부산대학교 기계공학부
PUSAN NATIONAL UNIVERSITY
SCHOOL OF MECHANICAL ENGINEERING

Prediction of Reactor Core Design Parameters using Vision Transformer

KNS Workshop
A New Paradigm in Reactor Analysis Enabled by Artificial Intelligence
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Vision Transformer (ViT)

- What is Transformer and Vision Transformer ?
- 이미지 분류를 위한 신경망의 발전사

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ViT 이용한 OPR-1000 핵설계 인자 예측

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- LP 생성형 ViT 개발 : LP Transformer

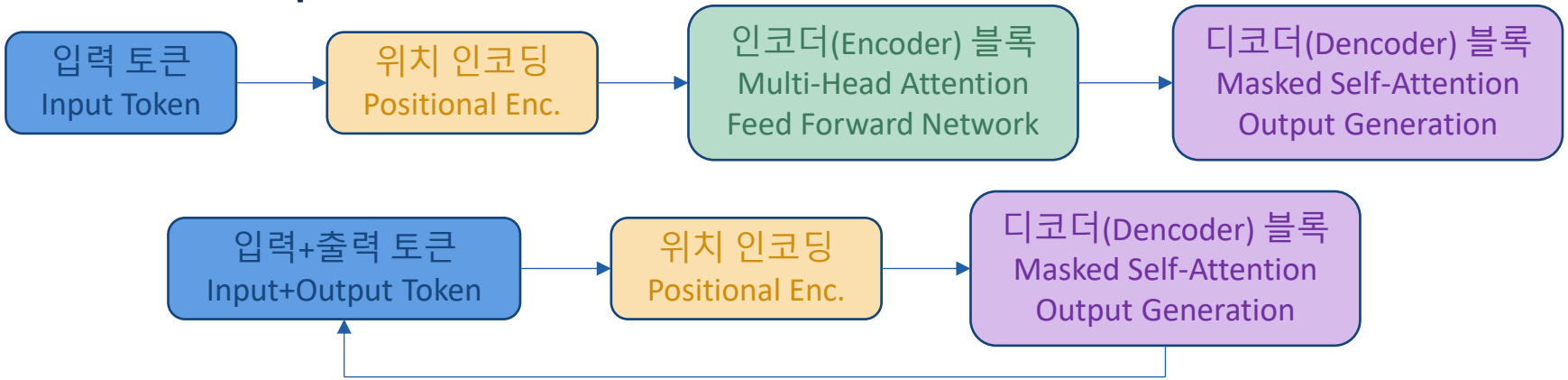
Vision Transformer (ViT)

What is Transformer?

- 구글이 2017년 논문 “Attention is all you need”에서 처음 제안
  - Vaswani et al., “Attention is all you need,” Advances in Neural Information Processing Systems (NeurIPS), 2017, vol. 30, pp. 5998–6008.
- GPT, Claude 등 최신 대형 언어 모델(LLM)의 표준
- 특징 :
  - Self-Attention : 입력 문장 내부의 모든 단어 간 관계와 문맥적 유사도를 동시에 계산
  - Parallelism : 단어를 순차적으로 처리하던 RNN과 달라, 입력 시퀀스 전체를 한번에 병렬로 연산
  - Positional Encoding : 모든 단어 동시 처리로 손실되는 순서 정보를 보완하기 위해 위치 정보 추가
  - Multi-Head Attention : 어텐션 연산을 여러 개의 헤드로 나누어 병렬 수행, 다각도 분석
- RNN 대비 우수성 :
  - RNN은 문장이 길수록 앞부분 정보 소실, Transformer는 거리에 상관없이 직접 관계성 계산
  - RNN은 순차 연산으로 병렬 처리 불가, Transformer는 전체 시퀀스를 동시 계산하여 학습 시간 단축

Vision Transformer (ViT)

Transformer 구조

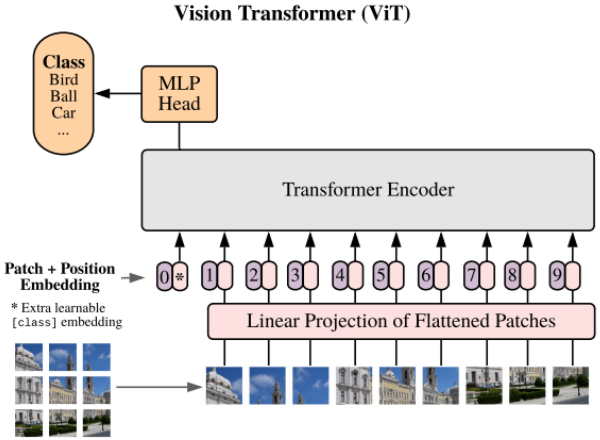


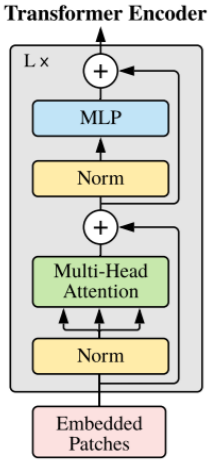
구분	인코더	디코더
주요 역할	입력 텍스트를 고차원 문맥 벡터로 변환 (이해)	이전 토큰 기반 다음 토큰을 확률적으로 예측 (생성)
어텐션 방식	양방향 Self-Attention	단방향 Self-Attention
주요 응용	텍스트 분류, 감정 분석, 개체명 인식	텍스트 생성, 대화형 AI, 문서 요약
대표 모델	BERT, RoBERTa	GPT, LLaMA, Claude

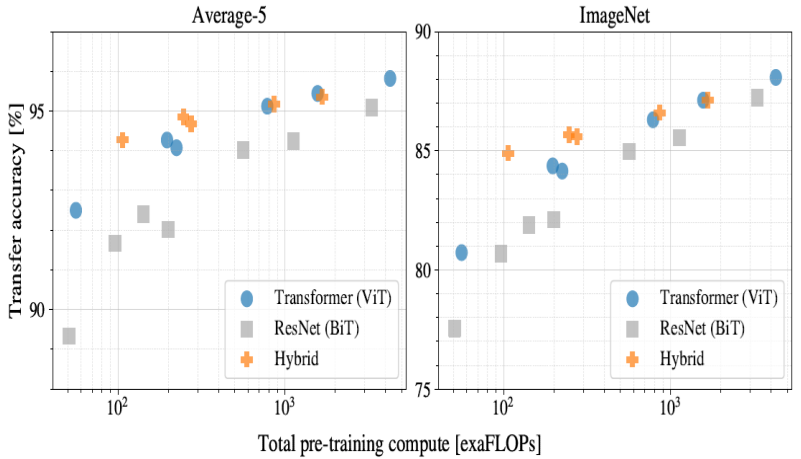
Vision Transformer (ViT)

What is Vision Transformer ?

- 구글이 2020년 논문(초안) “An image is worth 16x16 words: Transformers for image recognition at scale”에서 처음 제안
  - A. Dosovitskiy et al., "An image is worth 16x16 words: Transformers for image recognition at scale," in *International Conference on Learning Representations (ICLR)*, 2021.
- 자연어 처리에 사용되는 Transformer 구조를 **이미지 분류** 분야에 그대로 확장 적용







Vision Transformer (ViT)

이미지 분류를 위한 신경망의 발전사

- LeNet-5 (1998) : 현대식 CNN의 시초
  - Y. LeCun, et al., "Gradient-based learning applied to document recognition," *Proceedings of the IEEE*, vol. 86, no. 11, pp. 2278-2324, Nov. 1998.
- AlexNet (2012) : CNN, ReLU 활성화 함수 도입, 딥러닝 열풍의 시발점
  - A. Krizhevsky, et al., "ImageNet classification with deep convolutional neural networks," *Advances in Neural Information Processing Systems(NeurIPS 2012)*, 2012, vol. 25, pp. 1097-1105.
- VGGNet (2014) : CNN, Network을 16~19개 레이어로 깊게 쌓음
  - K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," *arXiv preprint arXiv:1409.1556*, 2014.
- ResNet (2016) : CNN, 기울기 소실 문제를 스킵 연결로 해결, DNN의 한계 극복
  - K. He, et al., "Deep residual learning for image recognition," *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR 2016)*, 2016, pp. 770-778.
- ViT (2020) : Vision Transformer, 텍스트 처리 AI와 이미지 처리 AI의 아키텍처 통합
  - A. Dosovitskiy et al., "An image is worth 16x16 words: Transformers for image recognition at scale," in *International Conference on Learning Representations (ICLR)*, 2021.

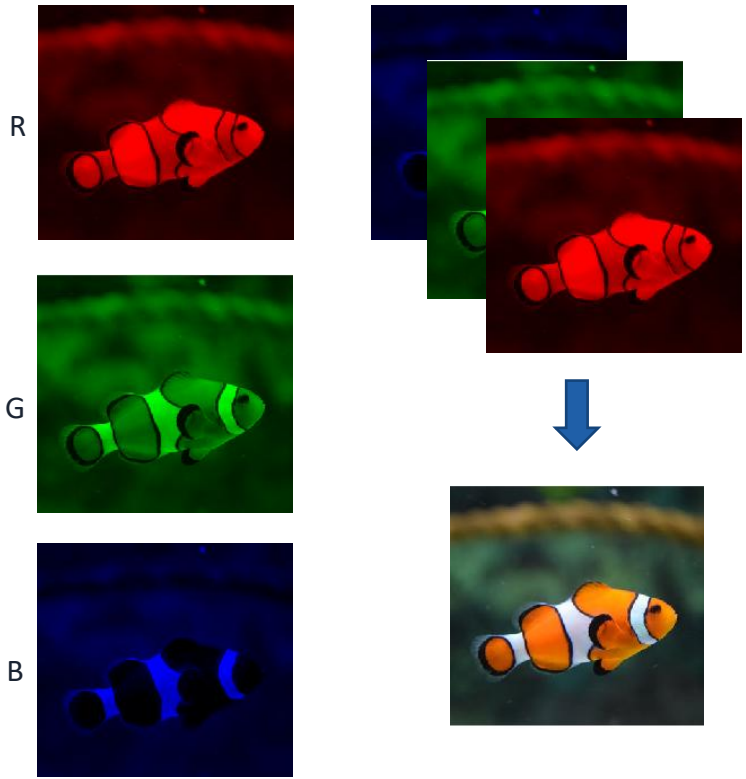
Vision Transformer (ViT)

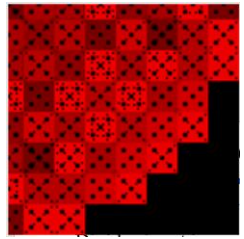
CNN vs. ViT

	CNN (ResNET 등)	ViT
장점	- 국소적 특징을 매우 빠르고 효율적으로 학습 - 귀납적 편향(사전 지식, 편견, 고정관념)이 내장되어 적은 학습 데이터로도 높은 성능	- Self-Attention 덕분에 이미지 전체의 넓은 영역을 한눈에 바라보면 관계 파악 - 데이터의 양과 모델의 크기가 커질수록 성능이 우상향하는 확장성이 뛰어남
단점	- 필터의 시야가 국한되어 이미지 전체의 맥락이나 멀리 떨어진 객체 간의 관계 파악 한계	-귀납적 편향(사전 지식, 편견, 고정관념)이 부족하여 학습 데이터가 부족하면 성능 떨어짐

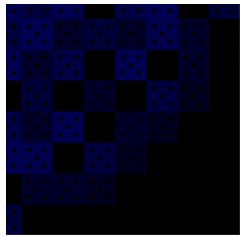
ViT를 이용한 OPR-1000 핵설계 인자 예측

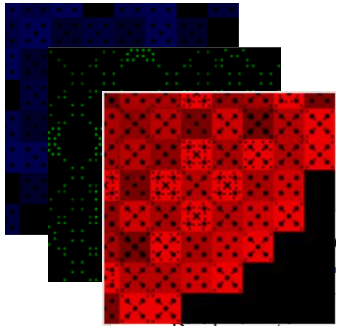
- **A Loading Pattern is an Image !!**

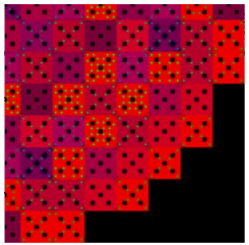



Fuel Enrichment


BP Fraction

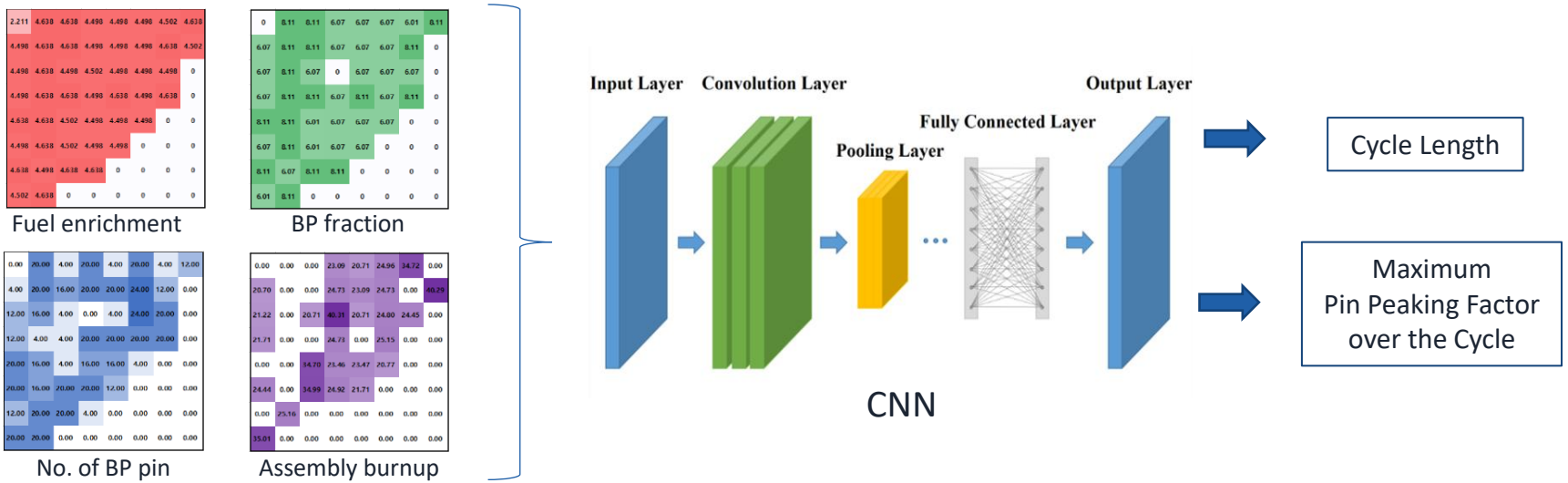

Burnup





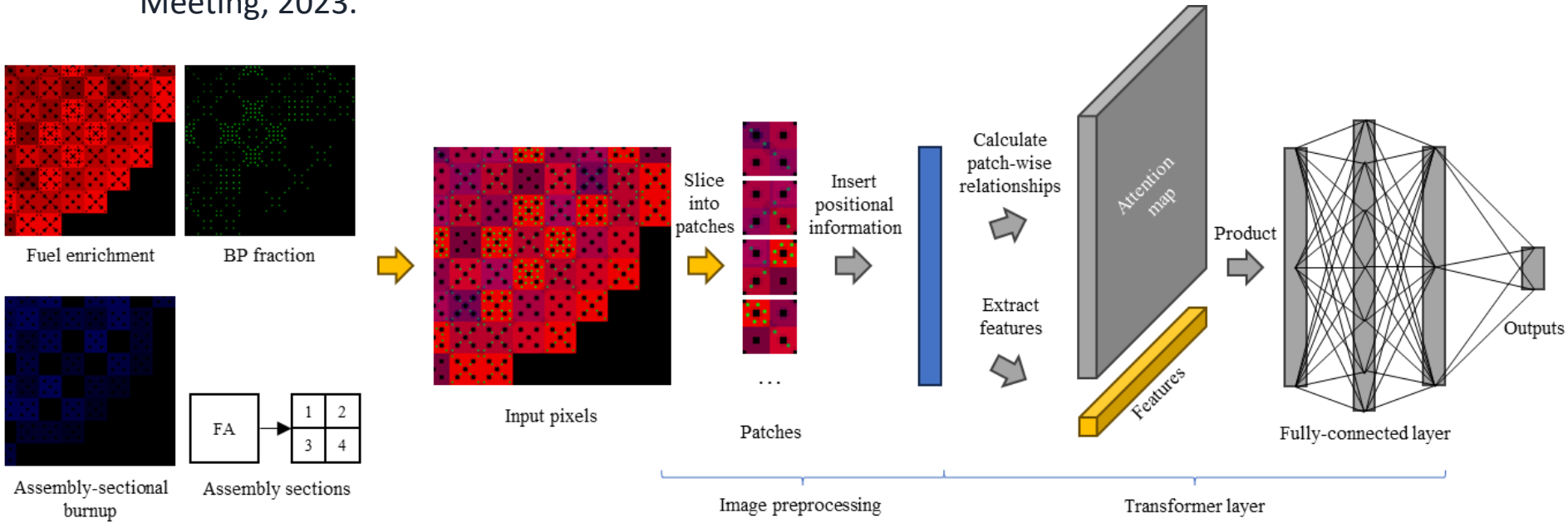
ViT를 이용한 OPR-1000 핵설계 인자 예측

- **Assembly-wise CNN을 이용한 핵설계 인자 예측 및 응용**
  - 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.



ViT를 이용한 OPR-1000 핵설계 인자 예측

- **Pin-wise Vision Transformer를 이용한 핵설계 인자 예측**
  - 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.



ViT를 이용한 OPR-1000 핵설계 인자 예측

학습 자료 생산

- Random Generation
  - C01, C02 : YGN3 NDR 참조 노심 LP로 부터 Random Shuffling (Assembly Swap, Assembly Rotation)
  - C03-C10 : 과도 주기 - 평형 주기를 계산 후 Random Shuffling
  - Max F_{xy} < 5.0
  - Shuffling 후 임의 LP에서 일부 신연료 농축도·BP로 교체 (농축도 4.3, 4.8 wt%, BP(Gd_2O_3) 7 wt%)
  - 총 100,000 cases (STREAM/RAST-K)
- Near-Optimal (low peaking factor, long cycle length) LPs
  - Simulated Annealing을 이용한 장전모형 최적화 계산을 통해 Near Optimal LP 생산
  - 2,000 cases per Cycle (Total 20,000 cases)
- Data Labeling
  - (LP, Cycle length), (LP, Max F_{xy} over the cycle)
- Training Subset : Test Subset = 9 : 1

ViT를 이용한 OPR-1000 핵설계 인자 예측

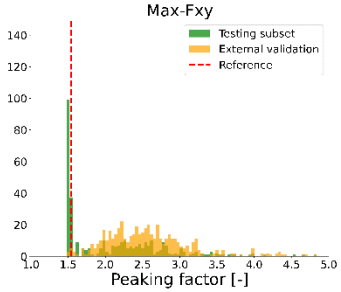
예측 결과

- 평가 자료
  - Test subset (10%) + External Validation (EV) dataset
  - EV : 학습에 없는 FA 사양, 5,000 cases
  - 농축도 4.3–4.8 wt%, BP 0–24 rods, Gd_2O_3 6·7·8 wt%
- 비교 : Assembly-wise CNN
- 오차 지표 : RMSRE, MaxARE

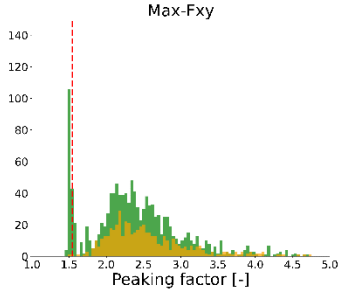
ViT 설정	Cycle length	Max Fxy
Patch size	8×8 pins	2×2 pins
Encoder layers	3	5
Token dim. / Heads	256 / 4	256 / 4
MLP dim.	512	512
Training time	8 h	16 h

ViT를 이용한 OPR-1000 핵설계 인자 예측

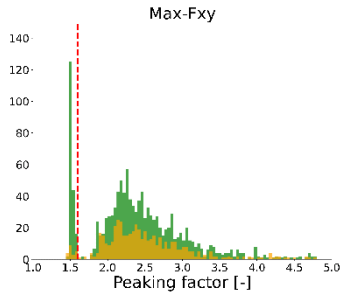
- 학습 자료 생산 – Max F_{xy}



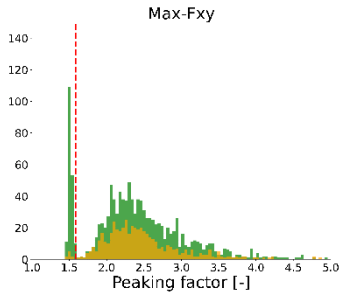
C01



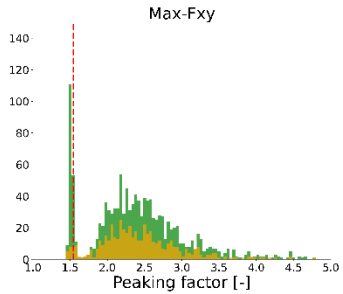
C02



C03



C04



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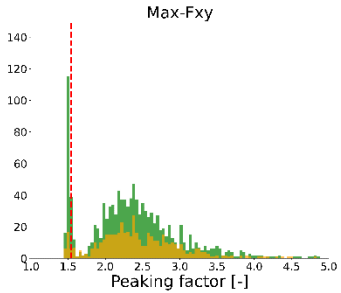

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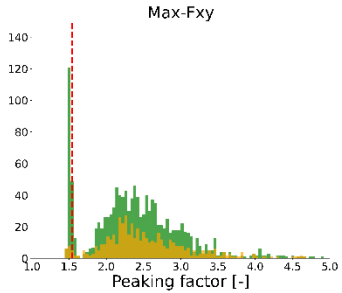

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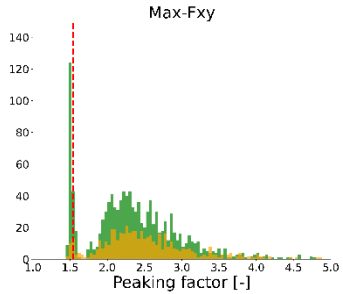
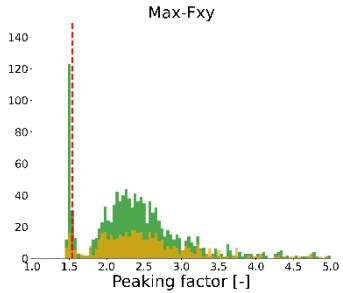


C08



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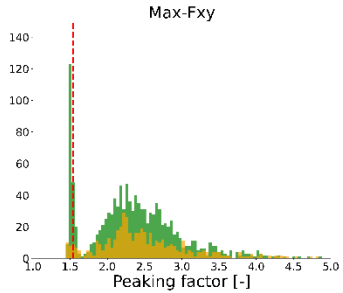
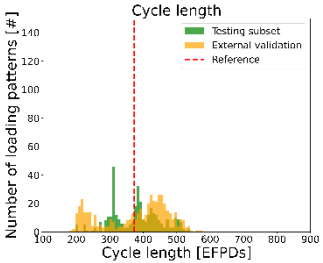


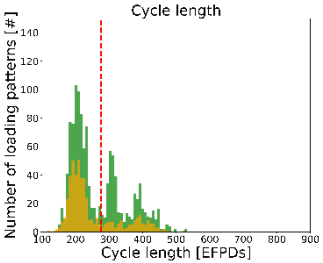
C10

ViT를 이용한 OPR-1000 핵설계 인자 예측

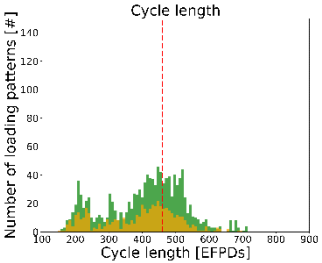
- **학습 자료 생산 – Cycle Length**



C01



C02



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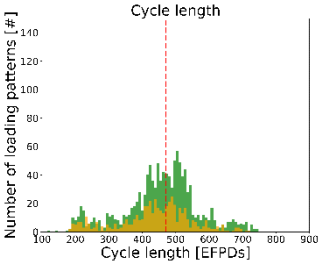

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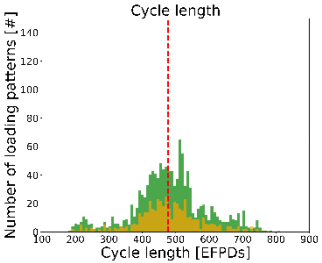

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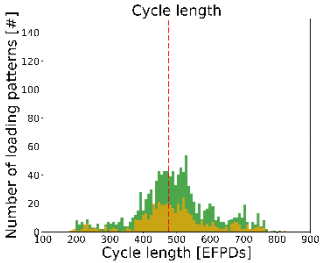

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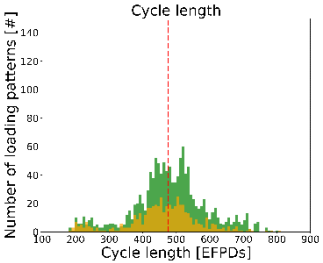

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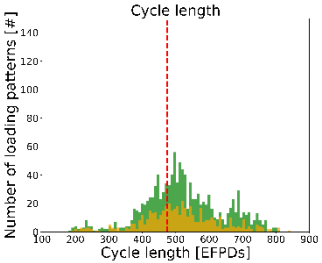
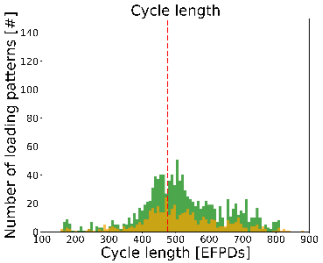
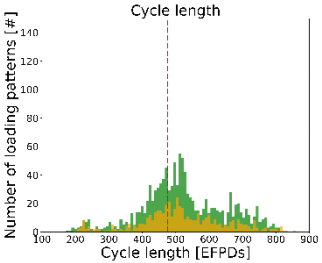


C08



C09



C10

ViT를 이용한 OPR-1000 핵설계 인자 예측

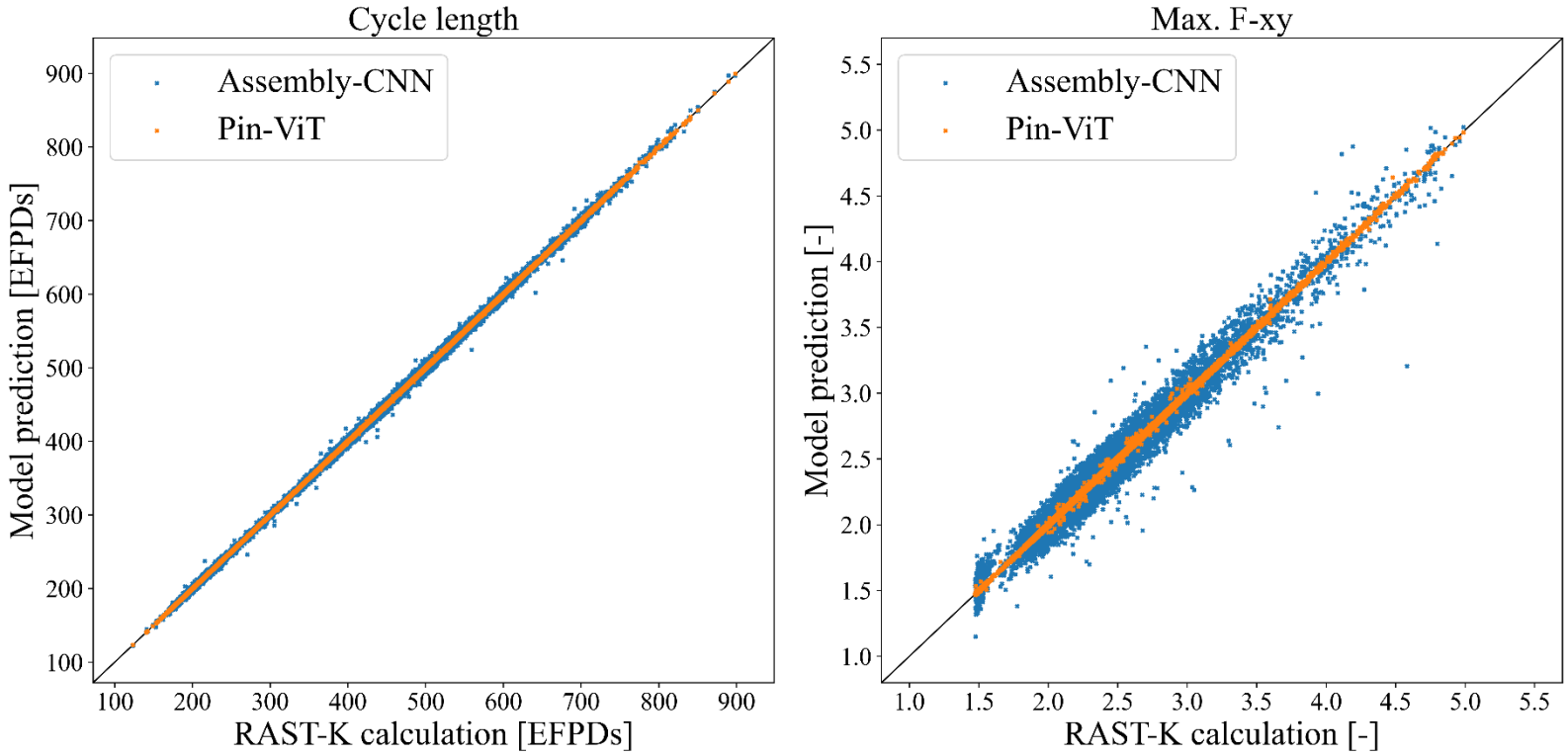
예측 결과

- Assembly-wise CNN vs. Pin-wise ViT (EV dataset + Pre-SA LPs test subset)
  - Cycle length : 두 모델 모두 정확하게 예측
  - Max F_{xy} : CNN은 outlier 발생, ViT는 대각선 주위에 밀집
  - ViT는 모든 지표에서 CNN 대비 **오차 1/5 이하**
  - CNN은 추가 학습 후에도 Max F_{xy} MaxARE 40.5% 잔존

Error metric	Cycle length (%)		Max F_{xy} (%)	
	CNN	ViT	CNN	ViT
RMSRE	0.94	**0.16**	8.19	**0.86**
MaxARE	10.0	**0.90**	40.5	**4.37**

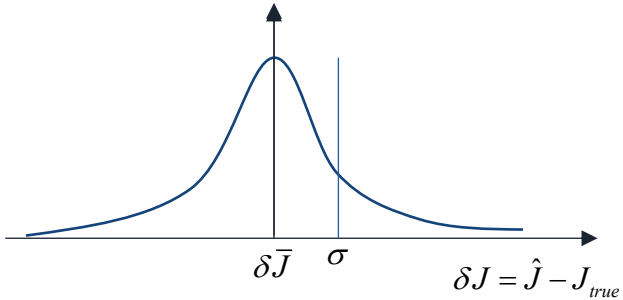
ViT를 이용한 OPR-1000 핵설계 인자 예측

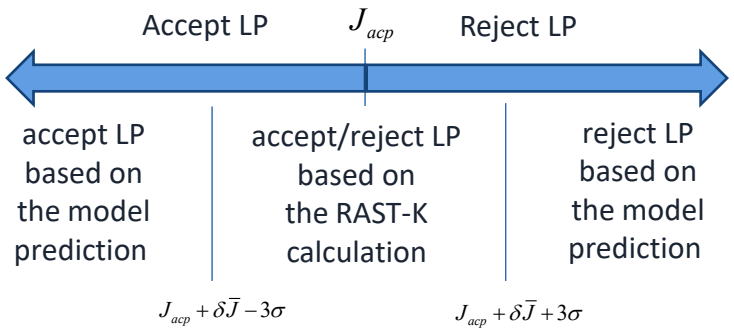
- 예측 결과



ViT 핵설계 인자 예측 모델의 응용

- **Adaptive SA with Screening Technique**
  - **Adaptive SA[1] : 초기 T와 냉각 속도 자동 조정**
    - 초기 T_0 : 1st stage uphill move로 수락 확률 χ = 0.99에 맞춤
    - $T_0 = \frac{\Delta J^+}{\ln\left[\frac{m_2}{m_2\chi - m_1(1-\chi)}\right]}$
    - $T_{k+1} = T_k \exp\left(-\frac{\lambda T_k}{\sigma_k}\right)$, λ = 0.1 → σ_k가 크면 천천히 냉각
    - 종료 : $\frac{\sigma_k^2}{T_k(\bar{J}_\infty - J_{k,best})} < \varepsilon_s = 0.005$
  - 수락 조건 및 Screening[2]
    - $p = \min\left(1, \exp\left(-\frac{\Delta J}{T}\right)\right) \rightarrow J_{acp} = J(x_{cur}) - T\ln\xi$
    - Bias $\delta J = \hat{J} - J_{true}$, 불확실도 σ : Test subset 오차 기반
    - ViT 예측 $\hat{J} - \delta J \pm 3\sigma$가 J_{acp}를 벗어나면 Accept/Reject
    - 판정 불가 또는 J = 0 예측 후보는 RAST-K 3D 계산





1) H. C. Lee, H. J. Shim, and C. H. Kim, "Parallel Computing Adaptive Simulated Annealing Scheme for Fuel Assembly Loading Pattern Optimization in PWRs," Nucl. Technol., 135(1), 39–50 (2001).
2) T. K. Park, H. G. Joo, C. H. Kim, and H. C. Lee, "Multiobjective Loading Pattern Optimization by Simulated Annealing Employing Discontinuous Penalty Function and Screening Technique," Nucl. Sci. Eng., 162(2), 134–147 (2009).

ViT 핵설계 인자 예측 모델의 응용

SA Screening 적용 결과 – Cycle 1

- YGN3 C01, 독립 SA 10회 평균 · 제한값 : **373.2 EFPD, Max F_{xy} 1.5412 (NDR)**
  - Fixing type : 신규 FA는 위치 이동·회전만 허용 (농축도·BP 교체 없음)
  - ViT : Screening 효율 95.2% → 99.9%, 계산 시간 **93.7 h → 2.7 h**
  - 모든 run에서 두 제한 만족, 최적 LP는 NDR LP와 유사

Surrogate	RAST-K eval.	Surrogate eval.	Screening efficiency* (%)	Process time (h)	Estimated Process time w/o screening (h)	Cycle length (EFPD)	Max F_{xy}
CNN	1,912.8	38,266.1	95.2	93.7	1,953	374.8	1.5258
ViT	37.4	40,109.6	**99.9**	**2.7**	2,007	377.1	1.5295
Reference LP (NDR)						373.2	1.5412

* Screening efficiency = Surrogate eval. / (Surrogate eval. + RAST-K eval.)

ViT 핵설계 인자 예측 모델의 응용

Screening by CNN

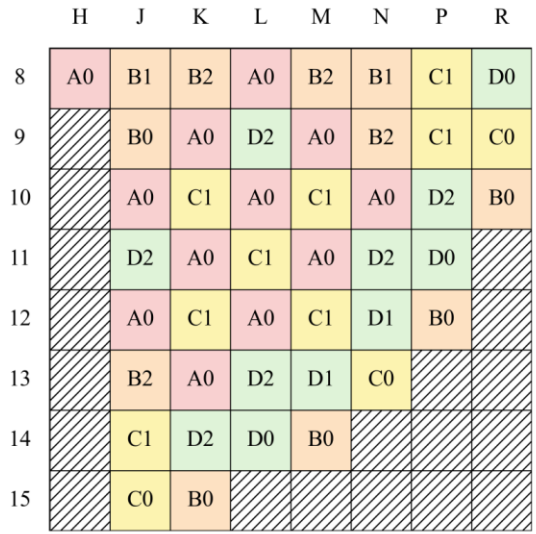
SA run	RAST-K evaluations	CNN evaluations	Screening efficiency (%)	Process time (h)	Estimated process time without screening (h)	Cycle length (EFPDs)	Max-F_{xy} (-)
1	1,844	37,835	95.4	90.4	1,928	373.4	1.5407
2	1,860	36,608	95.2	91.1	1,870	376.1	1.5354
3	2,133	43,114	95.3	104.5	2,199	375.9	1.5078
4	1,834	35,642	95.1	89.8	1,821	373.5	1.5339
5	1,759	35,689	95.3	86.2	1,820	374.5	1.5336
6	2,001	41,349	95.4	98.1	2,107	374.2	1.5078
7	1,779	36,479	95.3	87.2	1,859	**376.3**	**1.5286**
8	2,171	42,041	95.1	106.4	2,149	373.9	1.5221
9	1,702	34,281	95.3	83.4	1,749	375.3	1.5128
10	2,045	39,623	95.1	100.2	2,025	375.0	1.5354
Average	1,912.8	38,266.1	95.2	93.7	1,953	374.8	1.5258

Screening by ViT

SA run	RAST-K evaluations	ViT evaluations	Screening efficiency (%)	Process time (h)	Estimated process time without screening (h)	Cycle length (EFPDs)	Max-F_{xy} (-)
1	26	34,443	99.9	2.0	1,723.5	377.2	1.5182
2	58	41,278	99.9	3.7	2,066.8	379.3	1.5247
3	22	41,707	99.9	1.9	2,086.5	376.3	1.5325
4	34	41,065	99.9	2.5	2,055.0	375.4	1.5322
5	47	44,368	99.9	3.2	2,220.8	375.3	1.5333
6	49	39,881	99.9	3.2	1,996.5	376.9	1.5296
7	20	35,288	99.9	1.7	1,765.4	376.6	1.5347
8	41	33,181	99.9	2.7	1,661.1	379.3	1.5308
9	42	47,786	99.9	3.0	2,391.4	375.3	1.5350
10	35	42,099	99.9	2.6	2,106.7	**379.7**	**1.5238**
Average	37.4	40,109.6	99.9	2.7	2,007.4	377.1	1.5295

ViT 핵설계 인자 예측 모델의 응용

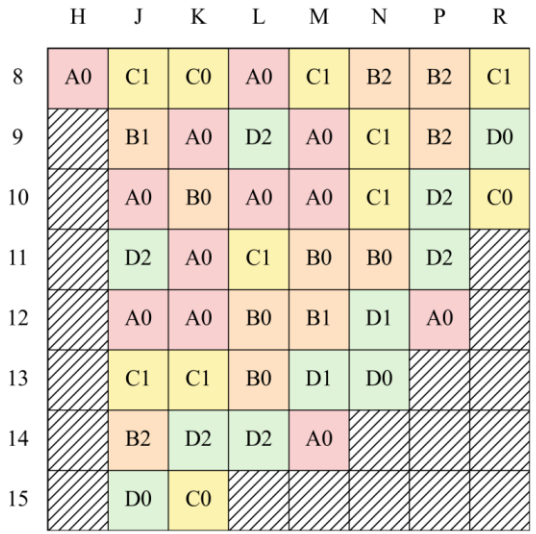
- **SA 적용 결과 – Cycle 1 최적 LP**



	H	J	K	L	M	N	P	R
8	A0	B1	B2	A0	B2	B1	C1	D0
9		B0	A0	D2	A0	B2	C1	C0
10		A0	C1	A0	C1	A0	D2	B0
11		D2	A0	C1	A0	D2	D0	
12		A0	C1	A0	C1	D1	B0	
13		B2	A0	D2	D1	C0		
14		C1	D2	D0	B0			
15		C0	B0					

Reference LP (NDR)

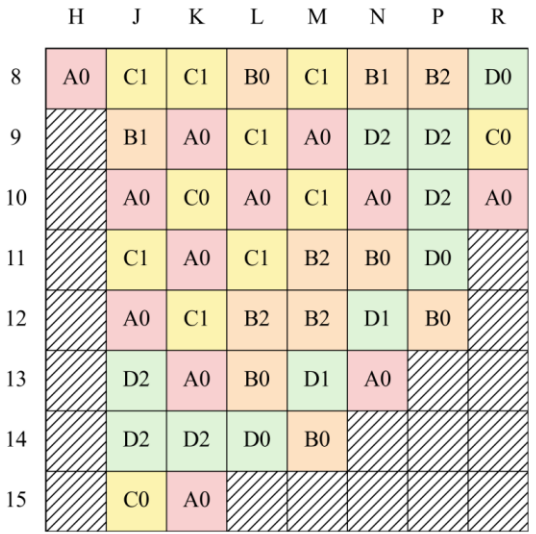
CL 373.2 EFPD · Max F_{xy} 1.5412



	H	J	K	L	M	N	P	R
8	A0	C1	C0	A0	C1	B2	B2	C1
9		B1	A0	D2	A0	C1	B2	D0
10		A0	B0	A0	A0	C1	D2	C0
11		D2	A0	C1	B0	B0	D2	
12		A0	A0	B0	B1	D1	A0	
13		C1	C1	B0	D1	D0		
14		B2	D2	D2	A0			
15		D0	C0					

CNN 최적 LP

CL 376.3 EFPD · Max F_{xy} 1.5286



	H	J	K	L	M	N	P	R
8	A0	C1	C1	B0	C1	B1	B2	D0
9		B1	A0	C1	A0	D2	D2	C0
10		A0	C0	A0	C1	A0	D2	A0
11		C1	A0	C1	B2	B0	D0	
12		A0	C1	B2	B2	D1	B0	
13		D2	A0	B0	D1	A0		
14		D2	D2	D0	B0			
15		C0	A0					

ViT 최적 LP

CL 379.7 EFPD · Max F_{xy} 1.5238

ViT 핵설계 인자 예측 모델의 응용

주어진 핵연료 대체

- Fixing Type : 주어진 핵연료를 가지고 위치와 회전만 바꿔서 LP 결정
- Fixing Enrichment : 주어진 핵연료에서 같은 농축도를 가진 핵연료로 대체 가능 (BP 는 변경 가능; B0↔B1, C0↔C1, D0↔D1↔D2)
- Free Type : 주어진 핵연료에서 다른 농축도를 가진 핵연료도 대체 가능

SA를 이용한 YGN3 1주기 LP 최적화

Option	RAST-K evaluations	ViT evaluations	Screening efficiency (%)	Process time (h)	Estimated process time without screening (h)	Cycle length (EFPDs)	Max-F_{xy} (-)
Fixing Type	37.4	40,109.6	99.9	2.7	2,007.4	377.1	1.5295
Fixing Enr.	46.6	42,963.5	99.9	3.2	2,150.5	380.6	1.5166
Free Type	58.2	43,516.1	99.9	3.8	2,178.7	382.1	1.5189
Reference LP (NDR)						373.2	1.5412

각 10번 SA 계산 후 평균

ViT 핵설계 인자 예측 모델의 응용

SA 적용 결과 – Cycles 2–10 계산 효율

- C01의 독립 SA 10회 각각을 C10까지 이어서 최적화
  - 각 run은 직전 Cycle에서 **자신이 찾은 최적 LP**의 burnt FA를 상속
  - 목표 (CL / Max F_{xy}) : **C02** 275.8 / 1.5442 · **C03–04** 490 / 1.60 · **C05–10** 490 / 1.55
  - Run당 약 32,000 LP 평가, 그 중 65–83개만 RAST-K → 효율 99.7% 이상
  - 계산 시간 **3.4–6.0 h** (RAST-K 단독 시 1,233.9–2,192.5 h 추정)

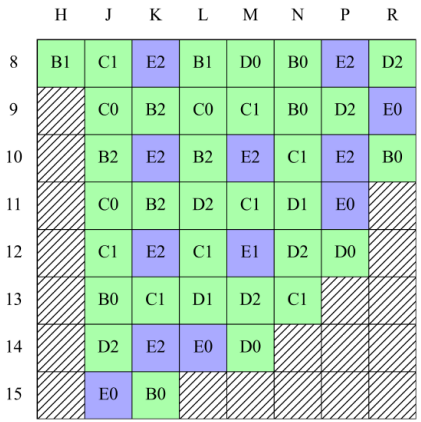
Cycle	2	3	4	5	6	7	8	9	10
RAST-K eval.	74.9	76.2	68.2	65.6	71.9	66.8	65.2	72.0	82.8
ViT eval.	33,031.2	30,254.9	31,047.9	33,506.3	34,013.6	30,862.9	32,598.6	31,763.5	32,634.3
Screening efficiency (%)	**99.8**	**99.7**	**99.8**	**99.8**	**99.8**	**99.8**	**99.8**	**99.8**	**99.7**
Process time (h)	**3.4**	**5.3**	**4.9**	**4.9**	**5.3**	**4.9**	**4.8**	**5.2**	**6.0**
Estimated Process time w/o screening (h)	1,233.9	1,884.6	1,977.6	2,161.3	2,192.5	1,989.1	2,093.6	2,045.2	2,104.1

ViT 핵설계 인자 예측 모델의 응용

- **SA 적용 결과 – Cycles 2–10 최적 LP**

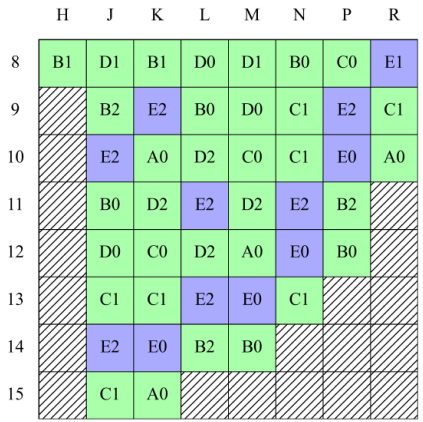
Fresh FA
Once-burnt FA
Twice-burnt FA

Cycle 02



Reference LP

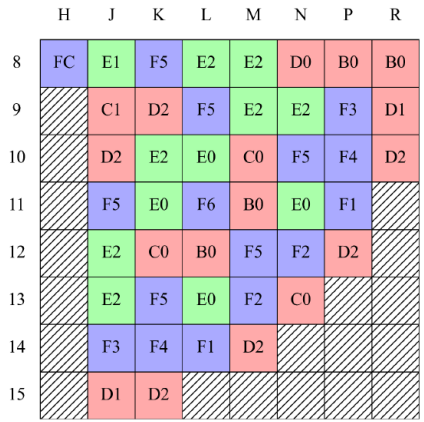
CL 275.8 EFPD
Max F_{xy} 1.5442



Optimized LP

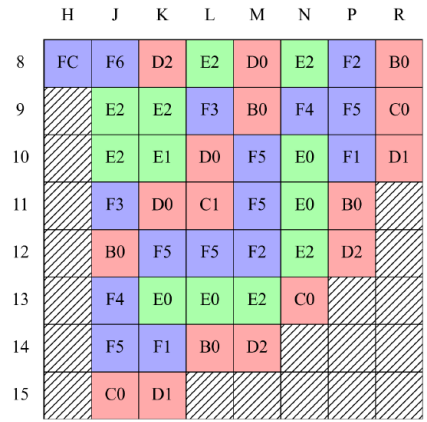
CL 281.3 EFPD
Max F_{xy} 1.5098

Cycle 03



Reference LP

CL 459.8 EFPD
Max F_{xy} 1.5994



Optimized LP

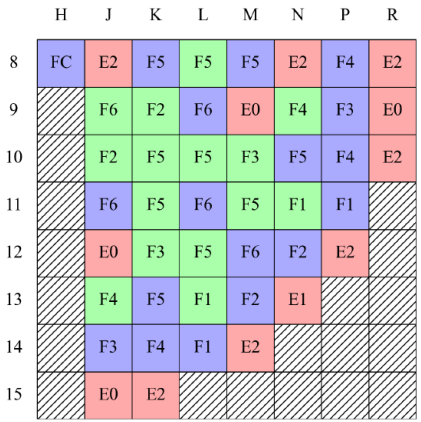
CL 469.4 EFPD
Max F_{xy} 1.5818

ViT 핵설계 인자 예측 모델의 응용

- **SA 적용 결과 – Cycles 2–10 최적 LP**

Fresh FA
Once-burnt FA
Twice-burnt FA

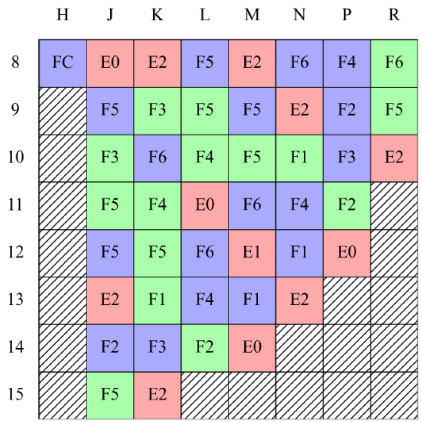
Cycle 04



	H	J	K	L	M	N	P	R
8	FC	E2	F5	F5	F5	E2	F4	E2
9		F6	F2	F6	E0	F4	F3	E0
10		F2	F5	F5	F3	F5	F4	E2
11		F6	F5	F6	F5	F1	F1	
12		E0	F3	F5	F6	F2	E2	
13		F4	F5	F1	F2	E1		
14		F3	F4	F1	E2			
15		E0	E2					

Reference LP

CL 470.3 EFPD
Max F_{xy} 1.5812

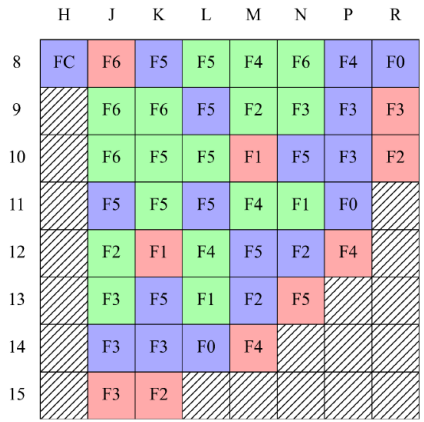


	H	J	K	L	M	N	P	R
8	FC	E0	E2	F5	E2	F6	F4	F6
9		F5	F3	F5	F5	E2	F2	F5
10		F3	F6	F4	F5	F1	F3	E2
11		F5	F4	E0	F6	F4	F2	
12		F5	F5	F6	E1	F1	E0	
13		E2	F1	F4	F1	E2		
14		F2	F3	F2	E0			
15		F5	E2					

Optimized LP

CL 479.5 EFPD
Max F_{xy} 1.5589

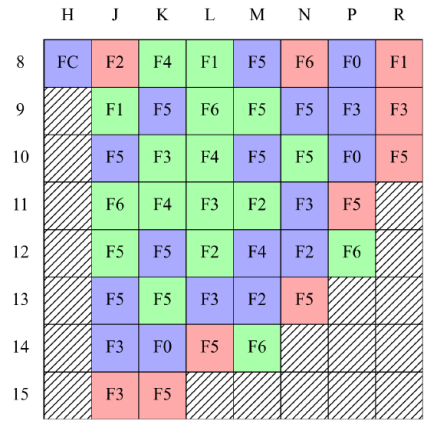
Cycle 05



	H	J	K	L	M	N	P	R
8	FC	F6	F5	F5	F4	F6	F4	F0
9		F6	F6	F5	F2	F3	F3	F3
10		F6	F5	F5	F1	F5	F3	F2
11		F5	F5	F5	F4	F1	F0	
12		F2	F1	F4	F5	F2	F4	
13		F3	F5	F1	F2	F5		
14		F3	F3	F0	F4			
15		F3	F2					

Reference LP

CL 476.4 EFPD
Max F_{xy} 1.5443



	H	J	K	L	M	N	P	R
8	FC	F2	F4	F1	F5	F6	F0	F1
9		F1	F5	F6	F5	F5	F3	F3
10		F5	F3	F4	F5	F5	F0	F5
11		F6	F4	F3	F2	F3	F5	
12		F5	F5	F2	F4	F2	F6	
13		F5	F5	F3	F2	F5		
14		F3	F0	F5	F6			
15		F3	F5					

Optimized LP

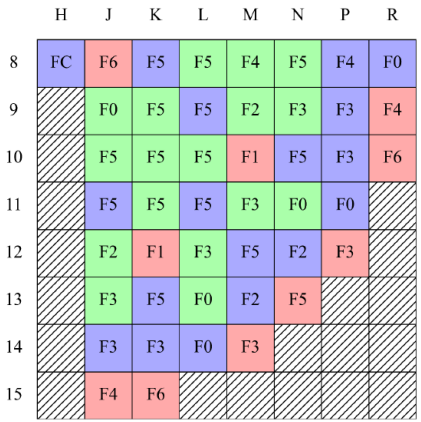
CL 480.6 EFPD
Max F_{xy} 1.5070

ViT 핵설계 인자 예측 모델의 응용

- **SA 적용 결과 – Cycles 2–10 최적 LP**

Fresh FA
Once-burnt FA
Twice-burnt FA

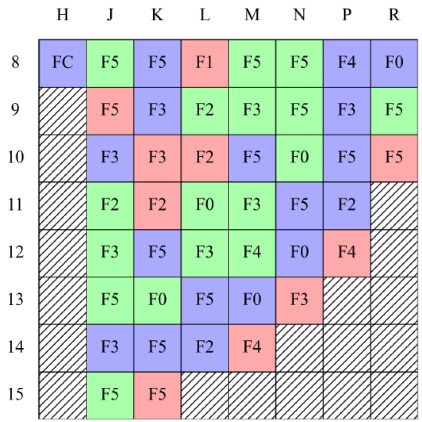
Cycle 06



	H	J	K	L	M	N	P	R
8	FC	F6	F5	F5	F4	F5	F4	F0
9		F0	F5	F5	F2	F3	F3	F4
10		F5	F5	F5	F1	F5	F3	F6
11		F5	F5	F5	F3	F0	F0	
12		F2	F1	F3	F5	F2	F3	
13		F3	F5	F0	F2	F5		
14		F3	F3	F0	F3			
15		F4	F6					

Reference LP

CL 476.0 EFPD
Max F_{xy} 1.5356

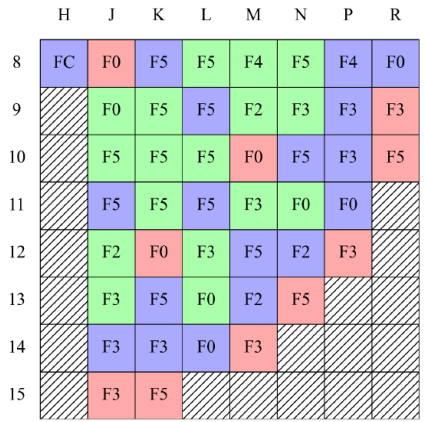


	H	J	K	L	M	N	P	R
8	FC	F5	F5	F1	F5	F5	F4	F0
9		F5	F3	F2	F3	F5	F3	F5
10		F3	F3	F2	F5	F0	F5	F5
11		F2	F2	F0	F3	F5	F2	
12		F3	F5	F3	F4	F0	F4	
13		F5	F0	F5	F0	F3		
14		F3	F5	F2	F4			
15		F5	F5					

Optimized LP

CL 485.8 EFPD
Max F_{xy} 1.5109

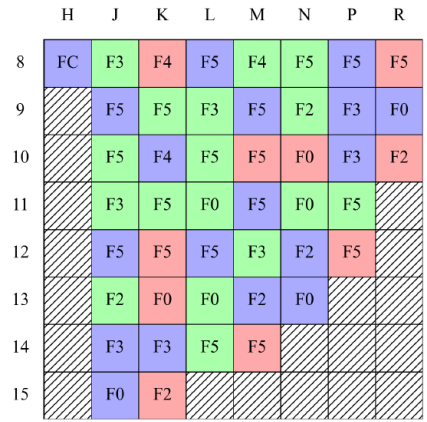
Cycle 07



	H	J	K	L	M	N	P	R
8	FC	F0	F5	F5	F4	F5	F4	F0
9		F0	F5	F5	F2	F3	F3	F3
10		F5	F5	F5	F0	F5	F3	F5
11		F5	F5	F5	F3	F0	F0	
12		F2	F0	F3	F5	F2	F3	
13		F3	F5	F0	F2	F5		
14		F3	F3	F0	F3			
15		F3	F5					

Reference LP

CL 475.9 EFPD
Max F_{xy} 1.5354



	H	J	K	L	M	N	P	R
8	FC	F3	F4	F5	F4	F5	F5	F5
9		F5	F5	F3	F5	F2	F3	F0
10		F5	F4	F5	F5	F0	F3	F2
11		F3	F5	F0	F5	F0	F5	
12		F5	F5	F5	F3	F2	F5	
13		F2	F0	F0	F2	F0		
14		F3	F3	F5	F5			
15		F0	F2					

Optimized LP

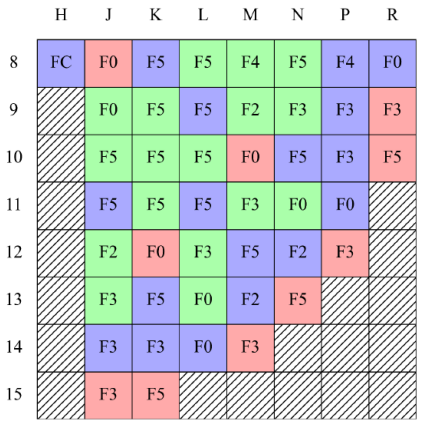
CL 488.6 EFPD
Max F_{xy} 1.5257

ViT 핵설계 인자 예측 모델의 응용

- **SA 적용 결과 – Cycles 2–10 최적 LP**

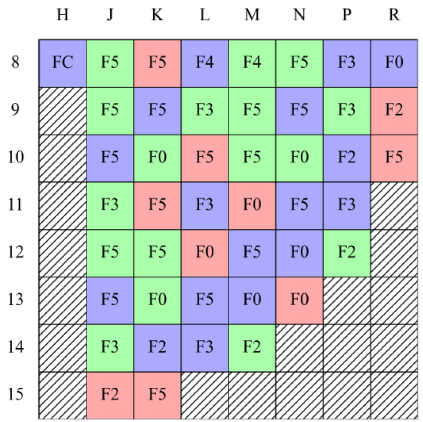
Fresh FA
Once-burnt FA
Twice-burnt FA

Cycle 08



Reference LP

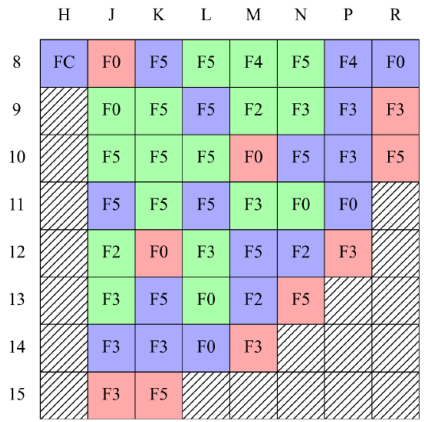
CL 474.3 EFPD
Max F_{xy} 1.5355



Optimized LP

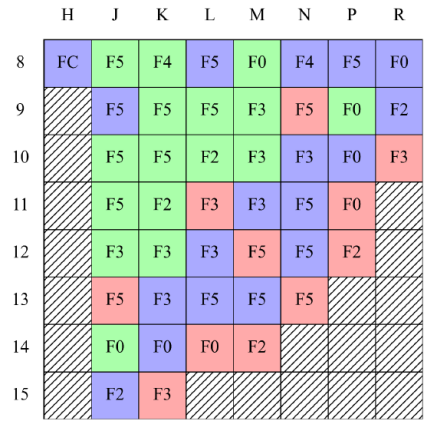
CL 489.1 EFPD
Max F_{xy} 1.5117

Cycle 09



Reference LP

CL 475.4 EFPD
Max F_{xy} 1.5344



Optimized LP

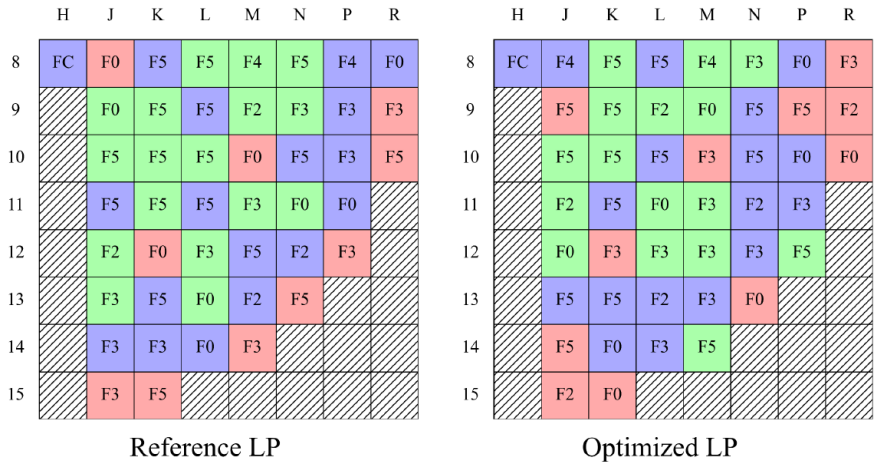
CL 487.1 EFPD
Max F_{xy} 1.5201

ViT 핵설계 인자 예측 모델의 응용

- **SA 적용 결과 – Cycles 2–10 최적 LP**

Fresh FA
Once-burnt FA
Twice-burnt FA

Cycle 10



Reference LP

CL 475.9 EFPD
Max F_{xy} 1.5349

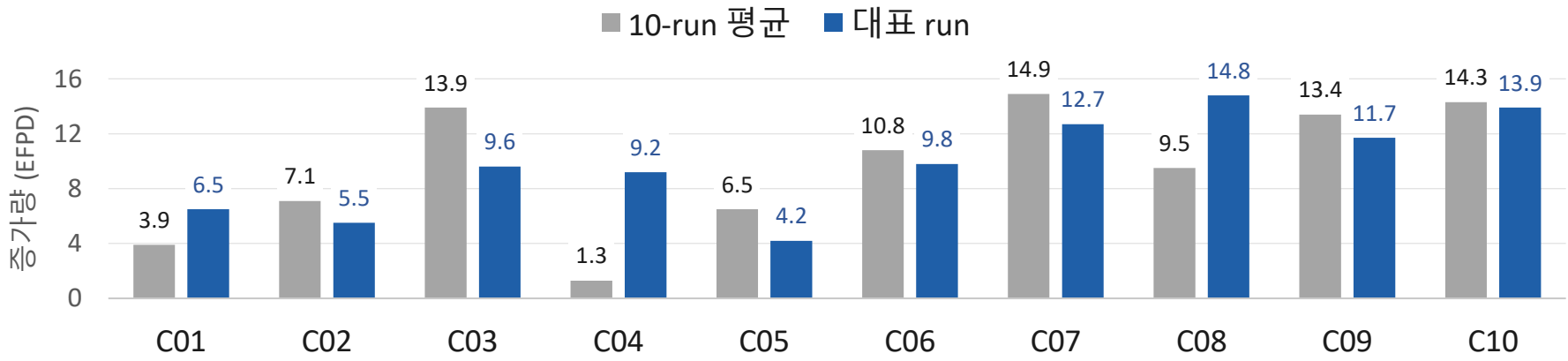
Optimized LP

CL 489.8 EFPD
Max F_{xy} 1.5291

ViT 핵설계 인자 예측 모델의 응용

- **SA 적용 결과 – Cycle length**
  - 누적 Cycle length (EFPD)
    - Reference 4,433 → 평균 **4,529 (+96)**, 최대 **4,531 (+98)**
  - **C04 이득 감소** : C03 장주기화로 재장전 FA 연소도 증가

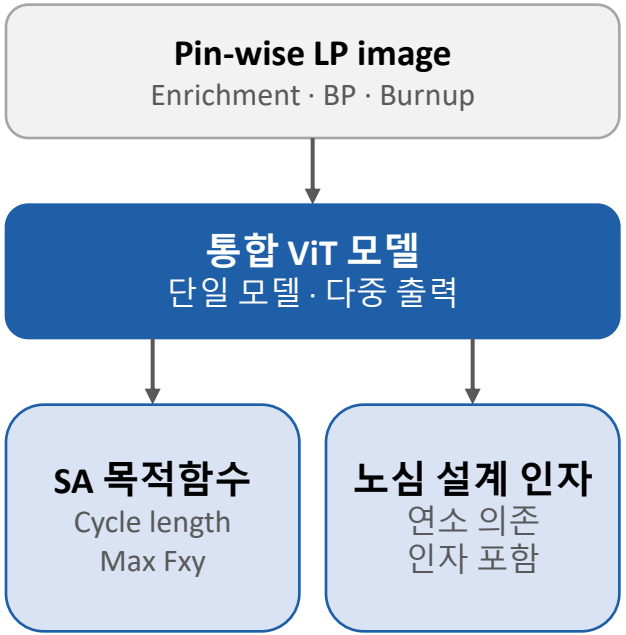
Reference 대비 Cycle length 증가량



향후 연구 계획

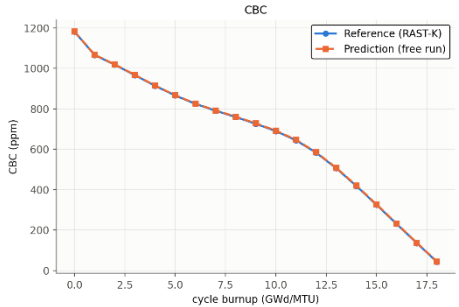
통합 노심설계인자 평가 모델

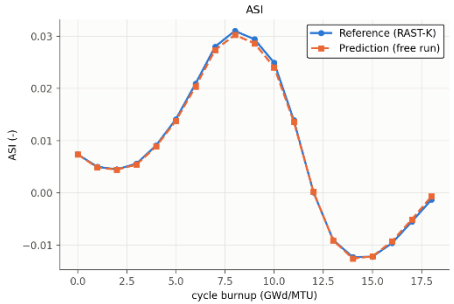
- 본 연구의 ViT 모델을 **다수 인자 예측으로 확장**
  - 기존: Cycle length, Max Fxy 단일 출력 모델 2개
  - 통합: 하나의 모델로 노심 설계 인자 동시 예측
- 목표: **3D 노심 계산 없이 LP 설계 검토**
  - LP 입력만으로 주요 설계 인자를 즉시 확인
  - 노심 설계인자를 연소도에 따라 시계열로 예측
  - 3D 계산은 최종 검증 단계에만 사용
- 확장성: **새로운 설계 인자 추가 용이**
  - 모델 하나로 여러 인자를 관리·확장

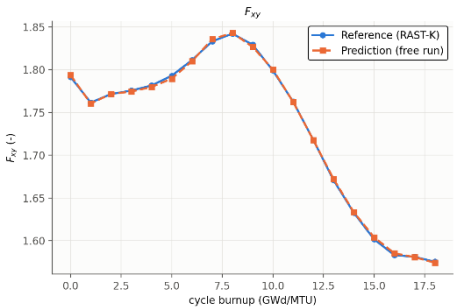


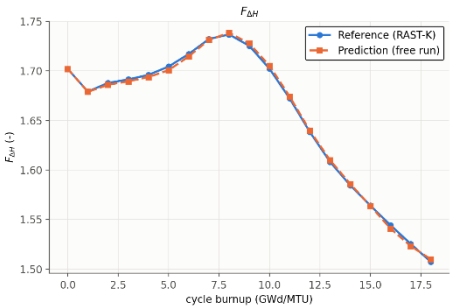
향후 연구 계획

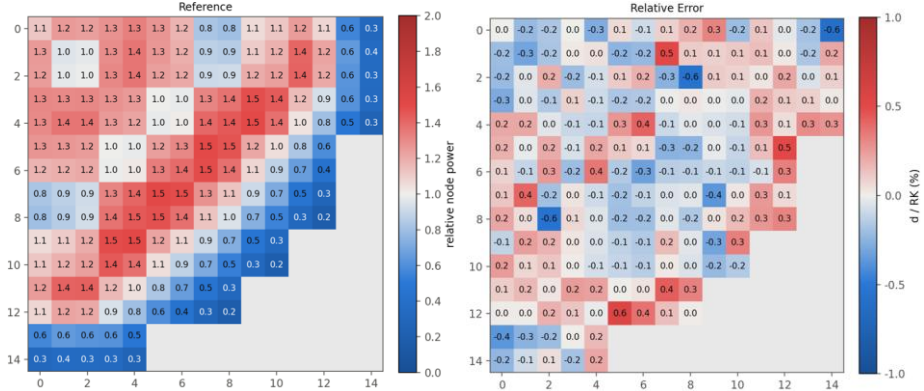
- 통합 노심설계인자 평가 모델 출력 예



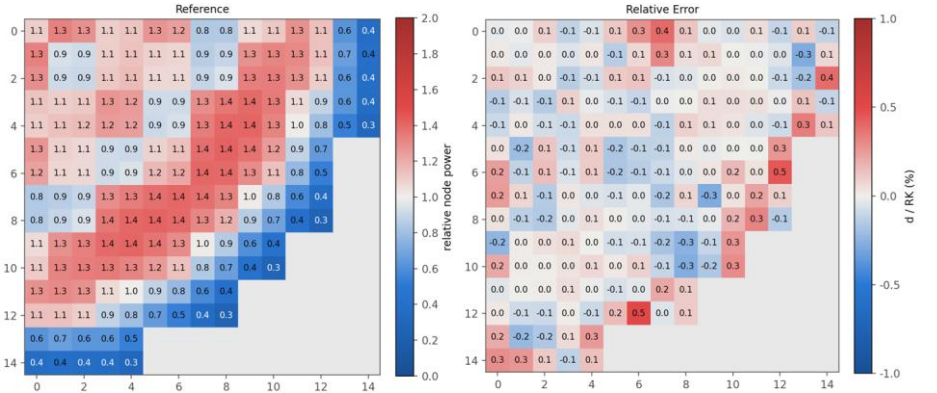








BOC(0.0 GWD/MTU)

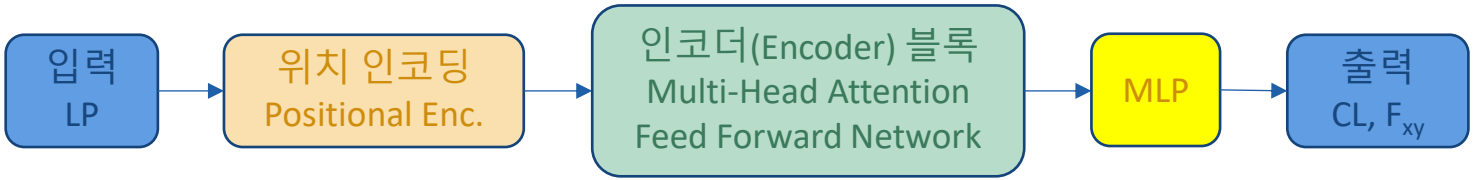


EOC(18.0 GWD/MTU)

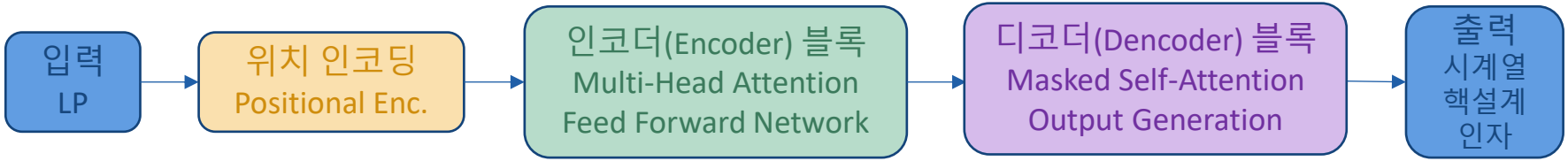
향후 연구 계획

인코더 vs 디코더

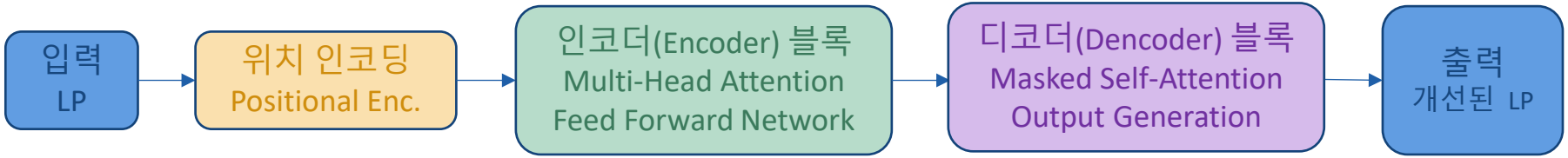
- 단일 모델 : LP 분석 → 단일 핵설계 인자 예측 (기존 연구)



- 통합 모델 : LP 분석 → 핵설계 인자 통합 예측



- LP Transformer : LP 분석 → 새로운 LP 생성 (개선된 LP)





Thank you ☺