부산대학교 기계공학부
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Development of a Unified Loading Pattern Evaluation Model Using a Vision Transformer

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Introduction

Reactor Physics & **P**article Transport
Computation Simulation **L**ab. **(RPL)**

Background

➢ Core design parameters in loading pattern (LP) design

- An acceptable LP must satisfy limits on **various core design parameters**.
  - Cycle length (CL), maximum peaking factors (PF), ASI, etc.
- Optimizers such as SA[1], GA[2], PSO[3] and RL[4] evaluate **tens of thousands of LPs**.
  - Evaluating all of them with 3D core calculations takes **thousands of hours**.

➢ Surrogate models for core parameter prediction

- **Fast surrogate models** screen candidates and skip most 3D calculations[5].
  - If models predict only CL and PF, **violations of other parameters** pass screening.
  - Hard to give an insight to optimize the LP further.
- A **unified LP evaluation model** is needed to predict various core parameters.

1) Kropaczek, D.J., Turinsky, P.J., 1991. In-core nuclear fuel management optimization for pressurized water reactors utilizing simulated annealing. Nucl. Technol. 95 (1), 9-32.
2) Yamamuto, A., 1997. A quantitative comparison of loading pattern optimization methods for in-core fuel management of PWR. J. Nucl. Sci. Technol. 34 (4), 339-347.
3) Babazadeh, D., Boroushaki, M., Lucas, C., 2009. Optimization of fuel core loading pattern design in a VVER nuclear power reactors using Particle Swarm Optimization (PSO). Ann. Nucl. Energy 36, 923-930.
4) Seurin, P., Shirvan, K., 2022. PWR Loading Pattern Optimization with Reinforcement Learning. PHYSOR 2022, 1166-1175.
5) Park, T.K., Joo, H.G., Kim, C.H., Lee, H.C., 2009. Multiobjective loading pattern optimization by simulated annealing employing discontinuous penalty function and screening technique. Nucl. Sci. Eng. 162, 134-147.

Objective

➢ Construct training and validation datasets

- Training datasets: Random generated LPs, near-optimal LPs created via SA.

➢ Develop an Unified Vision Transformer (Unified-ViT) model

- Make **a backbone structure** using transformer-encoder architecture.
- Attach **output heads** after the backbone to predict various core design parameters.
- Train the model for fast and accurate prediction of core parameters for OPR-1000 cores.

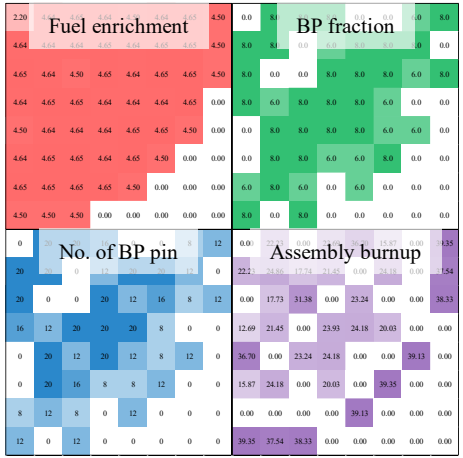
➢ Accelerate LP optimization using ViT-screened SA

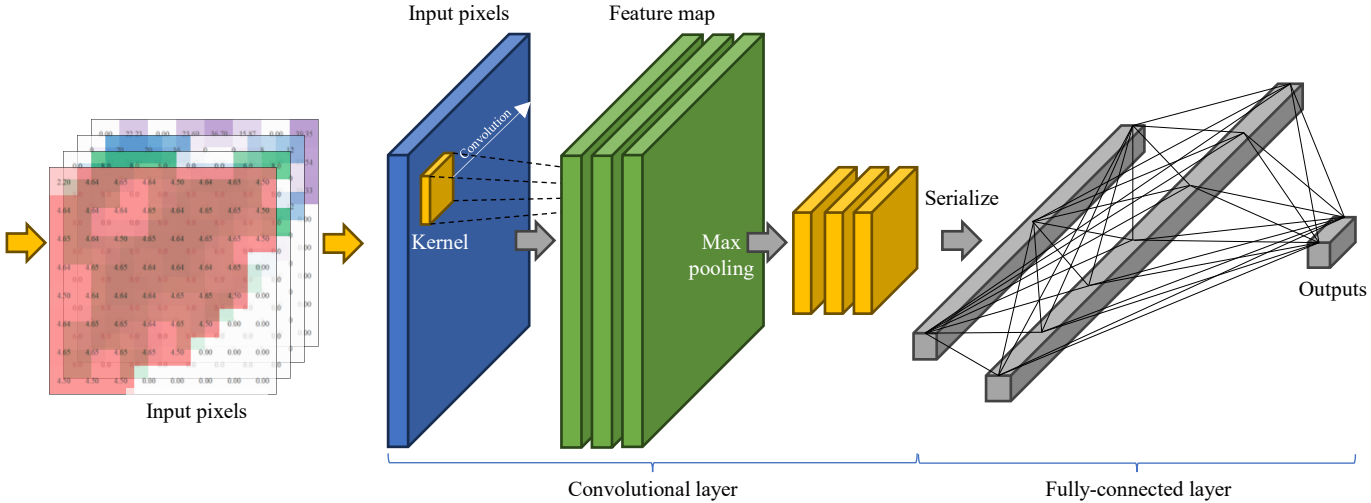
- Evaluate the bias and deviation of the model to filter out clearly good or bad candidates.
- Perform cycle-by-cycle optimization for an OPR-1000 core.

Previous Research (1/2): Assembly-wise CNN

➢ Application of Assembly-wise CNN for Screening

- Processes 2D data by extracting local features through convolution layer.
- Effective for capturing neighborhood patterns in images.
- Limitation:
  - Focuses only on **local regions**, making it inefficient to model global relationships.
  - Predicts only at the **assembly level**, losing pin-wise details.



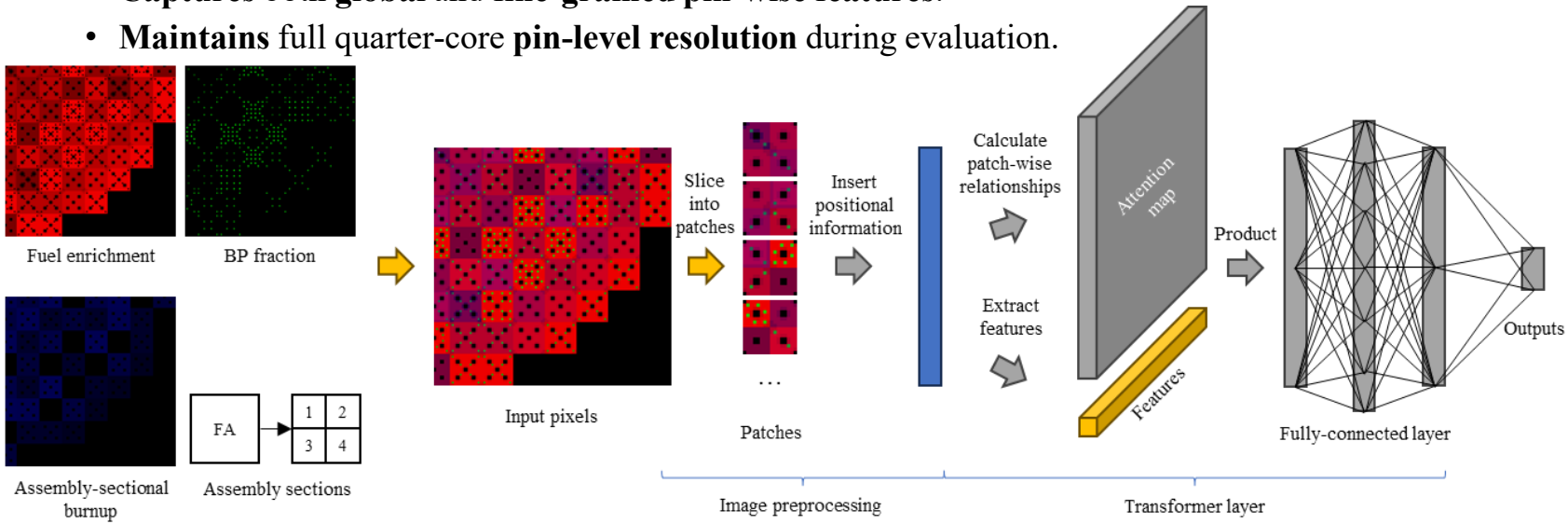


Ref.) H. Jang and H.C. Lee, "Prediction of Pressurized Water Reactor Core Design Parameters using Artificial Neural Network for Loading Pattern Optimization," Korea Nuclear Society Spring Meeting, 2019.

Previous Research (2/2): Pin-wise ViT

➢ Application of Pin-wise ViT for Screening

- Divides input images into small patches and treats them as a sequence of tokens.
- Applies self-attention to model **global relationships** across all patches.
- Advantages over the assembly-wise CNN:
  - **Captures** both **global** and **fine-grained pin-wise features**.
  - **Maintains** full quarter-core **pin-level resolution** during evaluation.



Ref.) Seongjin Jeong, Howon Lee, and Hyun Chul Lee, "Application of a Vision Transformer for Prediction of Peaking Factors and Cycle Lengths in OPR1000," Korean Nuclear Society Spring Meeting, 2023.

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Methodology

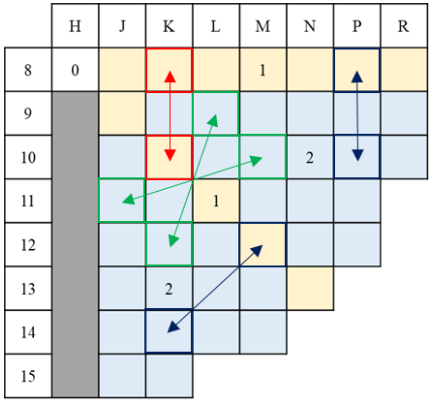
Datasets for Model Training and Validation

➢ LP dataset

- **Random generation (RG)**
  - Created using YGN3 reference cores from NDR (C01, C02) and LP design paper (C03 – C10).
    - Assembly swapping and rotation are conducted randomly.
    - Use random LP in previous cycle for the burnt FAs.
  - Generated with a relaxed constraint (max-F_{xy} < 5.0) to cover diverse cases.
  - 10,000 cases per cycle (**Total 100,000 cases**)
- **Near-optimal (NO)**
  - Generated **using SA** Guided by pin-wise ViT model pre-trained with the RG dataset.
  - 2,000 cases per cycle (**Total 20,000 cases**)

➢ Dataset split

- Training subset
  - using training process directly.
- Test subset
  - LPs for model evaluation only. Not participate in the training.
- Training : Test = 9 : 1



Methods of LP shuffling

Fuel Assembly Types

- **C01 and C02**: Based on **NDR[1].**
  - **A0 – D2** were used for **C01** fresh fuel assemblies and **E0 – E2** were used for **C02** fresh fuel assemblies.
- **C03 – C10**: Based on **loading pattern design paper[2].**
  - **FXs** were used for **18-month equilibrium cores (C03 – C10)**.

Name	Enrichment [wt.% ^{235}U]		No. of rods (Zoned / BP)	BP fraction [wt.% Gd_2O_3]	Name	Enrichment [wt.% ^{235}U]		No. of rods (Zoned / BP)	BP fraction [wt.% Gd_2O_3]
	Normal	Zoned				Normal	Zoned		
A0	1.30	-	- / -	-	E1	4.08	3.61	52 / 8	6.0
B0	2.37	-	- / -	-	E2	5.60	3.11	52 / 8	6.0
B1	2.36	1.30	52 / 8	4.0	FC	2.20	-	- / -	-
B2	2.37	-	- / 4	4.0	F0	4.65	4.10	52 / -	-
C0	2.87	2.35	52 / -	-	F1	4.65	4.10	52 / 4	6.0
C1	2.87	2.36	52 / 8	4.0	F2	4.65	4.10	52 / 8	6.0
D0	3.35	2.87	52 / -	-	F3	4.65	4.10	52 / 12	6.0
D1	3.36	2.85	52 / 8	4.0	F4	4.65	4.10	52 / 16	8.0
D2	3.35	2.87	100 / 8	4.0	F5	4.65	4.10	52 / 20	8.0
E0	4.08	3.61	52 / -	-	F6	4.65	4.10	52 / 24	8.0

1) 1996. Nuclear design report for Yonggwang nuclear power plant unit 3 cycle 2. KAERI/TR-605/96, Korea Atomic Energy Research Institute.
2) Lee, J., Lee, H.C., 2023. Loading pattern design and economic evaluation for 24-month cycle operation of OPR-1000 in Korea. Nuc. Eng. Technol. 55 (3), 1167-1180.

Core Parameters Calculation

➢ Calculation code

- STREAM/RAST-K, two step nodal diffusion code system.
- Developed by UNIST CORE.

➢ Core parameters

- Scalar parameters:
  - Cycle length: EFPDs when the CBC is 10 ppm.
  - Peaking factor: max-F_{xy} during the cycle.
- Time-series parameters:
  - CBC / ASI / Radial box-wise power
  - Peaking factors: F_q, F_r, $F_{\Delta H}$, F_{xy}, F_z

Ref.) Park, J., Jang, J., Kim, H., Et Al., 2020. RAST-K v2-three dimensional nodal diffusion code for pressurized water reactor core analysis. Energies, 13:6324.

Unified ViT Model for LP Evaluation

➢ Previous ViT models

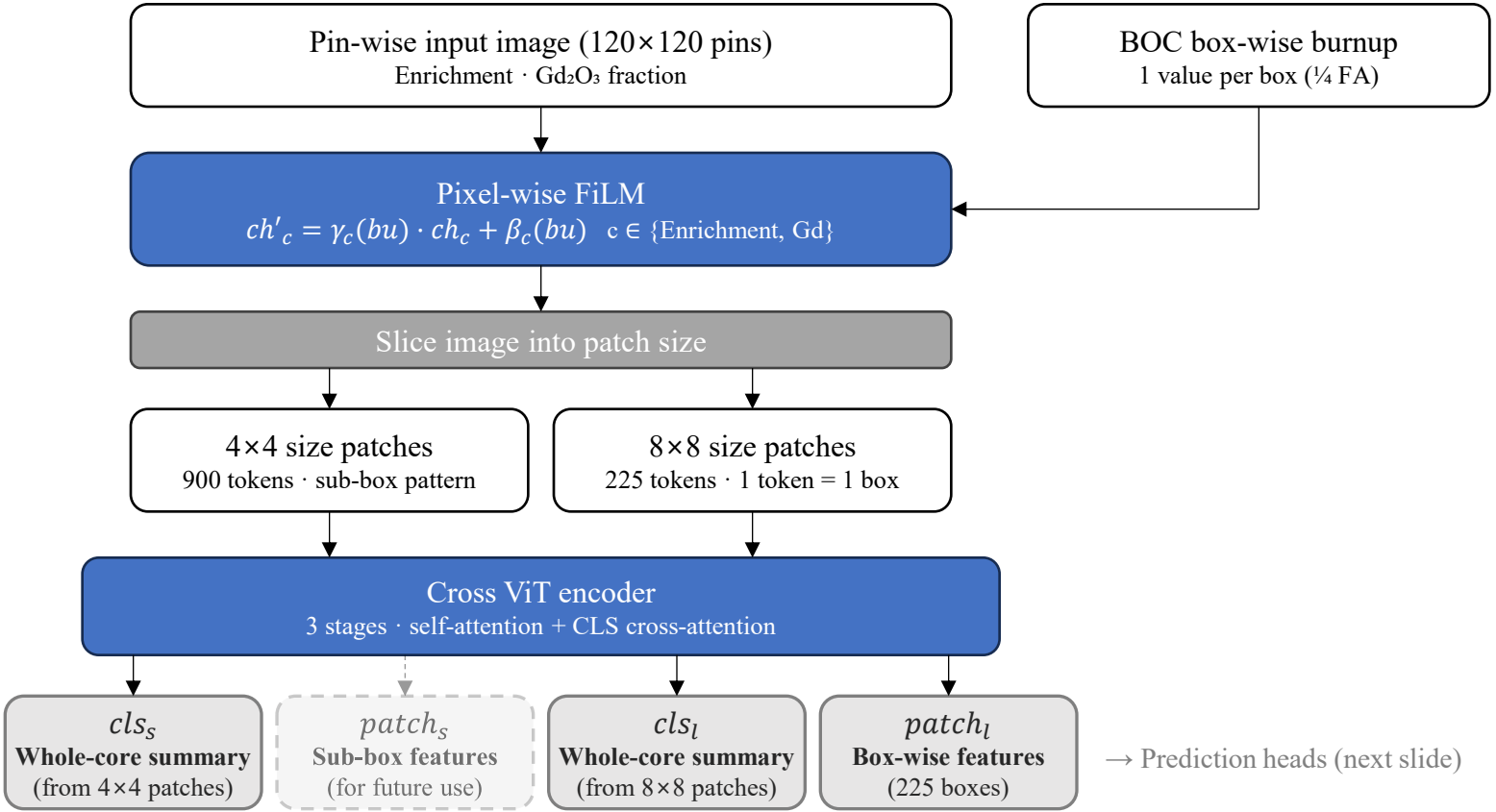
- Two separate single-task ViTs for cycle length (ViT-CL) / max-F_{xy} (ViT-PF) prediction.

➢ Unified ViT model

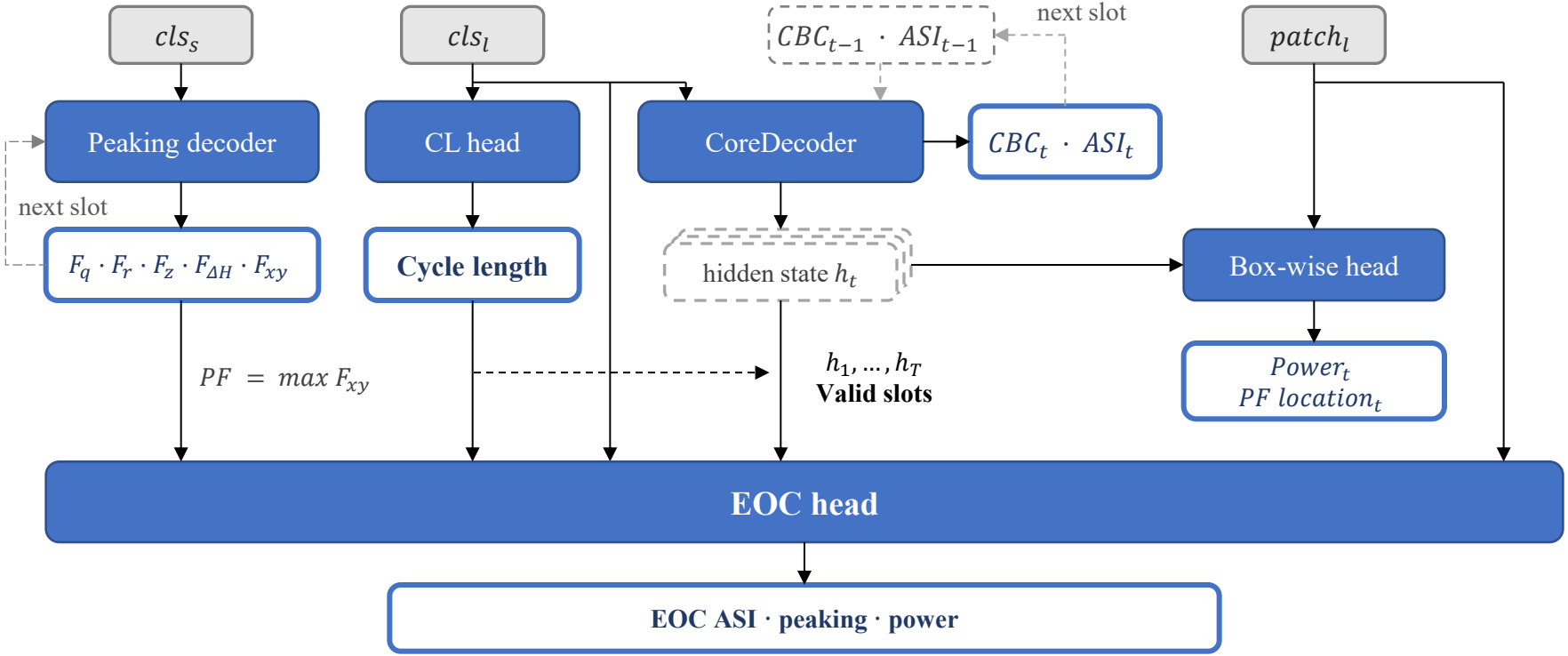
- One unified model
  - Scalar prediction: Cycle length / max-Fxy
  - Time-series prediction: CBC / ASI / 5 peaking factors / radial box-wise power
    - Fixed burnup slots for the time-series parameters. (0.0, 0.05, 0.10, 0.15, 0.25, 0.5, 1.0, 2.0, …, 30.0 GWd/MTU)

	Original ViT		Unified ViT
TOKENS	single scale 8×8 pin-size patch	➡	**dual scale — 4×4 + 8×8 pin-size patch** **Cross-attention ViT**
BURNUP	raw 3D input channel (Enrichment / BP fraction / Burnup)	➡	**FiLM (Feature-wise Linear Modulation)** modulates enrichment & BP fraction using FA burnup
OUTPUT	2 models, 1 metric each (Cycle length / max-Fxy)	➡	**Cycle length / max-F_{xy}** **Time-series CBC / ASI / peaking / power**

Model Overview: Encoder

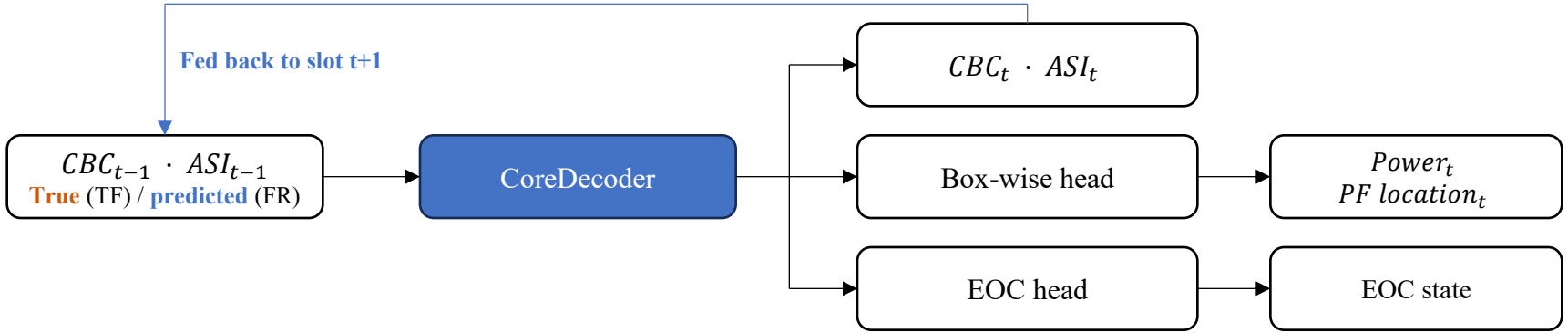


Model Overview: Prediction Heads



Teacher Forcing vs. Free Running

	Teacher forcing[1] Training	Free-running[2] Validation · Prediction
SLOT t INPUT	True CBC · ASI at slot t−1	Own predicted CBC · ASI at slot t−1
COMPUTATION	Parallel; loss on valid slots only	Sequential; used up to predicted EOC



Fed-back errors **accumulate over slots** (exposure bias[3]), so the model is selected by free-running validation error.

1) Williams, R.J., Zipser, D., 1989. A learning algorithm for continually running fully recurrent neural networks. Neural Comput. 1 (2), 270-280.
2) Williams, R.J., Zipser, D., 1989. Experimental analysis of the real-time recurrent learning algorithm. Connect. Sci. 1 (1), 87-111.
3) Ranzato, M., Chopra, S., Auli, M., Zaremba, W., 2016. Sequence level training with recurrent neural networks. ICLR 2016.

Model Training Process

➢ Model training strategy

- Optimizer: **AdamW**, Scheduler: **ReduceLROnPlateau**

Loss	Formula	Outputs
Relative error	$((\hat{y} - y)/y)^2$	Cycle length, peaking factors
Absolute error	$((\hat{y} - y)/\text{scale})^2$	ASI (scale = 0.2)
Mean of both	$1/2\,((\hat{y} - y)/y)^2 + 1/2\,((\hat{y} - y)/\text{scale})^2$	CBC, box-wise power
Cross-entropy	–	PF location

➢ Model training resources

- GPU: **NVIDIA RTX PRO 5000 Blackwell** (48 GB memory)
- Training time: **17.3 hrs**
- Framework: PyTorch 2.9 with CUDA

Results

Prediction Accuracy for Test Subset

➢ Relative prediction error with RAST-K calculation [%] (RMS / Max)

Model	Cycle length	Max-F_{xy}	CBC	Peaking factors	Power map
ViT-CL/PF	0.16 / 0.90	0.86 / 4.37	-	-	-
Unified ViT	0.07 / 0.26	0.50 / 1.83	1.6 / 32.0	0.37 / 2.86	0.19 / 2.61

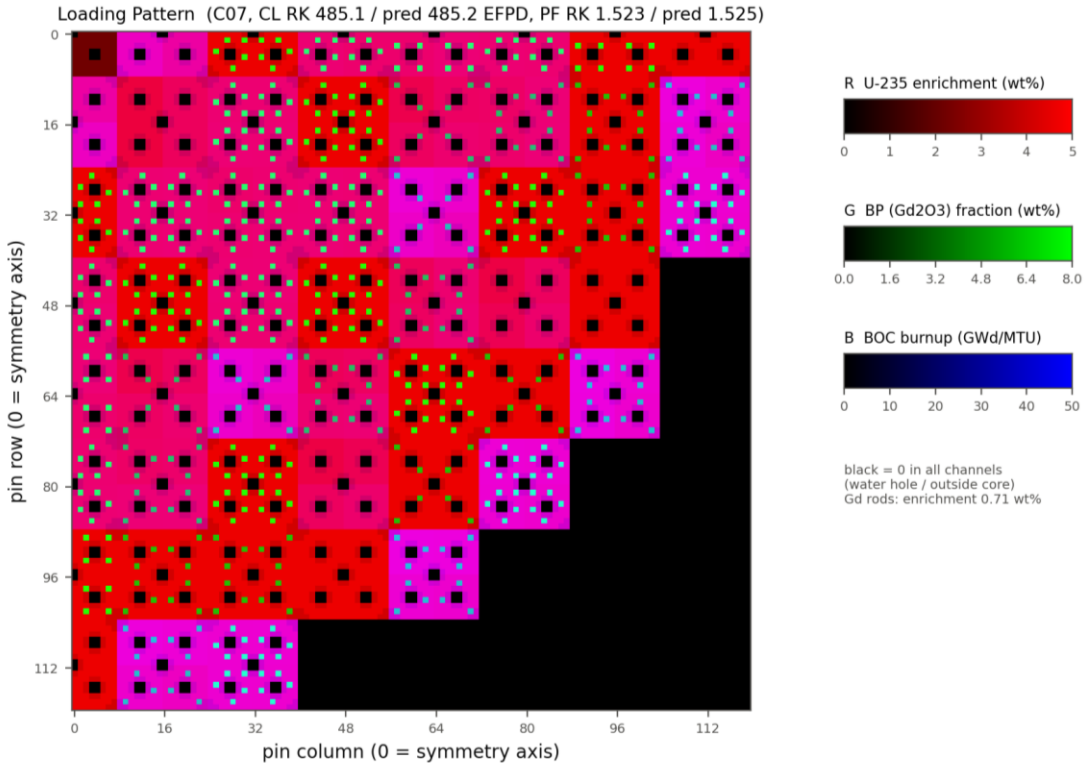
➢ Absolute prediction error with RAST-K calculation (RMS / Max)

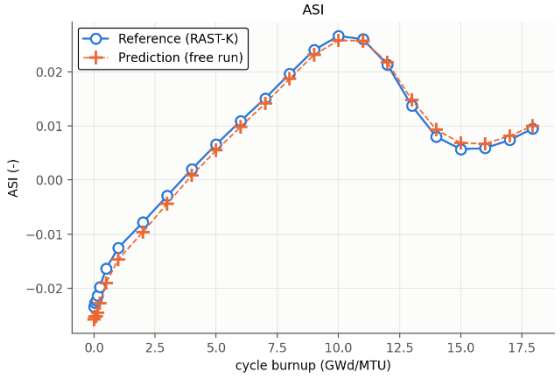
Model	Cycle length [EFPDs]	Max-F_{xy}	CBC [ppm]	ASI [%]	Peaking factors	Power map [%]
ViT-CL/PF	0.64 / 5.50	0.014 / 0.179	-	-	-	-
Unified ViT	0.29 / 1.17	0.010 / 0.048	2.5 / 10.2	0.12 / 0.82	0.006 / 0.055	0.18 / 3.30

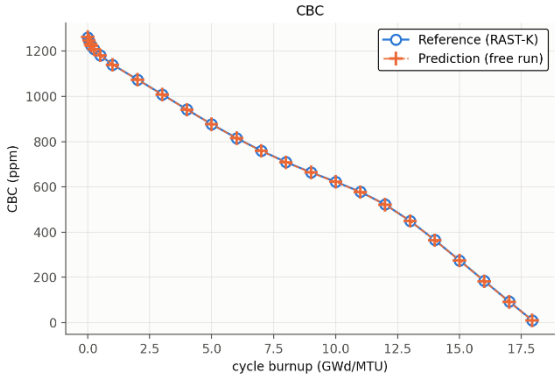
➢ Peak location hit rate: radial **77.2%** (89.4% including symmetric positions), axial height **73.5%**

Prediction Accuracy for Test Subset

➢ Example of model prediction: loading pattern, ASI and CBC

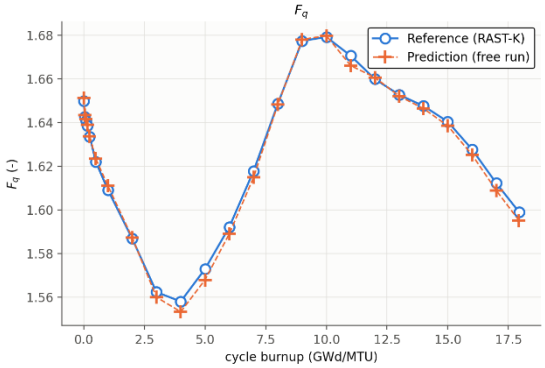


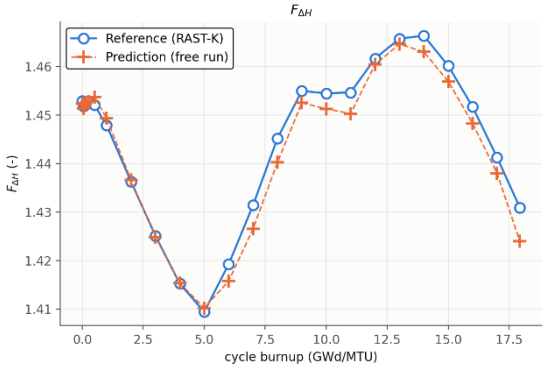


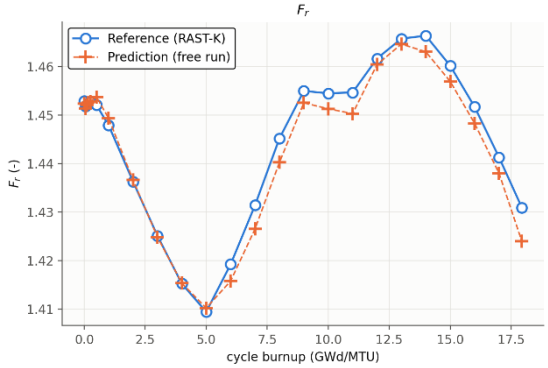


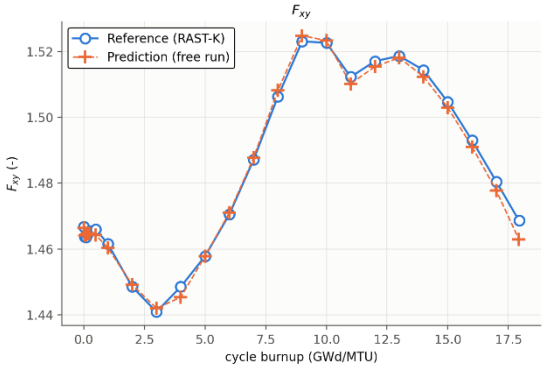
Prediction Accuracy for Test Subset

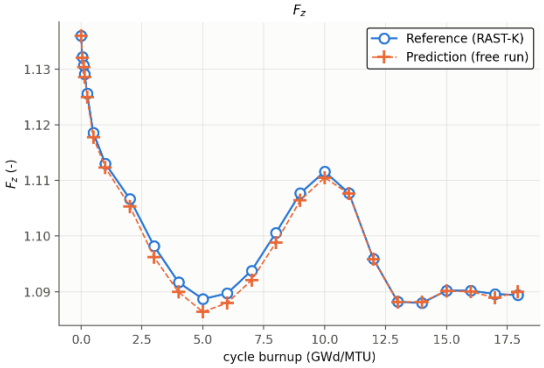
➢ Example of model prediction: peaking factors





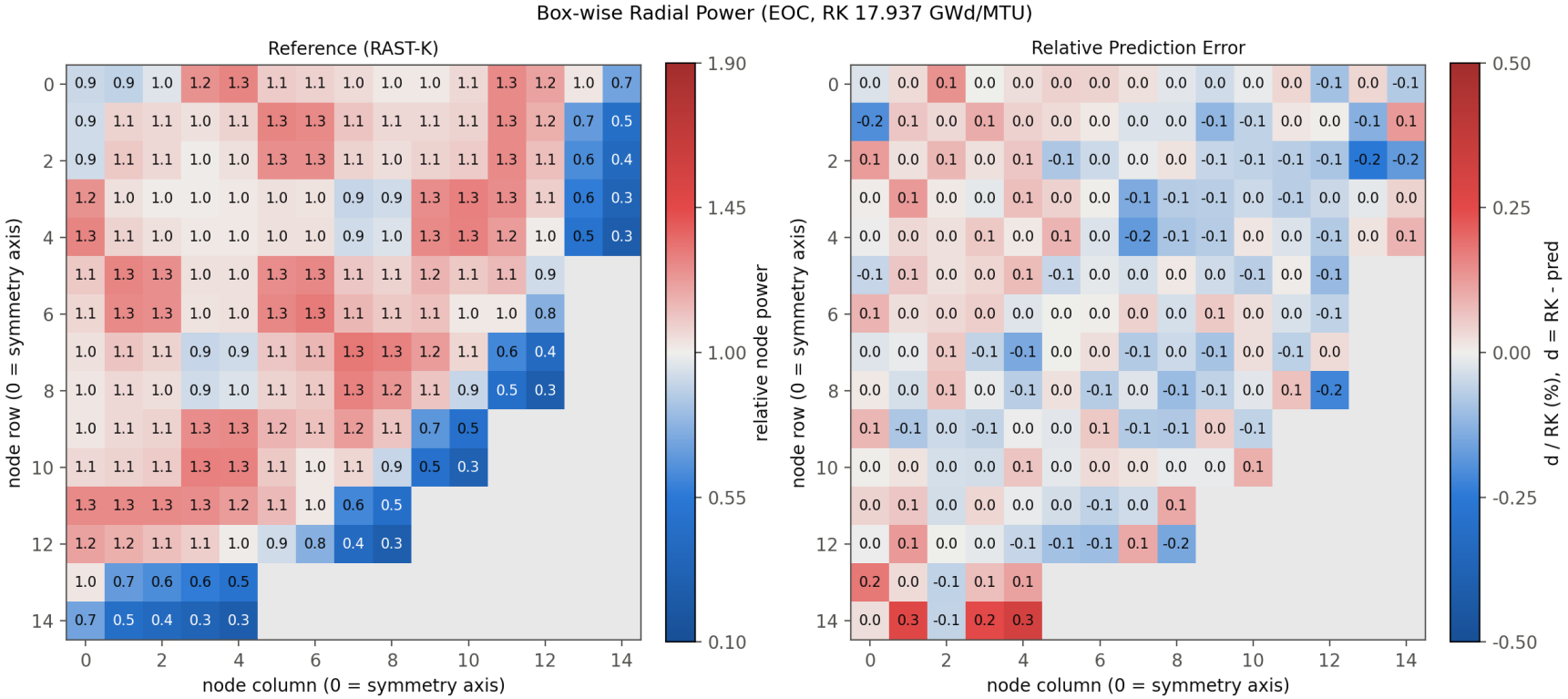






Prediction Accuracy for Test Subset

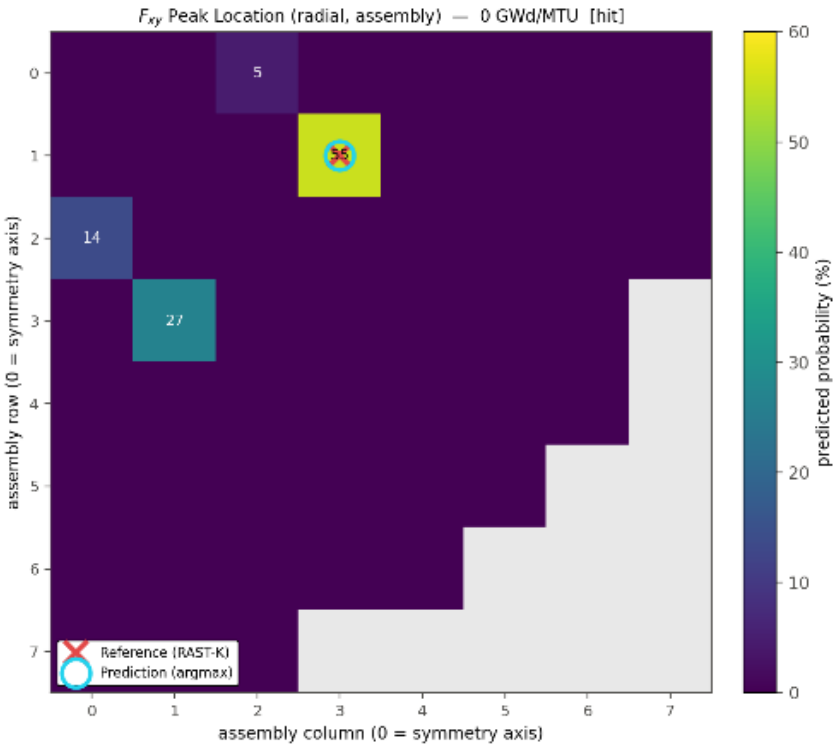
➢ Example of model prediction: box-wise radial power

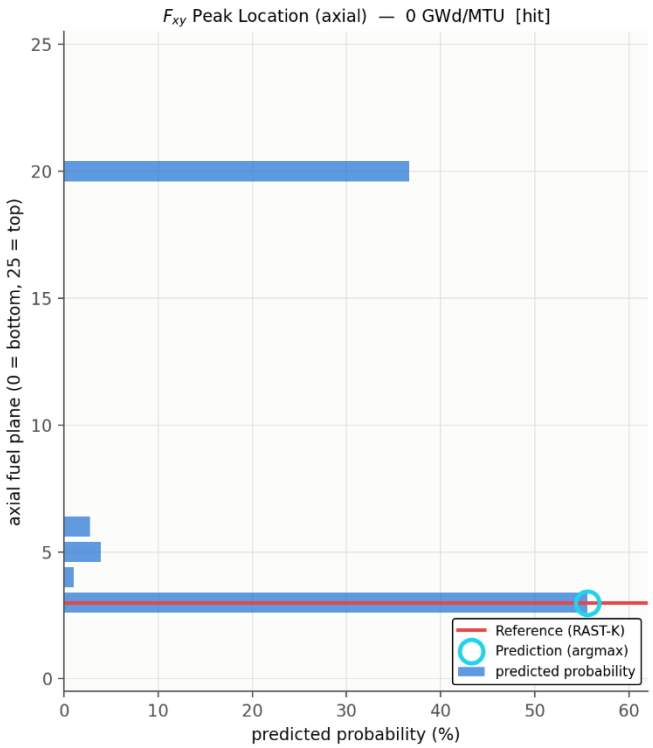


Prediction Accuracy for Test Subset

➢ Example of model prediction: peak location (hit rate: radial **77.2%**, 89.4% incl. symmetry; axial **73.5%**)

F_{xy} (assembly)





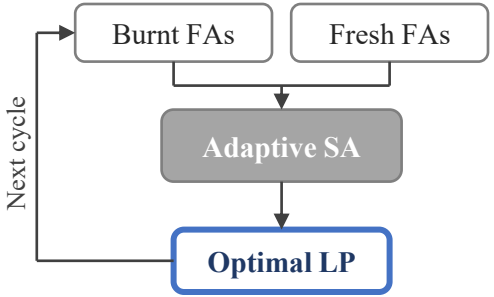
Optimal LPs Generation Method

➢ LP candidate generation

- **Preserve the number of types in fresh fuel assemblies**.
- Keeps overall U-235 mass unchanged.

➢ LP optimization process

- **Initial LP**: Random generation LP based on reference.
- **Burnt fuel assemblies**: Taken from the previous cycle's optimized LP.
- **Optimization method**:
  - SA is performed **10 times independently**.
  - Among the LPs *satisfying PF limit*, the LP with the **longest cycle length** is selected as the optimal LP.
  - The optimal LP for each SA process is passed to the next cycle as the **basis for burnt fuel assemblies**.



LP optimization process

➢ Search algorithm

- **Adaptive SA**[1]: cooling rate and stage termination adapt to the spread of objective values.
- **Objective function**: cycle length and max-F_{xy} of each candidate LP.
- **Screening**[2]: RAST-K runs only when the Unified ViT result is within 3σ of the acceptance criterion.

Ref.) 1. Lee, H.C., Shim, H.J., Kim, C.H., 2001. Parallel Computing Adaptive Simulated Annealing Scheme for Fuel Assembly Loading Pattern Optimization in PWRs. Nuclear Technology, 135:39-50.
2. Park, T.K., Joo, H.G., Kim, C.H., Lee, H.C., 2009. Multiobjective loading pattern optimization by simulated annealing employing discontinuous penalty function and screening technique. Nucl. Sci. Eng. 162, 134-147.

Results of SA Runs

➢ Effect of screening with Unified ViT

- 34,600 ~ 53,500 evaluations performed → ~ 99.9% screened by Unified ViT.
  - If all were RAST-K evaluations → 1,360 ~ 3,600 hours.
  - Proposed framework → 3.0 ~ 7.0 hours on average.

Cycle	RK	Unified ViT	Efficiency [%]	Process time [hr.]	Est. process time w/o screening [hr.]
1	45.2	34573.3	99.9	3.3	1801.1
2	52.5	35424.2	99.9	3.0	1361.4
3	84.4	51602.1	99.8	6.9	3327.3
4	81.6	51614.3	99.8	6.8	3392.5
5	82.9	53425.0	99.8	7.0	3591.0
6	77.5	50901.3	99.8	6.7	3451.0
7	78.3	50206.5	99.8	6.7	3416.6
8	80.5	52111.8	99.8	7.0	3603.4
9	68.8	45344.5	99.8	6.0	3103.9
10	72.6	46337.1	99.8	6.3	3179.7

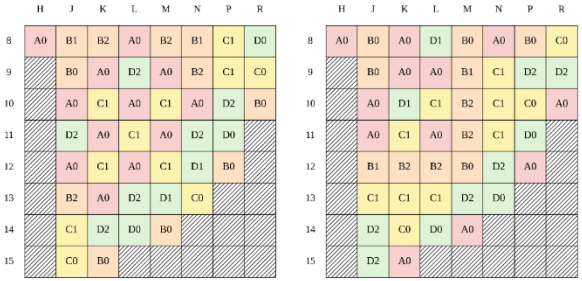
Average evaluation counts, screening efficiency (Unified ViT evaluation / Total evaluation) and process time for each cycle

Optimal LPs by Cycle

➢ SA results

Fresh FA Once-burnt FA Twice-burnt FA

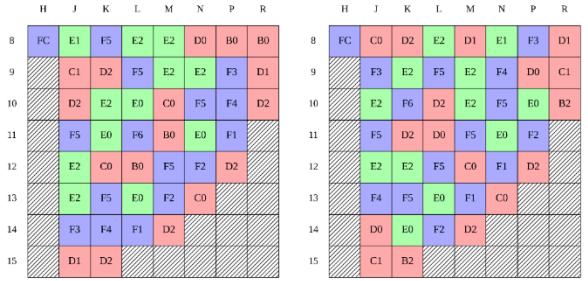
Cycle 1



Reference
CL 373.2 EFPD
Max-F_{xy} 1.5412

Optimized
CL 374.6 EFPD
Max-F_{xy} 1.4839

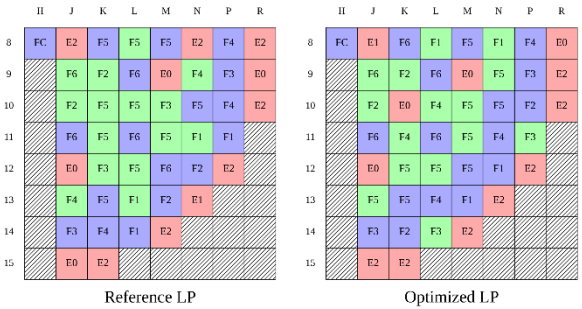
Cycle 3 (SA limits: CL 490 EFPD, Max-F_{xy} 1.60)



Reference
CL 459.8 EFPD
Max-F_{xy} 1.5994

Optimized
CL 463.5 EFPD
Max-F_{xy} 1.5762

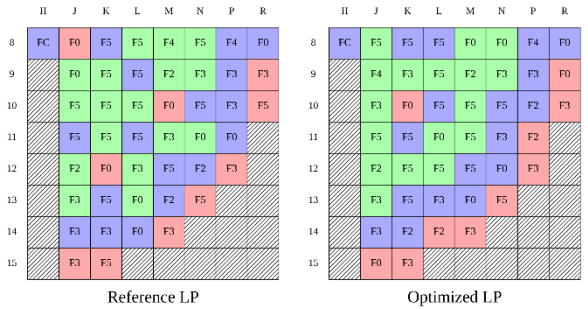
Cycle 4 (SA limits: CL 490 EFPD, Max-F_{xy} 1.60)



Reference
CL 470.3 EFPD
Max-F_{xy} 1.5812

Optimized
CL 472.5 EFPD
Max-F_{xy} 1.5502

Cycle 10 (SA limits: CL 490 EFPD, Max-F_{xy} 1.55)



Reference
CL 475.9 EFPD
Max-F_{xy} 1.5349

Optimized
CL 493.3 EFPD
Max-F_{xy} 1.5483

Conclusions

Conclusion

➢ Unified Vision Transformer Model

- Trained with both **random generation, near-optimal** LPs.
- Achieved **high accuracy** in predicting time-series core parameters with **only loading pattern image**.

Prediction error of Unified ViT with RAST-K calculation

Error metric	Cycle length [EFPD]	Max-F_{xy}	CBC [ppm]	ASI [%]	Peaking factors	Power map [%]
Absolute error (RMS / Max)	0.29 / 1.17	0.010 / 0.048	2.5 / 10.2	0.12 / 0.82	0.006 / 0.055	0.18 / 3.30

➢ Future work

- Direct LP optimization
  - Transformer encoder-decoder **generates a full LP in one pass** under hard fuel-budget constraints.
  - Conditioned on target parameters (cycle length / peaking factor).
- Application of Reinforcement Learning
  - LP construction as **a sequential decision process**.
  - Policy trained against the Unified-ViT predictions.

References

1) Babazadeh, D., Boroushaki, M., Lucas, C., 2009. Optimization of fuel core loading pattern design in a VVER nuclear power reactors using Particle Swarm Optimization (PSO). Ann. Nucl. Energy 36, 923-930.

2) Jang, H., Lee, H.C., 2019. Prediction of Pressurized Water Reactor Core Design Parameters using Artificial Neural Network for Loading Pattern Optimization. Korean Nuclear Society Spring Meeting.

3) Jeong, S., Lee, H., Lee, H.C., 2023. Application of a Vision Transformer for Prediction of Peaking Factors and Cycle Lengths in OPR1000. Korean Nuclear Society Spring Meeting.

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Thank you ☺

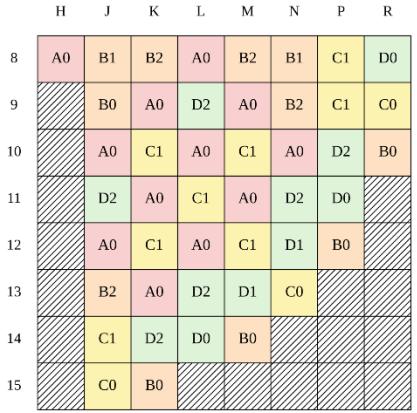
Appendix A

Optimal LPs by Cycle

➢ SA results

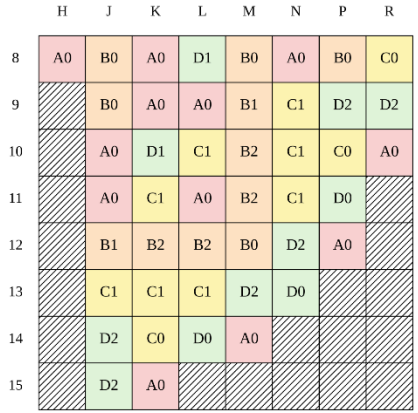
Fresh FA
Once-burnt FA
Twice-burnt FA

Cycle 1



Reference LP

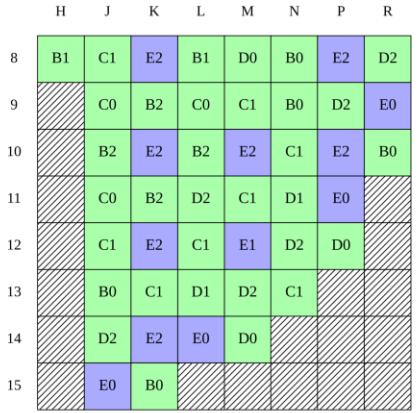
CL 373.2 EFPD
Max-F_{xy} 1.5412



Optimized LP

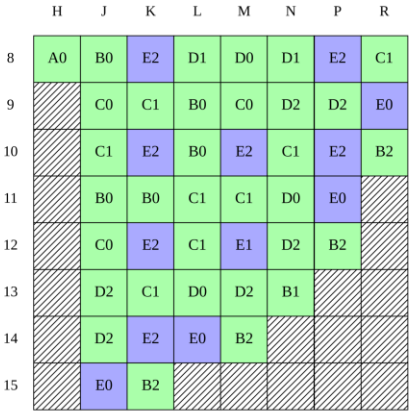
CL 374.6 EFPD
Max-F_{xy} 1.4839

Cycle 2



Reference LP

CL 275.8 EFPD
Max-F_{xy} 1.5442



Optimized LP

CL 276.3 EFPD
Max-F_{xy} 1.5361

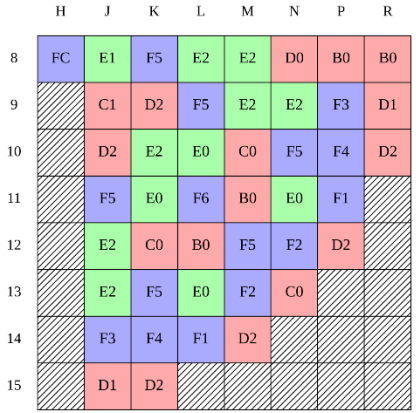
Optimal LPs by Cycle

➢ SA results

Fresh FA
Once-burnt FA
Twice-burnt FA

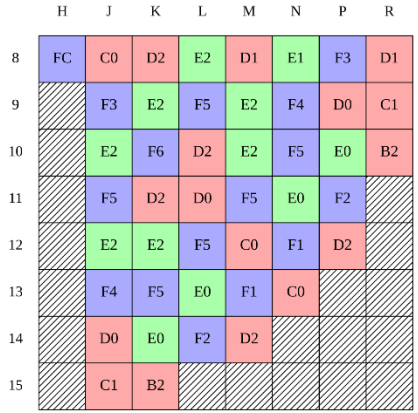
Cycle 3

(SA limits: CL 490 EFPD, Max-F_{xy} 1.60)



Reference LP

CL 459.8 EFPD
Max-F_{xy} 1.5994

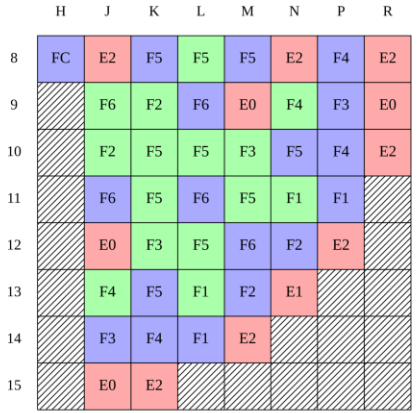


Optimized LP

CL 463.5 EFPD
Max-F_{xy} 1.5762

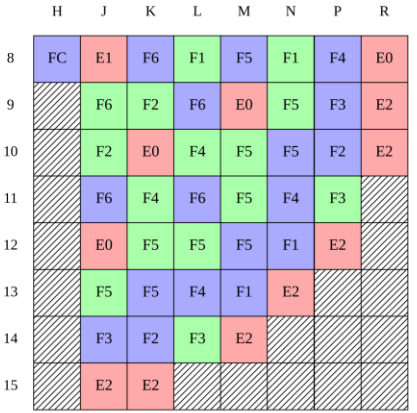
Cycle 4

(SA limits: CL 490 EFPD, Max-F_{xy} 1.60)



Reference LP

CL 470.3 EFPD
Max-F_{xy} 1.5812



Optimized LP

CL 472.5 EFPD
Max-F_{xy} 1.5502

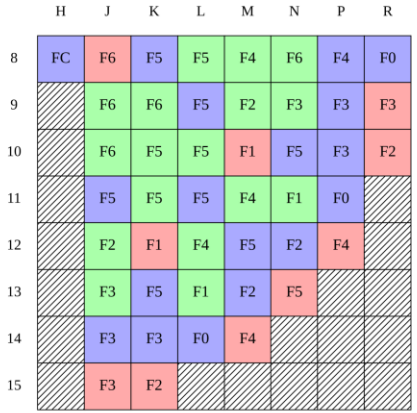
Optimal LPs by Cycle

➢ SA results

Fresh FA
Once-burnt FA
Twice-burnt FA

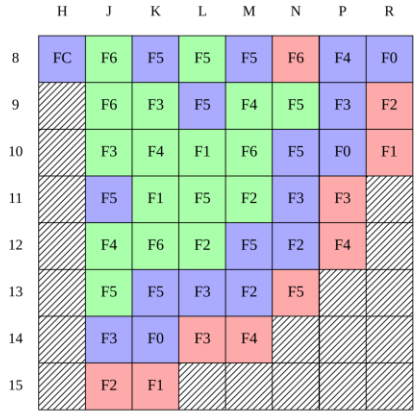
Cycle 5

(SA limits: CL 490 EFPD, Max-F_{xy} 1.55)



Reference LP

CL 476.4 EFPD
Max-F_{xy} 1.5443

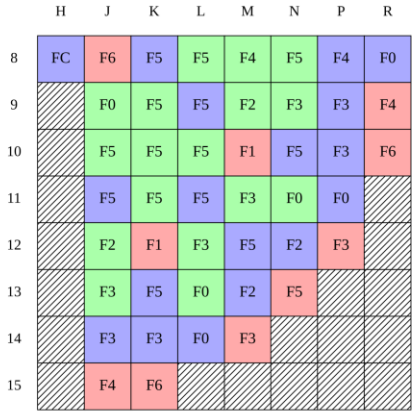


Optimized LP

CL 483.2 EFPD
Max-F_{xy} 1.5479

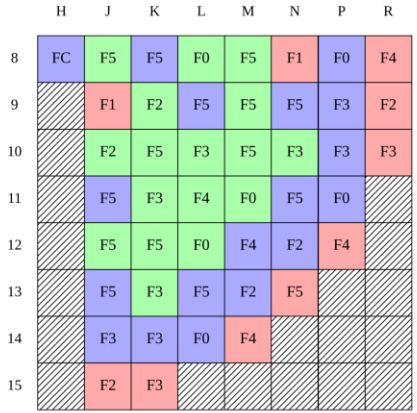
Cycle 6

(SA limits: CL 490 EFPD, Max-F_{xy} 1.55)



Reference LP

CL 476.0 EFPD
Max-F_{xy} 1.5356



Optimized LP

CL 487.4 EFPD
Max-F_{xy} 1.5357

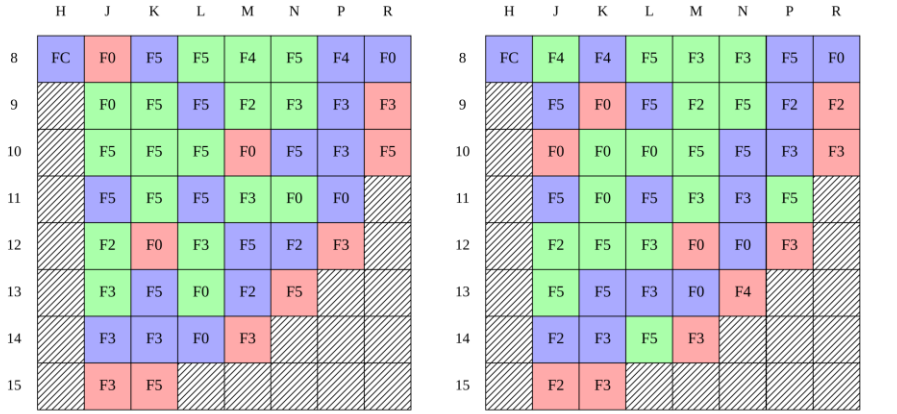
Optimal LPs by Cycle

➢ SA results

Fresh FA
Once-burnt FA
Twice-burnt FA

Cycle 7

(SA limits: CL 490 EFPD, Max-F_{xy} 1.55)



Reference LP

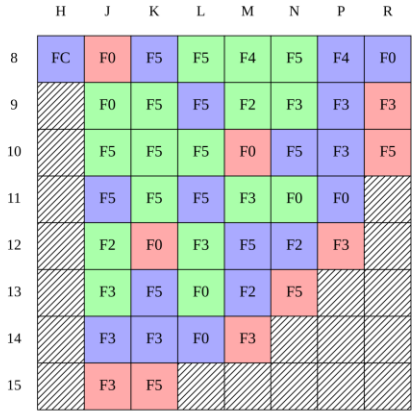
CL 475.9 EFPD
Max-F_{xy} 1.5354

Optimized LP

CL 489.2 EFPD
Max-F_{xy} 1.5372

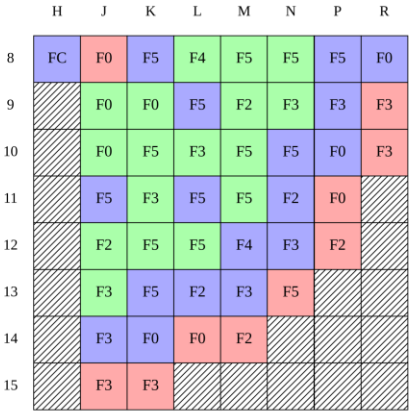
Cycle 8

(SA limits: CL 490 EFPD, Max-F_{xy} 1.55)



Reference LP

CL 474.3 EFPD
Max-F_{xy} 1.5355



Optimized LP

CL 497.1 EFPD
Max-F_{xy} 1.5405

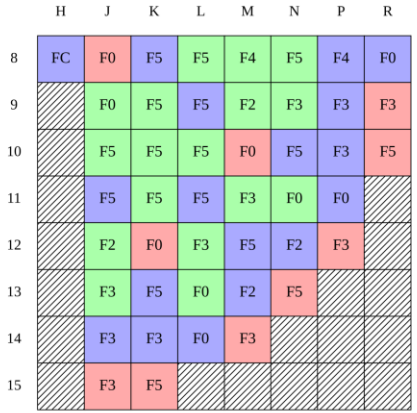
Optimal LPs by Cycle

➢ SA results

Fresh FA
Once-burnt FA
Twice-burnt FA

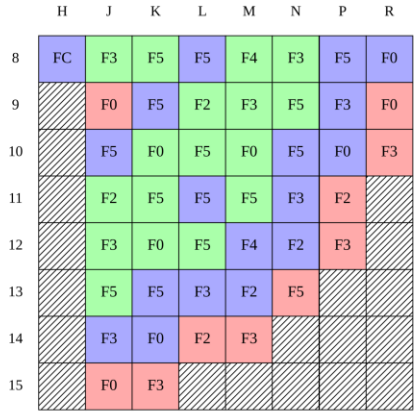
Cycle 9

(SA limits: CL 490 EFPD, Max-F_{xy} 1.55)



Reference LP

CL 475.4 EFPD
Max-F_{xy} 1.5344

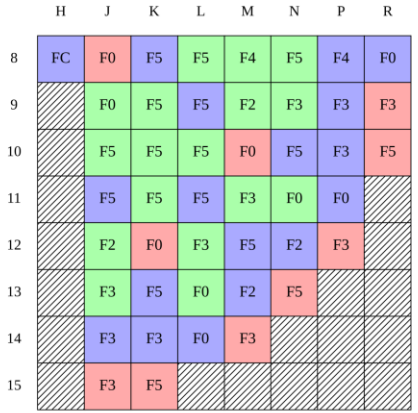


Optimized LP

CL 492.1 EFPD
Max-F_{xy} 1.5430

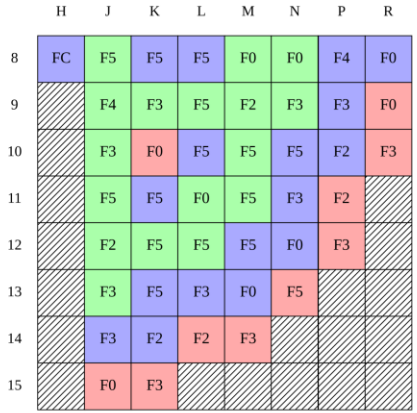
Cycle 10

(SA limits: CL 490 EFPD, Max-F_{xy} 1.55)



Reference LP

CL 475.9 EFPD
Max-F_{xy} 1.5349



Optimized LP

CL 493.3 EFPD
Max-F_{xy} 1.5483

부산대학교 기계공학부
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SCHOOL OF MECHANICAL ENGINEERING

Appendix B

LP Optimization using SA

➢ SA using screening technique

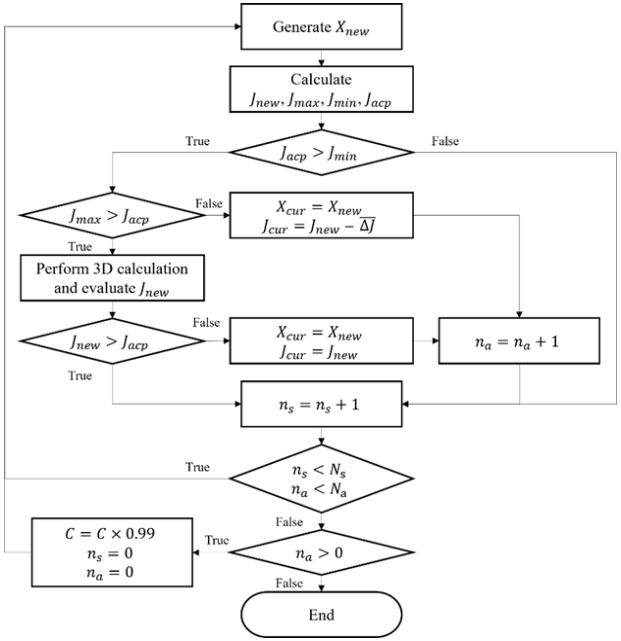
- Evaluate **bias($\overline{\Delta J}$)** and **standard deviation(σ)** between objective values of surrogate model and 3D calculations.
- Skip 3D calculation if the surrogate result is beyond $\pm 3\sigma$ from SA criteria.
  - $J_{\max/\min} = J_{new} - \overline{\Delta J} \pm 3\sigma$

$$p = \begin{cases} 1 & (J_{new} < J_{cur}) \\ \exp\left(-\frac{\Delta J}{T}\right) & (J_{new} \geq J_{cur}) \end{cases} \longrightarrow J_{acp} = J_{cur} - C \ln \xi$$

Transition probability in metropolis algorithm — Acceptance criteria of Simulated Annealing

➢ Multi-Objective function design

- Combined score **in peaking factor(PF) and cycle length(CL).**
  - $J(X) = J_{PF}(X) + J_{CL}(X)$
  - $J_{PF}(X) = \begin{cases} 1 + \frac{1}{\delta PF^2}\left(PF(X) - PF_{\lim}\right)^2 & \left(PF(X) > PF_{\lim}\right) \\ 0 & \left(PF(X) < PF_{\lim}\right) \end{cases}$
  - $J_{CYC}(X) = \begin{cases} 1 + \frac{1}{\delta CL^2}\left(CL(X) - CL_{\lim}\right)^2 & \left(CL(X) < CL_{\lim}\right) \\ 0 & \left(CL(X) > CL_{\lim}\right) \end{cases}$



Flow chart of Simulated Annealing with screening technique.

Ref.) Park, T.K., Joo, H.G., Kim, C.H., Lee, H.C., 2009. Multiobjective loading pattern optimization by simulated annealing employing discontinuous penalty function and screening technique. Nucl. Sci. Eng. 162, 134-147.

Adaptive SA

➢ Initialization with the result of the first stage

- Estimate parameters from initial sampling:
  - m_1: # of trials with decreased objective value
  - m_2: # of trials with increased objective value
  - $\overline{\Delta f^+}$: Average increase in objective value when increased
  - χ: Transition probability
- Initial temperature:

$$c_0 = \frac{\overline{\Delta f^+}}{\ln\left(\frac{m_2}{m_2\chi - m_1(1-\chi)}\right)}$$

➢ Stage termination condition

- Stop stage if:
  - Total trials $\geq N_{stg}$, or
  - Accepted trials $\geq N_a \left(= \frac{N_{stg}}{10}\right)$

➢ Temperature cooling

- Update temperature using standard deviation
  - λ: Cooling rate coefficient
  - σ_k: Standard deviation of objective values at stage k
- Cooling parameter:

$$\alpha_k = \exp\left(-\frac{\lambda c_k}{\sigma_k}\right)$$

➢ Algorithm termination

- Evaluate convergence at the end of each stage
  - $\langle f \rangle_\infty$: Average objective value in initial stage
  - f_k^{best}: Best objective value at stage k
- Converged if σ_k is sufficiently small:

$$\frac{(\sigma_k)^2}{\langle f \rangle_\infty - f_k^{best}} < \epsilon_s$$

➢ Smoothing standard deviation

- Reduce fluctuation of σ_k across stages
  - ω: Smoothing factor
- Used in both cooling and termination conditions.
- Smoothed standard deviation:

$$\sigma_k^s = (1-\omega)\sigma_k + \omega\sigma_{k-1}^s \cdot \alpha_{k-1}$$

Ref.) Lee, H.C., Shim, H.J., Kim, C.H., 2001. Parallel Computing Adaptive Simulated Annealing Scheme for Fuel Assembly Loading Pattern Optimization in PWRs. Nuclear Technology, 135:39-50.

Adaptive SA – Application

➢ SA constants

- Set maximum numbers of trials per stage
  - $N_{stg} = 4000,\ \ N_{acp} = \frac{N_{stg}}{10} = 400$
- Default parameters used in this stage
  - Transition probability, $\chi = 0.99$
  - Cooling rate coefficient, $\lambda = 0.1$
  - Smoothing factor, $\omega = 0.9$
  - Termination threshold, $\epsilon_s = 0.005$

➢ Limit values of core parameters

- C01 – C02
  - Core constraints based on NDR reference core data
- C03 – C10
  - Cycle length limit : 490 EFPDs
  - Peaking factor limit : 1.6 (C03, C04), 1.55 (C05 – C10)