Study on Innovative Reactor Monitoring and Protection Systems Based on Artificial Neural Network

인공신경망 (ANN) 기반 혁신적 원자로 감시 및 보호 시스템 연구



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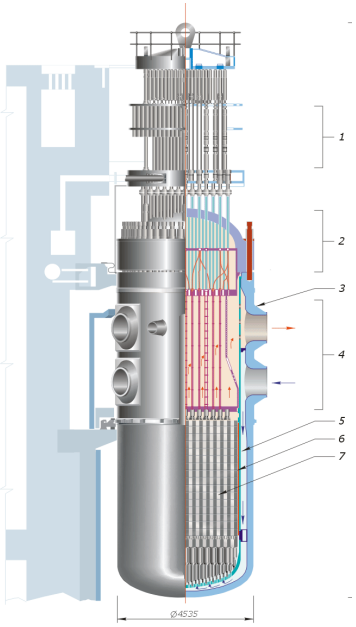
What are COLSS and CPCS?

COLSS (Core Operating Limit Supervisory System) & CPCS (Core Protection Calculator System)

- Digital computer system for core monitoring and protection of 'System 80' plants, **still used in APR-1400**
- Developed by Combustion Engineering Inc., **patented by WEC.**







Core monitoring system (COLSS)

Aids the plant operator in monitoring selected Limiting Conditions for Operation (LCOs).
Does not provide any direct protection functions.

Core protection system (CPCS)

In the case of **design basis events, automatically initiate the trip** sequence to protect the reactor.
More conservative in DNBR/LPD calculations.[1)]

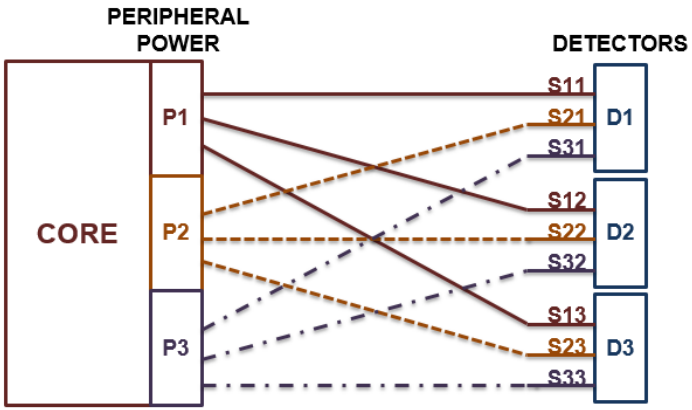
What are the limitations of COLSS and CPCS?

Limitations of COLSS (Core Operating Limit Supervisory System)

- It relies on rhodium-based in-core self-powered-neutron-detectors (SPNDs).
- *Rhodium-based SPNDs response may be delayed up to 5 mins[2] → **unsuitable for protection uses.**
  - * Cobalt-based prompt SPNDs suffer γ noise, lifetime is also limited by the insulation integrity.[3]
- SPND's are costly and require regular maintenance/replacements.

Limitations of CPCS (Core Protection Calculator System)

- CPCS doesn't use in-core instrumentations, **lacks radial information (pre-calculated radial factors).**
- CPCS only calculates the **1-dimensional** pseudo-hot-rod axial power distribution.
- In calculating the axial power, it simply uses **a 3x3 matrix** and cubic spline basis functions.



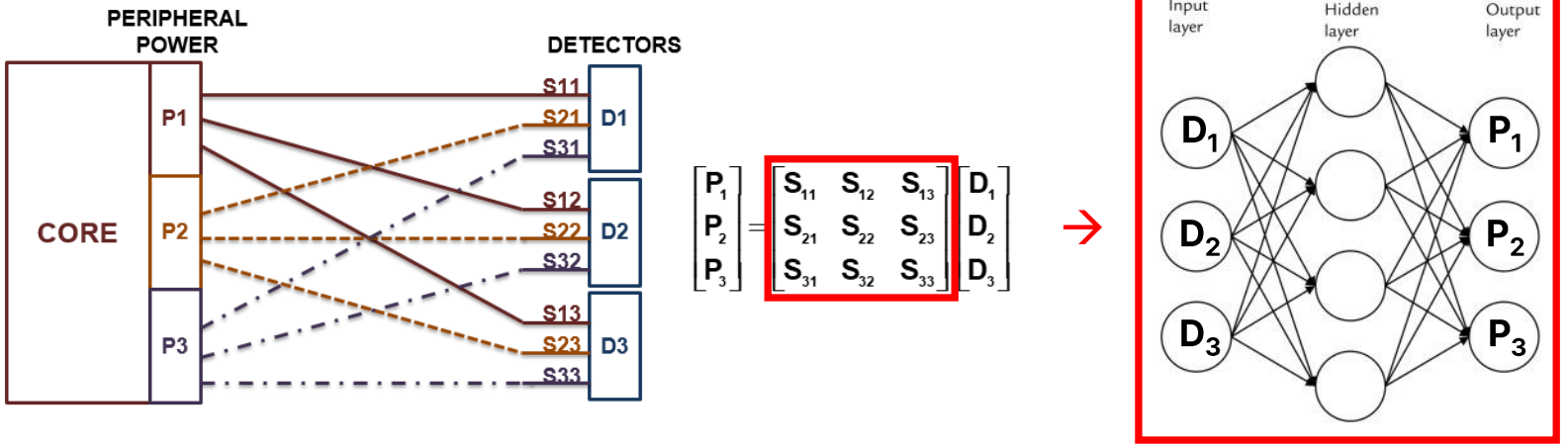
$$\begin{bmatrix} P_1 \\ P_2 \\ P_3 \end{bmatrix} = \begin{bmatrix} S_{11} & S_{12} & S_{13} \\ S_{21} & S_{22} & S_{23} \\ S_{31} & S_{32} & S_{33} \end{bmatrix} \begin{bmatrix} D_1 \\ D_2 \\ D_3 \end{bmatrix}$$

- To compensate the inaccuracies, it introduces many conservative penalty factors → **less thermal margin!**

A previous ANN approach – ICOPS

Key ideas of ICOPS (In-COre Protection System) – replacing CPCS

- Replacing the 3x3 matrix, called **SAM (shape annealing matrix)** with **a single-layered neural network.**



ICOPS achievements

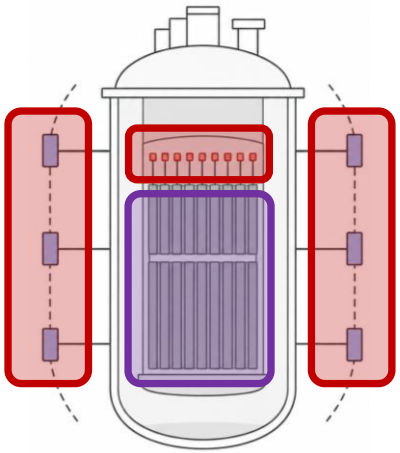
- Compared to the previous method (SAM), axial power prediction error was reduced in *all scenarios.
- ICOPS demonstrates **the viability of ANN-based safety features.**
- ICOPS is designed to meet the **latest global safety standards,** required by IAEA, WENRA, EUR, etc.
- ANN-based ICOPS **has been adopted in the APR-1000[4]** and is being evaluated as part of its licensing review.

* Hanul unit 4, cycle 8 & 10 / Shin-Kori unit 1, cycle 1 / Shin-Wolsong unit 1, cycle 1

Research proposal

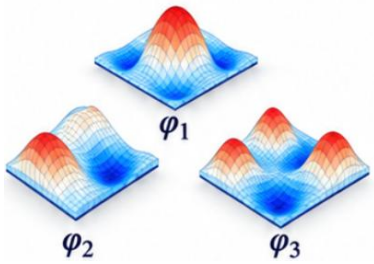
Problem definition

- Development of a 3D core power reconstruction using sparse sensor signals → sensor minimisation.
- Default sensor set: **ex-core detector + core-exit thermocouple (CET).**
- Optional extra sensor (for large reactors): **in-core neutron flux detector (SPND).**



Input: sensor signals
ex-core detector / CET
***optional in-core flux detector**
for large reactors

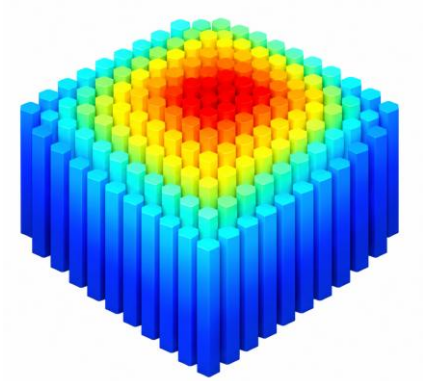
→



$$\hat{\mathbf{a}} = \begin{bmatrix} \hat{a}_1 \\ \hat{a}_2 \\ \hat{a}_3 \end{bmatrix}$$

Method: linear combination
(coefficient found by ANN)

→



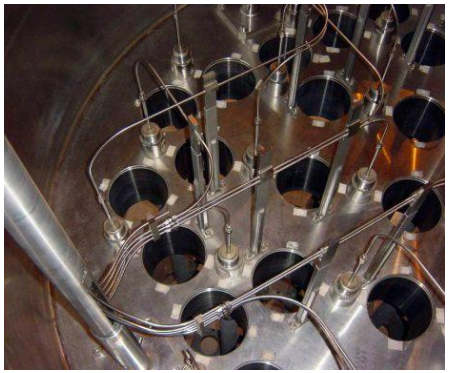
$$\hat{\mathbf{P}} = \sum_{i=1}^{k} \hat{a}_i \, \boldsymbol{\varphi}_i$$

Result: 3D power
distribution

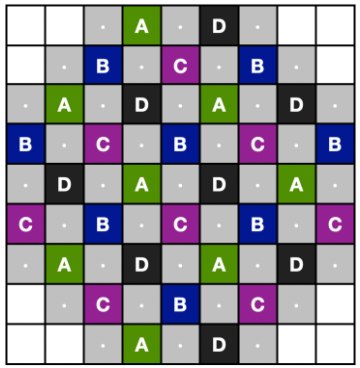
Proposed approaches (1) – temperature integration

Utilisation of core-exit thermocouples (CETs) with ex-core neutron detectors

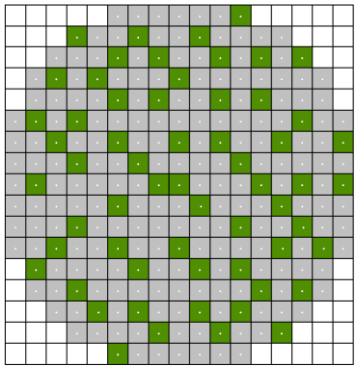
- CETs has fast response[5] (~0.7s) and provides radial information → **viable for protection use!**



CETs viewed from the top



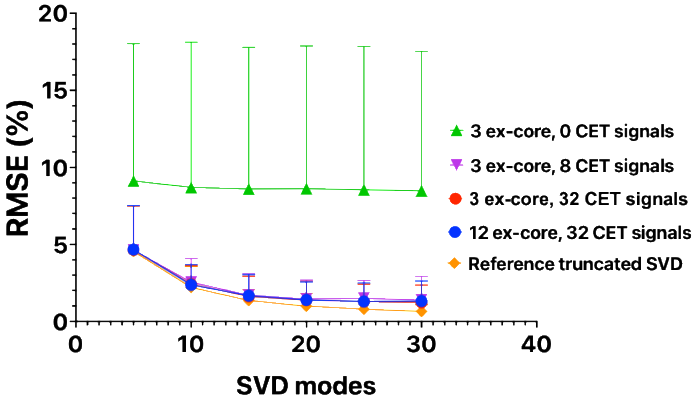
Proposed SMR CET locations

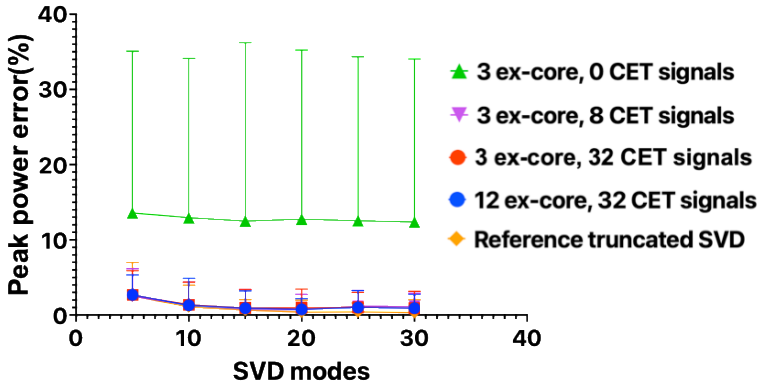


APR-1400's CET locations

CETs vastly improve the 3D power prediction performance, combined with ex-core neutron detectors

- **w/o CETs**: maximum **RMSE ~18%, peak power error ~34%**
- **with CETs**: maximum **RMSE ~3%, peak power error ~3%**





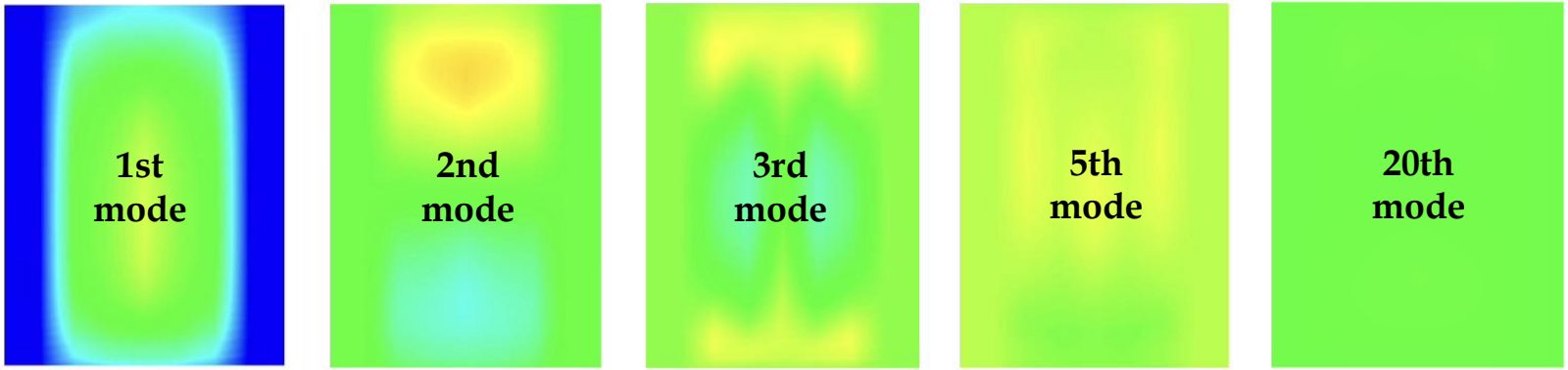
A single CET group out of 4 enhances the accuracy a lot!

Proposed approaches (2) – basis extraction using SVD

The two roles of SVD:

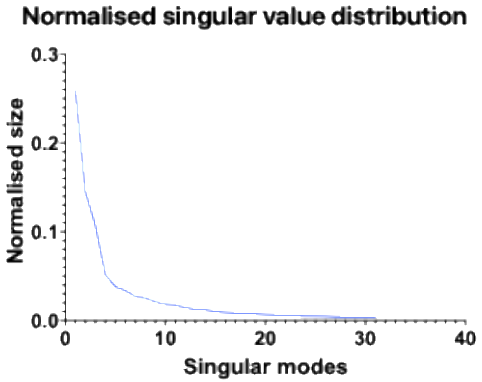
Role (1): **extract dominant spatial modes** from power distributions.

- **Multiple power distributions** are decomposed as a **linear combination of multiple orthonormal vectors.**
- The power prediction problem is then **reduced to simply finding a few scalar coefficients.**



Role (2): **reduce the dimension** of the higher-dimensional 3D power **(low-rank approximation).**

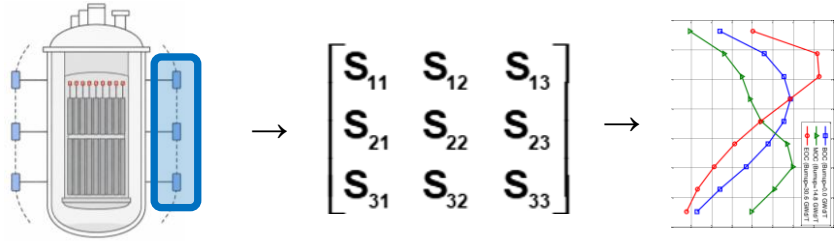
- Each spatial mode has a corresponding **singular value → a good index for rank-k approximation!**



Proposed approaches (3) – in summary

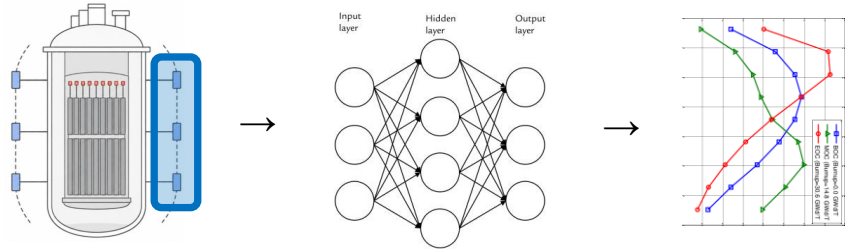
Traditional CPCS

- Ex-core signals ($\mathbb{R}^3$) → 3x3 matrix → 1D axial power ($\mathbb{R}^{3}$)



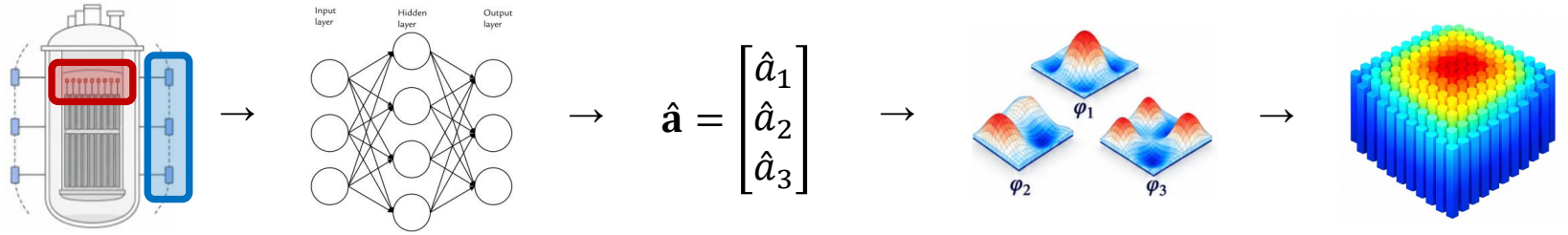
Korean ICOPS

- Ex-core signals ($\mathbb{R}^3$) → Neural network → 1D axial power ($\mathbb{R}^{20}$)



Proposed approach

- Ex-core/CET signals ($\mathbb{R}^{44}$) → Neural network → SVD coefficients → Linear comb. → 3D power ($\mathbb{R}^{2760}$)



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SVD-based compact power distribution representation

SVD-based orthogonal basis-wise power reconstruction

- **Enhanced interpretability, compact representation of 3D power.**
- Only **a few detectable modes used** for full power reconstruction.

Step 1. SVD Basis Construction

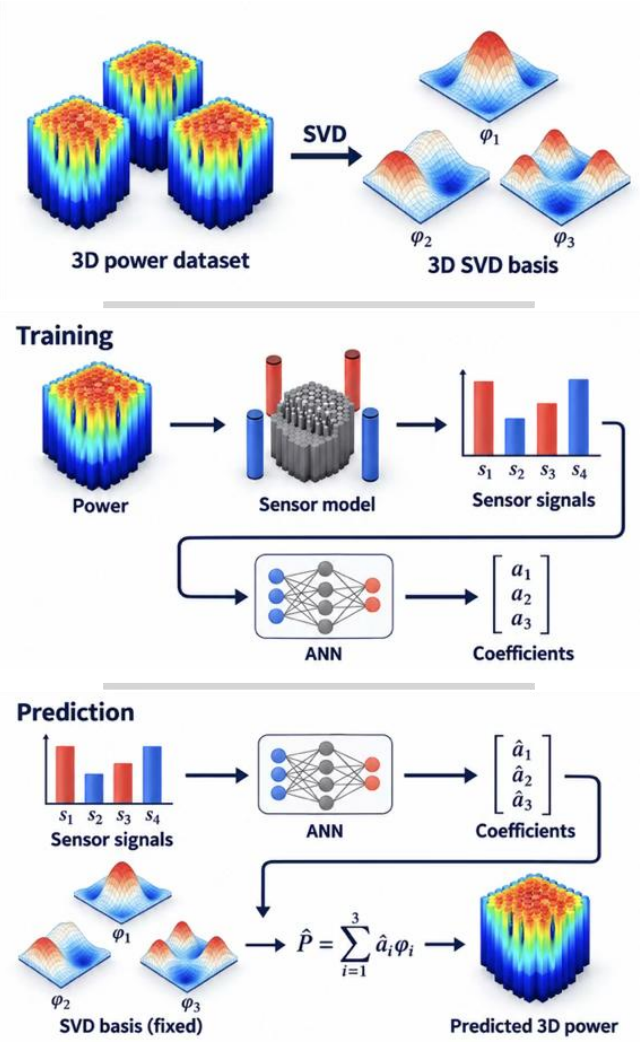
- Generate a dataset of a wide range of 3D power distributions.
- Extract dominant spatial modes using SVD.

Step 2. Coefficient Prediction Model Training

- **80% training dataset** used.
- Generate corresponding sensor responses using sensor models.
- Train ANN models for sensor-to-coefficient mapping.

Step 3. Performance Validation

- **20% validation dataset** used.
- Predict SVD mode coefficients from sensor signals.
- Reconstruct the 3D power distribution.
- Evaluate coefficient prediction and reconstruction accuracy.

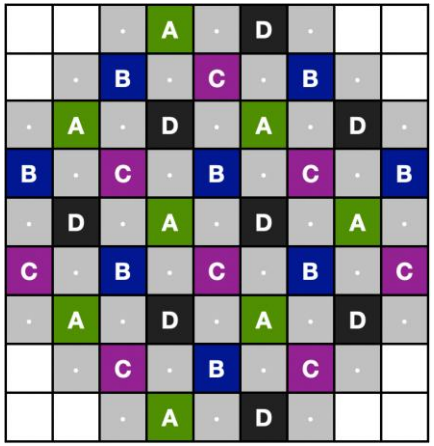


Target reactor: ATOM

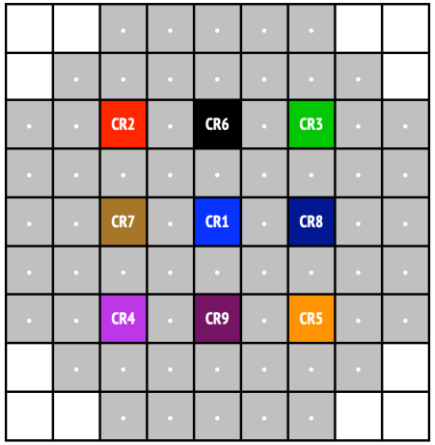
Reactor model for the proof-of-concept study – ATOM[6)]

- A KAIST-designed **soluble-boron free** SMR reactor, used as a surrogate model for i-SMR.
- 450 MWth nominal power, 69 assemblies with 2m active core height.
- 4 ex-core detectors, 32/69 assemblies equipped with CETs.

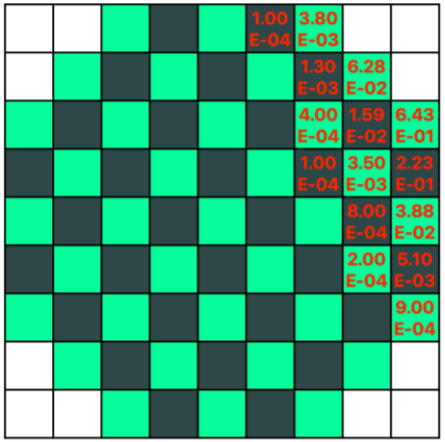
Thermal output	450 MWth
System pressure	15.5 MPa
FA type/ number	17 x 17, 69
Fuel material	UO2, 4.95w/o
Avg. fuel temp.	900.00 K



32 CETs divided into 4 groups (8 for each)

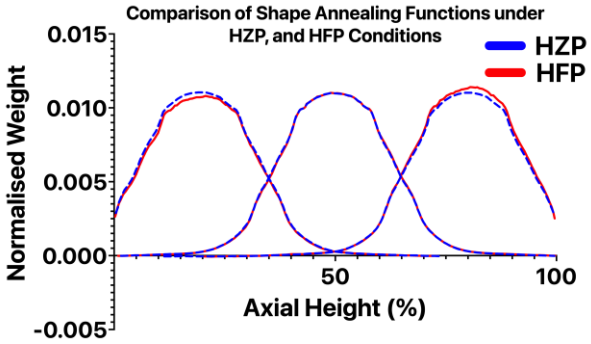


9 control rods



*Ex-core detector radial[7)] weights

*Ex-core detector[7)] axial weights



*Adopted from SMART-660;
both reactors share 69 assemblies, 17x17 lattice, 2m active core height.

Training dataset generation

Dataset generation method: KAIST in-house PWR analysis code, KANT[8].

- A total of 5 scenarios, with **8:2** training/validation **random** partitioning.
- **All transients induced by control rods; soluble-boron free reactor.**

Datasets generated:

1) Radially symmetric dataset: 4 scenarios included, each of which has 2,280 datapoints in total.

- Dataset A: 100 – 20 - 50 load-follow. **(baseline)**
- Dataset B: central CR withdrawn, other CRs moving randomly. **(peripheral flux oscillation)**
- Dataset C: All CRs moving randomly. **(whole-core flux oscillation)**
- Dataset D: All CRs gradually inserted from 0% to 100%. **(supplementary)**
- 2,280 * 4 = 9,120 datapoints.

2) Radially asymmetric dataset: 9 sub-scenarios included, each containing a single CR failure case.

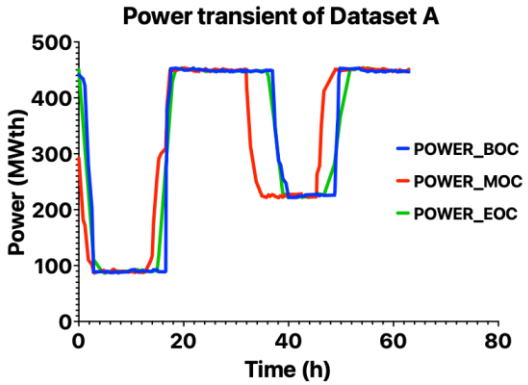
- Dataset E - CR#, (#: 1~9): CR# is moved arbitrarily, other CRs fixed fully withdrawn. **(asymmetric tilt)**
- 756 * 9 = 6,804 datapoints.

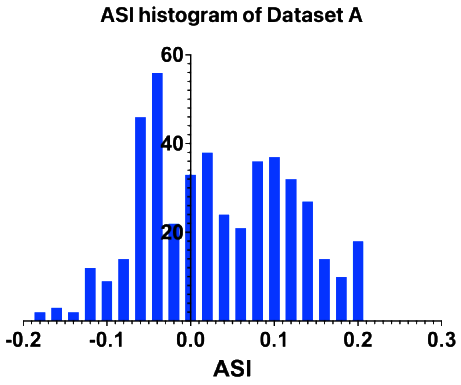
Characteristics of datasets (1)

Radially symmetric datasets

1) Dataset A: a load-follow operation (2,280 datapoints).

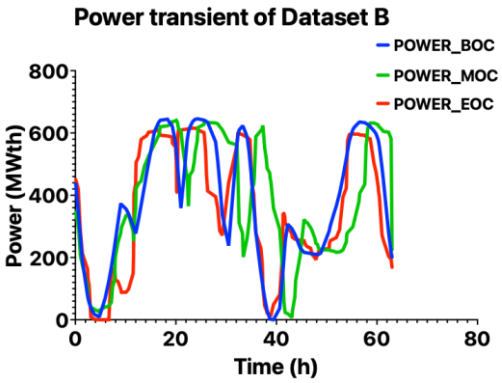
- Power: 100MWth ~ 450MWth, ASI: -0.2 ~ 0.2.

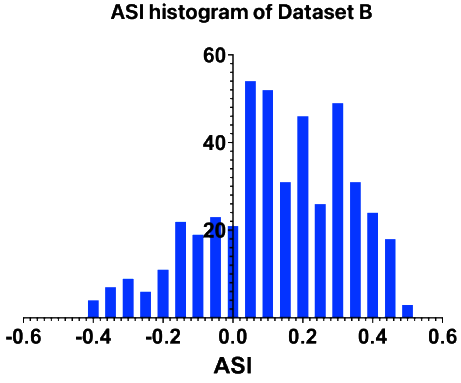




2) Dataset B: Central CR fixed withdrawn, other CRs moving randomly (2,280 datapoints).

- Power: 0MWth ~ 630MWth (nominal: 450MWth), ASI: -0.4 ~ 0.5



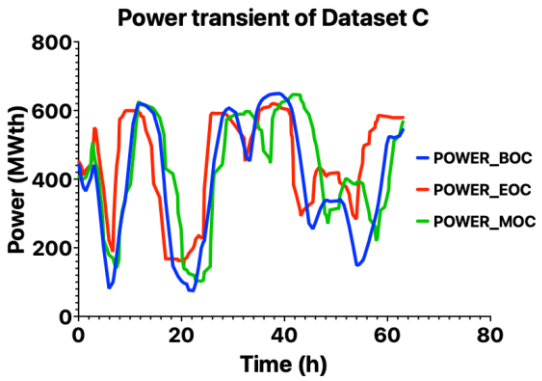


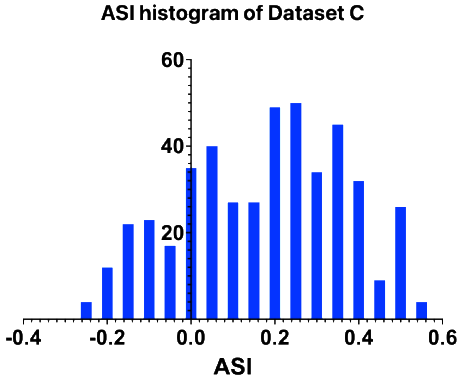
Characteristics of datasets (2)

Radially symmetric datasets

1) Dataset C: All CRs moving randomly(2,280 datapoints).

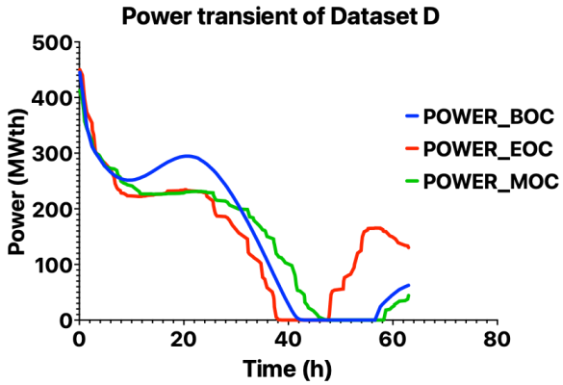
- Power: 80MWth ~ 650MWth (nominal: 450MWth), ASI: -0.24 ~ 0.55.

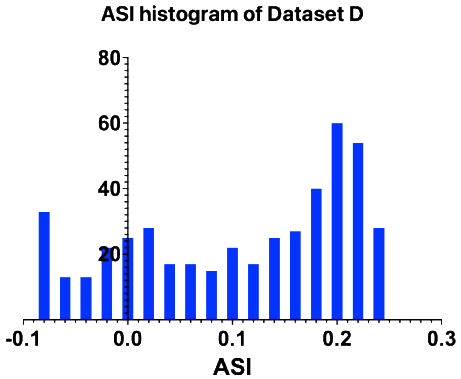




2) Dataset D: Gradual insertion of all CRs(2,280 datapoints).

- Power: 0MWth ~ 450MWth (nominal: 450MWth), ASI: -0.08 ~ 0.24.



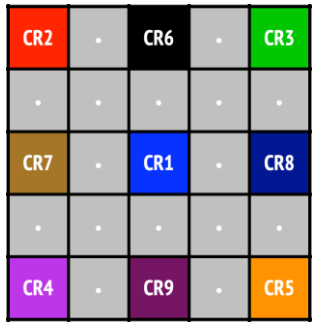


Characteristics of datasets (3)

Radially asymmetric datasets

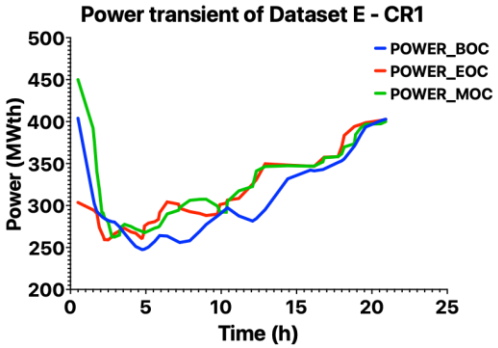
1) Dataset E(**CR#**) : **CR# moving randomly**, others withdrawn (756 points for each CR#).

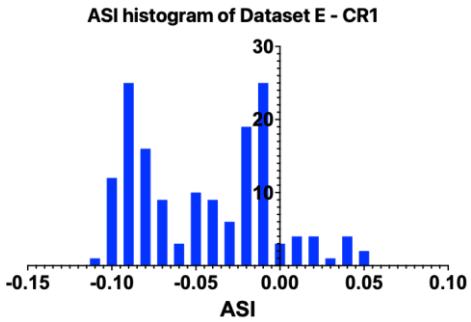
- Only a single CR manoeuvre, relatively mild transient (cf. Dataset B/C).



CR1

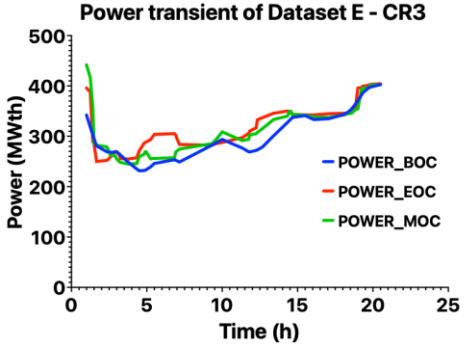
Power: 250 ~ 450MWth
ASI: -0.10 – 0.05

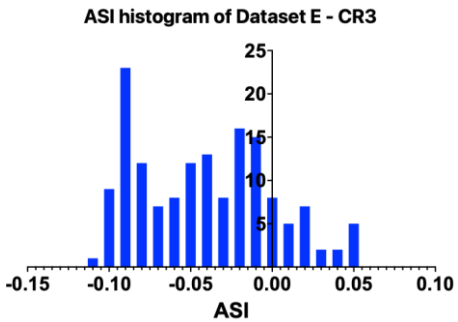




CR3

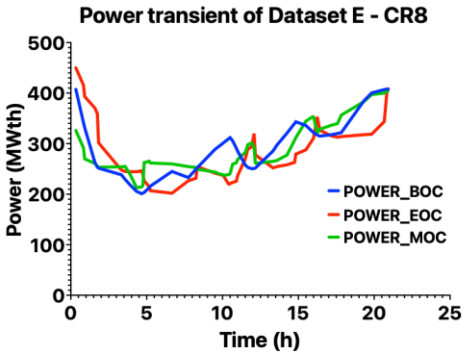
Power: 230 ~ 450MWth
ASI: -0.10 – 0.05

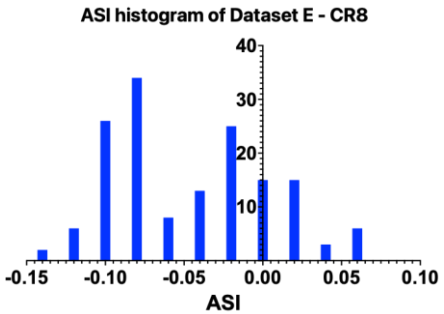




CR8

Power: 230 ~ 450MWth
ASI: -0.10 – 0.05

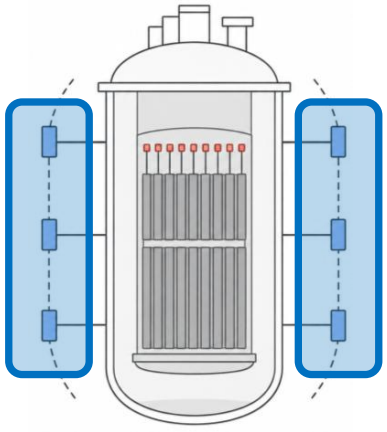


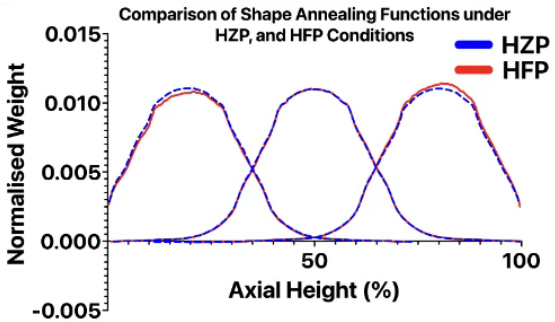


ANN inputs: ex-core detector and CET

ANN's 1st input: 12-channel (4 radial locations, 3 axial locations) ex-core detector signals

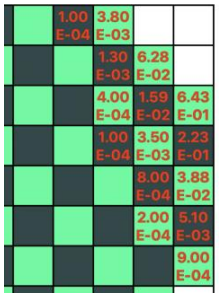
- ATOM's 3D ex-core detector assembly weights.





Axial weighting function[7] (AWF)

X



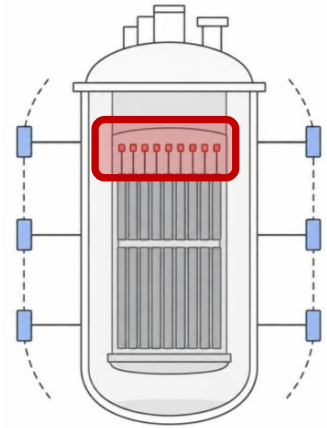
Radial weighting function[7] (RWF)

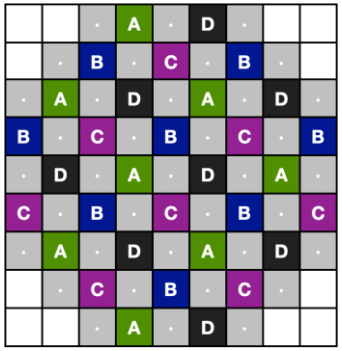
=

3D node-wise weights map for ex-core detectors

ANN's 2nd input: 32-channel CET signal

- Assembly-wise axial integral power used as surrogate, no time delay, no TH effects.



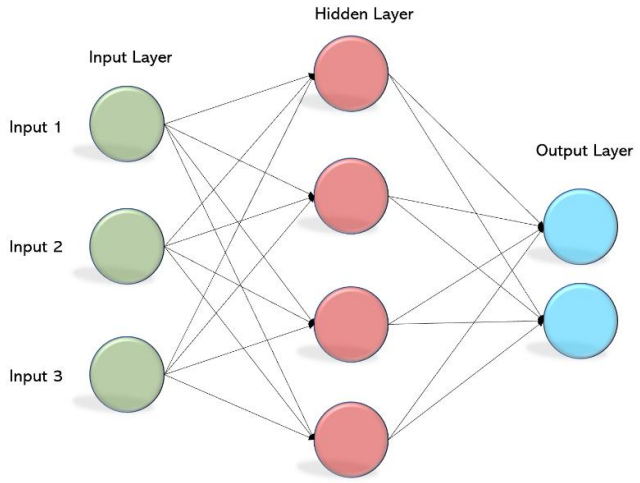


Core exit coolant temperature obtained from 32/69 assemblies (**8 for each of group A, B, C, D**)

ANN model structure

A three-hidden-layer ANN

- **Input:** ex-core detector & CET signals.
- **Output:** predicted SVD coefficients.



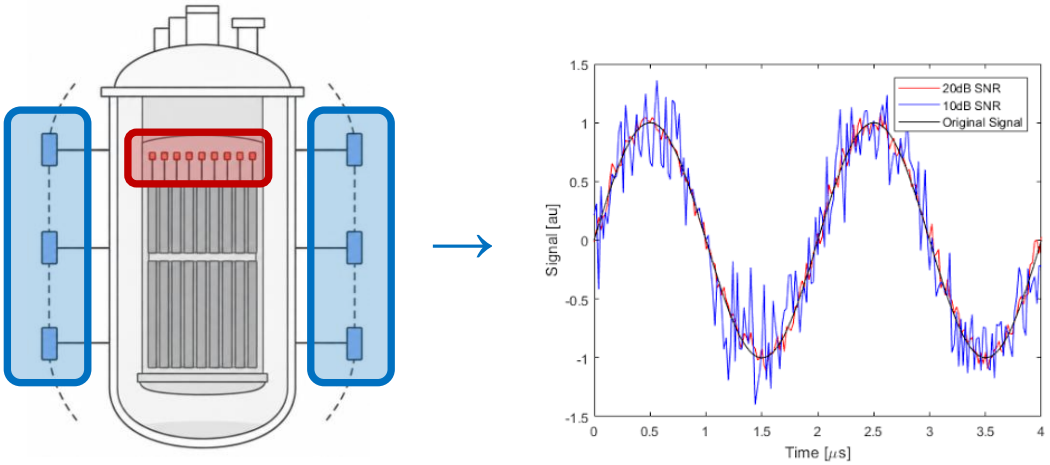
Parameter	Value / Specification
Input Shape	(44)
Hidden Layer 1	Dense (4096)
Hidden Layer 2	Dense (1024)
Hidden Layer 3	Dense (256)
Activation func.	LeakyReLU
Output Shape	(5) – (30)
Optimiser	Adam
Epochs	300 (with early stopping)

Model name	1st layer	2nd layer	3rd layer	SVD modes	Loss
Funnel-M30	4096	1024	256	30	SVD coefficients
Funnel-M25	4096	1024	256	25	SVD coefficients
Funnel-M20	4096	1024	256	20	SVD coefficients
Funnel-M15	4096	1024	256	15	SVD coefficients
Funnel-M10	4096	1024	256	10	SVD coefficients
Funnel-M5	4096	1024	256	5	SVD coefficients

Noise injection in signal

Signal measurement always has uncertainties

- They are mixed with errors from measurement, computing, physical, etc.



Noise modelling: **Signal-proportional Gaussian noise**[9)]

- Gaussian distribution: provides the **maximum uncertainty(entropy)** for the given mean and variance.
- Each detector (3 x 4ch ex-core detector, 32ch CET) noise is **independent** and is based on the **original signal amplitude.**

$$x_i^{perturbed} = x_i(1 + \sigma\xi) \quad \sigma \sim \mathrm{N}(0,1), \xi = 2\% \text{ or } 5\%$$

- **Models are trained with/without noises and evaluated with/without noises (4 cases).**

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- Target reactor: ATOM
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3. **Numerical results**
- Ex-core detector response sensitivity
- Benchmark with full/reduced sensor sets
- Noise robustness test
4. **Conclusions and future works**

Evaluation Metrics: RMSE and peak power error

Metric 1: Whole core root mean square error (RMSE)

- An index of overall power shape prediction accuracy.
- Total RMSE for all 2,760 valid nodes, with no separate normalisation(power values already normalised to an average of 1).

$$RMSE = \sqrt{\frac{1}{N}\sum_{\mathrm{i}=1}^{N}(P_{\mathrm{i}}^{ANN} - P_{\mathrm{i}}^{Actual})^2}$$

Metric 2: Peak power absolute relative error

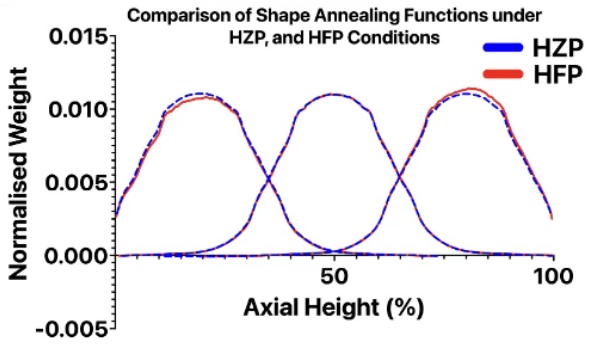
- Absolute relative error of the output, based on the peak power location in the original output distribution.

$$\text{Peak power error} = \left|\frac{Peak\ power_i^{ANN} - Peak\ power_i^{Actual}}{Peak\ power_i^{Actual}}\right|$$

Ex-core detector response sensitivity

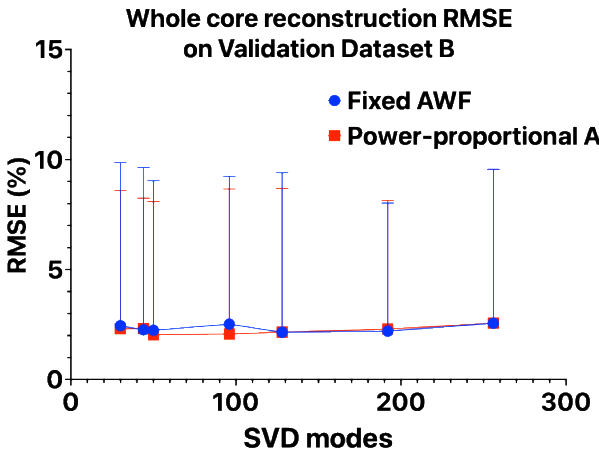
Sensitivity of ex-core detector response model

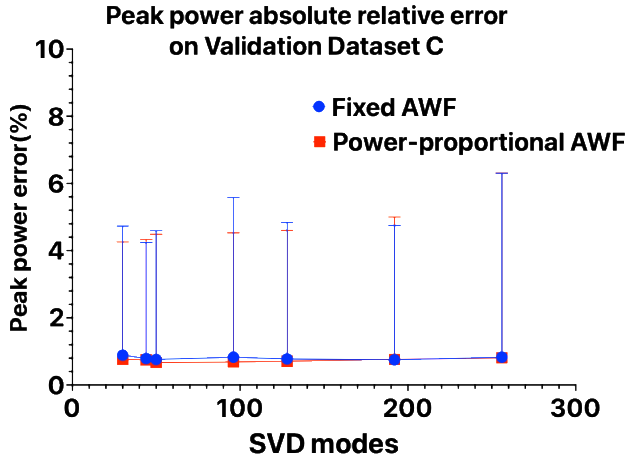
- The axial weighting functions slightly vary with the power levels.



Power-proportional axial weighting factor (AWF) vs fixed AWF

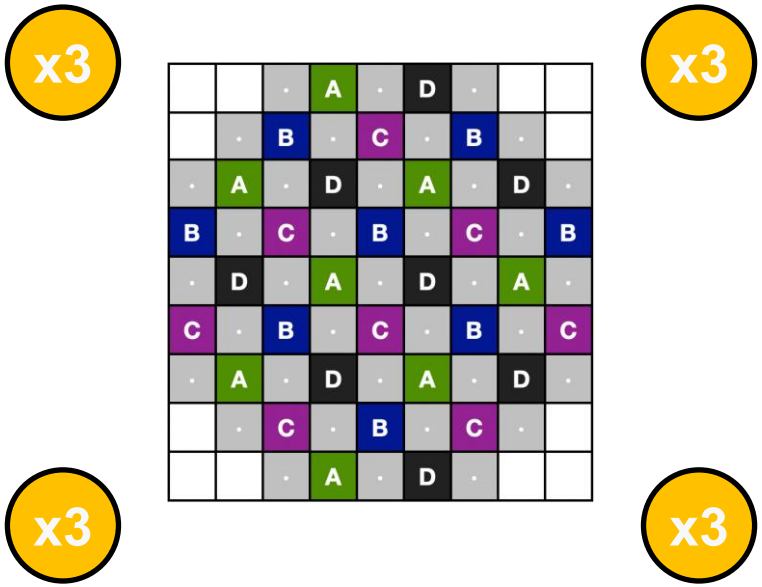
- The impact of power levels on AWFs is **negligible.**





Preliminary results, before rank-k optimisation

Benchmark with the full sensor set
12 ex-core signals, 32 CET signals



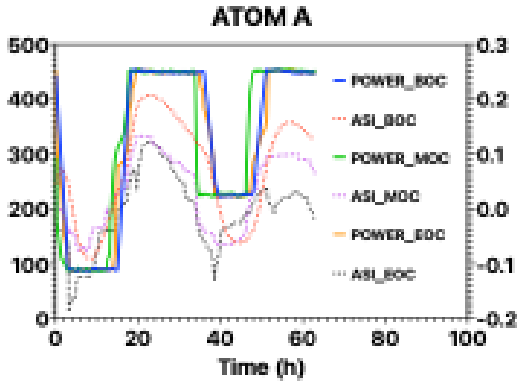
4 x 3 ex-core signals

32 CET signals (all A/B/C/D groups)

Performance benchmark under symmetric scenarios (1)

1st symmetric dataset – an LFO scenario

- Using all sensors - 12 ex-core detector, 32 CET signals.
- The error decreases with increasing number of SVD modes.
- ANN performance **close to the mathematical cap of rank-k SVD.**



ANN performance with 30 modes
Max. RMSE: ~2.6%
Max peak error: ~2.7%

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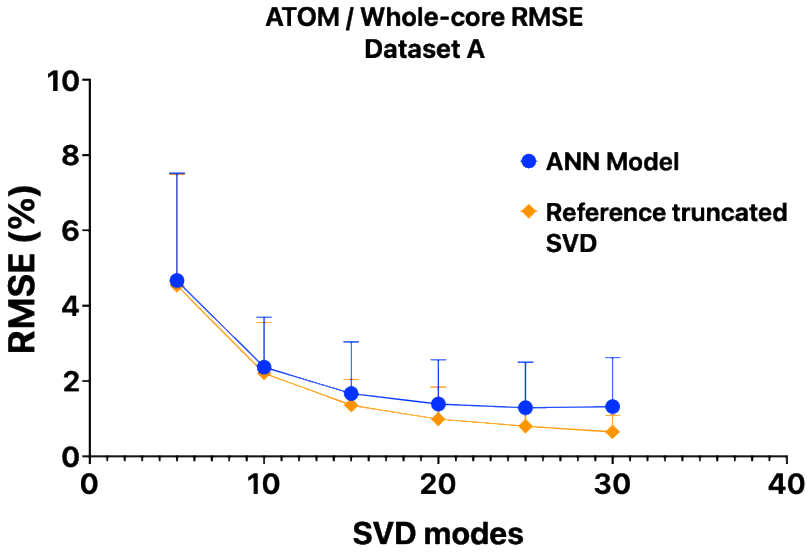
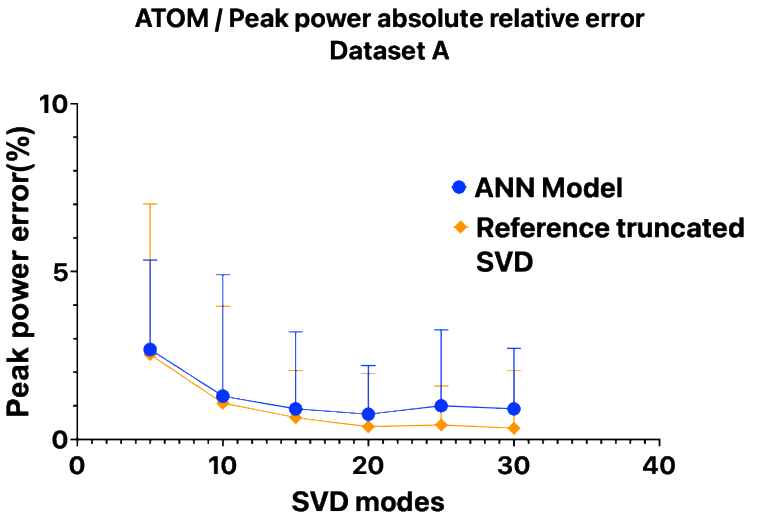
Rank-30 SVD analytical error
Max. RMSE: ~1.1%
Max peak error: ~2.0%

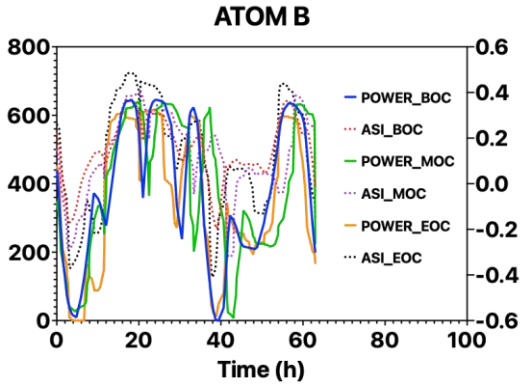




Performance benchmark under symmetric scenarios (2)

2nd symmetric dataset – control rods random movement

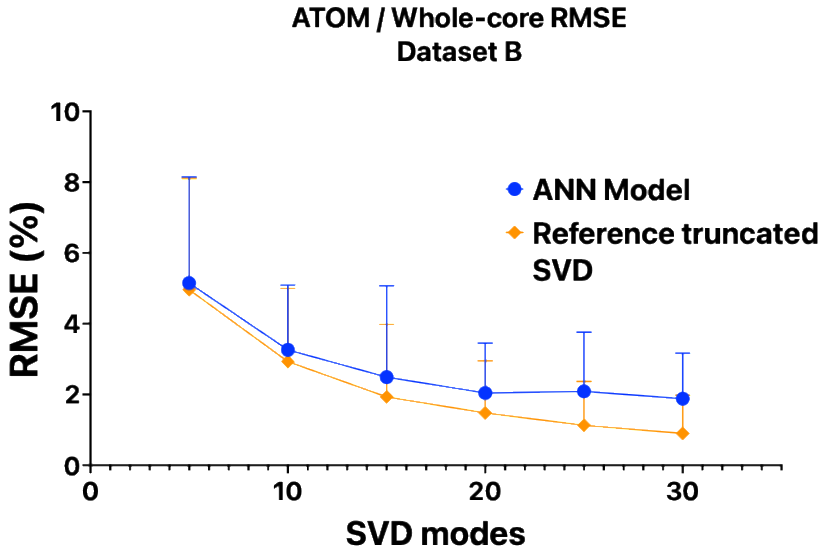
- Using all sensors - 12 ex-core detector, 32 CET signals.
- The error decreases with increasing number of SVD modes.
- ANN performance **close to the mathematical cap of rank-k SVD.**

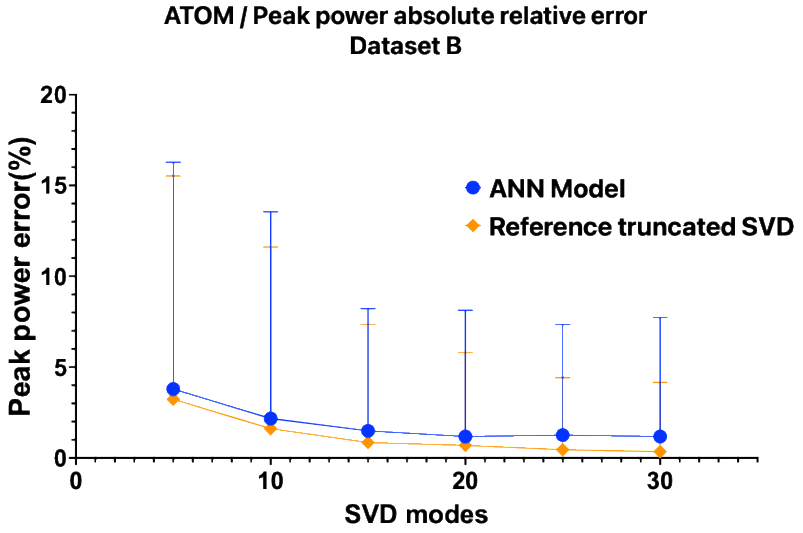


ANN performance with 30 modes
Max. RMSE: ~3.2%
Max peak error: ~7.7%

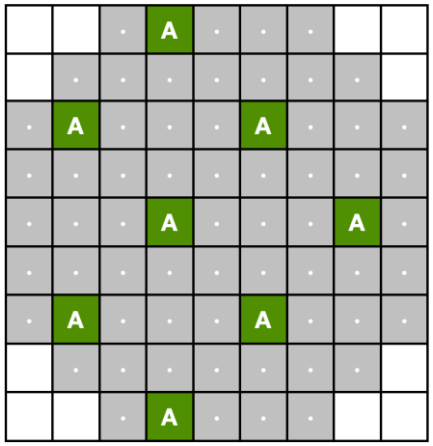
~

Rank-30 SVD analytical error
Max. RMSE: ~1.9%
Max peak error: ~4.2%





Benchmark with the 1/4* sensor set
3 ex-core signals, 8 CET signals



x3

1 x 3 ex-core signals

8 CET signals (group A only)

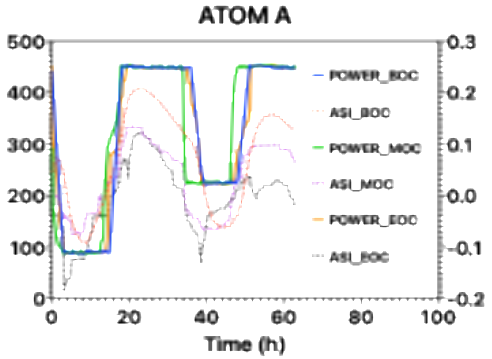
*** For 4-independent, redundant protection channels**

Performance benchmark with reduced sensors (1)

1st symmetric dataset – an LFO scenario

- **3 ex-core, 0 CET signals** → No CET – very low performance.
- **3 ex-core, 8 CET signals**
- **3 ex-core, 32 CET signals**
- **12 ex-core, 32 CET signals**

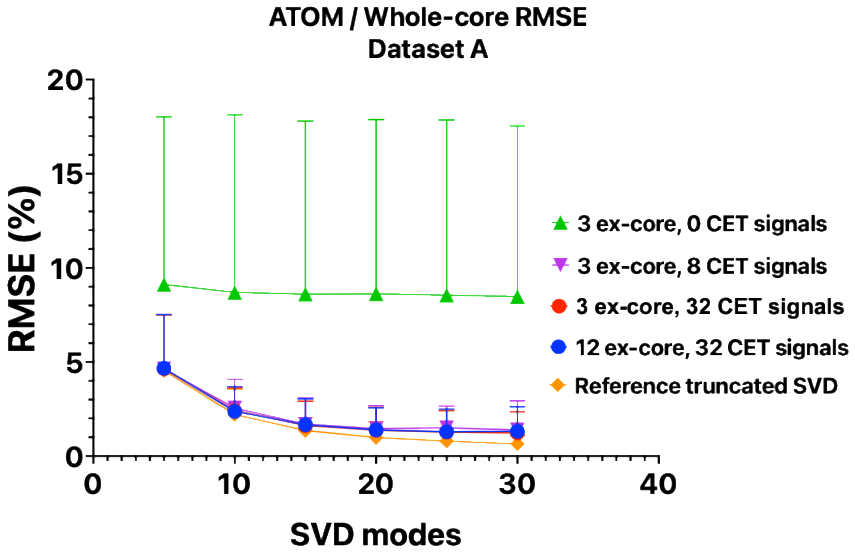
} **When at least a single group of CET is used, performances are on par.**

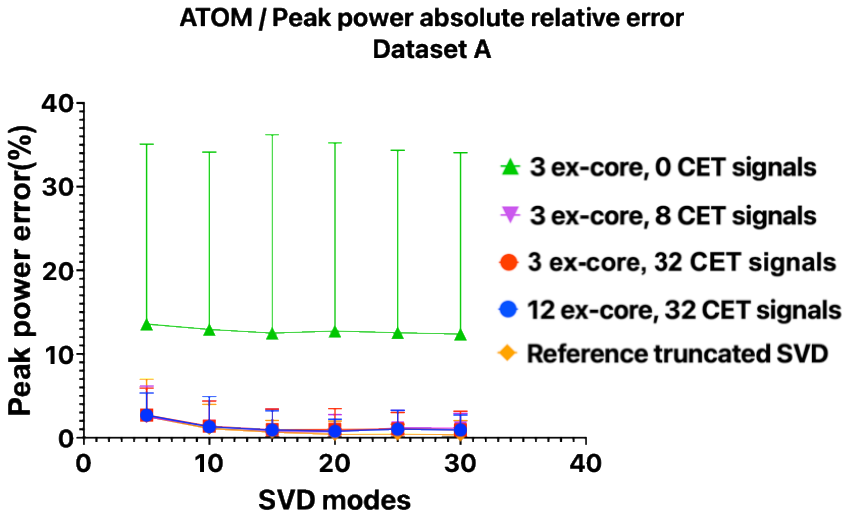


Model with 30 modes,
3 ex-core, 8 CET signals
Max. RMSE: ~2.9%
Max peak error: ~2.9%

~

Model with 30 modes,
12 ex-core, 32 CET signals
Max. RMSE: ~2.6%
Max peak error: ~2.7%



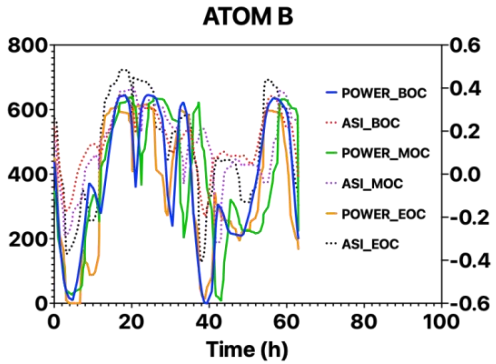


Performance benchmark with reduced sensors (2)

2nd symmetric dataset – control rods random movement

- **3 ex-core, 0 CET signals** → No CET – very low performance.
- **3 ex-core, 8 CET signals**
- **3 ex-core, 32 CET signals**
- **12 ex-core, 32 CET signals**

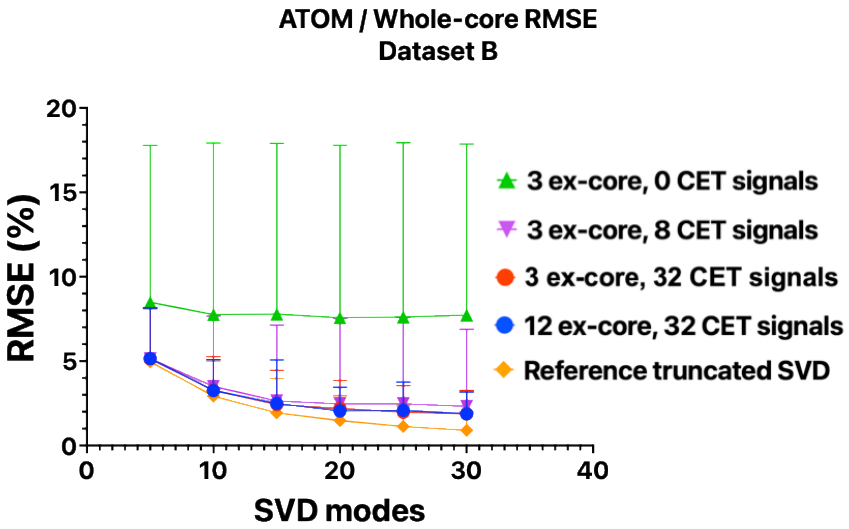
} **When at least a single group of CET is used, performances are on par.**

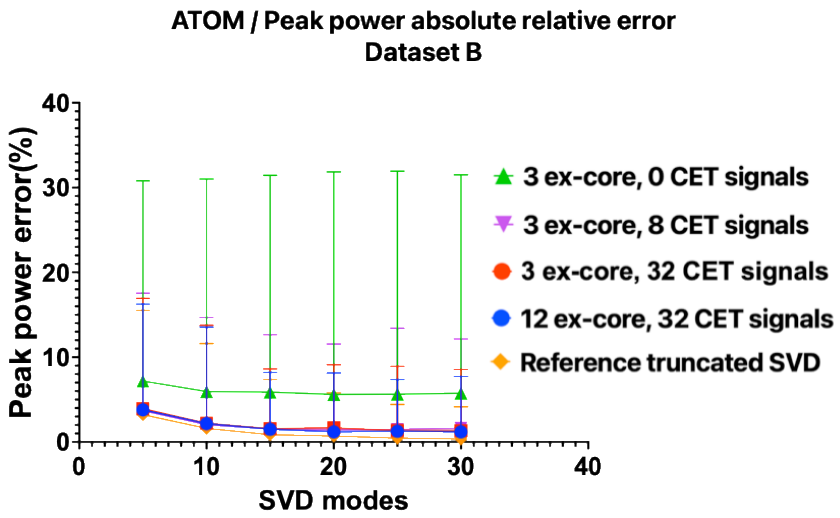


Model with 30 modes,
3 ex-core, 8 CET signals
Max. RMSE: ~6.9%
Max peak error: ~12.0%

~

Model with 30 modes,
12 ex-core, 32 CET signals
Max. RMSE: ~3.2%
Max peak error: ~7.7%

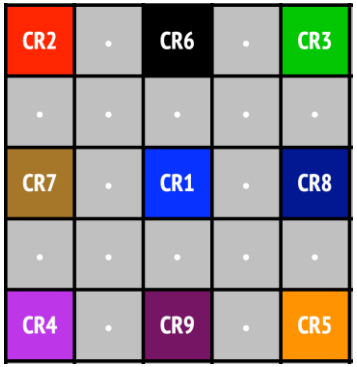




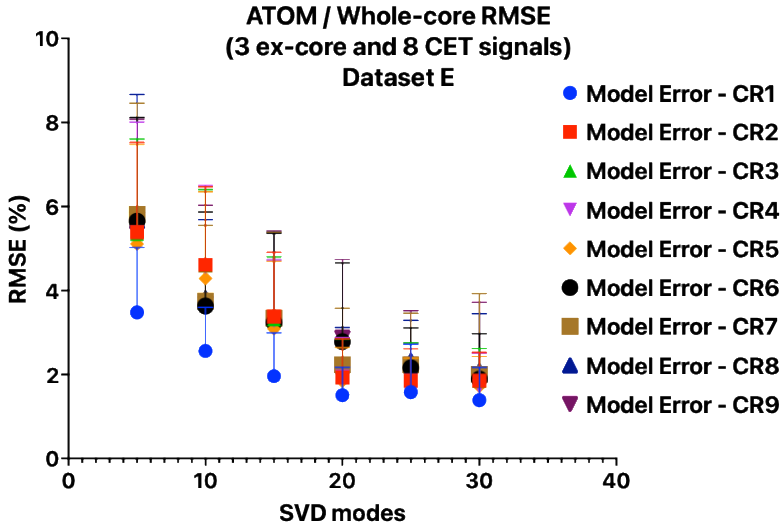
Performance benchmark with reduced sensors (3)

Asymmetric dataset – induced by a single control rod failure

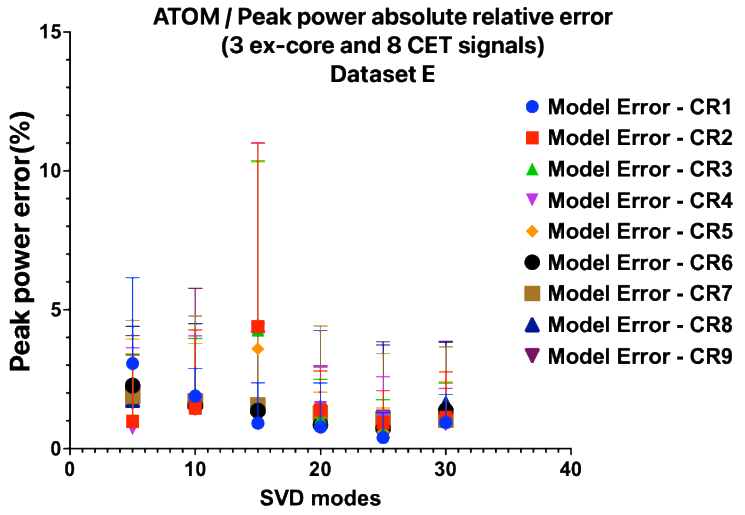
- 9 scenarios considered.
  - 1 central CR failure → Minimal effects on performance
  - 8 peripheral CR failure → Bigger drop in performance
- The model is **robust to single CR failure cases.**



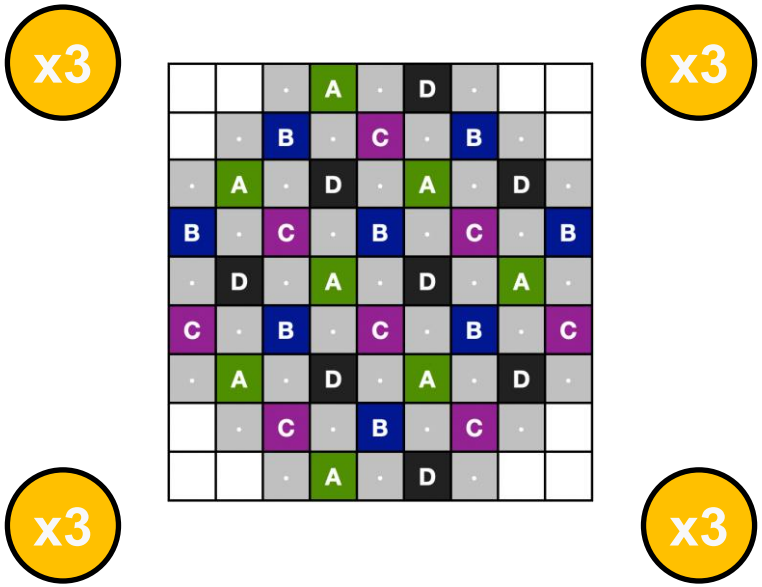
Model with 30 modes,
Central CR failure
Max. RMSE: ~2%
Max peak error: ~2%



Model with 30 modes,
Peripheral CR failure
Max. RMSE: ~4%
Max peak error: ~4%



Signal noise robustness test
12 ex-core signals, 32 CET signals



4 x 3 ex-core signals

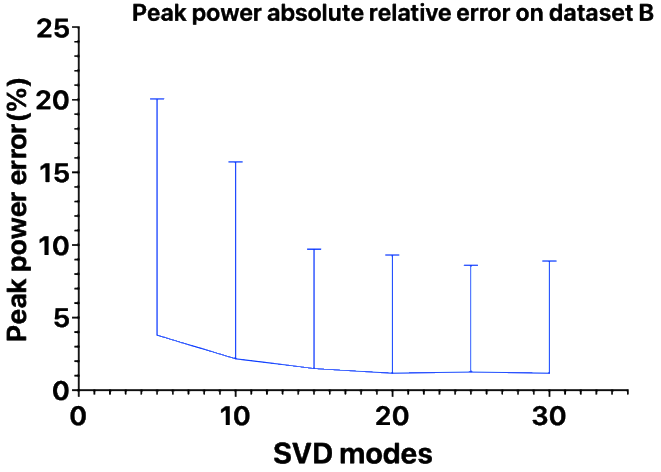
32 CET signals (all A/B/C/D groups)

Robustness test under noise-injected signal scenarios (1)

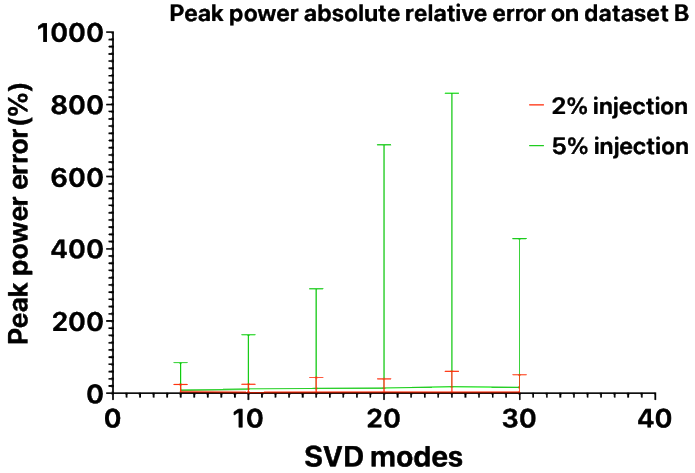
Noise-unaware model (0, 2, 5% noise)

- 2 scenarios considered.
  - Trained with clean signals/tested with clean signals. → baseline
  - Trained with clean signals/tested with noisy signals. → complete breakdown

Model with 30 modes,
Clean training
Clean validation
Max. RMSE: ~3%
Max peak error: ~8%



Model with 30 modes,
Clean training
Noisy (5%) validation
Max. RMSE: ~139%
Max peak error: ~412%

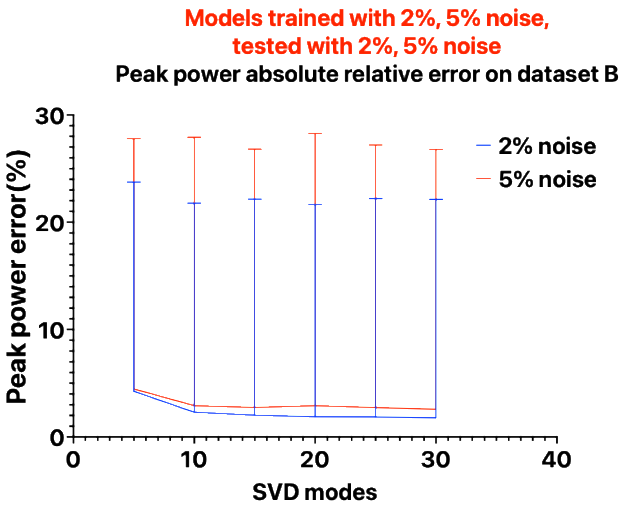


Robustness test under noise-injected signal scenarios (2)

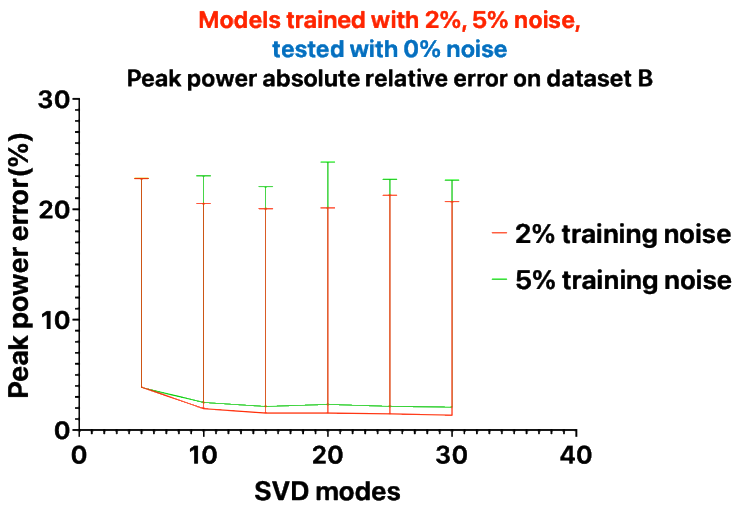
Noise-aware model (0, 2, 5% noise)

- 2 scenarios considered.
  - Trained with noisy signals/tested with noisy signals. → performance recovery under noise
  - Trained with noisy signals/tested with clean signals. → drop in baseline performance

Noisy training (5%)
Noisy validation (5%)
Max. RMSE: ~11%
Max peak error: ~24%



Noisy training (5%)
Clean validation
Max. RMSE: ~8%
Max peak error: ~21%



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Conclusions

Conclusions

- Integrating fast-response CET signals with ex-core measurements substantially improved power prediction accuracy.
- The SVD–ANN approach achieved accurate 3D power reconstruction using approximately 30 modes.
- A reduced configuration of 3 ex-core detector and 8 CET signals maintained good performance, supporting the potential for redundant sensor configurations.
- Reconstruction remained effective under asymmetric power conditions, including single-control-rod anomalies.
- Noise-injected training improved robustness to sensor noise.

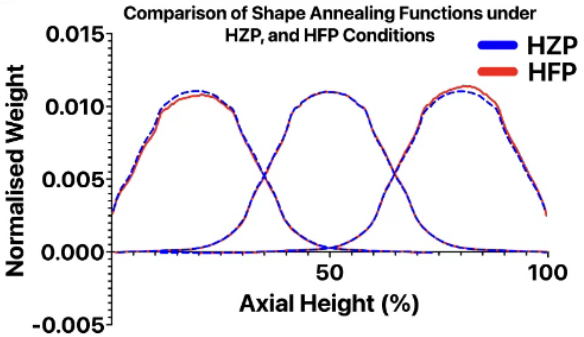
Future Works

- Quantify the uncertainty of reconstructed power distributions, the safety parameters (LPD/DNBR) derived from the 3D power distribution.
- Incorporate more realistic sensor models, including response delays and thermal-hydraulic effects.
- Develop Monte Carlo–based 3D ex-core detector weight maps and conduct V&V across various burnup and power conditions.
- Demonstrate the study design with larger reactor designs (e.g. APR-1400).

Monte-Carlo based 3D ex-core weight map

Under development – an MC based precise ex-core weight map

- Current ex-core detector 3D weight map



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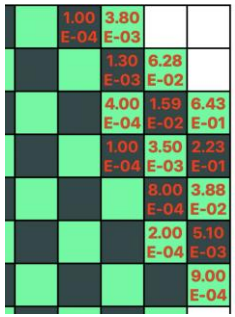

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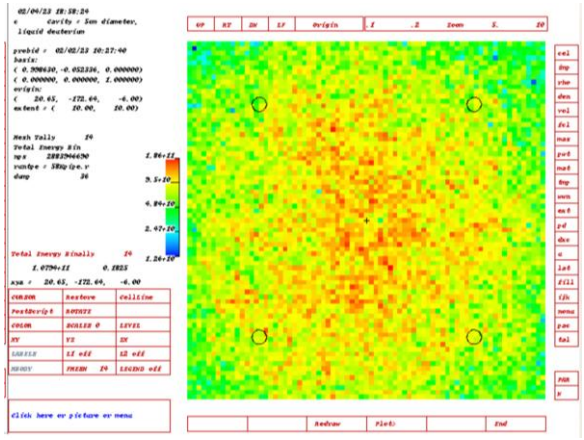
3D node-wise weights map for ex-core detectors

A new MC-based ex-core 3D weight map

- **A direct 3D map** of ex-core detector weights with multiple burnup conditions, power levels, with rigorous V&V.



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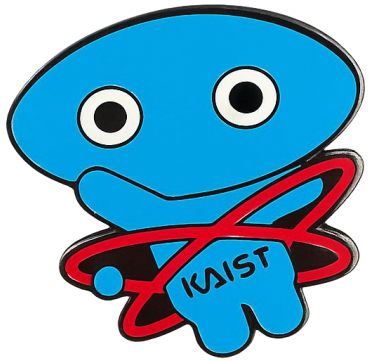
9) Urase, Yuki, Akio Yamamoto, and Tomohiro Endo. "Verification of In-Core Power Distribution Reconstruction Based on POD for High-Temperature Gas-Cooled Reactors Using Ex-Core Detectors." Journal of Nuclear Science and Technology, July 20, 2025, 1–16. https://doi.org/10.1080/00223131.2025.2533530.

Any questions?



Appendix

Singular value decomposition (SVD)

- a technique of matrix diagonalisation regardless of its dimension (cf. eigenvalue decomposition).

The decomposition procedure and the results meanings:

1) Take a (9 x 9 – 12) x 40 power distribution matrix, convert it into a $\mathbb{R}^{2,760}$ vector.

2) Stack column vectors, **representing multiple power distributions,** to form a data matrix $\mathbf{P} \in \mathbb{R}^{2,760 \times M}$ matrix. (**M: number of simulated power scenarios**) Then subtract the mean make a deviation matrix, **X**.

$$x_i = \begin{bmatrix} x_{i,1} \\ x_{i,2} \\ \vdots \\ x_{i,2760} \end{bmatrix}, \qquad X = [x_1 \quad x_2 \quad \cdots \quad x_M] = \begin{bmatrix} x_1^{(1)} & x_1^{(2)} & \cdots & x_1^{(M)} \\ x_2^{(1)} & x_2^{(2)} & \cdots & x_2^{(M)} \\ \vdots & \vdots & & \vdots \\ x_{2760}^{(1)} & x_{2760}^{(2)} & \cdots & x_{2760}^{(M)} \end{bmatrix} \in \mathbb{R}^{2760 \times M}$$

3) Perform SVD on the matrix, **X** to get, $\mathbf{X} = U\Sigma V^T$

- $U \in \mathbb{R}^{2,760 \times r}$: spatial modes (for r-orthogonal basis) **| fixed.**
- $\Sigma \in \mathbb{R}^{r \times r}$: scaling matrix (stretching or shrinking)
- $V^T \in \mathbb{R}^{r \times M}$: coordinate transformation matrix

4. Absorb Σ and V^T into a **single coefficient vector** $a \in \mathbb{R}^r$, so that $a = \Sigma V^T$ and $x_i = Ua \in \mathbb{R}^{2,760}$

5. Train the **coefficient vector – sensor signal relationship** a using a neural network.