CORTEX

Core monitoring techniques and experimental validation and demonstration

Deep learning technique for core abnormality detection and localization

Workshop on the demonstration of the methods for reactor noise analysis against plant data (Final event)

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Miao Yu

University of Lincoln, UK

myu@lincoln.ac.uk

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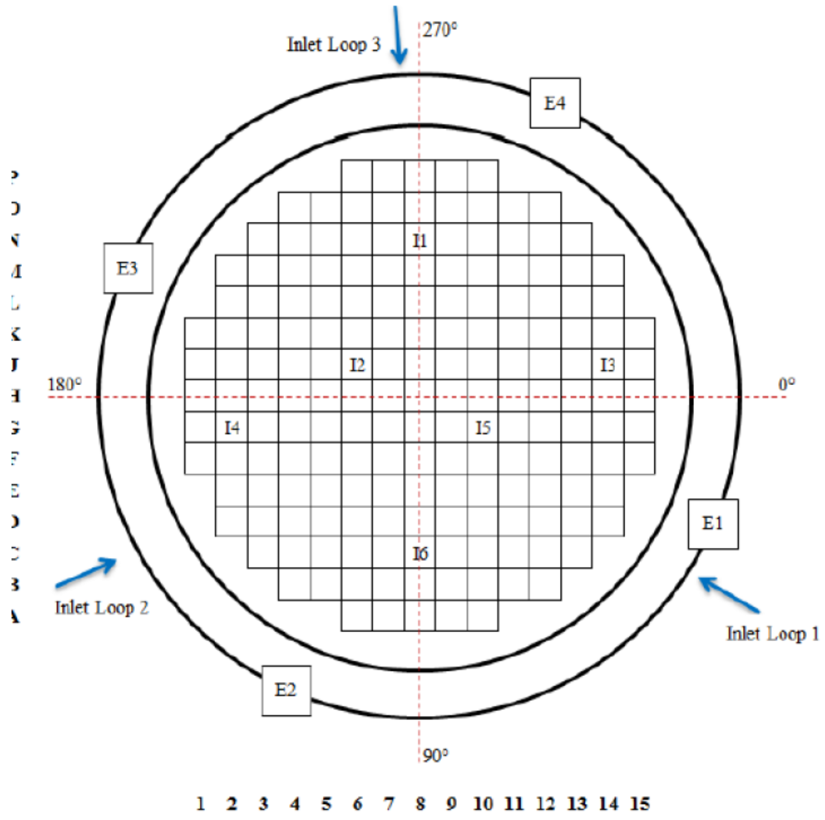
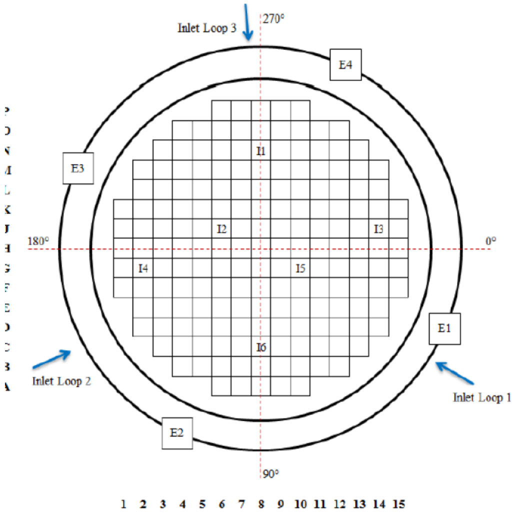
In this research,

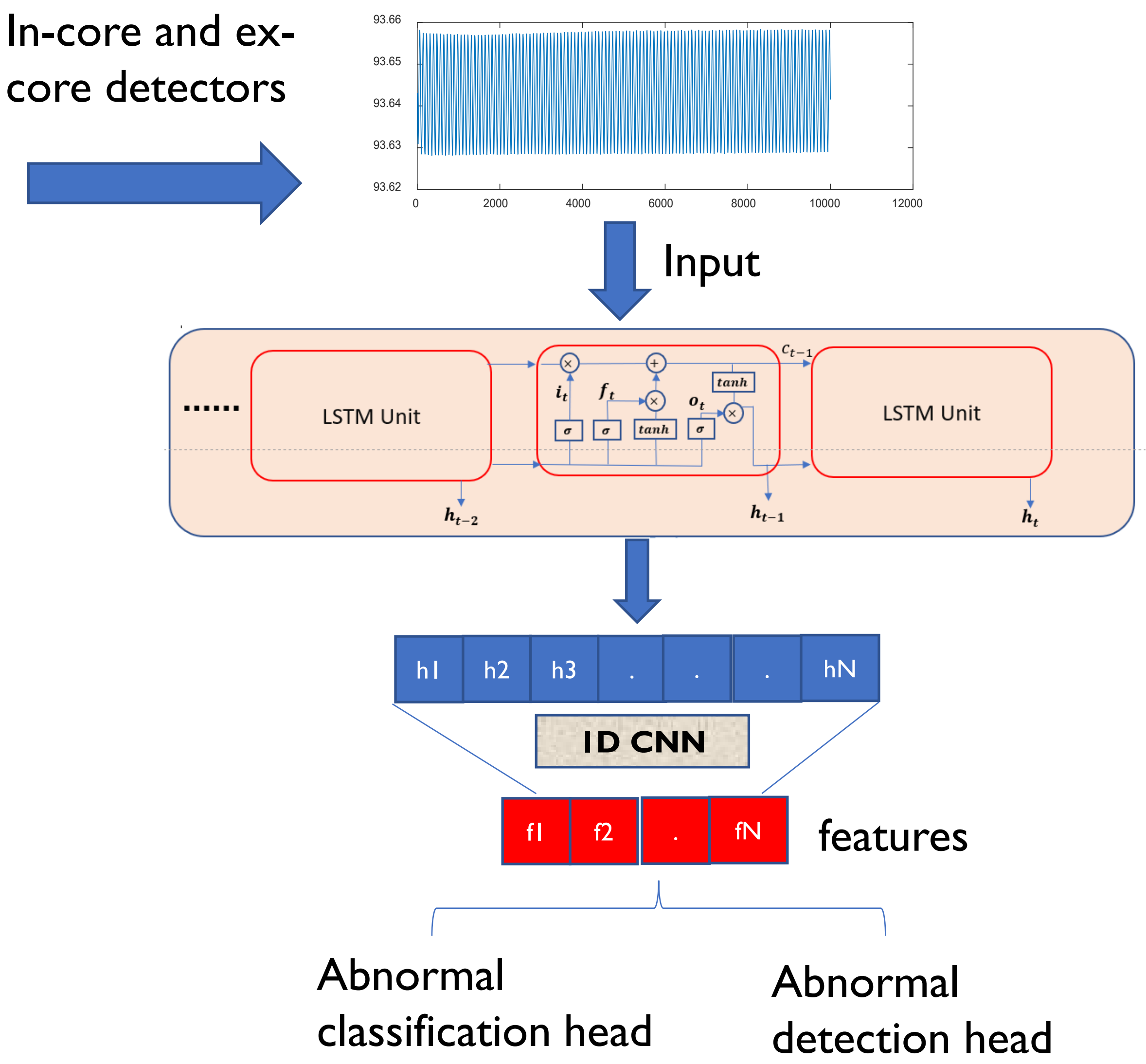
- We target to classify/locate different types of abnormalities which may occur in core:

- **Vibration of each fuel assembly individually, in cantilevered mode at MOC 39**
- **Vibration of each fuel assembly individually, in C-shaped mode at MOC 39**
- **Vibration of each fuel assembly individually, in S-shaped mode at MOC 39**
- **Random fluctuations of inlet coolant temperature**
- **Random fluctuations of inlet coolant flow**
- **Combination of simplistic vibration of 5x5 central cluster of FAs** in the **x-direction**
- **Combination of cantilevered mode vibration of 5x5 central cluster of FAs in the x-direction**
- **Combination of C-shaped mode vibration of 5x5 central cluster of FAs in the x-direction**
- **Combination of S-shaped mode vibration of 5x5 central cluster of FAs** in the **x-direction**

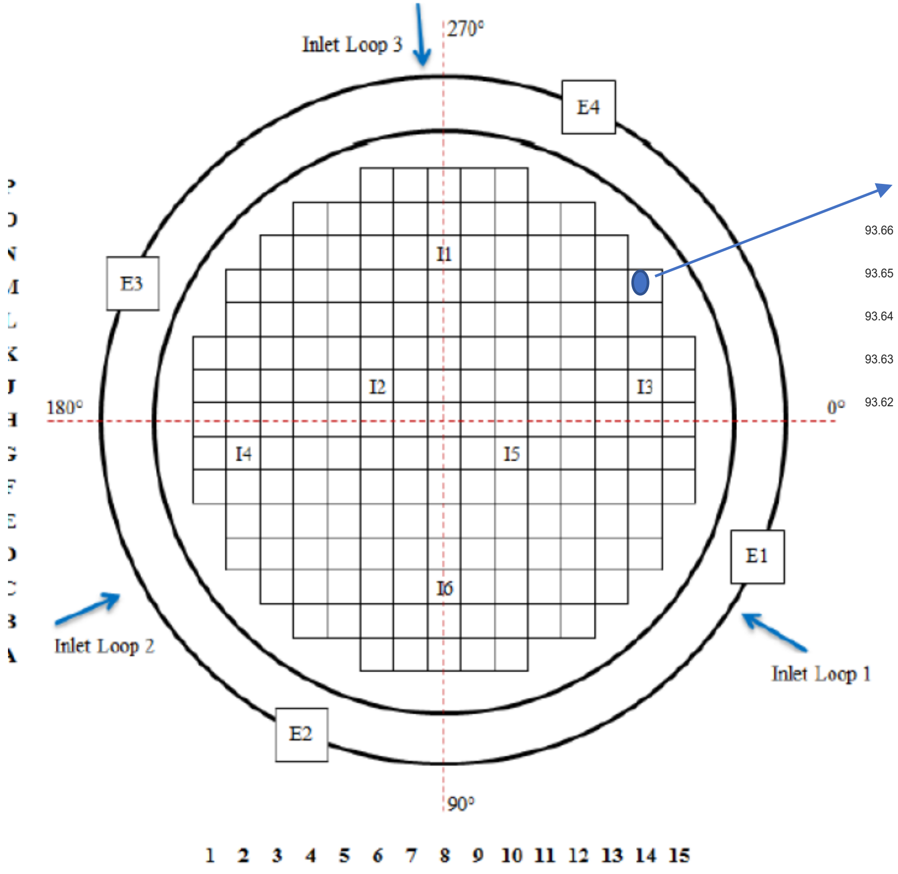


Proposed methodology

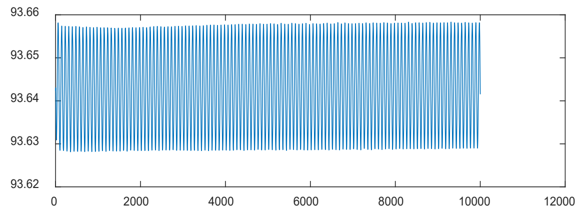




- Combination of recurrent neural network and convolutional neural network is applied
- Based on in-core and ex-core sensor recordings



Sensor recordings

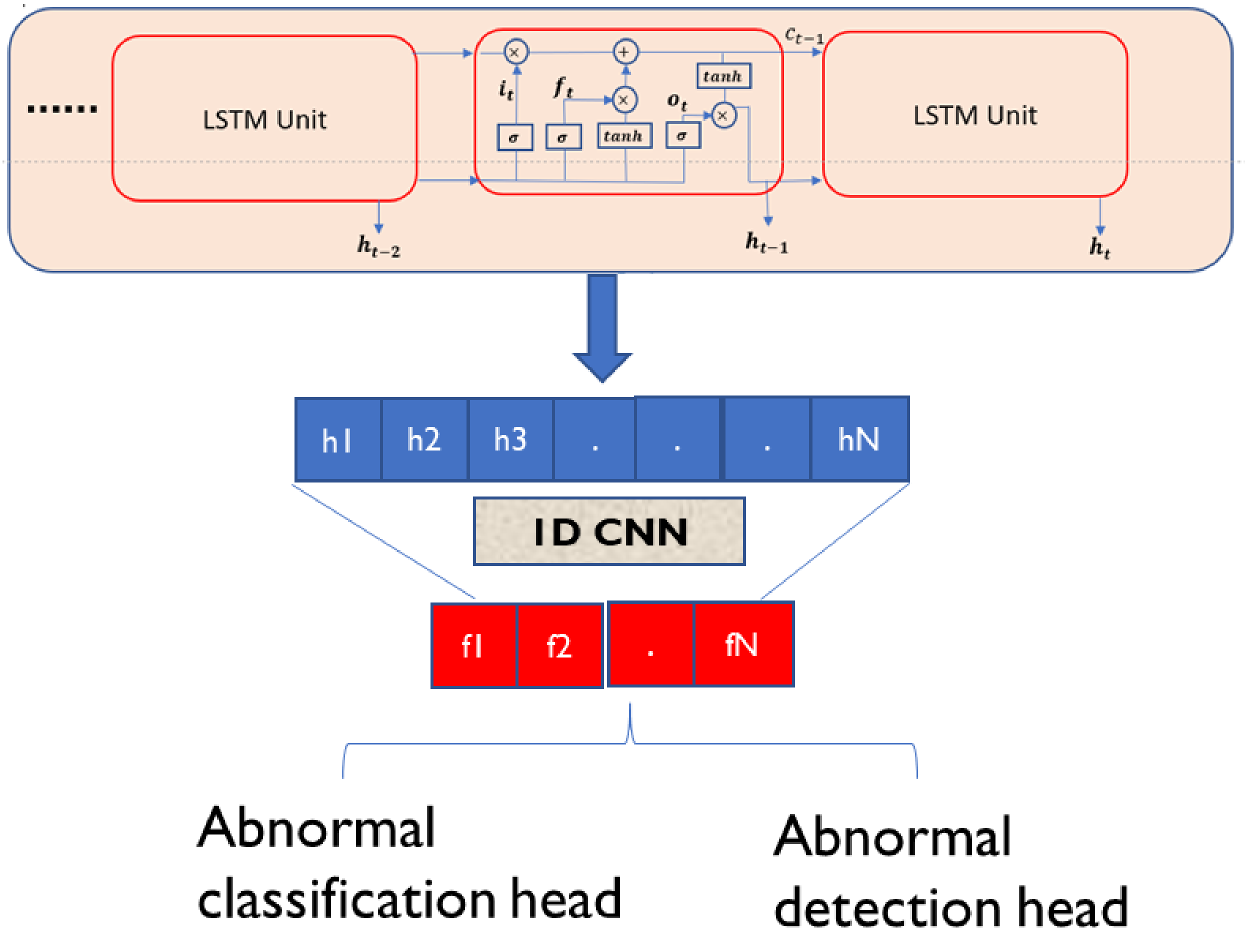


10001x36 double

	1	2	3	4	5	6
1	0.8069	1.0083	1.0400	1.0349	1.0219	0.9191
2	0.8068	1.0082	1.0399	1.0348	1.0217	0.9189
3	0.8066	1.0079	1.0397	1.0346	1.0214	0.9187
4	0.8064	1.0076	1.0395	1.0343	1.0211	0.9185
5	0.8062	1.0074	1.0393	1.0341	1.0209	0.9183
6	0.8061	1.0073	1.0391	1.0340	1.0207	0.9181
7	0.8060	1.0072	1.0390	1.0339	1.0207	0.9181
8	0.8061	1.0073	1.0391	1.0340	1.0208	0.9181
9	0.8062	1.0074	1.0392	1.0341	1.0209	0.9183
10	0.8064	1.0077	1.0395	1.0343	1.0212	0.9185
11	0.8067	1.0081	1.0398	1.0346	1.0216	0.9188
12	0.8070	1.0085	1.0401	1.0350	1.0220	0.9192
13	0.8073	1.0089	1.0404	1.0353	1.0224	0.9195
14	0.8076	1.0092	1.0407	1.0356	1.0227	0.9198
15	0.8077	1.0094	1.0409	1.0358	1.0230	0.9200
16	0.8079	1.0096	1.0411	1.0359	1.0231	0.9201
17	0.8079	1.0096	1.0411	1.0360	1.0231	0.9201
18	0.8078	1.0095	1.0410	1.0359	1.0230	0.9200
19	0.8076	1.0093	1.0408	1.0357	1.0228	0.9199
20	0.8074	1.0089	1.0406	1.0354	1.0225	0.9196
21	0.8071	1.0086	1.0402	1.0351	1.0221	0.9193
22	0.8068	1.0082	1.0399	1.0348	1.0217	0.9189
23	0.8065	1.0078	1.0396	1.0345	1.0213	0.9186

Normalization is applied to normalize the sensor input ranges to be [0,1]

- Normalized sensor recordings are fed into a RNN+CNN multi-task network
- RNN architecture with different units (LSTM, GRU) have been evaluated in our work:
- 1D CNN is applied for further processing RNN output to extract representative features
- Two heads for abnormal localization and classification



Network training

- Stochastic gradient descent algorithm is applied for minimizing the following multi-task objective function:

$$\mathrm{L}(\mathrm{D};\mathbf{W},\lambda_1,\lambda_2) = -\frac{1}{M}\sum_{i=1}^{M}\left[\underbrace{\frac{\lambda_1}{P}\sum_{j=1}^{P}\left[\mathbf{y}_j\log(\hat{\mathbf{y}}_j)+(1-\mathbf{y}_j)\log(1-\hat{\mathbf{y}}_j)\right]}_{\text{Classification}}\underbrace{-\frac{\lambda_2}{C}\sum_{c=1}^{C}\left\|\mathbf{y}_c-\hat{\mathbf{y}}_c\right\|^2}_{\text{Regression}}\right]_i$$

Evaluation Studies

- The proposed methodology is evaluated based on two datasets obtained from the Swiss pre-KONVOI pressurized water reactor (PWR)
  - 3-loop reactor
  - Simulated data only
  - Provided by the Paul Sherrer Institute (PSI)
    - CASMO-5/SIMULATE-3 code system, coupled with SIMULATE-3K transient nodal code

Dataset descriptions:

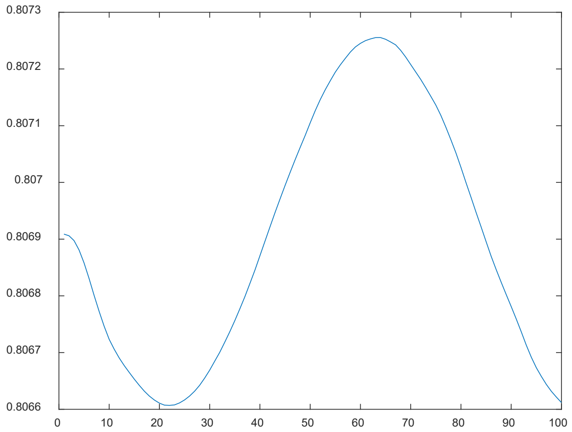
PSI 8: Containing 6 perturbations types, with 366 simulated perturbation scenarios

- Vibration of one FA in cantilevered mode
- Vibration of one FA in C-shape mode
- Random fluctuation in inlet temp
- Random fluctuation in inlet flow
- Simplistic lateral vibration of central 5x5 FA cluster + random TH fluctuations
- Cantilevered mode vibration of central 5x5 FA cluster + random TH fluctuations

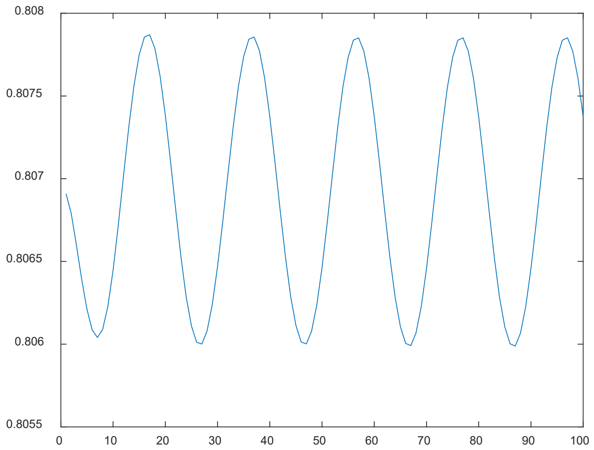
PSI 9: Containing 9 perturbations types, with 543 simulated perturbation scenarios

- Vibration of one FA in cantilevered mode
- Vibration of one FA in C-shape mode
- C-shape mode vibration of central 5x5 FA cluster + random TH fluctuations
- S-shape mode vibration of central 5x5 FA cluster + random TH fluctuations
- Random fluctuation in inlet temp
- Cantilevered mode vibration of central 5x5 FA cluster + random TH fluctuations
- Simplistic lateral vibration of central 5x5 FA cluster + random TH fluctuations
- Random fluctuation in inlet temp
- Vibration of one FA in S-shape mode

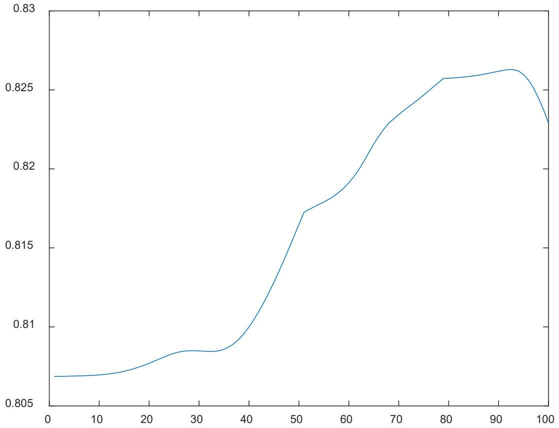
Some simulated sensor recording examples:



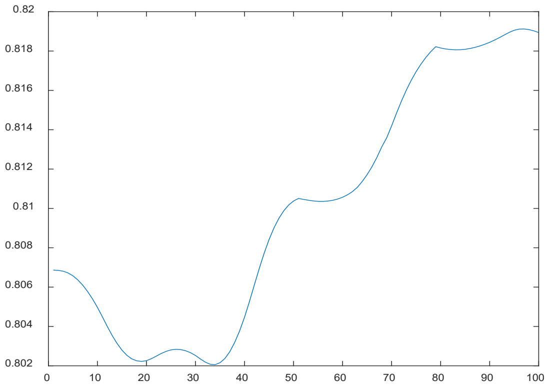
- Vibration of one FA in cantilevered mode



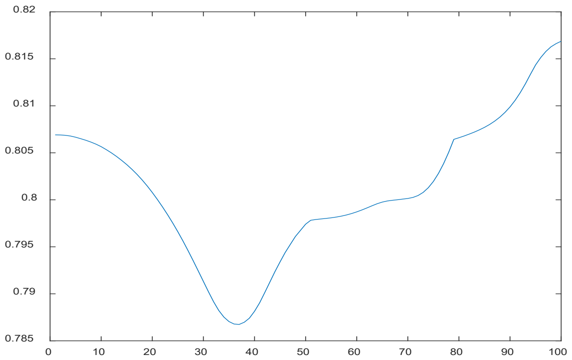
Vibration of one FA in S-shape mode



Random fluctuation in inlet temp



Random fluctuation in inlet flow



Simplistic lateral vibration of central 5x5 FA cluster + random TH fluctuations

- ***Every simulation scenario has a duration of 100s and a time step of 0.01s and includes the in/ex-core neutron responses of 36 in-core and 8 ex-core neutron detectors (so the dimension of each simulation scenario data--10001*44)***

- ***Sliding window method is applied for data augmentation for both PSI 8 and 9 (step:100, overlap rate:25%)***

Augmented PSI 8 data is divided into:
20982 training samples,
21326 validation data samples,
21326 test samples

Augmented PSI 9 data is divided into:
31524 training samples,
32043 validation data samples,
32043 test samples

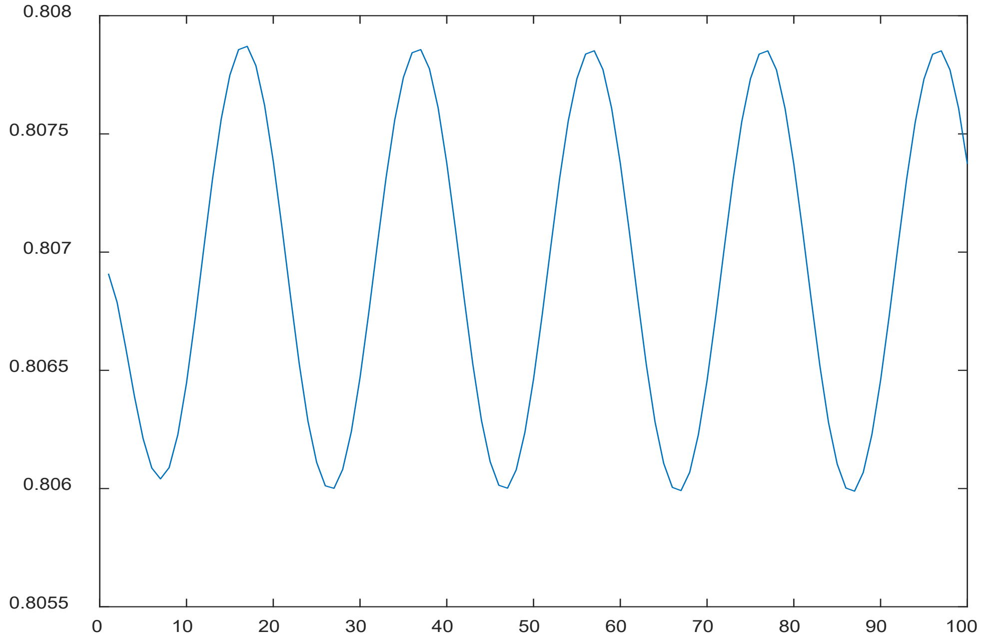
Comparison study—network model comparisons for abnormal classification&localization

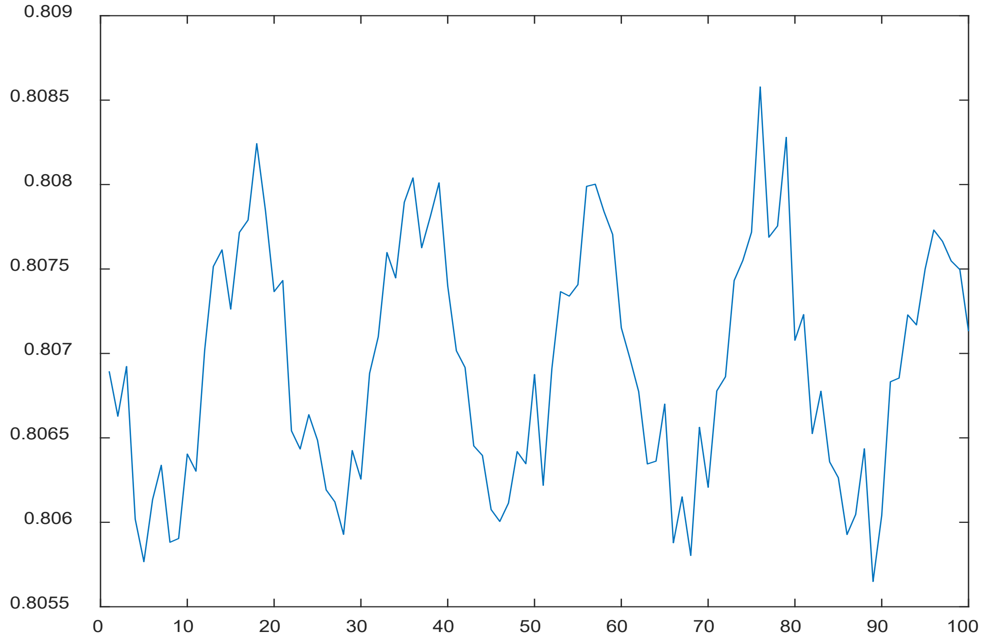
PSI 8	**LSTM**	**GRU**	**Multi-layer LSTM**	**Multi-layer GRU**	**CNN**	**CNN+RNN(LSTM unit)**	**CNN+RNN(GRU unit)**
Mean accuracy	93.72%	98.45%	98.08%	98.64%	**99.90%**	**99.90%**	**99.90%**
Mean RMSE	2.39	1.76	1.74	1.58	0.92	**0.39**	0.47

PSI 9	**LSTM**	**GRU**	**Multi-layer LSTM**	**Multi-layer GRU**	**CNN**	**CNN+RNN(LSTM unit)**	**CNN+RNN(GRU unit)**
Mean Accuracy	85.68%±17.01%	98.09%±0.27%	94.70%±10.24%	98.41%±0.09%	99.38%±0.12%	**99.59%**±0.12%	99.46%±0.14%
Mean RMSE	1.92±0.37	1.49±0.23	1.21±0.21	1.05±0.16	0.86±0.10	0.45±0.04	**0.44**±0.03

We have simulated to add some noises on the detector signals, to model imperfect sensor measurement

```
noise_signal = original_signal+simulated_white_noises
```





Net work performance under noisy scenarios

PSI 8	**LSTM**	**GRU**	**Multi-layer LSTM**	**Multi-layer GRU**	**CNN**	**CNN+RNN(LSTM unit)**	**CNN+RNN(GRU unit)**
Mean accuracy	86.04%±0.31%	85.60%±0.48%	76.69%±22.22%	86.53%±0.20%	84.56%±0.55%	**88.59**%±0.37%	88.30%±0.25%
Mean RMSE	3.51±0.0631	3.66±0.0812	4.06±1.8755	3.51±0.0751	4.09±0.0523	3.24±0.0563	**3.22**±0.0429

PSI 9	**LSTM**	**GRU**	**Multi-layer LSTM**	**Multi-layer GRU**	**CNN**	**CNN+RNN(LSTM unit)**	**CNN+RNN(GRU unit)**
Mean Accuracy	89.38%±1.61%	89.08%±0.64%	88.27%±7.31%	89.64%±1.36%	90.75%±0.27%	**93.12**%±0.17%	92.96%±0.22%
Mean RMSE	3.78±0.11	3.92±0.10	3.56±0.17	3.72±0.06	4.23±0.08	**3.02**±0.04	3.24±0.06

Multi-task network trained with different loss functions

Different loss functions have been applied to train the network:

1. BCElogitLoss

$$BCE = -\frac{1}{N}\sum_{i=1}^{N} y_i \log(\widehat{y_i}) + (1 - y_i)\log(1 - \widehat{y_i})$$

2. BCElogitLoss with class weight (class weight is set in reverse proportion to the data samples number in that class)

$$BCE = -\frac{1}{N}\sum_{i=1}^{N} c_i(y_i \log(\widehat{y_i}) + (1 - y_i)\log(1 - \widehat{y_i}))$$

Classification performance under different loss functions

	C1	C2	C3	C4	C5	C6	C7	C8	C9	Overall
BCElogitLoss	99.88%±0.04%	**99.97%**±0.01%	**99.99%**±0%	**55.61%**±9.34%	**99.71%**±0.57%	16.90%±16.89%	80.04%±27.76%	38.86%±19.10%	53.32%±9.18%	99.38%±0.12%
Weighted BCElogitLoss	**99.92%**±0.02%	99.96%±0.01%	**99.99%**±0%	54.03%±7.90%	99.58%±0.65%	**92.82%**±4.34%	**95.05%**±2.21%	**95.62%**±1.48%	**58.80%**±7.38%	**99.73%**±0.02%

- Weighted loss outperforms the non-weighted one for classifying 5 types of perturbations, slightly underperforms for 3 types
- The overall classification accuracy (both mean and standard deviation) is improved by adopting the weighted loss
- Drastically improve the classification accuracy for classes with small amount of data samples (such as C6 and C8)

Thank you