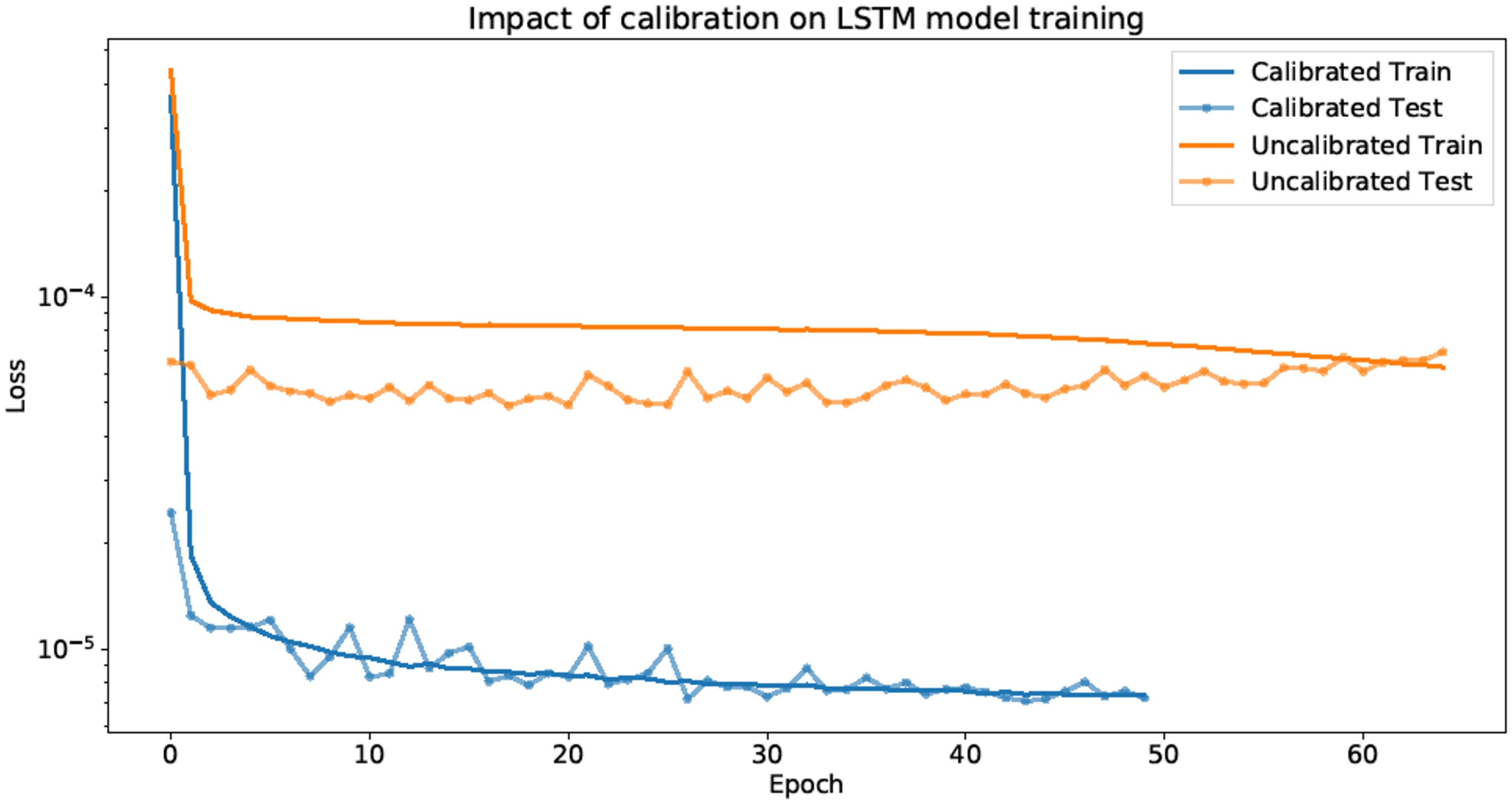




Can achieve performance beyond traditional statistical tests, s.t. certain experimental conditions



ML algorithms can be more sensitive to error representation than traditional approaches



ML can enhance safeguards when applied appropriately

- Results of current approach work very well when systematic error is controlled
- Good ML performance requires understanding of underlying process
- Working to resolve systematic error issues and increase TRL
- Visit with IAEA in spring to discuss ML based approaches

Developing Signatures-Based Safeguards for Enrichment Facilities

Nathan Shoman, Benjamin Cipiti, and Philip Honnold

Safeguards for enrichment facilities remains a high priority

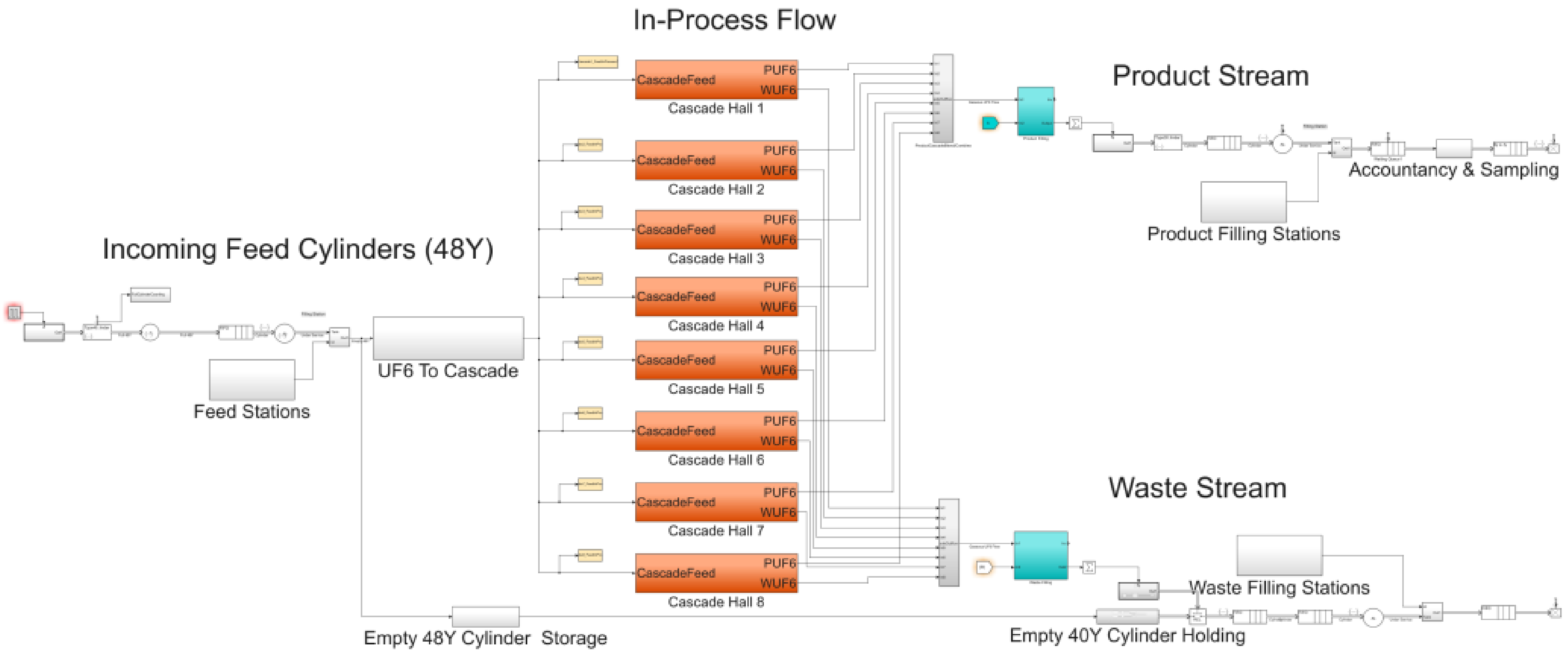
Safeguards at existing enrichment facilities rely on NDA and weight measurements in addition to unattended methods such as OLEM.

NDA uncertainties can be large and OLEM relies on accurate temperature and pressure measurements, which may be provided by the operator.

Goal of this work is to enhance safeguards at enrichment facilities while reducing attended measurements by developing a signature matrix approach.

Signature matrices are constructed from a wide range of existing process monitoring measurements that, when combined with machine learning, can be used to detect and locate off-normal conditions within a facility.

Process model



Inspiration:

(M)ulti
(S)cale
(C)onvolutional
(R)ecurrent
(E)ncoder
(D)ecoder

(Zhang, et al.)

Identifying anomalies in real-world datasets is challenging due to the temporal nature of anomalies

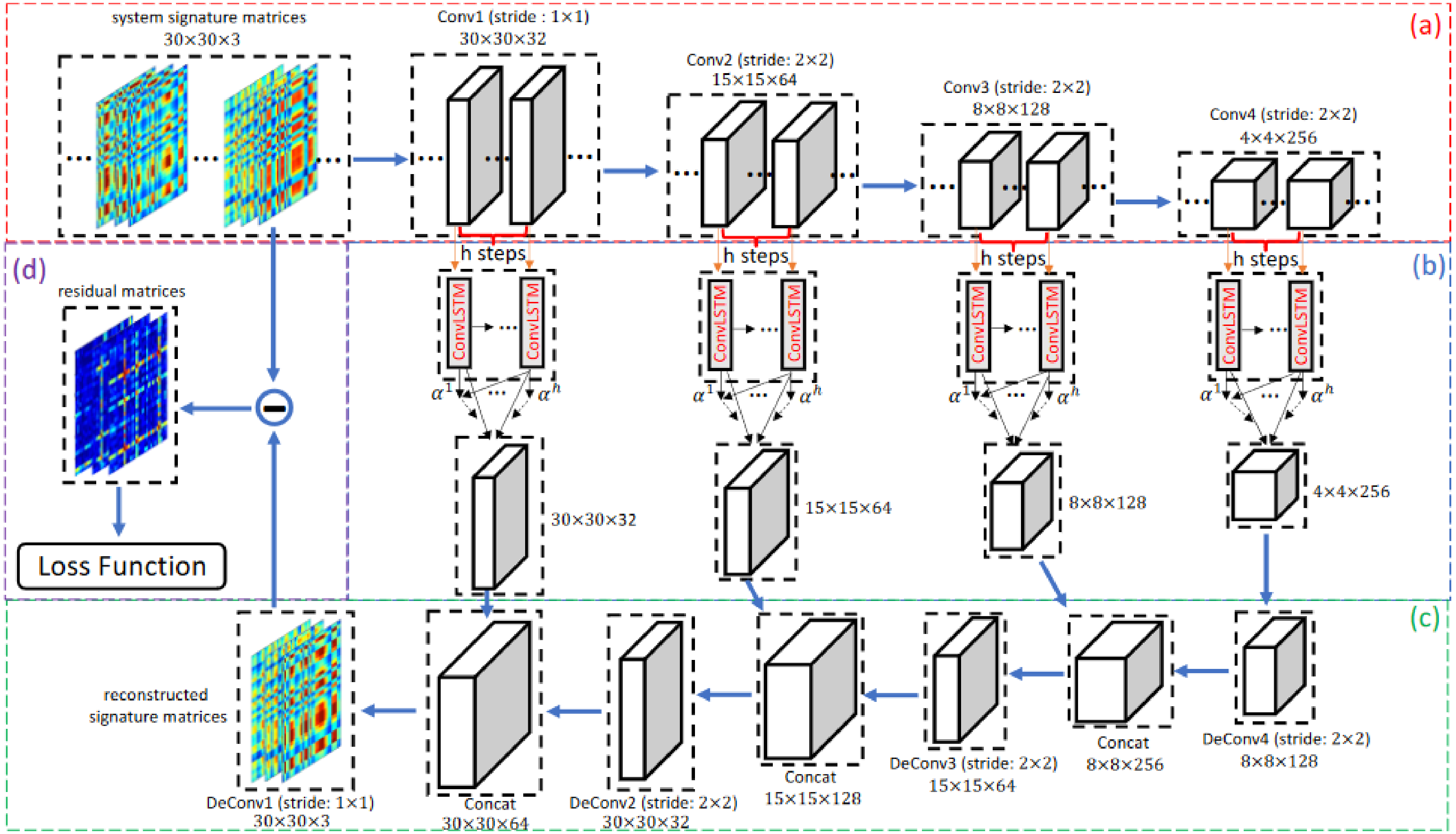
An ideal algorithm should capture temporal dependency, be robust to noise, and provide some metric of severity

MSCRED demonstrated excellent performance for detecting anomalies within a real-world power plant dataset

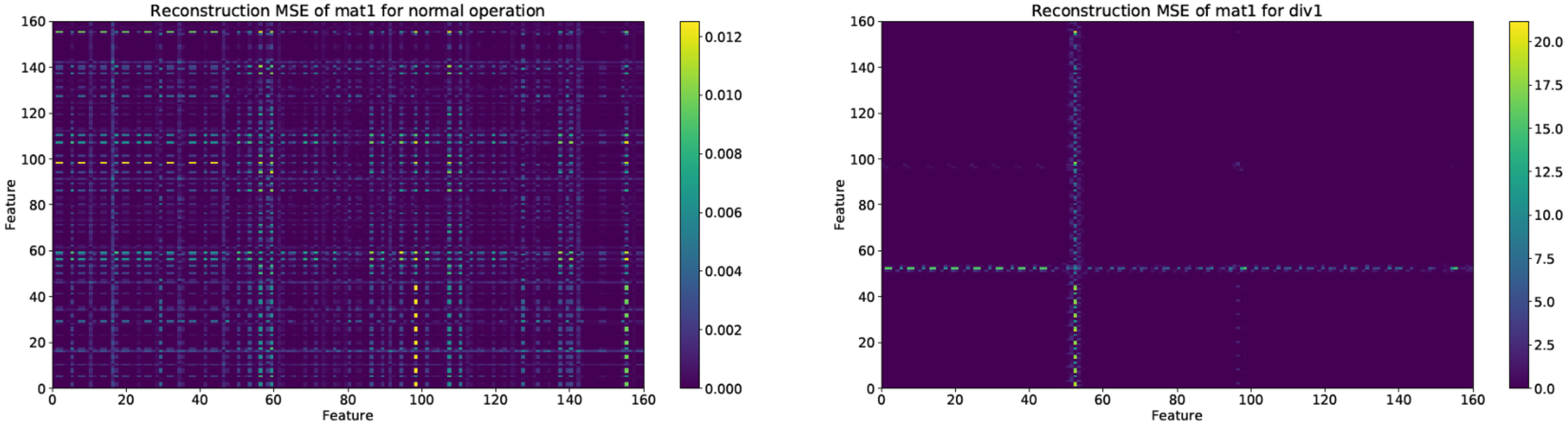
MSCRED is a CNN autoencoder with attention layers

Multi-scale signature matrices are created to characterize system status at different time steps

A convolutional autoencoder with attention (ConvLSTM) is used to capture correlations and temporal patterns.



Initial response to cascade anomaly



01

Improve algorithm through hyperparameter tuning (kernel sizes etc)

02

Evaluate limited sets of data

03

Determine required training data

Near term future work