DE-FE0031763: Deep Analysis Net with Causal Embedding for Coal Fired Power Plant Fault Detection and Diagnosis (DANCE4CFDD)

August 26, 2020

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Outline

- Project overview
- Project update
  - Algorithm and system development
  - Benchmarking with public datasets
  - Initial experiments with plant data
- Concluding remarks

Project objectives

Develop deep analysis net with causal embedding for coal-fired power plant fault detection and diagnosis (DANCE4CFDD), a novel end-to-end trainable artificial intelligence (AI)-based multivariate time series learning system for flexible and scalable coal power plant fault detection and root cause analysis

Program Team

GE Research

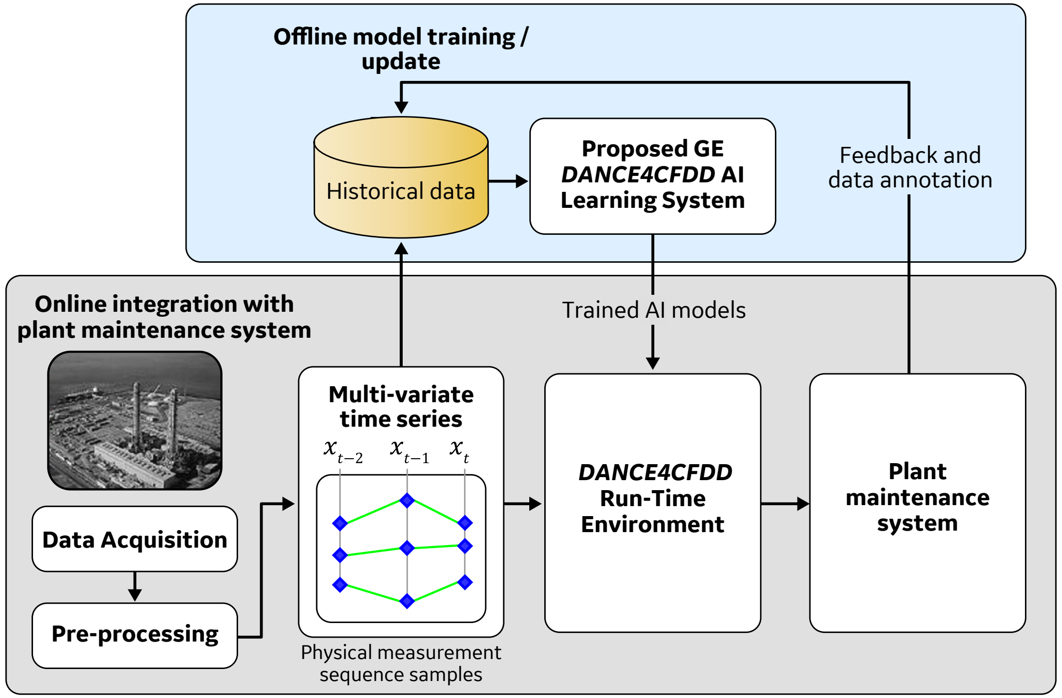
Decades of Developing AI and Machine Learning Technologies for Broad Range of Asset Health Management

EPRI ELECTRIC POWER RESEARCH INSTITUTE

Coal-Fired Power Plant Physical Asset Domain Expertise; Boiler Section Experts; Data Management

Southern Company

Coal-Fired Power Plant Historical Data, Unit Simulator, Subject Matter Expertise, and Host Site for Technology Demonstration



Expected outcomes

- Achieve TRL 5 technology maturity of end-to-end trainable AI learning system for fault detection and root cause analysis
- Validate AI learning system with data from a coal-fired power plant
- Demonstrate advantages comparing with state-of-the-art technologies
- Publicize anonymized training data

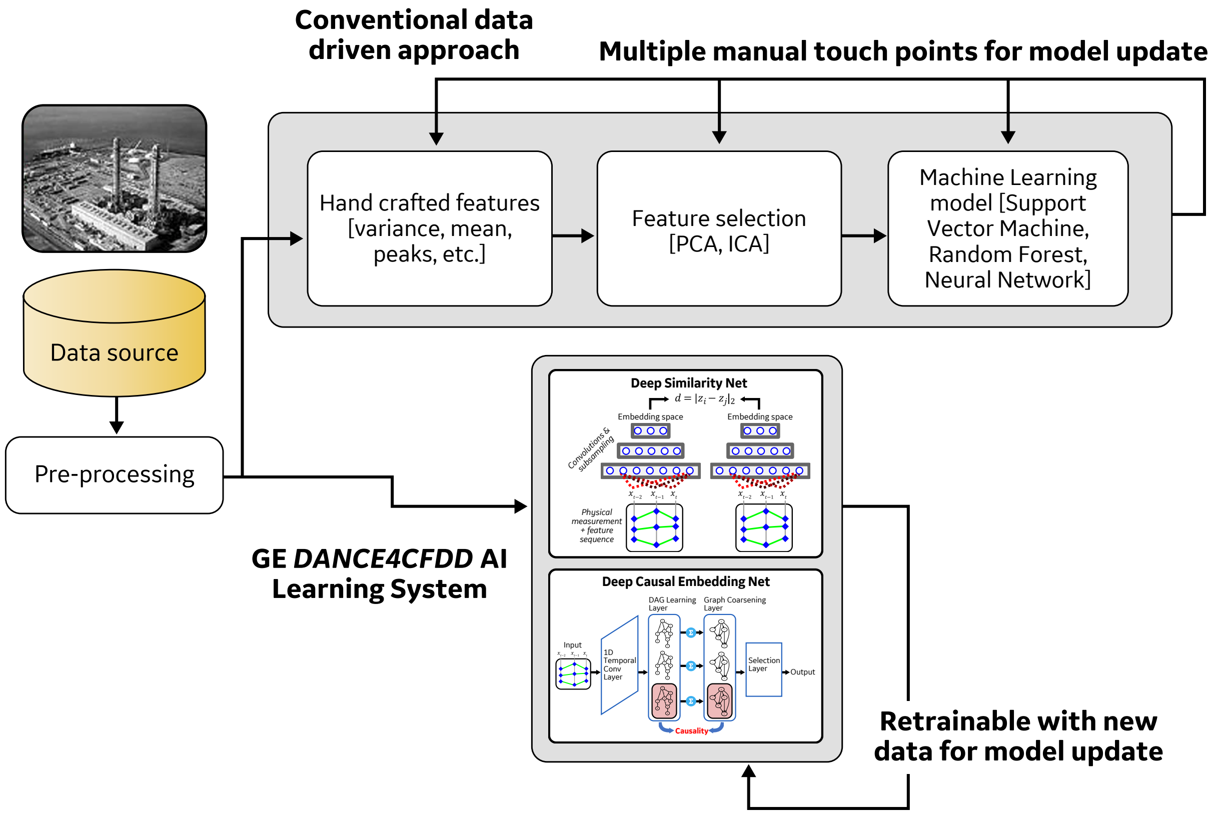
Project objectives

Motivation: Existing asset health management solutions have limited adaptability. Therefore, there is a critical need for a well-designed end-to-end solution that is applicable to a wide range of applications by leveraging large amounts of historical normal operation data from existing coal plants.

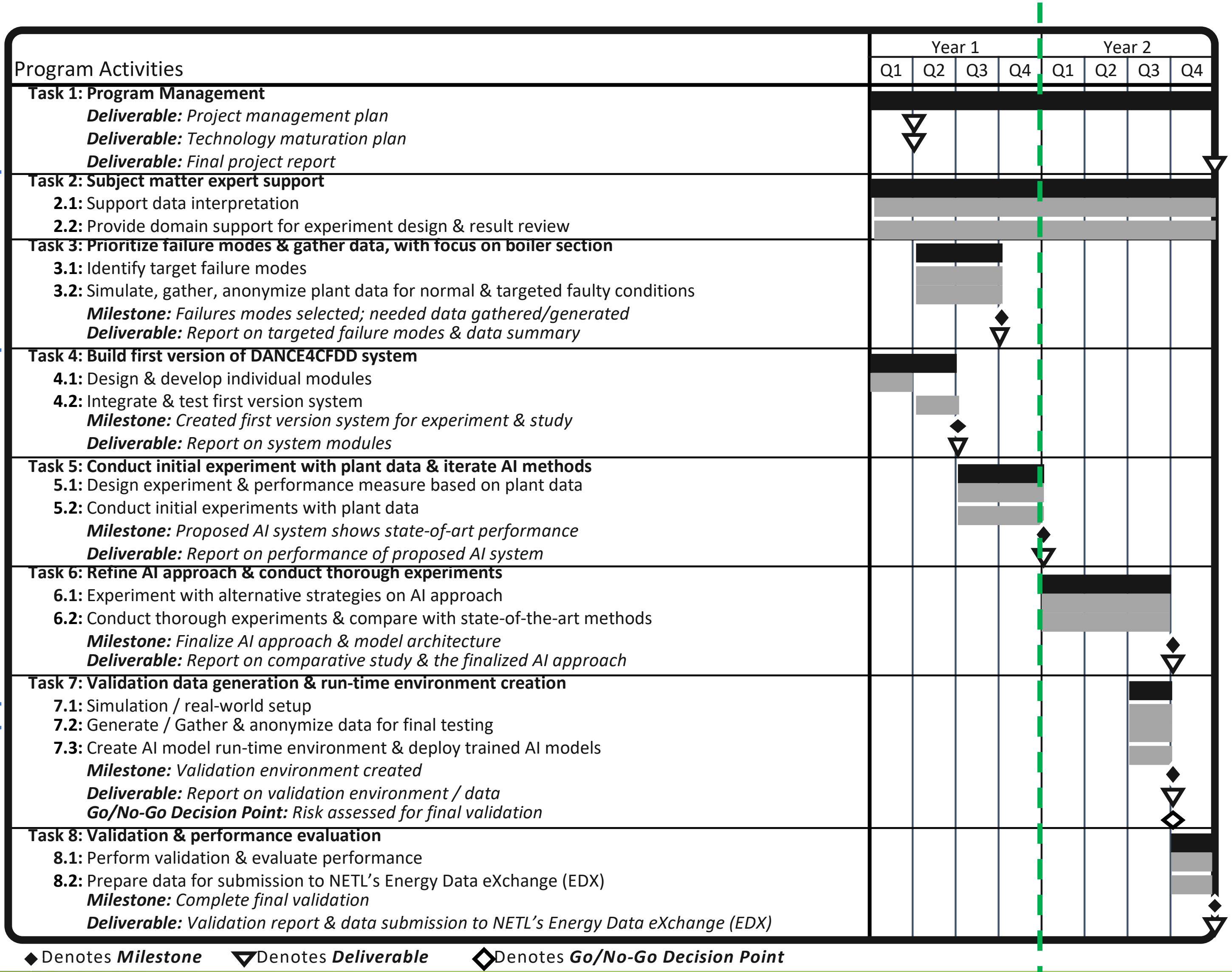
Technology Innovation: a novel end-to-end trainable artificial intelligence (AI)-based multivariate time series learning system for flexible and scalable coal power plant fault detection and root cause analysis.

Anticipated benefits:

- Applicability to a broad range of asset types and plant configurations for improving coal-fired power plant reliability
- High scalability—reduce development time by eliminating the need for manual and time-consuming domain expert feature engineering



Schedule and progress



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Status

Ongoing

✓ Completed with some delay

✓ Completed as planned

✓ Benchmarking on public datasets
Initial experiments on plant data

Current state of DANCE4CFDD system

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```
▼ time_series_ai  ~/repo/time_series_ai
  ▶ examples
  ▼ projects
    ▶ plant
    ▶ swat
    ▶ tep
  ▼ ts_ai
    ▼ models
        __init__.py
        base_model.py
        base_tcn.py
        base_transformer.py
        custom_lstms.py
        metric_model.py
        rnn_models.py
        tcn_models.py
        transformer_models.py
      __init__.py
      dataset.py
      evaluation.py
      functions.py
      losses.py
      modules.py
      preprocess.py
      utils.py
```

Carry research studies:
- Plant data study
- Secure Water Treatment (SWaT) dataset
- Tennessee Eastman Process (TEP) benchmark dataset

Core model libraries

Supporting functions:
- Time series data construction for training and testing
- Performance evaluation functions
- Other utility functions

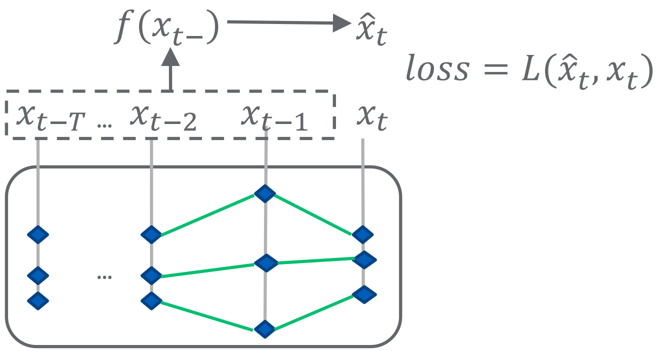
Research focus

Industry needs

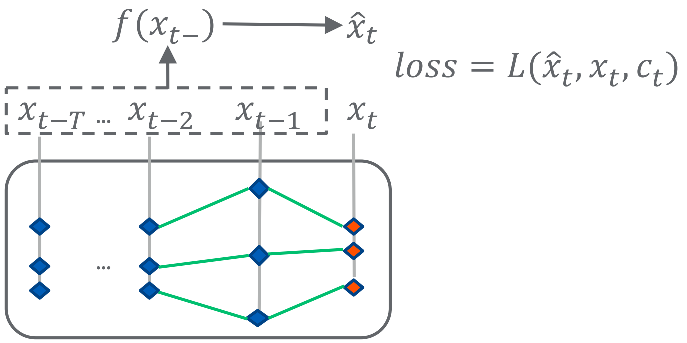
- Majority of data is under normal operation, only small number of faulty events to learn from

Approaches

- Unsupervised learning: only normal operation data is used

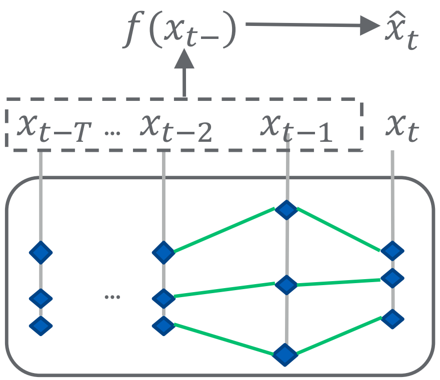


- Supervised learning: both normal operation data and faulty data are available
  - Few shot learning: normal operation data with a small sample of faulty data

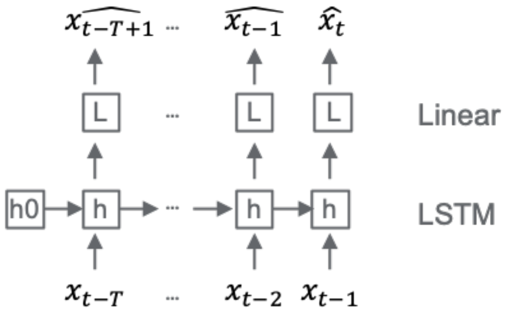


Unsupervised setting

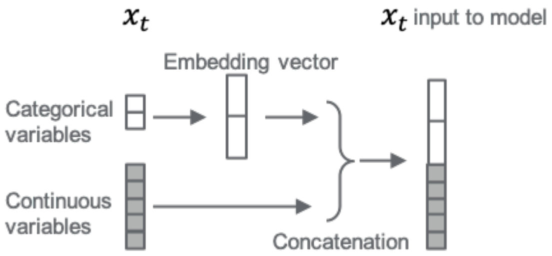
Autoregressive setting: learn spatial and temporal relationship



Network setting: Long Short-Term Memory (LSTM) network as example



Network input data process: vector embedding for discreate variables



Benchmarking with public datasets

Two datasets:

- Secure Water Treatment (SWaT) testbed dataset *
- Tennessee Eastman Process (TEP) dataset ^

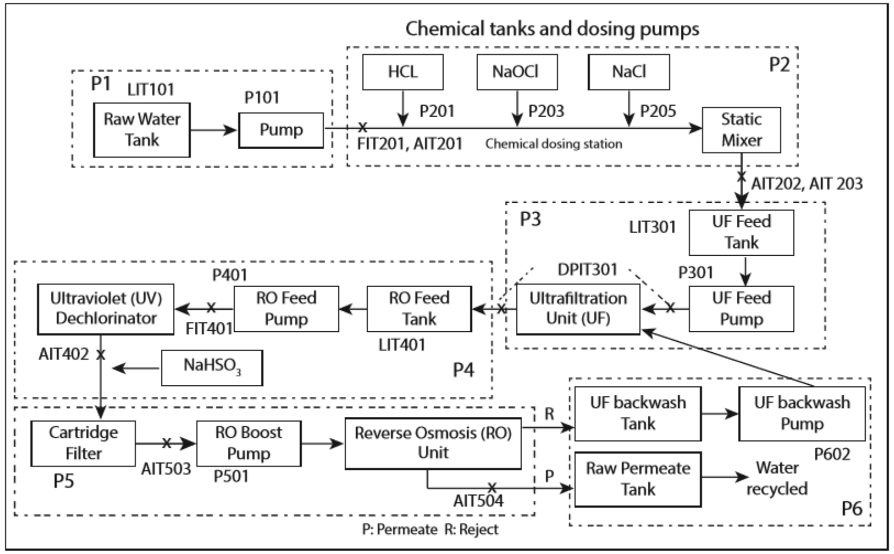
Dataset characteristics – similar to real-world coal plant data:

- Represent a complex plant
- Multivariate time series measurement
- Simulate anomalies during system operation

* https://itrust.sutd.edu.sg/itrust-labs_datasets/dataset_info/
^ https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/6C3JR1

SWaT testbed dataset

7 days of normal operation
4 days of 41 episodes of attack
36 attacks are physical, treated as faults
1/second sampling
24 sensor + 27 actuator tags



Attack #	Start Time	End Time	Attack Point	Start State	Attack	Actual Change
1	28/12/2015 10:29:14	10:44:53	MV-101	MV-101 is closed	Open MV-101	Yes
2	28/12/2015 10:51:08	10:58:30	P-102	P-101 is on where as P-102 is off	Turn on P-102	Yes
3	28/12/2015 11:22:00	11:28:22	LIT-101	Water level between L and H	Increase by 1 mm every second	No
4	28/12/2015 11:47:39	11:54:08	MV-504	MV-504 is closed	Open MV-504	Yes
5	28/12/2015 11:58:20		No Physical Impact Attack			

Reference: Goh, J., Adepu, S., Junejo, K. N., & Mathur, A. (2016). A Dataset to Support Research in the De- sign of Secure Water Treatment Systems. In *CRITIS*.
doi: 10.1007/978-3-319-71368-7-8

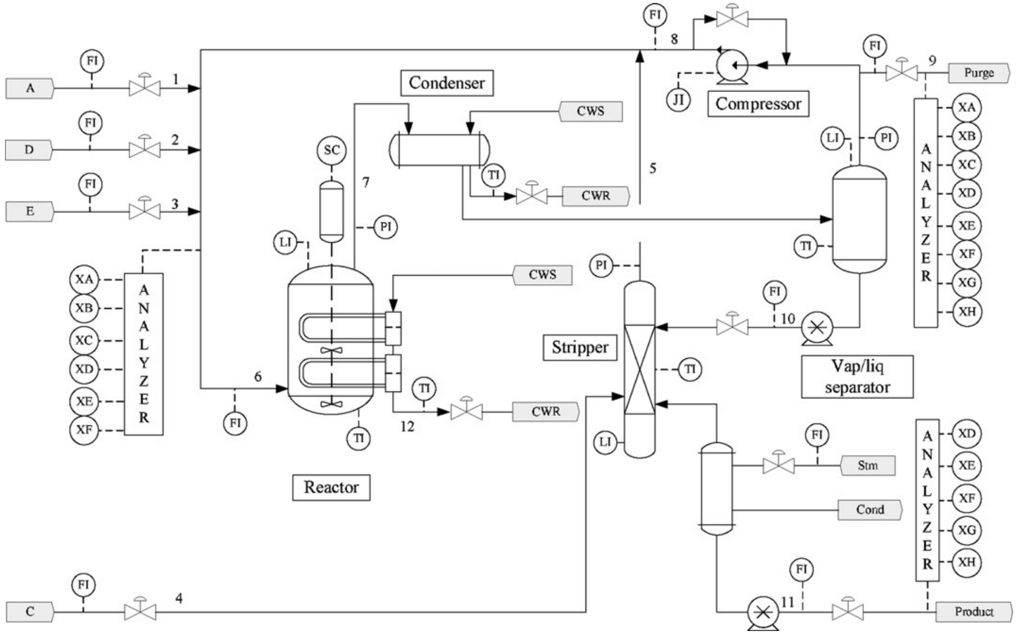
TEP benchmark dataset

Training data:
500 runs of normal operation data
20 faults, each has 500 runs
500 samples per run, 25 hours of operation

Testing data:
500 runs of normal operation, 960 samples / run
500 runs of faulty operation, 960 samples / run, fault is injected at 160th sample

41 sensor + 11 actuator tags

Fault number	Process variable	Type
IDV(1)	A/C feed ratio, B composition constant	Step
IDV(2)	B composition, A/C ration constant	Step
IDV(3)	D feed temperature	Step
IDV(4)	Reactor cooling water inlet temperature	Step
IDV(5)	Condenser cooling water inlet temperature	Step
IDV(6)	A feed loss	Step
IDV(7)	C header pressure loss-reduced availability	Step
IDV(8)	A, B, and C feed composition	Random variation
IDV(9)	D feed temperature	Random variation
IDV(10)	C feed temperature	Random variation
IDV(11)	Reactor cooling water inlet temperature	Random variation
IDV(12)	Condenser cooling water inlet temperature	Random variation
IDV(13)	Reaction kinetics	Slow drift
IDV(14)	Reactor cooling water valve	Sticking
IDV(15)	Condenser cooling water valve	Sticking
IDV(16)	Unknown	Unknown
IDV(17)	Unknown	Unknown
IDV(18)	Unknown	Unknown
IDV(19)	Unknown	Unknown
IDV(20)	Unknown	Unknown



Reference: S. Yin, S. Ding, A. Haghani, H. Hao, P. Zhang, A comparison study of basic data-driven fault diagnosis and process monitoring methods on the benchmark Tennessee Eastman process , Journal of Process Control 22 (2012)

Performance evaluation

Sample based:
FP = # alarms / total # of normal operation samples
TP = # alarms / total # of faulty operation samples

For public dataset study, we adopted sample-based evaluation for easy comparison with literature

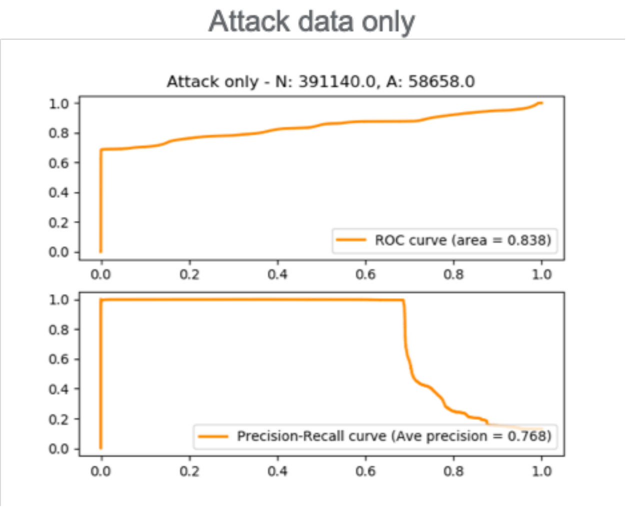
Operating segment/run based (e.g. a flight or a mission):
FP = # aggregated alarms / total # of normal operation segments
TP = # aggregated alarms / total # of faulty segments

Plant operation relevant:
FP = # alarms / total # of normal operation time
TP = # detected faulty events / total # of faulty events

SWaT data results

Measurement: ROC and Precision-Recall

Use last 4 days of attack data N A N A N



Overall performance comparison

Regular setting: autoregressive target are all continuous variables

$$L_{mse} = \frac{1}{C}\sum_{c\in C}\frac{1}{n}(\hat{x}_t^c - x_t^c)^2$$

Joint setting: autoregressive target includes discrete variables

$$L_{ce} = -\sum_{d\in D}\sum_{i\in|d|} x_t^{d_i}\log \hat{x^{d_i}}_t$$

$$L = L_{mse} + w_{ce}L_{ce}$$

Methods	AUC	Ave_Precision
LSTM	0.838	0.768
CNN	0.869	0.788
NN	0.874	0.788
LSTM joint	**0.881**	**0.815**
DeepSVDD	0.834	0.748

Compare with a recent study *

Point solution from the P-R curve for easy comparison with literature

Point solution represent the highest F score

	Methods	Precision	Recall	F score
Reference	DNN	0.98295	0.67847	0.80281
	One-class SVM	0.92500	0.69901	0.79628
Ours	LSTM	0.99402	0.68635	0.81202
	CNN	0.96897	0.67654	0.79677
	NN	0.96670	0.72458	**0.82831**
	LSTM joint	0.93730	0.71563	0.81161
	DeepSVDD	0.99060	0.63449	0.77353

Validate developed system, demonstrate competitive performance

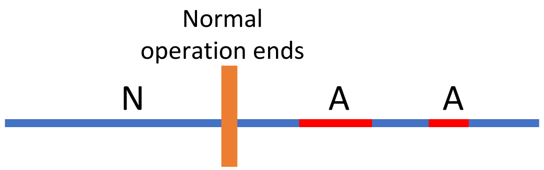
* Inoue, J., Yamagata, Y., Chen, Y., Poskitt, C. M., & Sun, J. (2017, November). Anomaly Detection for a Water Treatment System Using Unsupervised Machine Learning. In *2017 IEEE International Conference on Data Mining Workshops (ICDMW)*

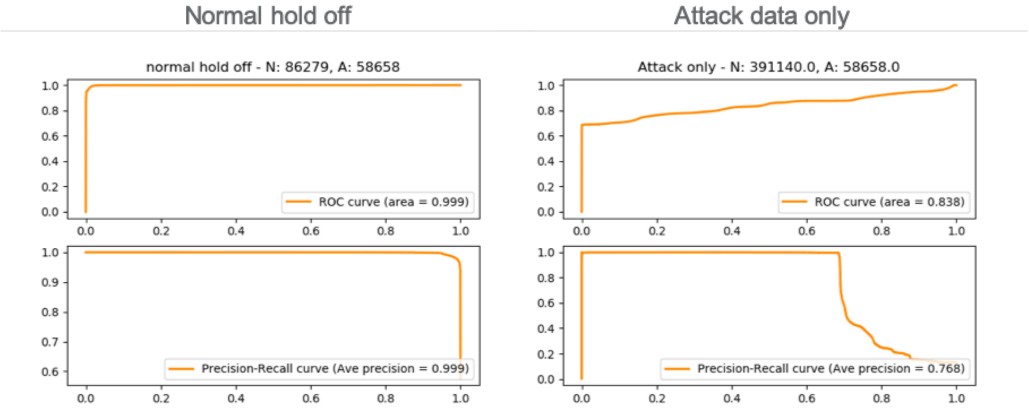
Limitations with SWaT dataset

Alternative data split for measurement: normal hold off

Use last 1 days of normal operation as 'normal'

Data during attack window as 'abnormal'

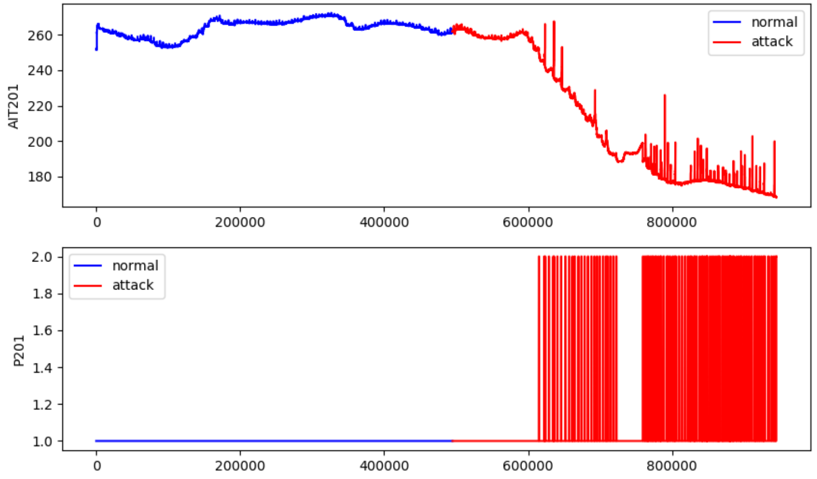




System operation drifting after episodes of attack

Measurement AIT201: 'abnormal' operating range

Actuation P201: new operating regime



Reference: Xue, F., Yan, W., Huang, H., Wang, T., Feng, B., Deep anomaly detection for industrial systems: a case study, Annual Prognostics and Health Management Conference, 2020 (to appear)

TEP benchmarking (sample based)

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Our models:

Detection and Diagnosis of **A**nomaly with **V**ariable **A**ssociation **C**hange (***DAVAC***)

Alternative models (adapted from recent neural network architectures):

- TCN - Temporal Convolution Network
- Attention-based LSTM
- Transformer architecture
- Basic architectures such as LSTM, CNN, NN

	Our experiments - unsupervised							**Reference results from literature* - unsupervised**				
Fault	LSTM	TCN	Attention LSTM	Transformer	CNN	NN	DAVAC	BRNN	r-PCA (a=12)	f-PCA (a=52)	r-DPCA (a=25)	f-DPCA (a=104)
1	99.95%	***99.96%***	***99.96%***	99.95%	99.95%	99.94%	**100.00%**	99.75%	99.75%	100.00%	99.75%	99.25%
2	99.10%	***99.61%***	99.16%	99.00%	99.31%	99.18%	**100.00%**	99.00%	98.75%	99.12%	98.62%	99.12%
3	5.57%	5.90%	6.07%	5.43%	6.31%	8.09%	5.55%	5.00%	7.00%	19.75%	6.12%	**22.25%**
4	**100.00%**	21.26%	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**	98.88%	**100.00%**	**100.00%**	**100.00%**
5	**100.00%**	99.78%	**100.00%**	**100.00%**	**100.00%**	**100.00%**	99.94%	**100.00%**	32.62%	**100.00%**	34.50%	**100.00%**
6	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**
7	**100.00%**	79.61%	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**
8	98.33%	***98.58%***	98.34%	98.31%	98.45%	98.39%	**100.00%**	98.12%	98.00%	98.25%	97.75%	98.38%
9	5.85%	11.16%	6.10%	5.71%	6.46%	7.36%	6.09%	5.00%	7.88%	15.25%	8.87%	**21.37%**
10	89.94%	58.09%	93.09%	87.98%	***97.14%***	***97.39%***	95.85%	87.38%	54.13%	93.50%	55.75%	94.63%
11	86.42%	53.32%	86.42%	83.14%	***99.11%***	93.92%	**100.00%**	74.75%	74.25%	87.25%	80.75%	92.75%
12	99.14%	***99.58%***	99.39%	99.20%	99.22%	99.28%	**100.00%**	99.75%	99.00%	**100.00%**	99.25%	**100.00%**
13	95.85%	***99.38%***	96.01%	95.84%	96.15%	96.03%	**99.69%**	95.75%	95.50%	95.75%	95.50%	96.25%
14	99.98%	92.01%	99.98%	99.98%	***99.98%***	99.98%	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**
15	5.60%	8.14%	8.89%	5.74%	5.88%	6.28%	9.84%	7.12%	10.62%	26.87%	11.13%	**36.63%**
16	90.78%	74.80%	92.64%	88.39%	97.19%	***97.74%***	**99.45%**	90.38%	46.50%	95.50%	48.50%	97.00%
17	96.49%	96.64%	96.51%	96.47%	96.50%	96.40%	**99.89%**	96.13%	93.13%	97.75%	94.78%	***98.12%***
18	94.56%	***98.12%***	94.69%	94.51%	94.55%	94.54%	**98.96%**	90.63%	90.38%	91.50%	90.50%	92.87%
19	87.14%	16.54%	86.34%	85.10%	90.43%	89.53%	**100.00%**	88.25%	25.12%	96.00%	34.00%	***99.50%***
20	95.92%	80.71%	95.92%	95.83%	***95.96%***	95.93%	**99.57%**	78.63%	58.25%	92.13%	61.75%	92.37%
False Positive	5.00%	5.00%	5.00%	5.00%	5.00%	5.00%	5.00%	4.75%	5.00%	4.88%	5.00%	5.00%

Our model DAVAC outperforms other unsupervised models in most of the fault types

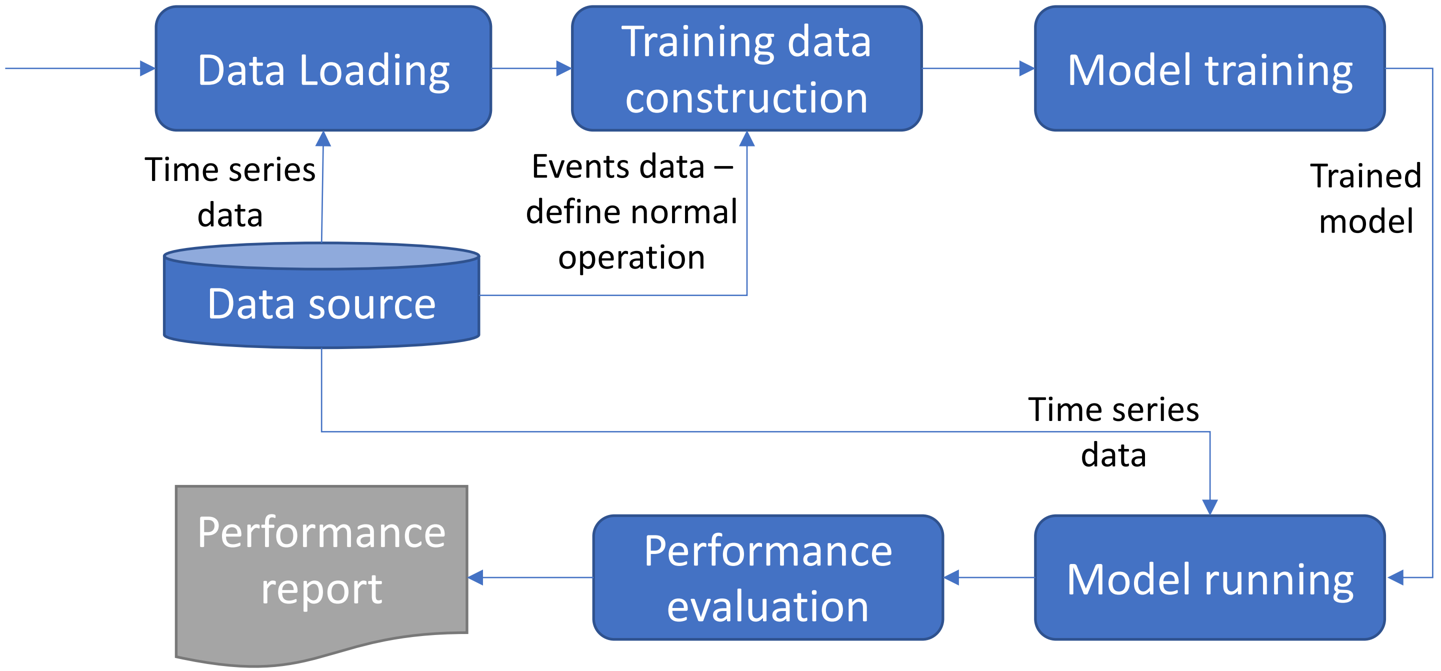
* Sun W. et al. Fault Detection and Identification using Bayesian Recurrent Neural Networks, https://arxiv.org/abs/1911.04386 (Preprint, 2019)

Process steps for plant data

Data tags and configuration

InInput	InTarget	InControl	SourceName
1		1	5-F-FDR-DMD
			5-F-FDR-DSCH-PRS
			5-F-FDR-RATE
1	1		5-F-FDR-SPD
			5-F-MILL-AMP
			5-F-MILL-DP
1	1		5-F-MILL-INT-T
1		1	5-F-MILL-PA-1-F
			5-F-MILL-PA-F
1		1	5-F-MILL-PA-T
1	1		5-F-MILL-T
1		1	5F-FDR-SPD-BIAS

Input: all time series measurements as input to model
Target: tags to predict
Control: command and actuation measurements



Barry unit 5 plant data experiments

Plant data:
- 16 months, 3994 tags, 1/min time series data
- NERC GADS report data

Based on plant events, developed initial priority list

NERC Cause Code	Description
9270	WET COAL (OMC) – FEEDER STOPPAGE
270	PRIMARY AIR DUCTS AND DAMPERS
3232	CONDENSER TUBE CLEANING SYSTEMS INCLUDING DEBRIS FILTER
3211	CIRCULATING WATER PUMP MOTORS

Barry unit 5 plant data experiments

Experiment setup: 3 month for training; 13 months for evaluation

Use case | **Data tags configuration** | **Performance evaluation**

WET COAL (OMC) – FEEDER STOPPAGE:

InInput	InTarget	InControl	SourceName
1		1	5-F-FDR-DMD
			5-F-FDR-DSCH-PRS
			5-F-FDR-RATE
1	1		5-F-FDR-SPD
			5-F-MILL-AMP
			5-F-MILL-DP
1	1		5-F-MILL-INT-T
1		1	5-F-MILL-PA-1-F
			5-F-MILL-PA-F
1		1	5-F-MILL-PA-T
1	1		5-F-MILL-T
1		1	5F-FDR-SPD-BIAS

System	Total Events	Detected Events (TP)	False Alarms / 13 months (LSTM)	False Alarms / 13 months (CNN)
Mill A	4	4	48	50
Mill B	2	2	29	34
Mill C	9	9	39	46
Mill D	6	6	22	27
Mill E	1	1	10	8
Mill F	6	6	14	22

CONDENSER TUBE CLEANING SYSTEMS INCLUDING DEBRIS FILTER:

CIRCULATING WATER PUMP MOTORS:

InInput	InTarget	InControl	SourceName
1	1		5-DEBRIS-FLT-A-DP
1	1		5-A-CRC-WTR-PMP-MTR-AMP
1	1		5-A-CWP-MTR-LWG-BRG-T
1	1		5-A-CWP-MTR-UPG-BRG-T
1	1		5-A-CWP-MT-THR-BRG-T
1	1		5-A-CWP-MTR-STAT-1-T
1	1		5-A-CWP-MTR-STAT-2-T
1	1		5-A-CWP-MTR-STAT-3-T

System	Total Events	Detected Events (TP)	False Alarms / 13 months (LSTM)	False Alarms / 13 months (CNN)
CWP A	4	4	5	11
CWP B	4	4	3	4

Demonstrated AI learning system on initial plant use cases

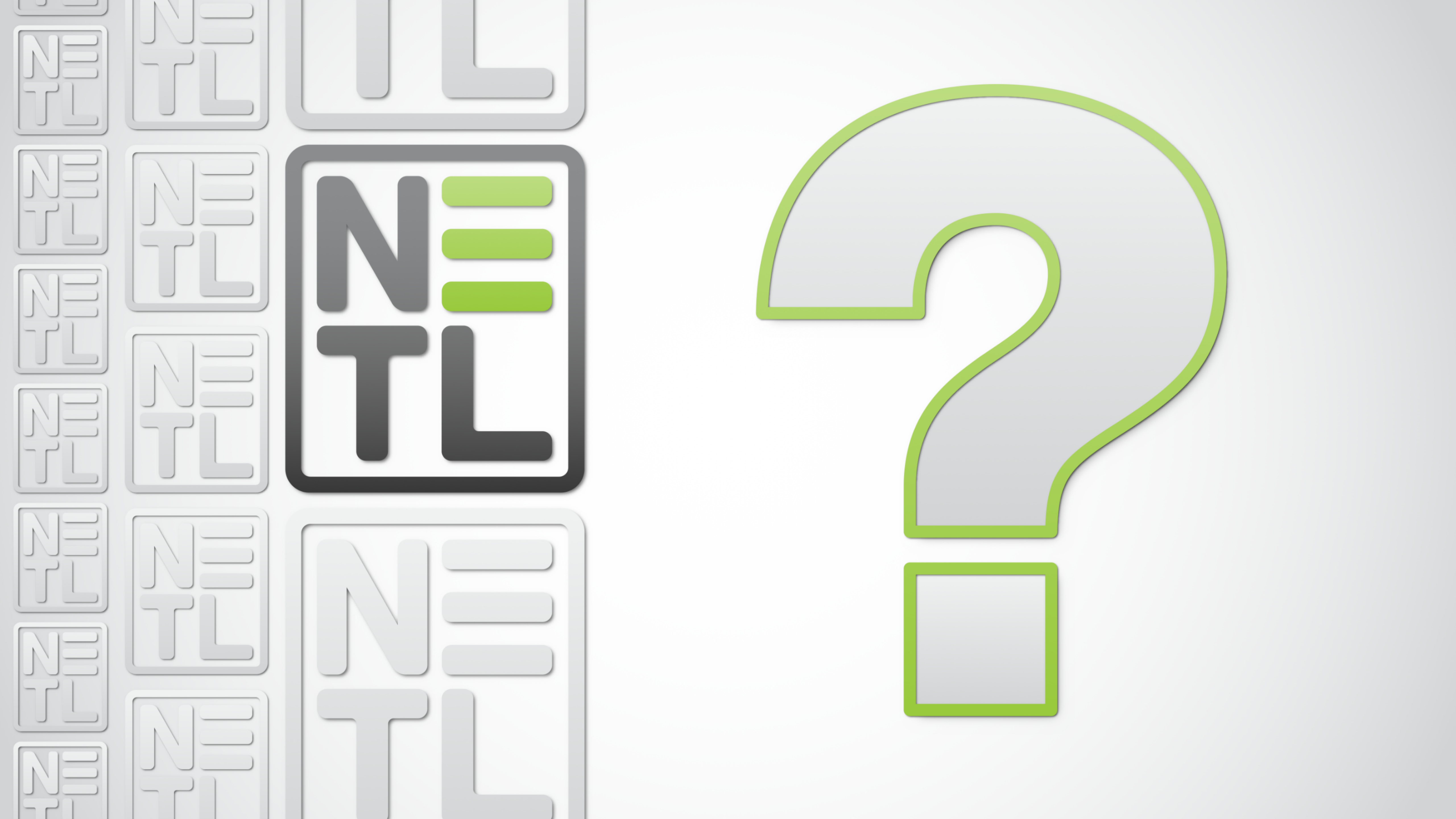
Concluding remarks

Demonstrated an AI learning system on time series data for fault detection:

- Applicability to broad range of problems
- Easy to adapt – directly model time series data
- High performance

Next steps

- Continue experimentation of model architectures and training methods
- Develop model outcome interpretation – diagnosis
- Conduct study on few shot learning: how to effectively leverage a small sample of faulty data
- Study a range of plant use cases – assess real-world utilities and gaps


NETL

DAVAC network architecture

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Detection and Diagnosis of **A**nomaly with **V**ariable **A**ssociation **C**hange (***DAVAC***)