

Impact of Axial Shape Annealing Function Formulation on Three-Dimensional Core Power Reconstruction Using Ex-Core Detectors



2026년 한국원자력학회 춘계학술발표회

Jeju island, Korea, 5th - 8th, May 2026

Minhyeok Bang, Junwoo Lee, and Yonghee Kim*

Department of Nuclear and Quantum Engineering

Korea Advanced Institute of Science and Technology (KAIST)

Table of Contents

I. Introduction

1. Motivations
2. Preview

II. Methodologies

1. Singular value decomposition (SVD)
2. Ex-core detector response simulation
3. Assembly-wise thermocouple simulation
4. Neural network model structure

III. Numerical Results

1. Training Results
2. Validation Results
3. Fixed SAF vs variable SAF

IV. Summary & Conclusions

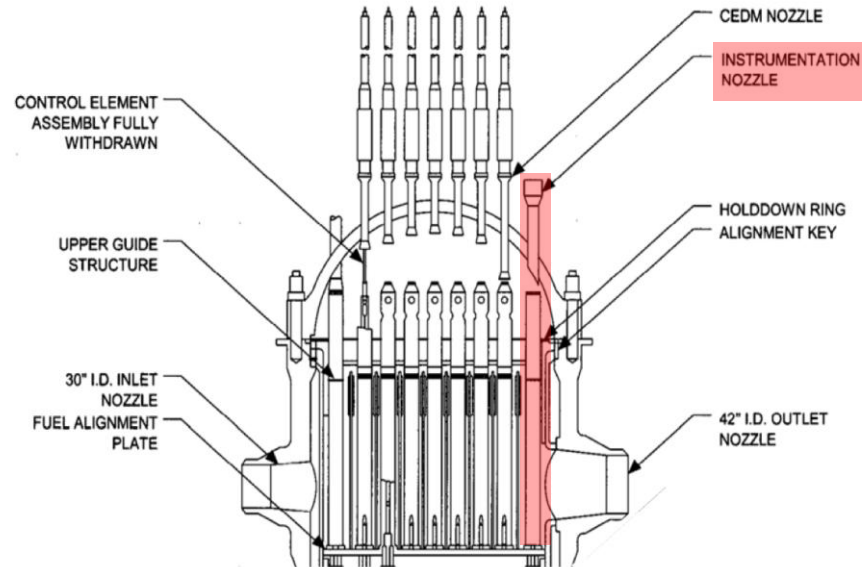
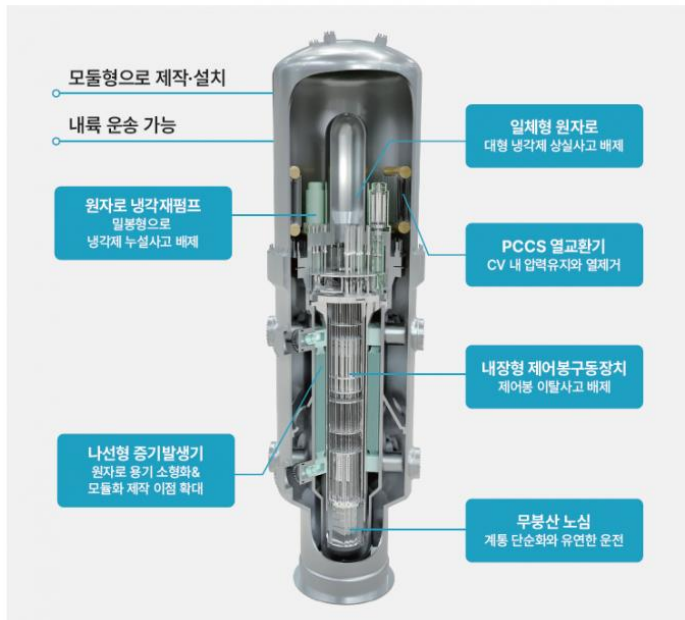
Motivations

Getting rid of in-core detectors in i-SMR

- Korean i-SMR design still relies on **in-core detector-based** reactor monitoring/protection systems.
- In-core detectors and pertinent systems:
 - 1) reduce i-SMR's **cost-effectiveness**,
 - 2) **are patented** by WEC, posing a **barrier to exports**.

Ex-core / core-exit thermocouple (CET) information may suffice for i-SMR.

- In i-SMR, as the reactor is much smaller:
 - 1) Distance from the central ass'y to the ex-core detector is shorter → much less blind spot.



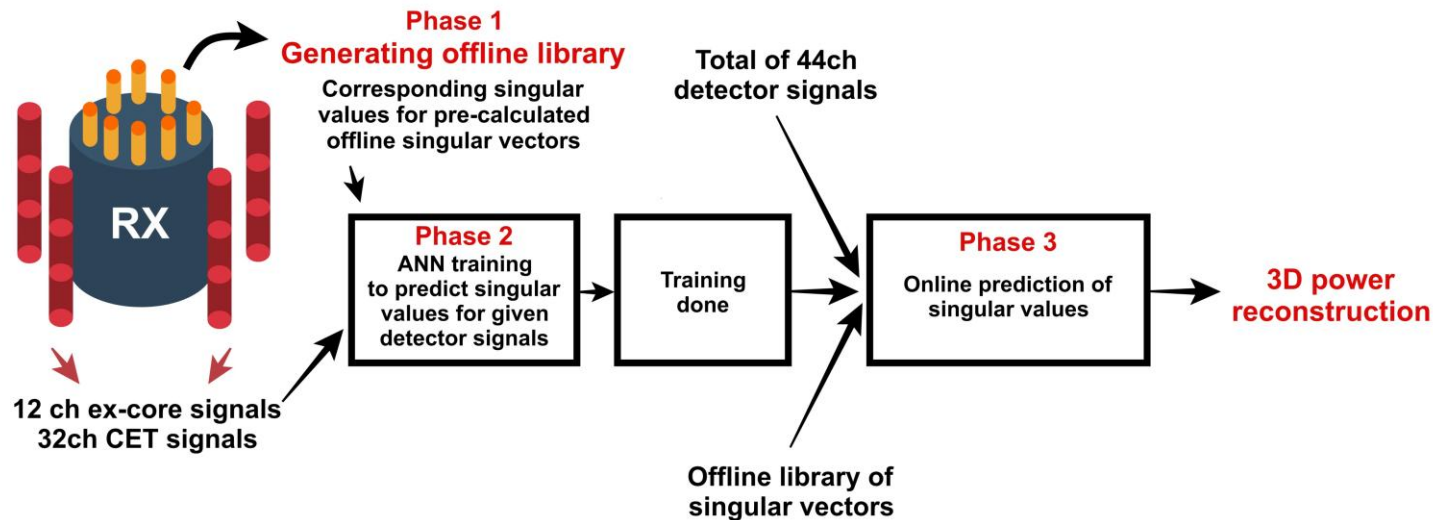
Preview

The goal

- To reconstruct an SMR-like reactor's **3D power distribution** using ex-core and core-exit thermocouple (CET) signals. ← **getting rid of commonly used in-core neutron flux detectors.**

Methodologies

- A combination of a traditional linear algebra technique – **singular value decomposition (SVD)** – with an artificial neural network.



Research specifics

- Target reactor system: ATOM⁽¹⁾ reactor, sharing the same core dimension as SMART-660 (69 ass'y, active core region height: 200cm).
- Dataset generation method: In-house nodal code, KANT⁽²⁾

Table of Contents

I. Introduction

1. Motivations
2. Preview

II. Methodologies

1. Singular value decomposition (SVD)
2. Ex-core detector response simulation
3. Assembly-wise thermocouple simulation
4. Neural network model structure

III. Numerical Results

1. Training Results
2. Validation Results
3. Fixed SAF vs variable SAF

IV. Summary & Conclusions

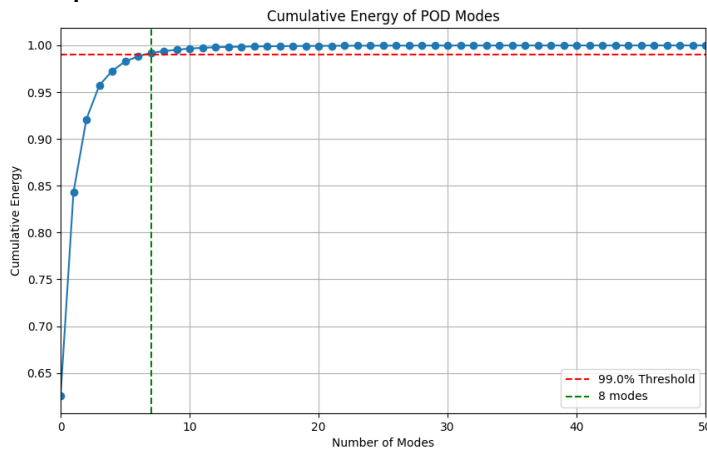
Singular value decomposition (SVD)

1. SVD allows us to extract dominant spatial modes of many power distributions.

- With given set of power distributions (matrix A), we can decompose the matrix, such that $A = U\Sigma V^T$.
- U : spatial modes, Σ : mode strength, V^T : coefficients per sample
- → **extract the orthonormal basis (U) in advance**, and **ANN guesses only the coefficients real-time ($c = \Sigma V^T$)**.

2. Utilising a few SVD modes **should, and could,** be sufficient.

- A power distribution consists of multiple modes, and **SVD is one of the efficient way of dimension reduction**.
- Higher order, oscillating modes contribute less to the power distribution and **are hardly captured by ex-core detectors** → w/o in-core detectors, observation of higher order modes are almost impossible.



← For our dataset, **8 modes were sufficient** to represent **99%** of the total power distribution

Ex-core detector response simulation

Simulation of the NN model's **first input, ex-core detector response**.

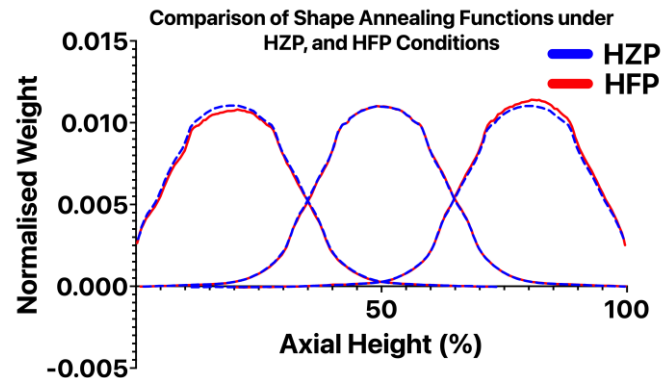
- The **Radial Weighting Function (RWF)** calculates the **radial 2D contribution** to ex-core detector signals.
- The **Shape Annealing Function (SAF)** determines **the axial 1D contribution** to ex-core detector signals.
- **2D RWF x 1D SAF = 3D power weighting factor** at each location.

RWF

1	0	0	0	0	1.00 E-04	3.80 E-03			
2	0	0	0	0	0	1.30 E-03	6.28 E-02		
3	0	0	0	0	0	4.00 E-04	1.59 E-02	6.43 E-01	
4	0	0	0	0	0	1.00 E-04	3.50 E-03	2.23 E-01	
5	0	0	0	0	0	0	8.00 E-04	3.88 E-02	
6	0	0	0	0	0	0	2.00 E-04	5.10 E-03	
7	0	0	0	0	0	0	0	9.00 E-04	
8	0	0	0	0	0	0	0	0	
9	0	0	0	0	0	0	0	0	
	A	B	C	D	E	F	G	H	I

X

SAF (fixed/variable)



= 3D ex-core
detector
weights

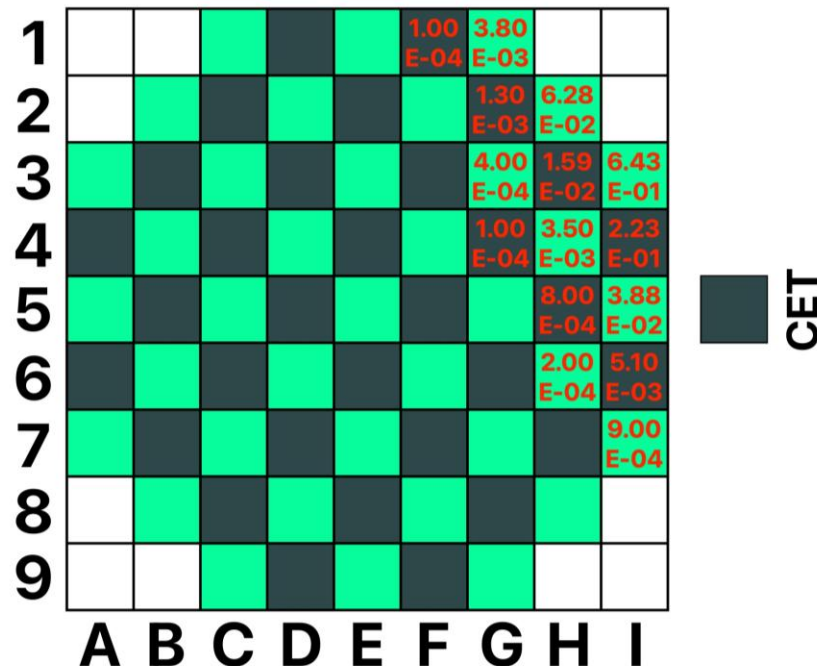
- SMART-660 RWF and SAF calculated with DORT code⁽³⁾ was used as **SMART-660 and ATOM reactor share the same core layout and dimension**.

Assembly-wise thermocouple simulation

Simulation of the NN model's **second input, core-exit thermocouple(CET) signals**.

- **CET signals** are approximated as the **axial integral power of assemblies**, providing the axially integrated **radial power distribution** to the model.
- 32 out of 69 assemblies assumed as equipped with CETs, following the **checker-board pattern** as shown below.

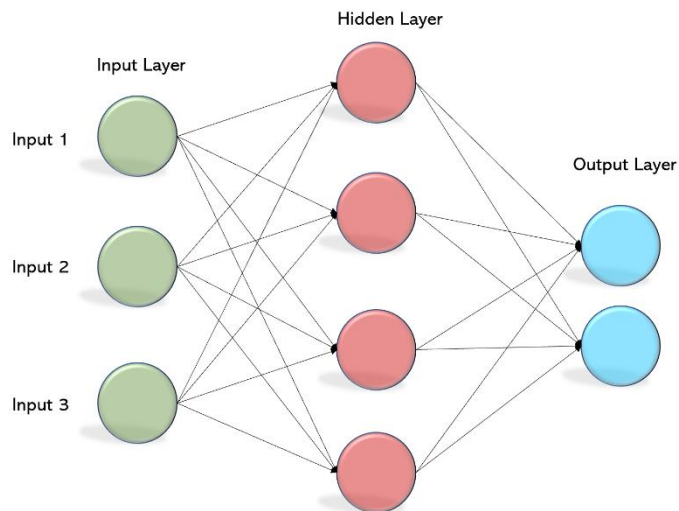
Core Map of RWF Distribution and CET Positions



Neural network model structure

Input: ex-core & CET **signals.**

Output: predicted singular **values.**



Parameter	Value / Specification
Input Shape	(44,)
Hidden Layer 1	Dense (4096)
Hidden Layer 2	Dense (1024)
Hidden Layer 3	Dense (256)
Output Shape	(30,) - (256,)
Optimiser	Adam
Epochs	300 (with early stopping)

Model version	1st layer	2nd layer	3rd layer	SVD modes	Loss
Funnel-M256	4096	1024	256	256	Singular value
Funnel-M192	4096	1024	256	192	Singular value
Funnel-M128	4096	1024	256	128	Singular value
Funnel-M96	4096	1024	256	96	Singular value
Funnel-M50	4096	1024	256	50	Singular value
Funnel-M44	4096	1024	256	44	Singular value
Funnel-M30	4096	1024	256	30	Singular value

Table of Contents

I. Introduction

1. Motivations
2. Preview

II. Methodologies

1. Singular value decomposition (SVD)
2. Ex-core detector response simulation
3. Assembly-wise thermocouple simulation
4. Neural network model structure

III. Numerical Results

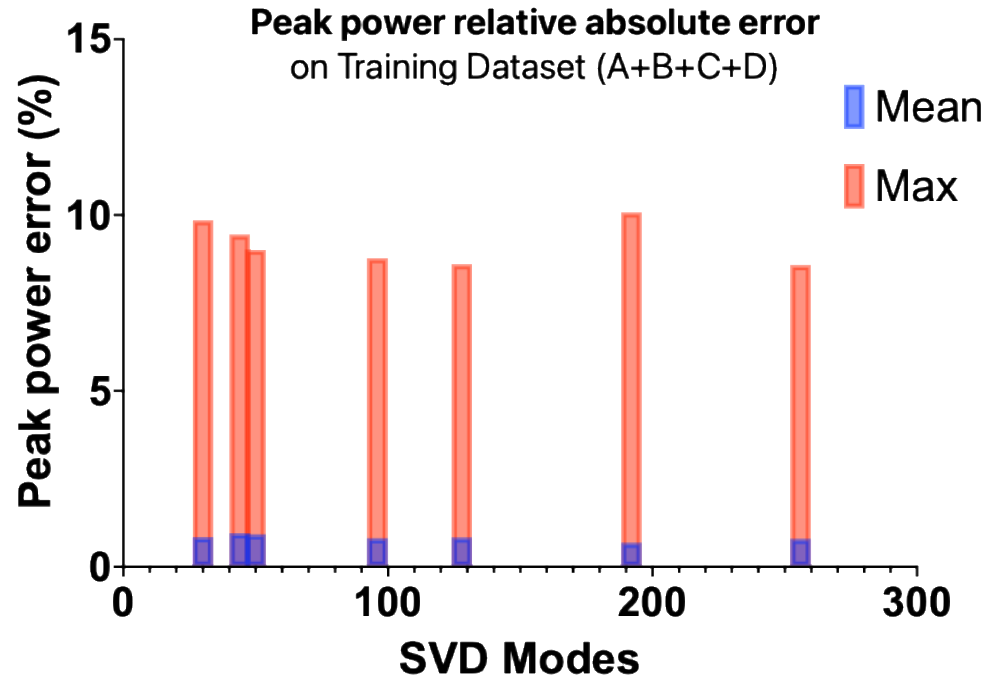
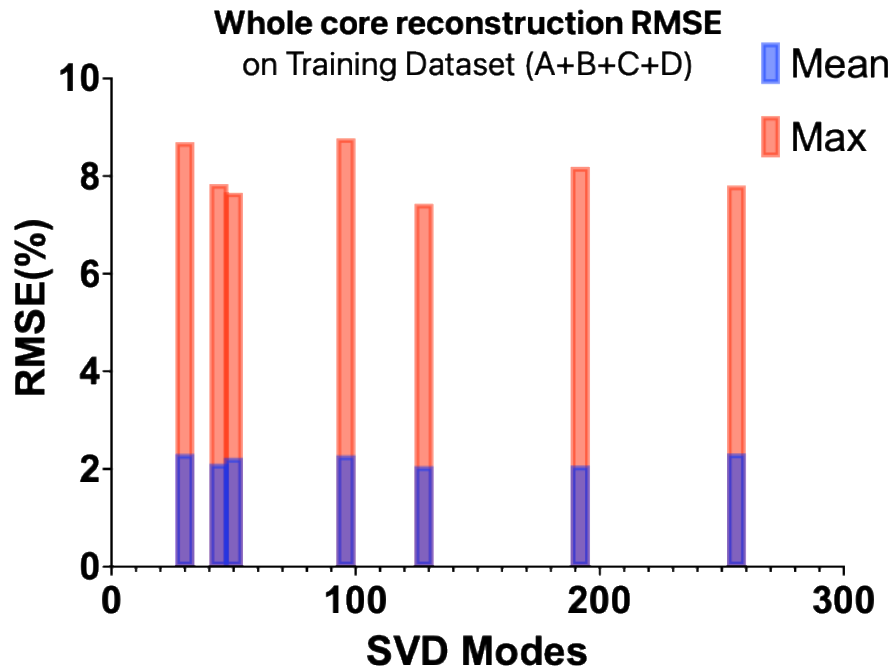
1. Training Results
2. Validation Results
3. Fixed SAF vs variable SAF

IV. Summary & Conclusions

Training performance

Training performance:

- **Mean 2.06%**, **max 7.44%** for whole core reconstruction RMSE.
- **Mean 0.69%**, **max 8.58%** for peak power absolute relative error.



Validation result - Dataset A

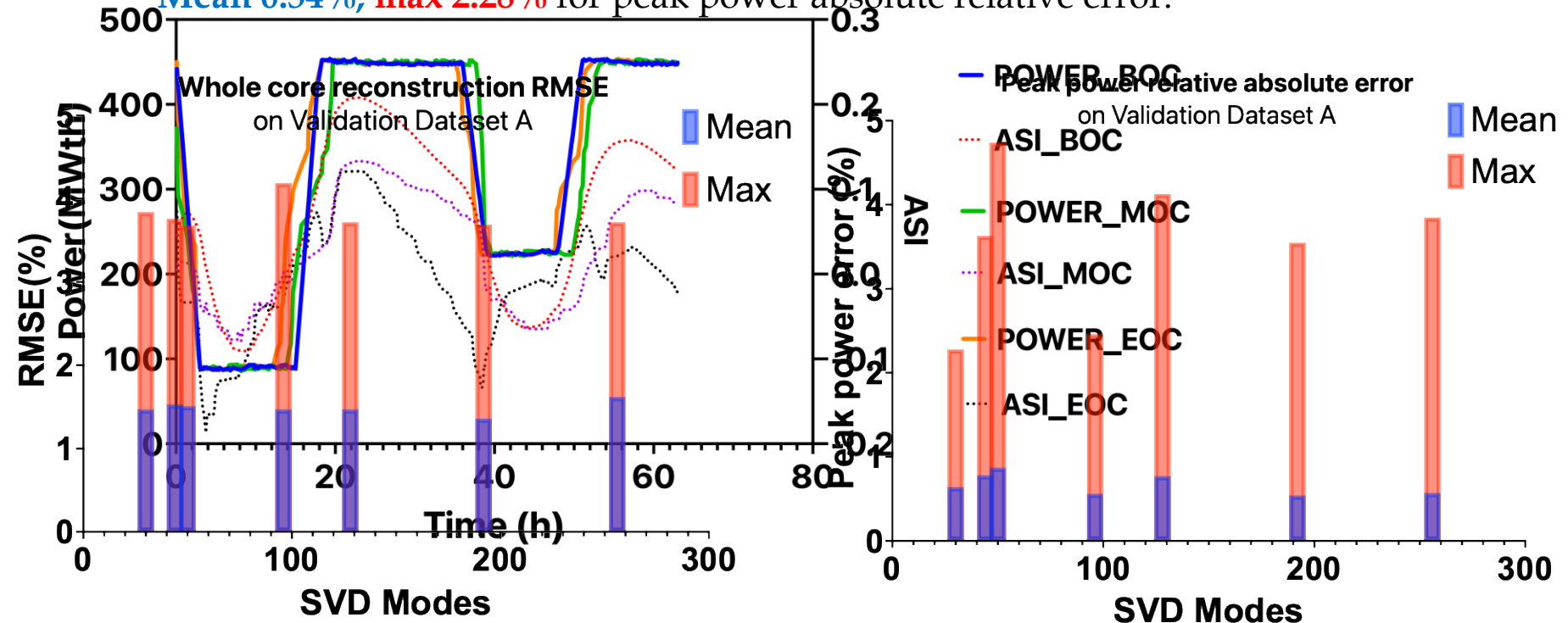
Dataset A:

- Rather slow, steady transient scenario with reasonably good performance.

- Mean 1.36%, max 3.68% for whole core reconstruction RMSE.

Power and ASI distribution of Dataset A

- Mean 0.54%, max 2.28% for peak power absolute relative error.



Validation result - Dataset B

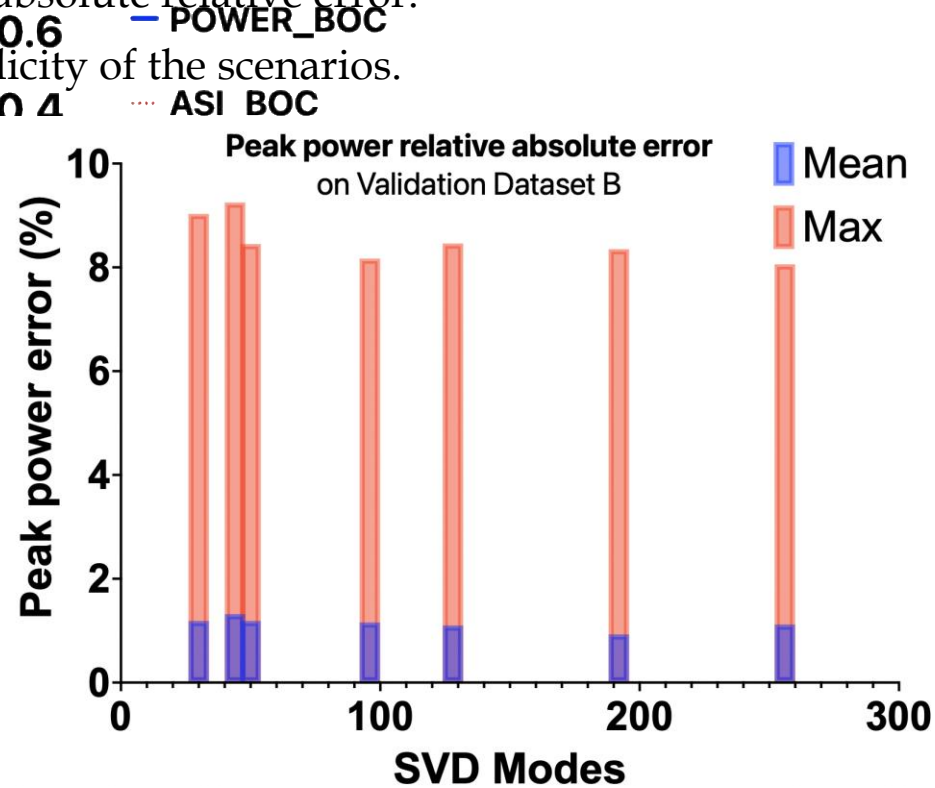
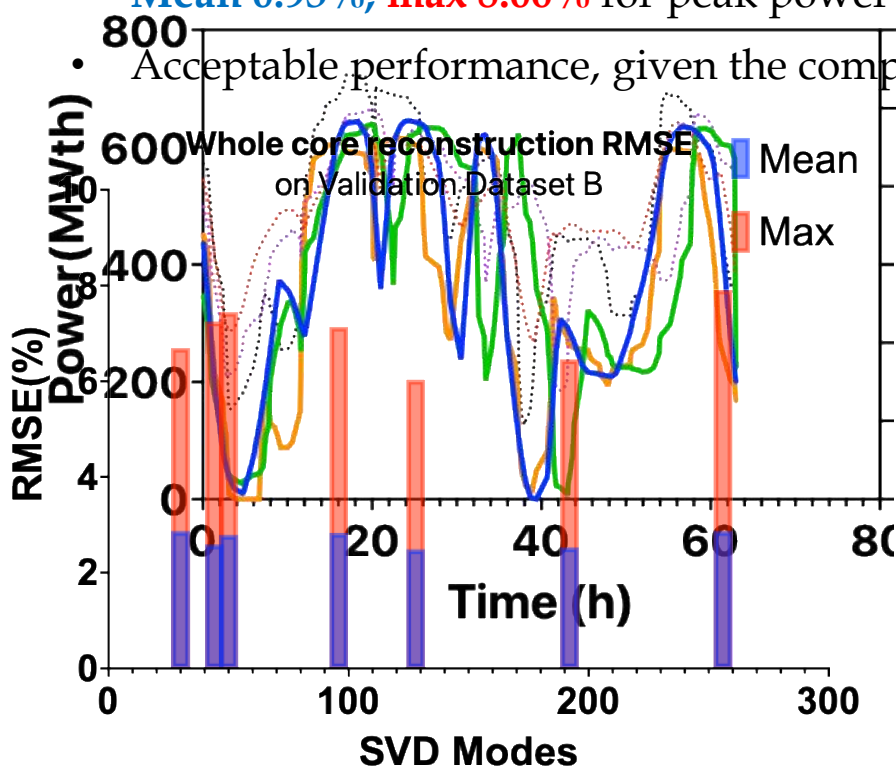
Dataset B:

- Central rod fully withdrawn, other rods controlled completely arbitrarily

- **Mean 2.49%, max 6.03%** for whole core reconstruction RMSE.

- **Mean 0.93%, max 8.06%** for peak power absolute relative error.

- Acceptable performance, given the complexity of the scenarios.



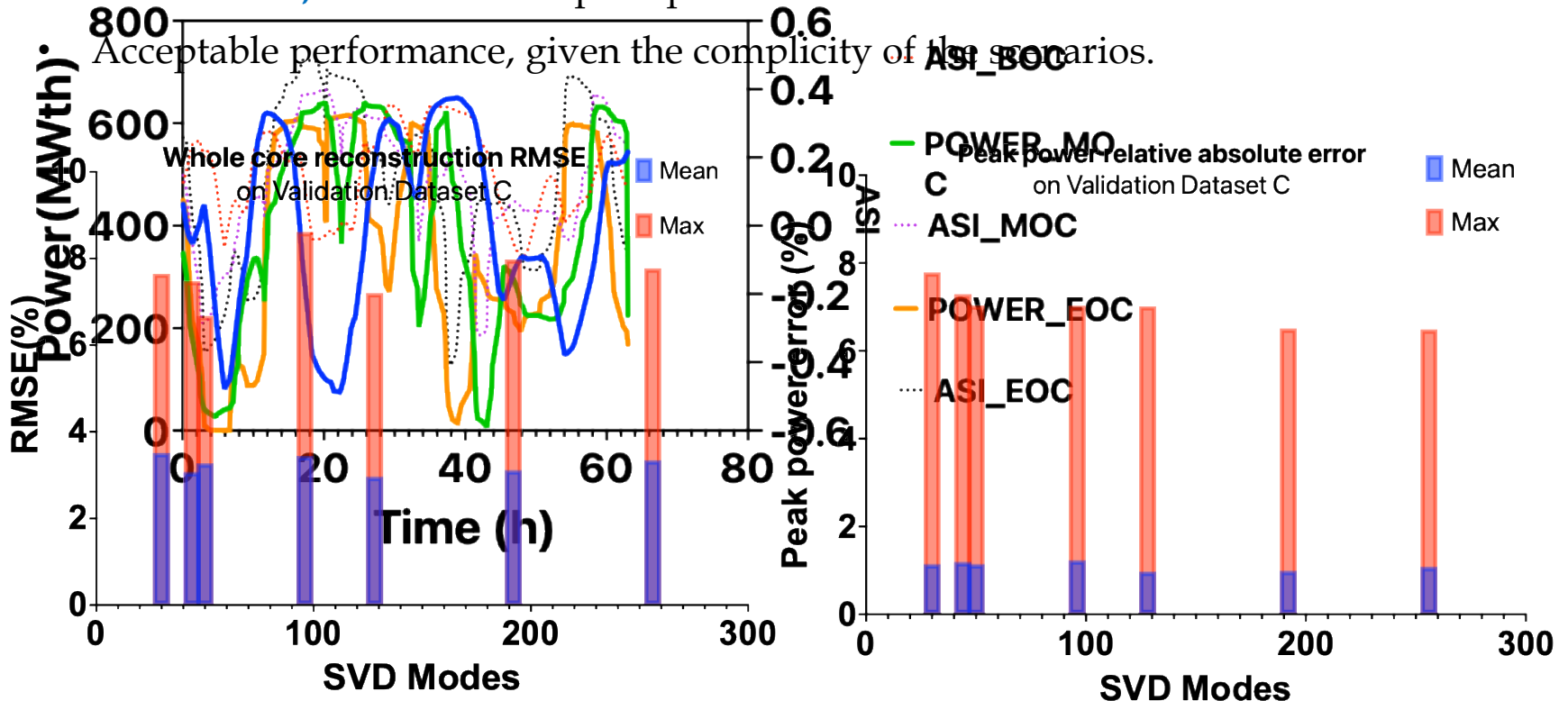
Validation result - Dataset C

Dataset C:

- All control rods controlled randomly

- Mean 2.96%, max 6.16% for whole core reconstruction RMSE.

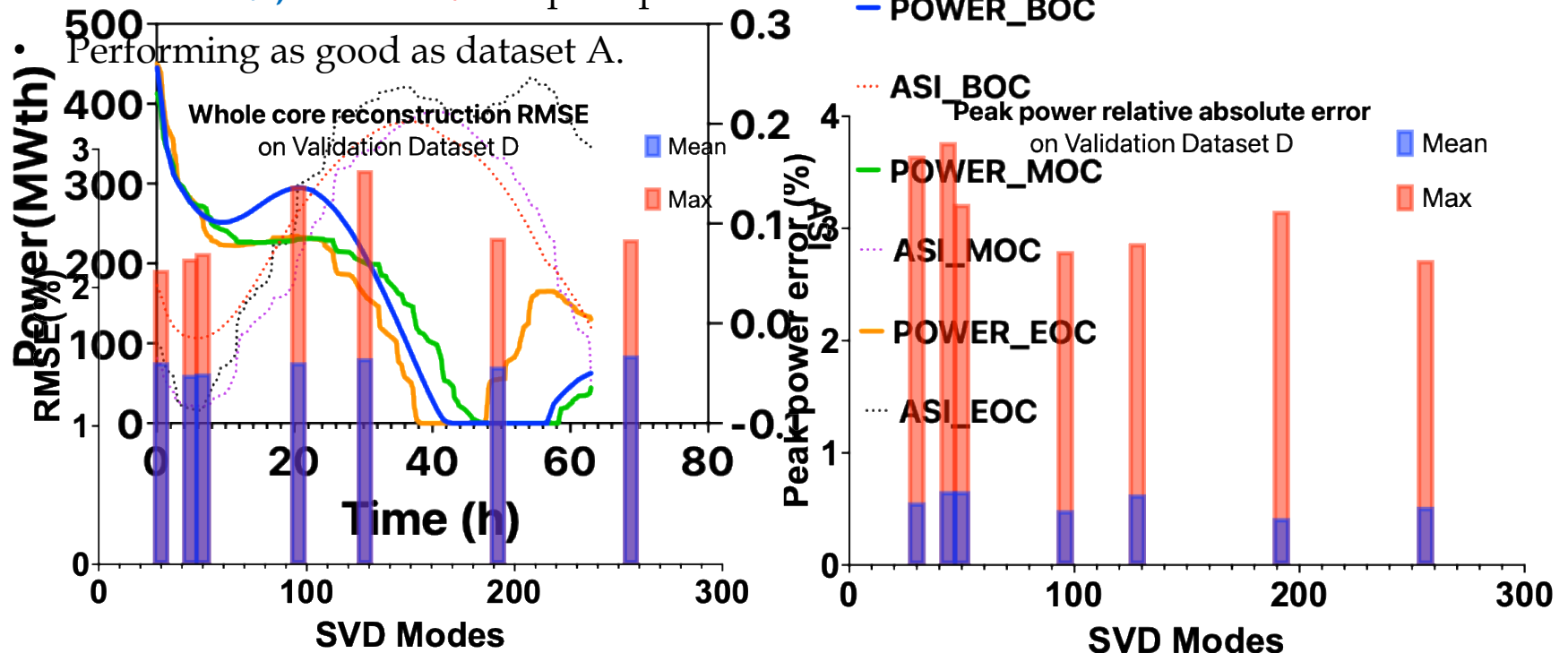
- Mean 0.97%, max 6.49% for peak power absolute relative error.



Validation result – Dataset D

Dataset D:

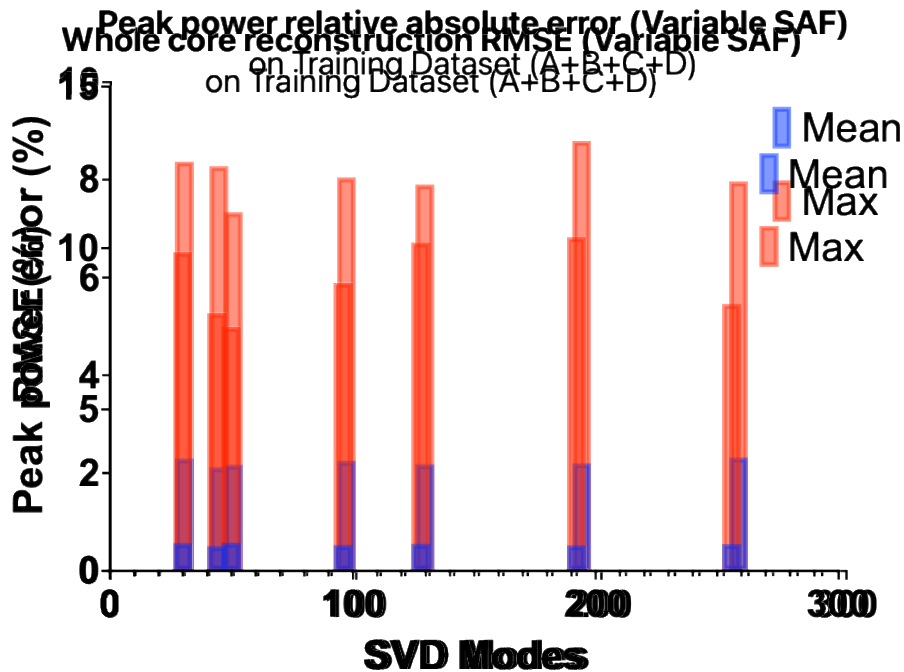
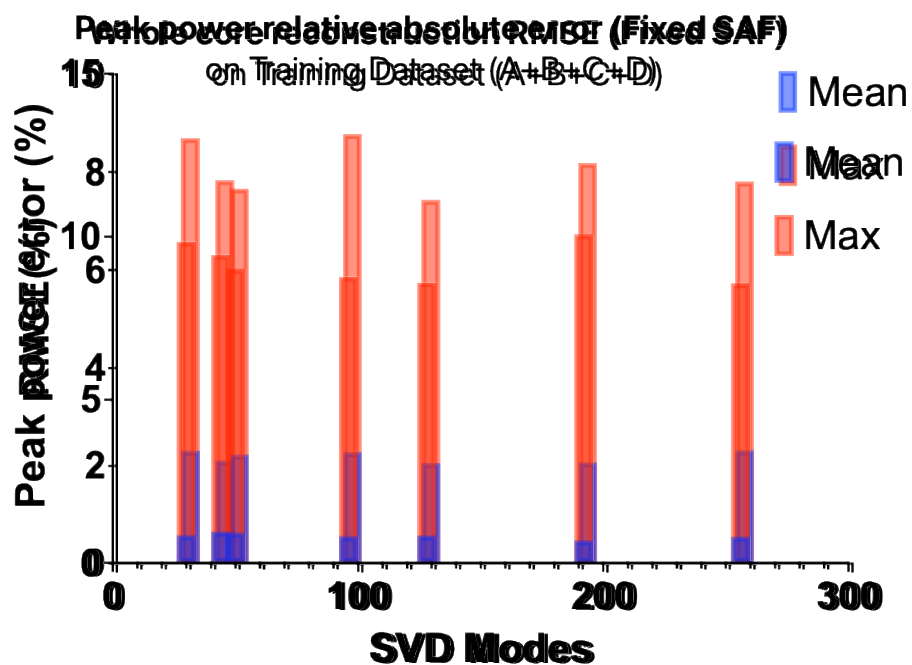
- Simultaneous, gradual insertion of all control rods.
- Mean 1.37%, max 2.13% for whole core reconstruction RMSE.
- Mean 0.42%, max 2.72% for peak power absolute relative error.
- Performing as good as dataset A.



Validation result – fixed SAF vs variable SAF

The effect of SAF formulation on reconstruction accuracy was marginal.

- The model demonstrates insensitivity to minor variations in the shape annealing function, suggesting robust performance.



Summary & Conclusion

Key Findings:

- The SVD-augmented ANN model shows good power reconstruction performance, even under extreme transient scenarios.
- The SVD-ANN model was found insensitive to the variation of axial shape annealing functions, proving its robustness.

Future Works:

- Future works include, but not limited to, (1) the systematic analysis on the relationships between the number of SVD modes and the reconstruction accuracy, (2) inclusion of more input parameters that may improve the performance (e.g. control rod positions, etc.), (3) optimising the model to make it light enough to run on safety-graded computers.

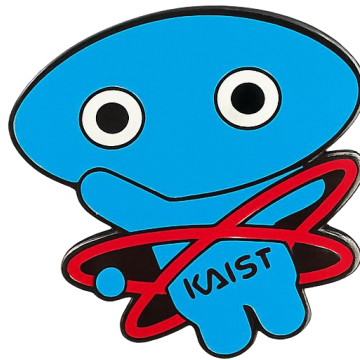
References

1. Jeong, Y., Choi, D., Oh, T., & Kim, Y. Load-Follow Operation Capability of Soluble Boron-Free Small Modular Reactor ATOM. *Frontiers in Energy Research*, 13, 1639569.
2. Oh, Taesuk, et al. "Development and validation of multiphysics PWR core simulator KANT." *Nuclear Engineering and Technology* 55.6 (2023): 2230-2245.
3. Roh, G., Kim, K. S., Koo, B. S., Lee, C. C., & Kim, K. Y. (2008). Ex-Core detector response evaluation of the SMART reactor by using the DORT code. *Journal of Nuclear Science and Technology*, 45(sup5), 78-81.
4. Li W. et al., Core power distribution reconstruction using artificial neural networks, *Nucl. Eng. Technol.*, 54 (2022) 617-626.
5. Urase Y. et al., POD-based in-core power distribution reconstruction using ex-core detectors for HTGRs, *J. Nucl. Sci. Technol.*, 2025.

This work was supported by the Innovative Small Modular Reactor Development Agency grant funded by the Korea Government (MIST/MCEE) (No. RS-2024-00405419) and by the Korea Energy Technology Evaluation and Planning (KETEP) grant funded by the Korean Government (MTIE) (No. RS-2024-00439210).

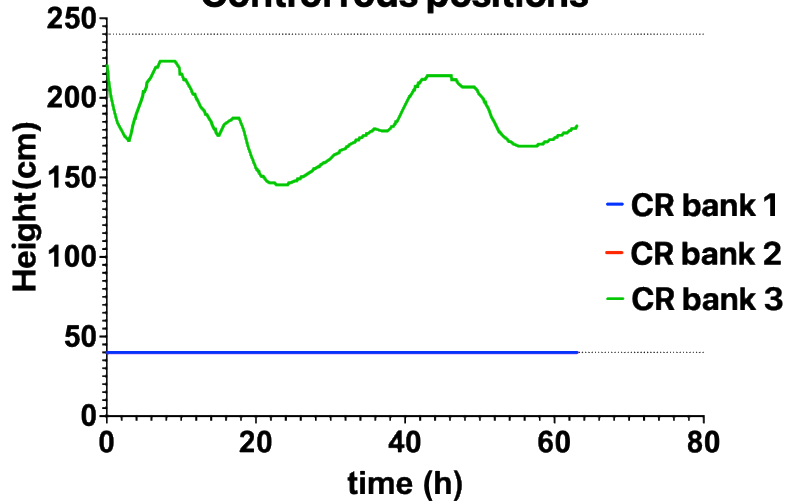
Thank you

Any questions?

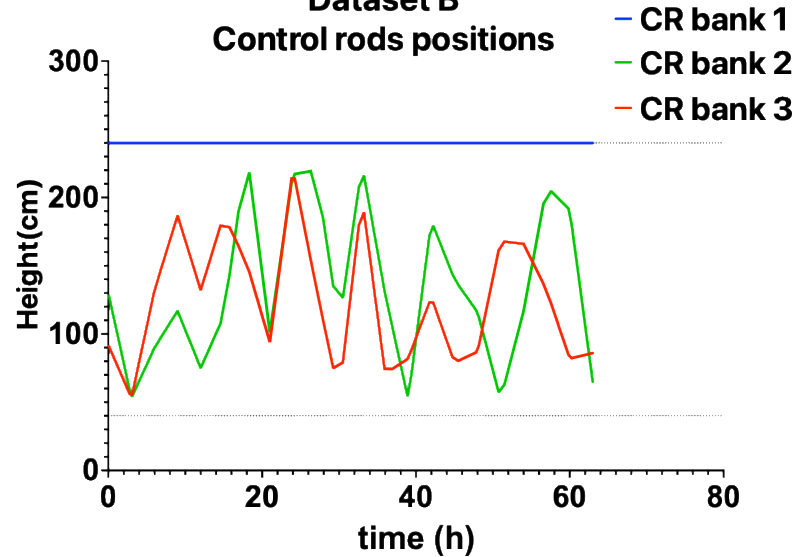


Dataset A-D control rod position evolution

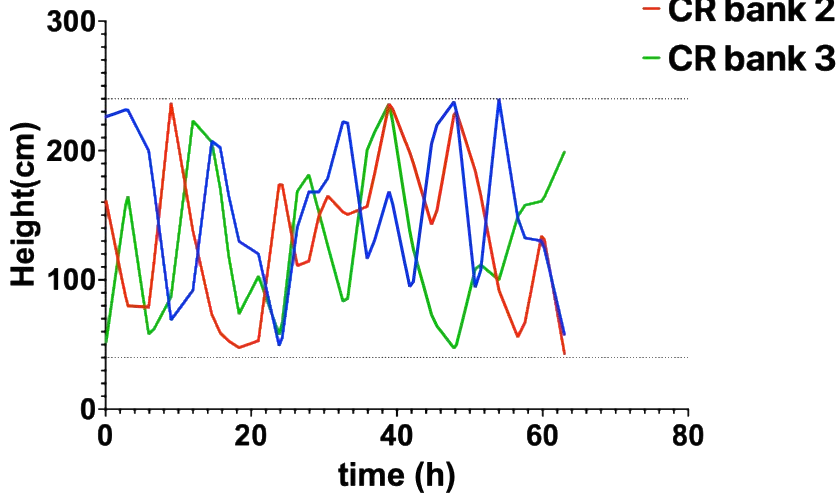
Dataset A
Control rods positions



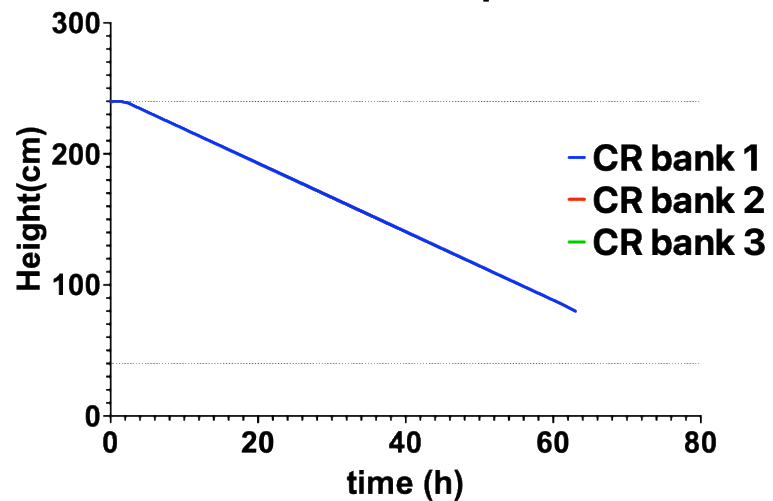
Dataset B
Control rods positions



Dataset C
Control rods positions



Dataset D
Control rods positions



Evaluation Metrics

Metric 1:

- **Whole core root mean square error(RMSE)**

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

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

Metric 2:

- **Peak power absolute relative error**

$$Error = \left| \frac{Peak\ power_{i,j,k}^{ANN} - Peak\ power_{i,j,k}^{Actual}}{Peak\ power_{i,j,k}^{Actual}} \right|$$

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

Dataset generation

Training data generation method:

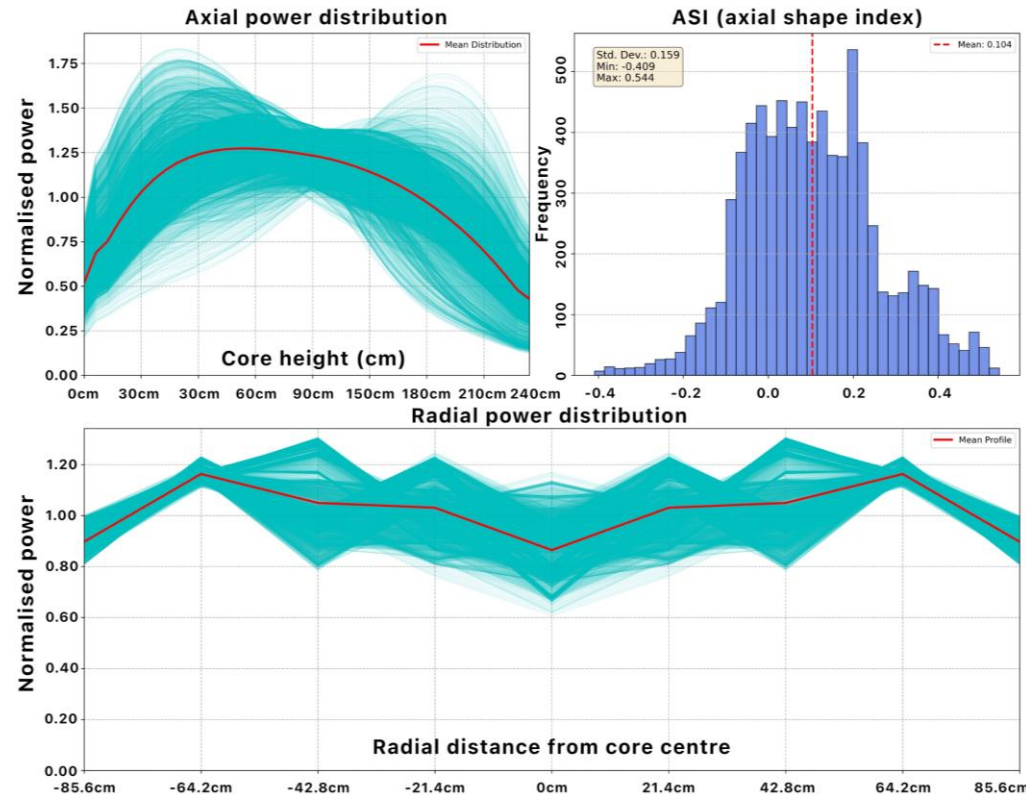
- Simulation using a PWR core simulator, KANT [1].

Simulated reactor type:

- ATOM reactor[2].

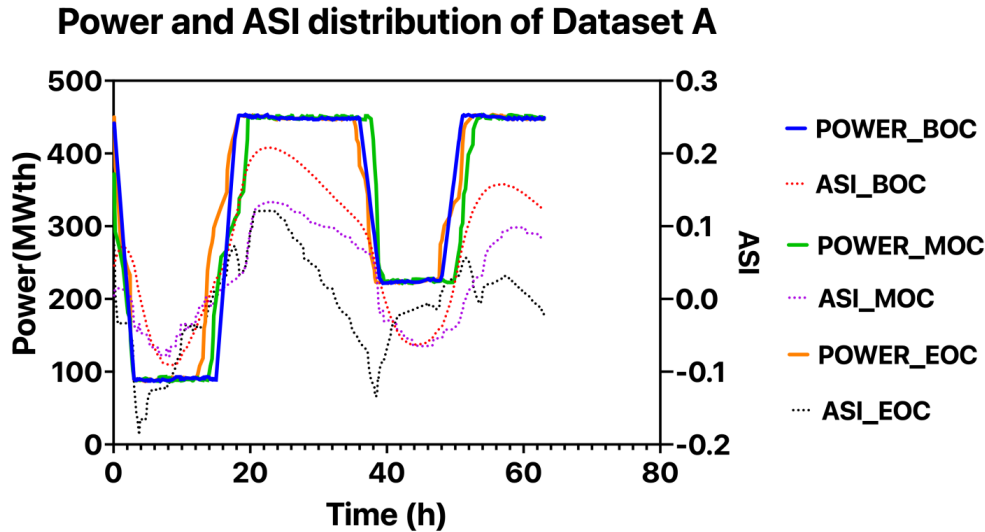
Simulation scenarios:

- Dataset A: **Load-follow operation.**
- Dataset B: Central control rod fixed, other rods manipulated arbitrarily.
- Dataset C: All control rods arbitrarily controlled.
- Dataset D: All control rods' gradual insertion over 63 hours.



Integral analysis of 4 dataset scenarios

Validation result – Dataset A



Dataset A:

- Rather slow, steady transient scenario.
- Reasonably good performance.

Whole-core reconstruction RMSE on validation Dataset A

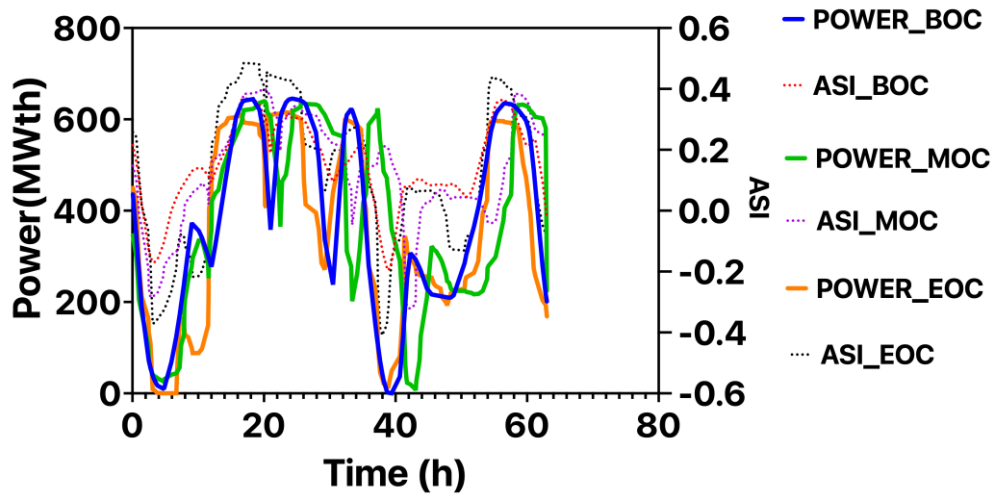
Model	Mean	Max	Min	Modes
Funnel-M256	1.62%	3.72%	0.79%	1.62%
Funnel-M192	1.36%	3.69%	0.64%	1.36%
Funnel-M128	1.47%	3.72%	0.72%	1.47%
Funnel-M96	1.47%	4.19%	0.62%	1.47%
Funnel-M50	1.51%	3.68%	0.65%	1.51%
Funnel-M44	1.53%	3.76%	0.64%	1.53%
Funnel-M30	1.47%	3.84%	0.74%	1.47%

Peak power absolute relative error on validation Dataset A

Model	Mean	Max	Min	Modes
Funnel-M256	0.57%	3.85%	0.00%	0.57%
Funnel-M192	0.54%	3.55%	0.00%	0.54%
Funnel-M128	0.77%	4.13%	0.00%	0.77%
Funnel-M96	0.56%	2.46%	0.00%	0.56%
Funnel-M50	0.87%	4.74%	0.00%	0.87%
Funnel-M44	0.78%	3.63%	0.00%	0.78%
Funnel-M30	0.64%	2.28%	0.01%	0.64%

Validation result - Dataset B

Power and ASI distribution of Dataset B



Dataset B:

- The hardest transient among all considered scenarios (central rod fully withdrawn, other rods controlled completely arbitrarily)
- **Acceptable performance, given the complicity of the scenarios.**

Whole-core reconstruction RMSE on validation Dataset B

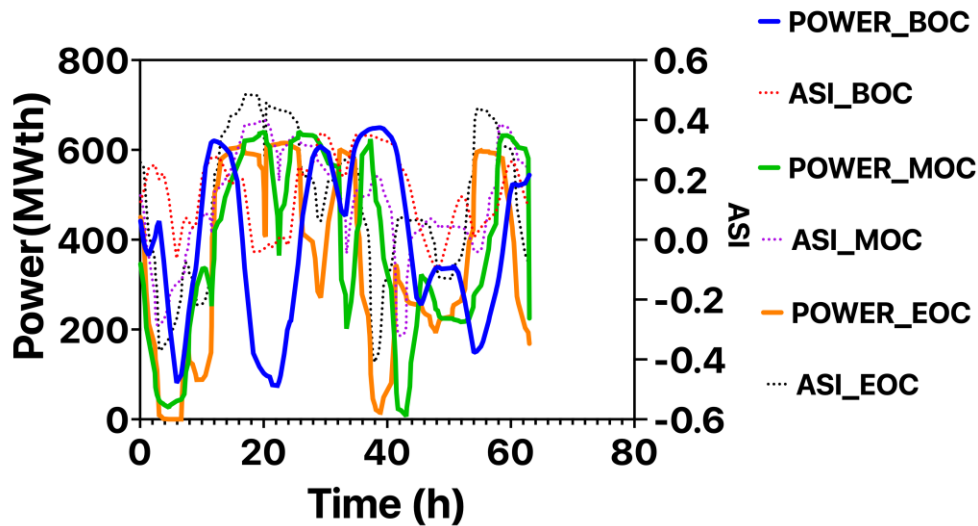
Model	Mean	Max	Min	Modes
Funnel-M256	2.87%	7.92%	1.51%	256
Funnel-M192	2.53%	6.46%	1.17%	192
Funnel-M128	2.49%	6.03%	1.28%	128
Funnel-M96	2.83%	7.14%	1.23%	96
Funnel-M50	2.79%	7.45%	1.23%	50
Funnel-M44	2.59%	7.25%	1.17%	44
Funnel-M30	2.87%	6.70%	1.36%	30

Peak power absolute relative error on validation Dataset B

Model	Mean	Max	Min	Modes
Funnel-M256	1.12%	8.06%	0.01%	256
Funnel-M192	0.93%	8.35%	0.00%	192
Funnel-M128	1.10%	8.46%	0.01%	128
Funnel-M96	1.16%	8.17%	0.00%	96
Funnel-M50	1.19%	8.45%	0.00%	50
Funnel-M44	1.32%	9.25%	0.00%	44
Funnel-M30	1.19%	9.03%	0.00%	30

Validation result - Dataset C

Power and ASI distribution of Dataset C



Dataset C:

- All control rods controlled randomly ← easier than dataset B.

Whole-core reconstruction RMSE on Validation Dataset C

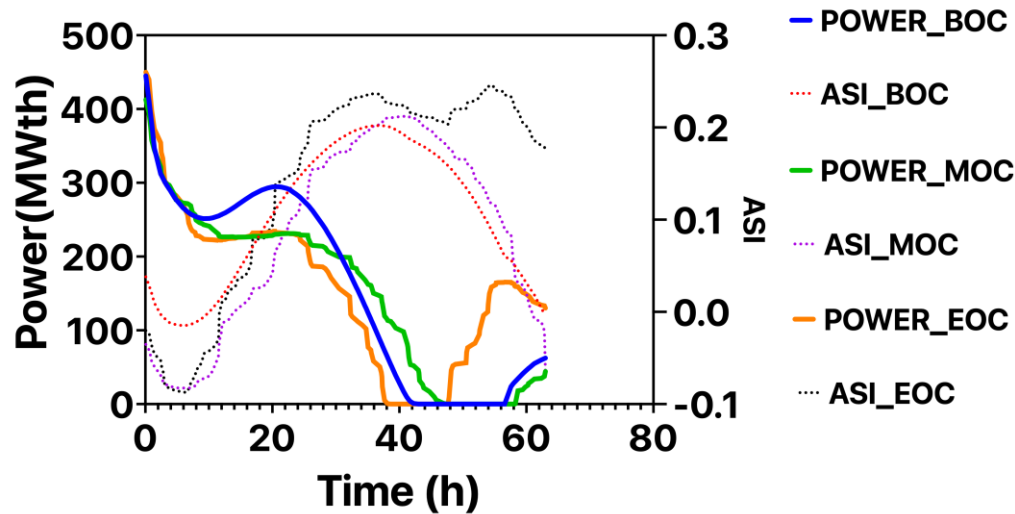
Model	Mean	Max	Min	Modes
Funnel-M256	3.34%	7.77%	1.71%	256
Funnel-M192	3.11%	7.98%	1.40%	192
Funnel-M128	2.96%	7.20%	1.50%	128
Funnel-M96	3.44%	8.61%	1.73%	96
Funnel-M50	3.27%	6.67%	1.72%	50
Funnel-M44	3.07%	7.48%	1.46%	44
Funnel-M30	3.51%	7.65%	1.62%	30

Peak power absolute relative error on validation Dataset C

Model	Mean	Max	Min	Modes
Funnel-M256	1.08%	6.49%	0.00%	256
Funnel-M192	0.99%	6.51%	0.00%	192
Funnel-M128	0.97%	7.02%	0.00%	128
Funnel-M96	1.23%	7.03%	0.00%	96
Funnel-M50	1.14%	7.04%	0.00%	50
Funnel-M44	1.19%	7.29%	0.01%	44
Funnel-M30	1.14%	7.79%	0.01%	30

Validation Result – Dataset D

Power and ASI distribution of Dataset D



Dataset D:

- Simultaneous, gradual insertion of all control rods.
- Performing as good as dataset A.

Whole-core reconstruction RMSE on Validation Dataset D

Model	Mean	Max	Min	Modes
Funnel-M256	1.51%	2.35%	1.0%	256
Funnel-M192	1.43%	2.36%	0.93%	192
Funnel-M128	1.49%	2.85%	1.05%	128
Funnel-M96	1.46%	2.74%	0.71%	96
Funnel-M50	1.38%	2.25%	0.95%	50
Funnel-M44	1.37%	2.21%	0.94%	44
Funnel-M30	1.46%	2.13%	1.07%	30

Peak power absolute relative error on validation Dataset D

Model	Mean	Max	Min	Modes
Funnel-M256	0.52%	2.72%	0.00%	256
Funnel-M192	0.42%	3.16%	0.00%	192
Funnel-M128	0.63%	2.87%	0.00%	128
Funnel-M96	0.49%	2.80%	0.00%	96
Funnel-M50	0.66%	3.22%	0.00%	50
Funnel-M44	0.66%	3.77%	0.00%	44
Funnel-M30	0.56%	3.65%	0.00%	30