

Deep Learning for 3-D Power Profile Prediction Using Both Ex-core Neutron Detector and In-core Temperature Data in Small Modular Reactors



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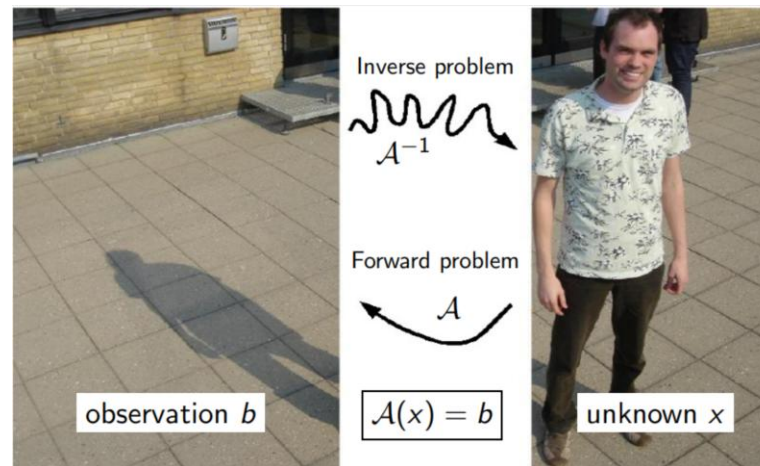
Motivation & Objectives (1/3)

Possibility of Getting Rid of In-core Detectors in i-SMR

- Korean i-SMR design still relies on **in-core detector-based** reactor monitoring/protection systems.
- However, high cost of in-core detectors reduces i-SMR's **cost-effectiveness**, and the monitoring/protection systems **patented** by WEC, poses a **barrier to exports**.

Novelty of This Work:

- Despite the **growing interest in AI for nuclear application**, **fully reconstructing 3D power distributions without in-core instrumentation**, as in our approach, **is rare** due to its complexity.
- This task is **an inverse problem**; when the power distribution is converted to instrument signals, significant information loss occurs, making the problem ill-posed.

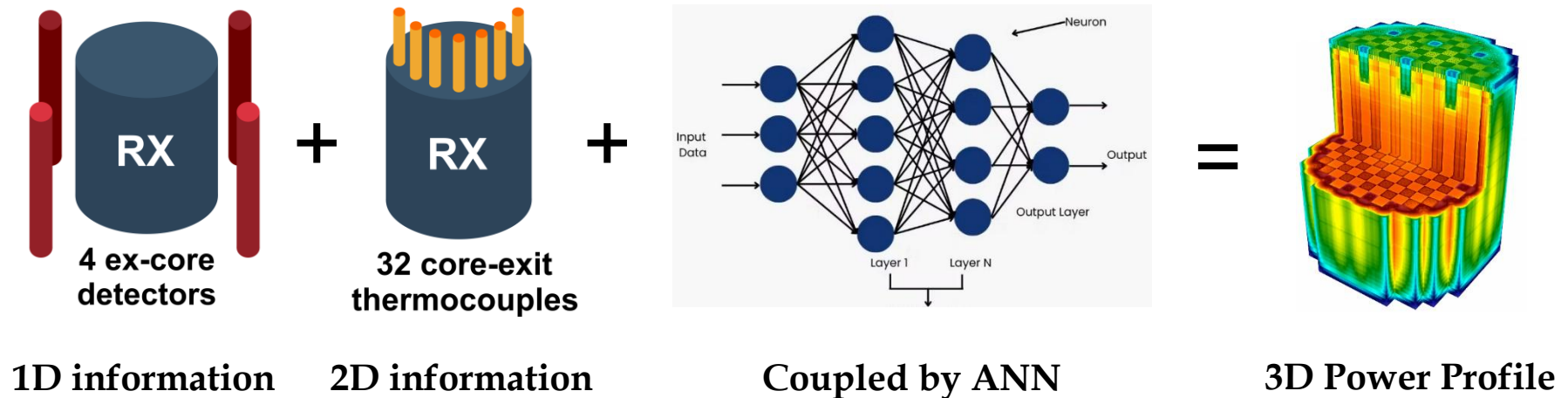


Shadows (signals) reveal the shape (power distribution) easily,
but **reversing the process is dauntingly difficult**.

Motivation & Objectives (2/3)

Solution to the Ill-Posedness of the Problem

1. Couple **1D axial information from ex-core detectors** with **2D radial information from core exit thermocouples(CET)** to yield complete 3D information.
2. **A neural network** integrates **four ex-core detector** signals and **32 CET signals** to accurately reconstruct the full 3D power distribution.



Motivation & Objectives (3/3)

Tactics of the Study

- 1st: **Generate multiple 3D power distributions** using a high-fidelity reactor analysis code.
- 2nd: Simulate the **corresponding ex-core and CET signals** through an appropriate conversion method.
- 3rd: **Train a neural network** model using the simulated input signals (ex-core and CET) and the reference 3D power distributions.
- 4th: **Validate** the trained model to assess **how well it predicts the 3D power distribution** from the detector signals.

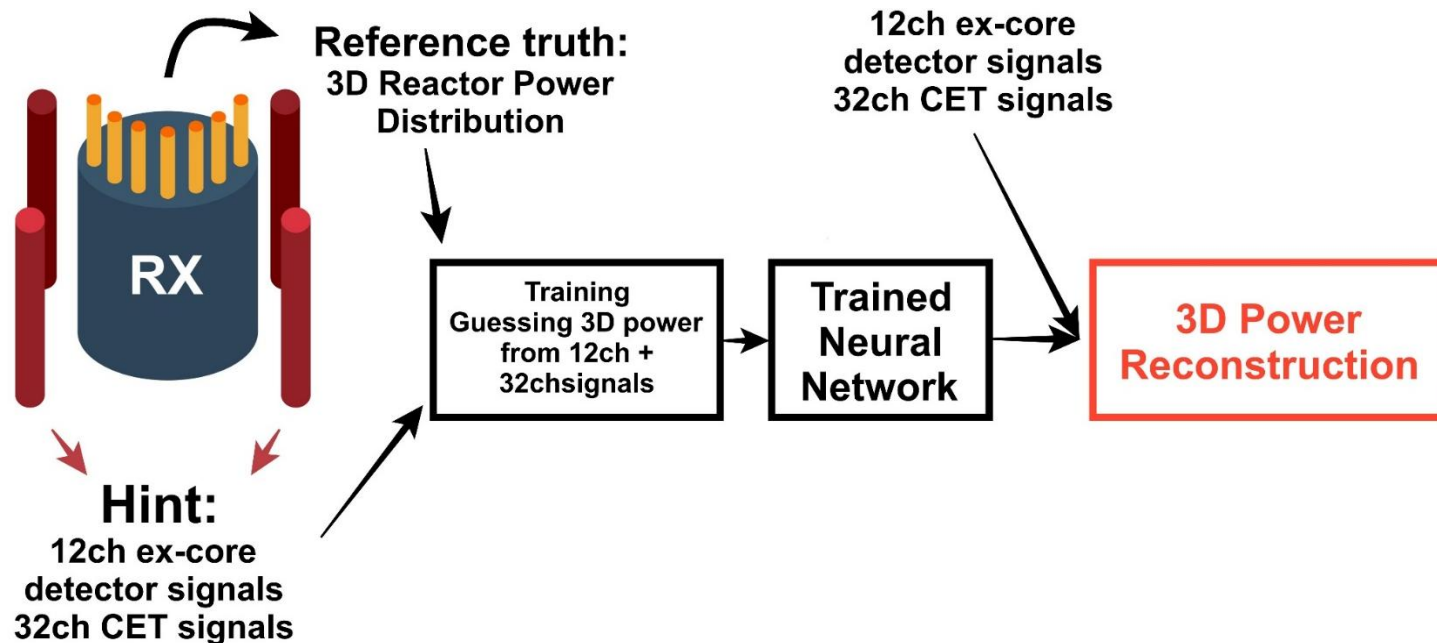


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Dataset Generation

Training data generation method:

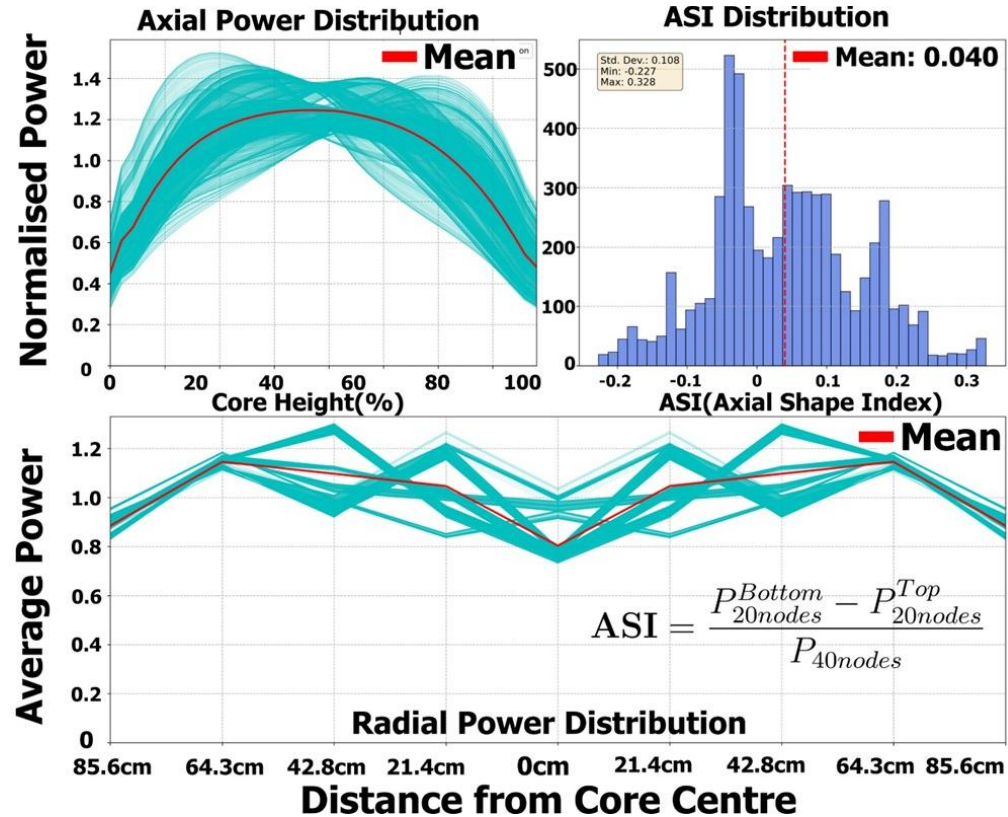
- Simulation using a PWR core simulator, KANT [1].

Simulated reactor type:

- ATOM reactor[2].

Simulation scenarios:

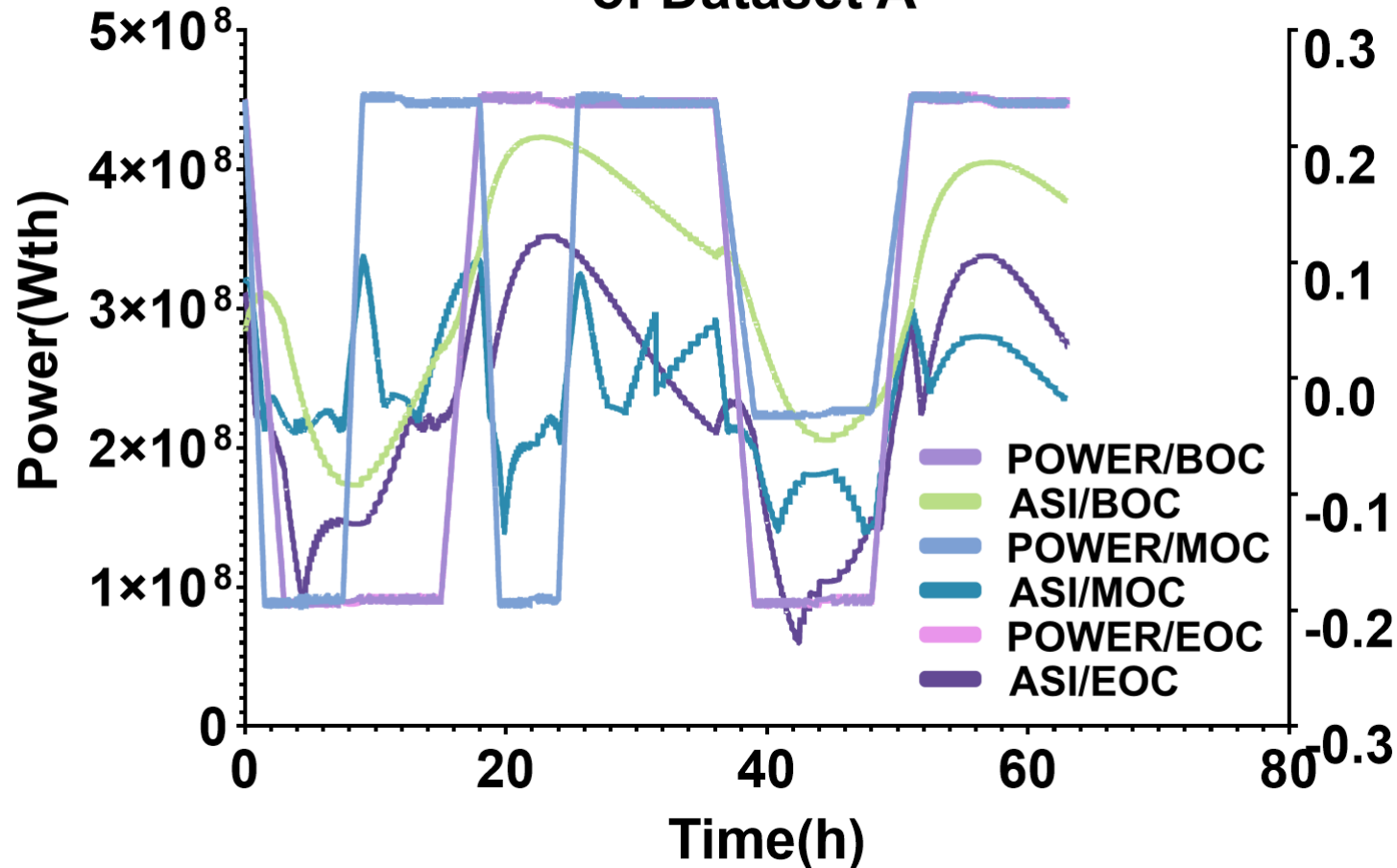
- Dataset A: **Load-follow operation**
- Dataset B: Manually controlled control rods, **rapid and spiky transient**
- Dataset C: Manually controlled control rods **overpower quasi-accident transient**



Integral analysis of 3 dataset scenarios

Dataset Generation - Dataset A

Power and ASI Distribution of Dataset A

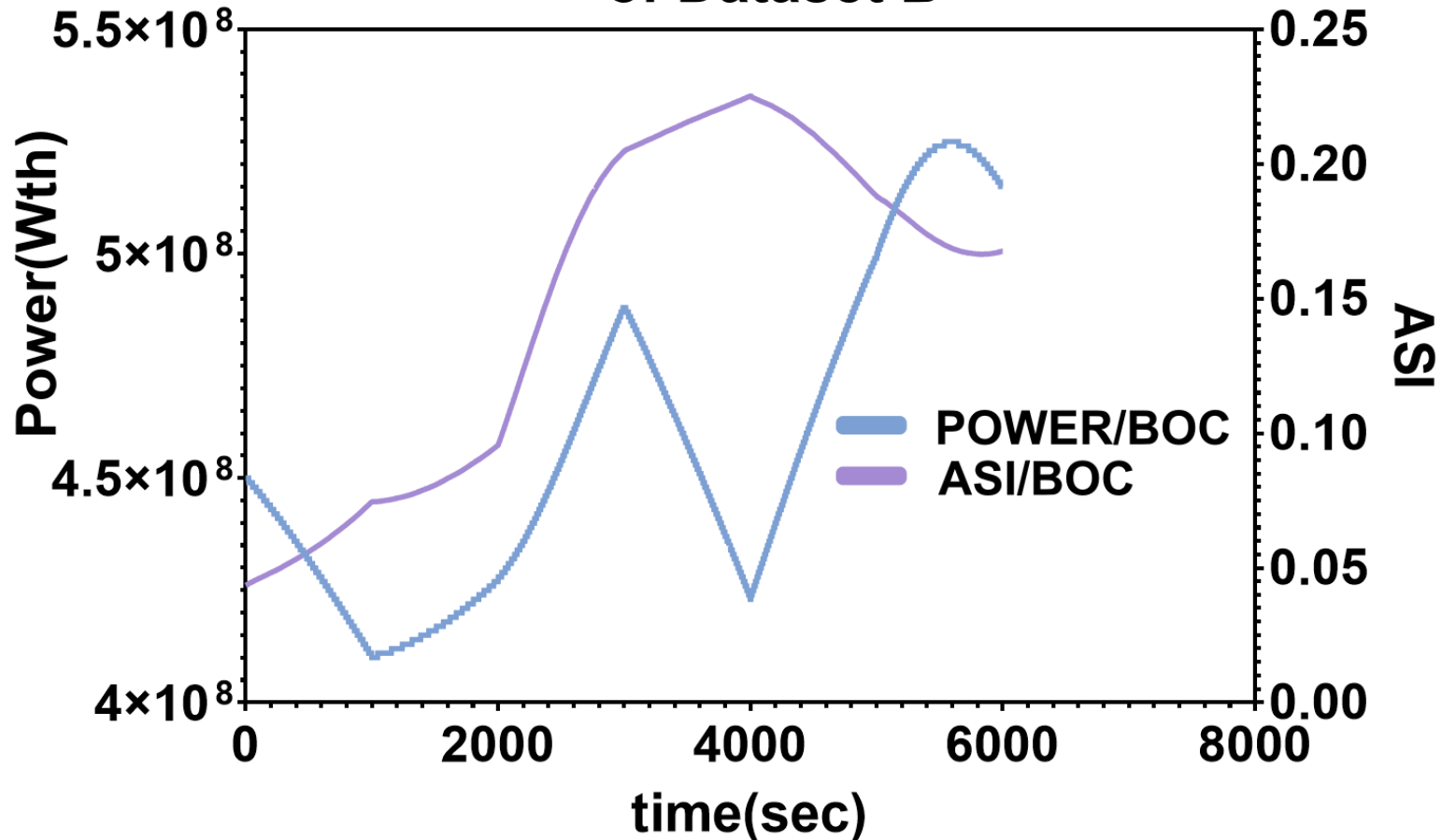


Total 11,342 load-follow Dataset

(4,865 used for training, 1,135 used for validation, separated at constant interval)

Dataset Generation - Dataset B

Power and ASI Distribution of Dataset B

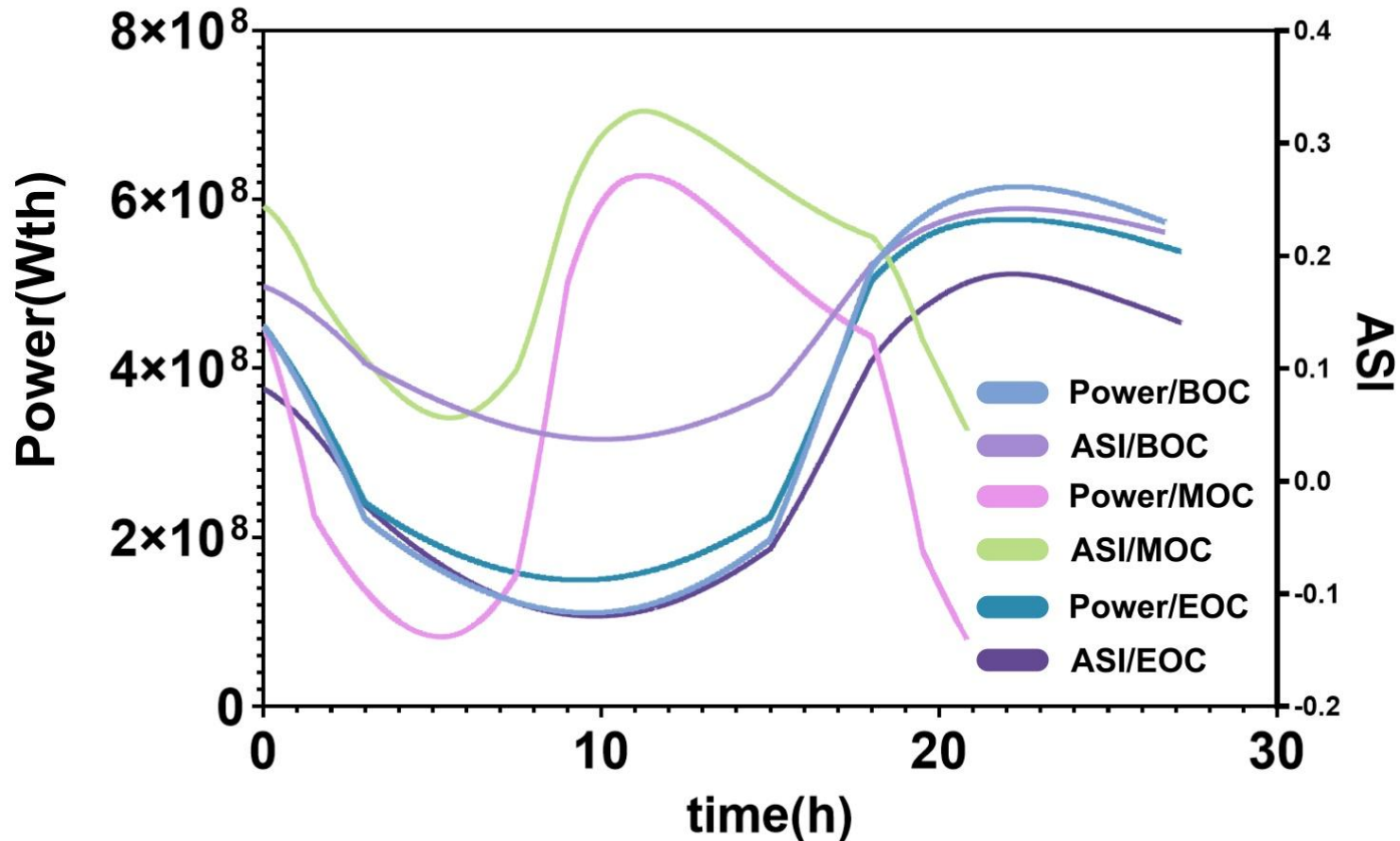


Total 3,001 **rapid, spiky transient** simulation data

(1,001 used for training, 2,000 used for validation, separated at constant interval)

Dataset Generation - Dataset C

Power and ASI Distribution of Dataset C



Total 5,382 **overpower transient** simulation data

(1,077 used for training, 431 used for validation, separated at constant interval)

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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.
- Two Radial Weighting Functions (RWFs): the raw-truncated RWF and the **extrapolated complete RWF**, where zero weights are filled using **one-tenth of the neighbouring values**.

Truncated RWF

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

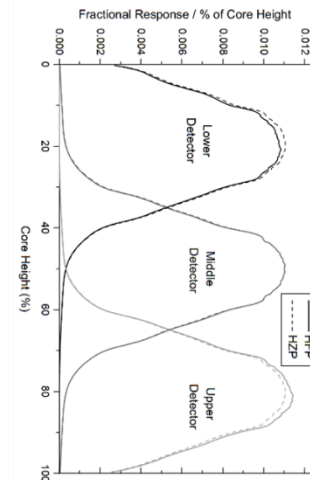
Complete RWF

1			1.000 E-07	1.000 E-06	1.000 E-05	1.000 E-04	3.800 E-03		
2		1.000 E-09	1.000 E-08	1.000 E-07	1.000 E-06	1.000 E-05	1.300 E-04	6.280 E-02	
3	4.000 E-10	4.000 E-09	4.000 E-08	4.000 E-07	4.000 E-06	4.000 E-05	4.000 E-04	1.590 E-02	6.427 E-01
4	1.000 E-10	1.000 E-09	1.000 E-08	1.000 E-07	1.000 E-06	1.000 E-05	1.000 E-04	3.500 E-03	2.233 E-01
5	1.000 E-11	1.000 E-10	1.000 E-09	1.000 E-08	1.000 E-07	1.000 E-06	1.000 E-05	8.000 E-04	3.880 E-02
6	2.000 E-11	2.000 E-10	2.000 E-09	2.000 E-08	2.000 E-07	2.000 E-06	2.000 E-05	2.000 E-04	5.100 E-03
7	2.000 E-12	2.000 E-11	2.000 E-10	2.000 E-09	2.000 E-08	2.000 E-07	2.000 E-06	2.000 E-05	9.000 E-04
8		2.000 E-12	2.000 E-11	2.000 E-10	2.000 E-09	2.000 E-08	2.000 E-07	2.000 E-06	
9			2.000 E-12	2.000 E-11	2.000 E-10	2.000 E-09	2.000 E-08		
	A	B	C	D	E	F	G	H	I

or

) x

SAF



= 3D ex-core detector weights

- SMART-660 RWF and SAF calculated with DORT code[3] was used as SMART-660 and ATOM reactor shares 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.

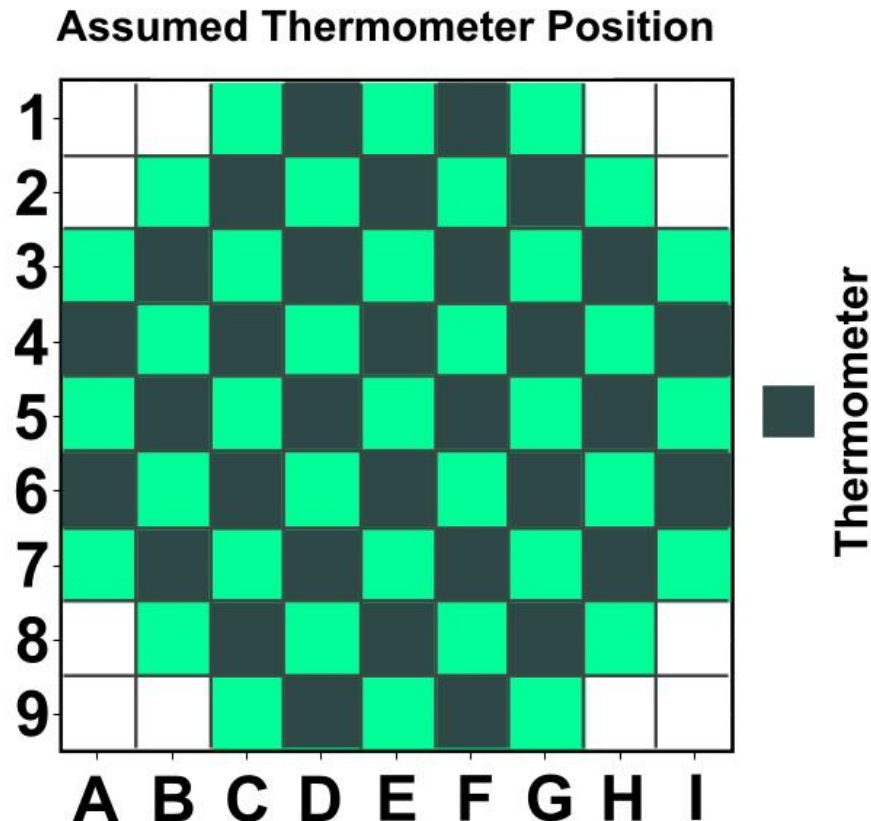


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Candidate Models

Truncated RWF

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

2 Models with Truncated RWF

1. Truncated RWF model, **without temperature** information (12ch input)
2. Truncated RWF model, **with temperature** information (44ch input)

Complete RWF

1					1.000 E-07	1.000 E-06	1.000 E-05	1.000 E-04	3.800 E-03	
2			1.000 E-09	1.000 E-08	1.000 E-07	1.000 E-06	1.000 E-05	1.300 E-03	6.280 E-02	
3	4.000 E-10	4.000 E-09	4.000 E-08	4.000 E-07	4.000 E-06	4.000 E-05	4.000 E-04	1.590 E-02	6.427 E-01	
4	1.000 E-10	1.000 E-09	1.000 E-08	1.000 E-07	1.000 E-06	1.000 E-05	1.000 E-04	3.500 E-03	2.233 E-01	
5	1.000 E-11	1.000 E-10	1.000 E-09	1.000 E-08	1.000 E-07	1.000 E-06	1.000 E-05	8.000 E-04	3.880 E-02	
6	2.000 E-11	2.000 E-10	2.000 E-09	2.000 E-08	2.000 E-07	2.000 E-06	2.000 E-05	2.000 E-04	5.100 E-03	
7	2.000 E-12	2.000 E-11	2.000 E-10	2.000 E-09	2.000 E-08	2.000 E-07	2.000 E-06	2.000 E-05	9.000 E-04	
8		2.000 E-12	2.000 E-11	2.000 E-10	2.000 E-09	2.000 E-08	2.000 E-07	2.000 E-06		
9			2.000 E-12	2.000 E-11	2.000 E-10	2.000 E-09	2.000 E-08			
	A	B	C	D	E	F	G	H	I	

2 Models with Complete RWF

1. Complete RWF model, **without temperature** information (12ch input)
2. Complete RWF model, **with temperature** information (44ch input)

Neural Network Model Structure

Parameter	Value / Specification
Total Samples	Training Samples: 4,865 dataset A, 1,001 dataset B, 1,077 dataset C Validation Samples: 1,135 dataset A, 2,000 dataset B, 431 dataset C
Input Shape	(12,) for temperature-unaware models, (44,) for temperature-informed models
Hidden Layer 1	Dense (256), LeakyReLU ($\alpha=0.2$), Dropout (0.3)
Hidden Layer 2	Dense (1024), LeakyReLU ($\alpha=0.2$), Dropout (0.3)
Hidden Layer 3	Dense (4096), LeakyReLU ($\alpha=0.2$)
Output Shape	(3240,)
Optimiser	Adam
Loss Function	Mean Squared Error (MSE)
Epochs	200

Model type

- Multi layer perceptron(MLP) model

Input layer

- 12ch for temperature-unaware models
- 12 + 32ch for temperature-aware, checkerboard models

Output layer

- 3240ch(40 axial nodes for 9x9 xy plane)

Hidden layer

- 3 dense layer(256, 1024, 4096)

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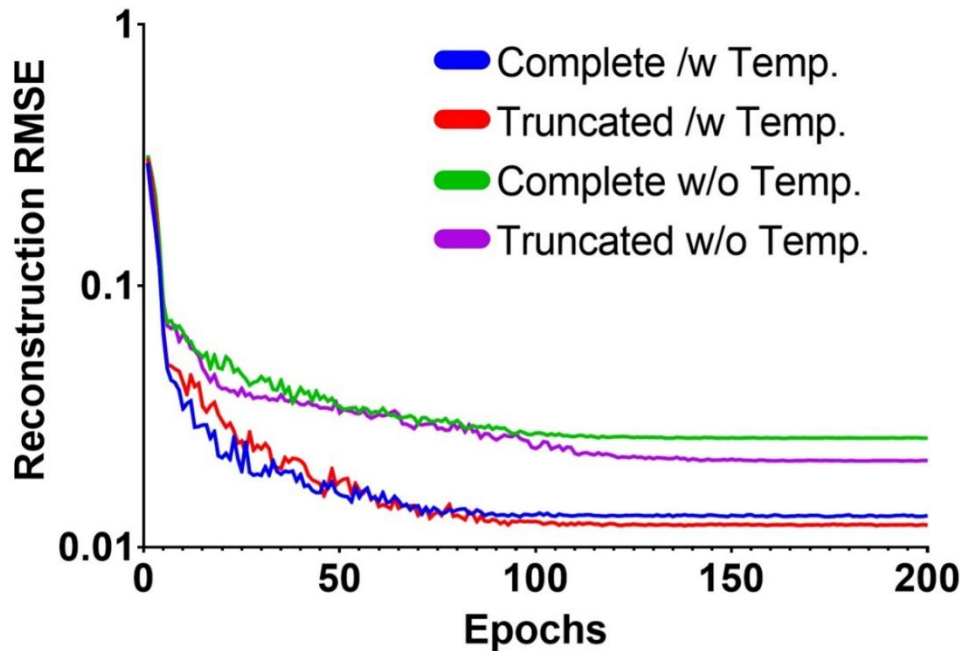
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Training Results

Whole Core Reconstruction RMSE
Evolution over Epochs



General trend:

Truncated RWF models were better than Complete RWF models.

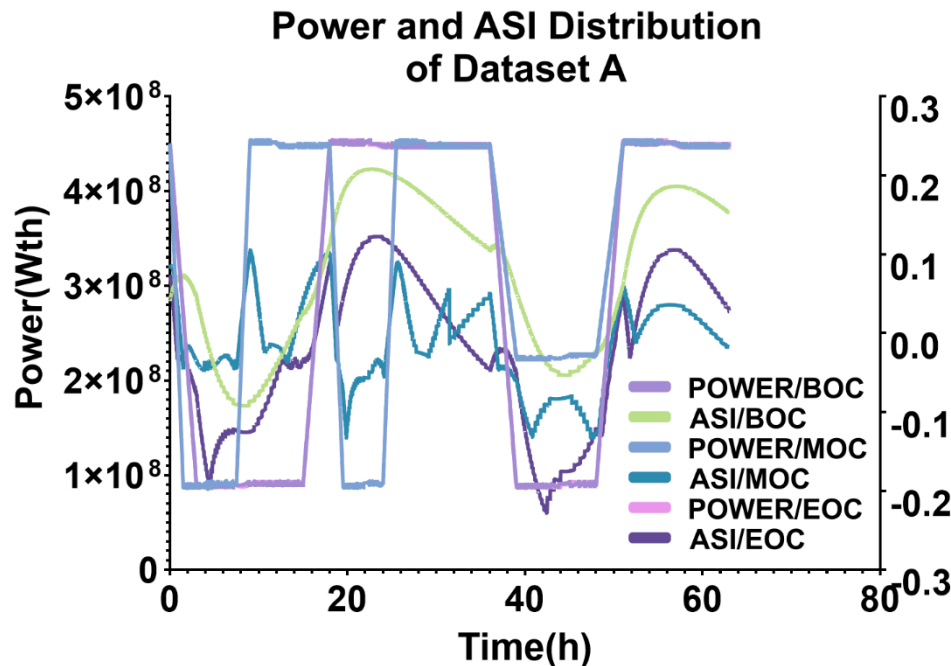
Temperature-aware models were better than temperature-unaware models.

Physically incorrect Complete RWF leads to poorer performance.

Peak Power Absolute Error of Training Dataset	Mean	Max	Min
Truncated w/o temp.	1.78%	14.73%	0.00%
Complete w/o temp.	2.33%	16.02%	0.00%
Truncated /w temp.	0.88%	7.05%	0.00%
Complete /w temp.	0.96%	7.59%	0.00%

Peak Power Absolute Error
on Training Dataset (A+B+C)

Validation Result – Dataset A



Dataset A:

- Training set contains **1,077 samples**, with **1,135 for validation**.
- The dataset is large and exhibits a generally stable load follow pattern, resulting in **satisfactory performance**.

Overall RMSE
on Validation Dataset A

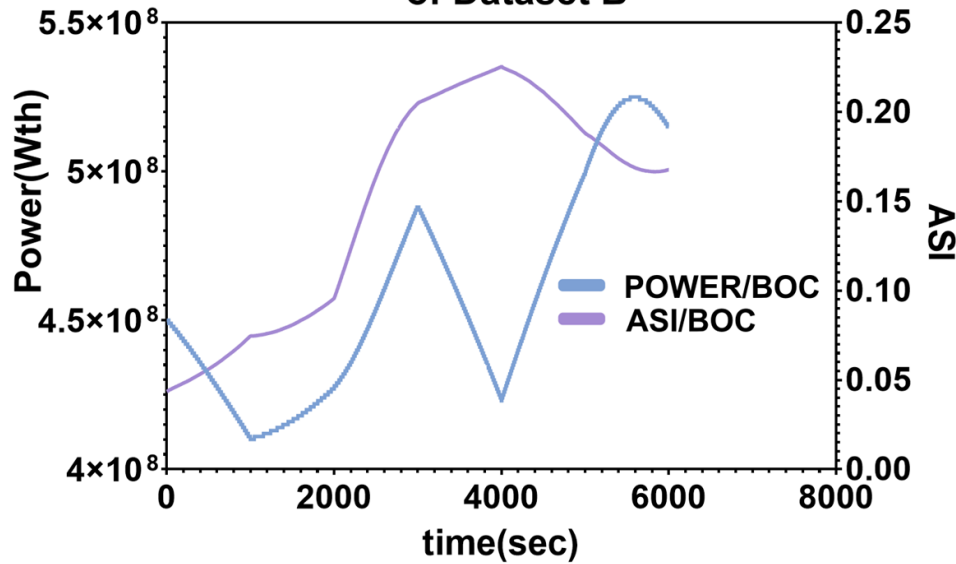
Overall RMSE	Mean	Max	Min
Truncated w/o temp.	2.06%	10.97%	0.83%
Complete w/o temp.	2.50%	9.93%	1.24%
Truncated /w temp.	1.37%	2.89%	0.60%
Complete /w temp.	1.47%	3.05%	0.96%

Peak Power Absolute Error
on Validation Dataset A

Peak Power Absolute Error	Mean	Max (Actual normalised power)	Min
Truncated w/o temp.	1.32%	7.28% (1.6837)	0.00%
Complete w/o temp.	1.60%	14.58% (1.6484)	0.00%
Truncated /w temp.	0.92%	3.93% (1.7468)	0.00%
Complete /w temp.	0.93%	3.18% (1.7468)	0.00%

Validation Result – Dataset B

Power and ASI Distribution of Dataset B



Dataset B:

- Training set contains **1,001 samples**, with **2,000 for validation**.
- The performance is **relatively poor**, likely **due to rapid transients**, and even the best truncated /w temp. model exhibits an error exceeding 7% for peak power.¹

Overall RMSE
on Validation Dataset B

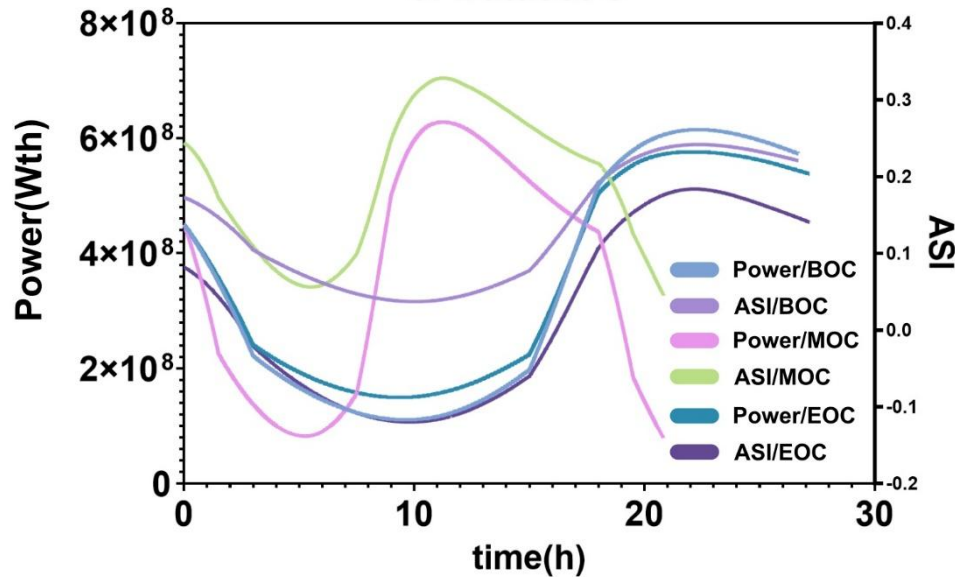
Overall RMSE	Mean	Max	Min
Truncated w/o temp.	2.89%	5.79%	1.66%
Complete w/o temp.	3.62%	6.87%	2.27%
Truncated /w temp.	1.06%	2.14%	0.66%
Complete /w temp.	1.23%	2.35%	0.81%

Peak Power Absolute Error
on Validation Dataset B

Peak Power Absolute Error	Mean	Max (Actual normalised power)	Min
Truncated w/o temp.	4.15%	14.71% (1.7229)	0.02%
Complete w/o temp.	5.78%	16.02% (1.8296)	0.35%
Truncated /w temp.	0.97%	7.08% (1.6609)	0.00%
Complete /w temp.	1.27%	7.61% (1.6609)	0.00%

Validation Result – Dataset C

Power and ASI Distribution of Dataset C



Dataset C:

- Training set contains **1,077 samples**, with **431 for validation**.
- With moderate power fluctuations, the validation performance was significantly better than Dataset B, despite the power exceeding the operational limit of 450 MWth.

Overall RMSE
on Validation Dataset C

Overall RMSE	Mean	Max	Min
Truncated w/o temp.	2.06%	10.97%	0.83%
Complete w/o temp.	2.50%	9.93%	1.24%
Truncated /w temp.	1.37%	2.89%	0.60%
Complete /w temp.	1.47%	3.05%	0.76%

Peak Power Absolute Error
on Validation Dataset C

Peak Power Absolute Error	Mean	Max (Actual normalised power)	Min
Truncated w/o temp.	1.92%	6.60% (1.7263)	0.00%
Complete w/o temp.	2.57%	7.74% (1.8554)	0.02%
Truncated /w temp.	0.60%	2.10% (1.6835)	0.00%
Complete /w temp.	0.81%	2.06% (1.7544)	0.00%

Summary & Conclusion

Key Findings:

- The feasibility of the methodology for **reconstructing the reactor 3D power** distribution through an ANN model **utilising ex-core detector and CET information** has been verified.
- **Contrary to our initial hypothesis**, the Complete RWF model, which assumes that assemblies far from ex-core detectors contribute to their signals, resulted in decreased model performance.
- The **integration of temperature information** into the model significantly enhanced performance, yielding substantial improvements over the previous study.

Future Works:

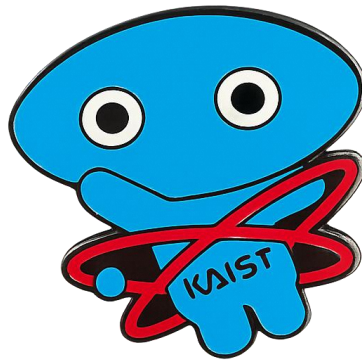
- Future work will include, but is not limited to, hyperparameter optimisation, exploring alternative ANN models beyond MLP, and incorporating additional ANN input data.

References

1. Oh, Taesuk, et al. "Development and validation of multiphysics PWR core simulator KANT." *Nuclear Engineering and Technology* 55.6 (2023): 2230-2245.
2. 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.
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., Ding, P., Xia, W., Chen, S., Yu, F., Duan, C., ... & Chen, C. (2022). Artificial neural network reconstructs core power distribution. *Nuclear Engineering and Technology*, 54(2), 617-626.
5. Lin, W., Miao, X., Chen, J., Duan, P., Ye, M., Xu, Y., ... & Lu, Y. (2025). Forecasting in-core power distributions in nuclear power plants via a spatial-temporal hierarchical-directed network. *Progress in Nuclear Energy*, 186, 105795.

Thank you

Any questions?



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.