Application of a Vision Transformer for Prediction of Peaking Factors and Cycle Lengths in OPR1000

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1. Introduction

The effective operation of nuclear power plants is crucial for addressing the growing need for eco-friendly energy solutions. The OPR1000, developed by the Korea Electric Power Corporation (KEPCO), plays a significant role in the South Korean nuclear energy generation sector [4,5]. Enhancing fuel use is associated with key parameters such as the Peaking Factor, which governs the maximum power distribution within the reactor core, and the Cycle Length, denoting the operational period between refueling outages. Accurate prediction of these parameters is imperative for ensuring the safety and efficacy of nuclear reactor operations.

Traditional methods for estimating Peaking Factors and Cycle Lengths rely on numerical simulations or empirical techniques. However, these approaches often show computational complexity or restricted predictive accuracy, hindering the optimization of loading patterns - the arrangement of fuel assemblies within the reactor core. To address these limitations, machine learning models, such as Convolutional Neural Networks (CNN), have been introduced [3]. Nevertheless, due to the black-box nature of CNN models, the reliability of their predictions is still debatable.

In this paper, we investigate the application of a Vision Transformer (ViT) for predicting the Peaking Factor and Cycle Length in OPR1000 reactors. ViT has shown remarkable potential in addressing intricate image recognition challenges. Our primary aim is to use the capabilities of ViT to enhance predictive accuracy while alleviating the computational burden associated with conventional methods. We present a comprehensive method for data preparation, model architecture, training, and evaluation.

2. Vision Transformer

In this section, we present an overview of the ViT and explore its potential as an Explainable Artificial Intelligence (XAI) model.

2.1 Development Process of ViT

The ViT is an image recognition adaptation of the Transformer model, which was originally designed for Natural Language Processing (NLP) tasks. In comparison to conventional models such as Recurrent Neural Networks (RNN) or Sequence-to-Sequence (seq2seq) models, Transformers have proved superior performance. Traditional models employ a sequential data processing approach to convey word position information, which may meet difficulties in capturing long-range dependencies between words within a sentence. In contrast, the Transformer model eschews sequential processing, opting instead for attention mechanisms that calculate relationships among all elements simultaneously, while encoding the positional information for each word. This approach allows the Transformer to find relationships between words, even in extended sentences, resulting in high performance in NLP tasks [1].

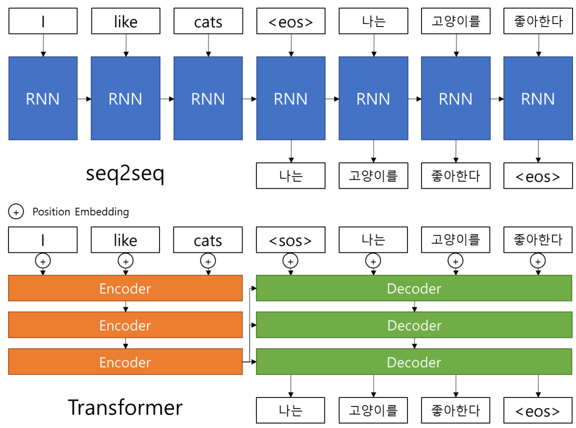

Fig. 1. Examples of seq2seq and Transformer model employed in English to Korean translation systems. In these models, individual words transform into vector representations, referred to as tokens. Notably, the tokens <eos> and <sos> denote 'End of Sentence' and 'Start of Sentence,' respectively, serving as essential markers to help the translation process.

Following the success of NLP, scholars postulated that the Transformer architecture could potentially show powerful performance in image recognition tasks as well. For over 3 years, CNN had been the prevailing model in this domain. Nonetheless, the performance of CNN models reached a plateau, prompting researchers to devise larger models in pursuit of enhanced accuracy. The ViT, a use of the Transformer architecture for image recognition tasks, yielded increased accuracy while reducing the computational expenses, such as time and floating-point operations (FLOPs), necessary for training the model. Presently, ViT is being employed in fields like autonomous vehicles, anomaly detection, and medical imaging [2].

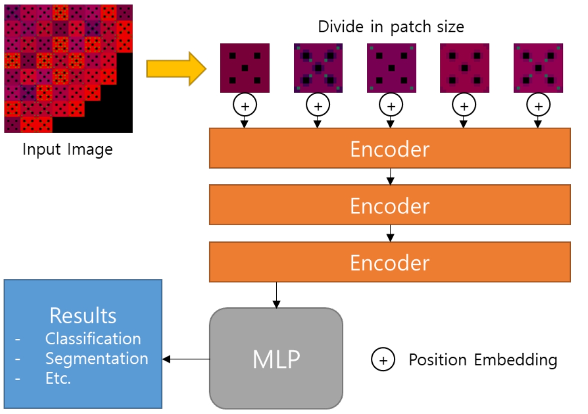

Fig. 2. Vision Transformer architecture for Image Recognition tasks. The Multi-Layered Perceptron (MLP) applies in the ViT to change the Encoders output vector to the result format.

2.2 ViT as an Explainable Artificial Intelligence

The ViT employs the transformer architecture, capitalizing on the self-attention mechanism to understand both local and global contexts present within an image. This self-attention mechanism produces attention maps, supplying valuable information about the connections between different areas of an image and aiding in the visualization of the model's thought process. Furthermore, the modular design of the transformer architecture allows the integration of diverse explainability techniques. Approaches such as layer-wise relevance propagation, saliency maps, and attention rollouts may implement in ViT to augment the interpretability of the ViT model. This improved interpretability enables a more profound comprehension of the model's decision-making process and cultivates confidence in its predictions [2].

3. Application of ViT to OPR1000

This section describes the process of employing the ViT model for the prediction of Peaking Factors and Cycle Lengths in the OPR1000 nuclear power plant. The STREAM and RAST-K (ST/RK) nodal diffusion code system, developed by UNIST CORE, is used to compute the Peaking Factors and Cycle Lengths for the loading pattern data.

2.1 Data Preparation Procedure

Effective data preparation is vital for the successful implementation of the ViT model. Initially, Nuclear Design Reports (NDR) for the 1st and 2nd cycles of YONGGWANG Units 3, which are OPR1000 nuclear power plants, were collected [4,5]. To integrate the data into the ST/RK system, a pin-wise analysis was performed, extracting the U-235 enrichment and Burnable Poison (BP) fraction for each pin from the NDR. It was assumed that all pins in an assembly have identical burnup, corresponding to the assembly burnup value at the Beginning-of-Cycle (BOC). Subsequently, randomized loading patterns were generated as the input dataset for the ViT model by introducing minor modifications to pin values.

To adapt the loading pattern parameters for use as ViT inputs, the parameters were treated as RGB data: R for U-235 enrichment, G for BP fraction, and B for burnup. The values were normalized from 0 to 1, with 0 representing 0 and the maximum values for each parameter being 6.0 wt.%, 10.0 wt.%, and 30.0 MWd/kgU.

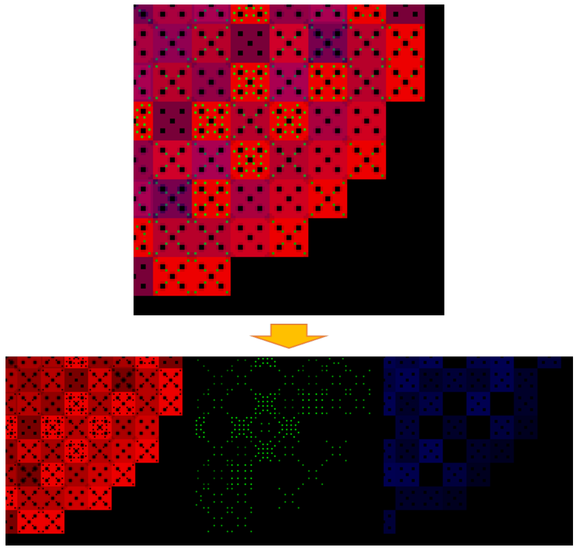

Fig. 3. Example of the Loading Pattern image. RGB values of Water holes and the outside of the bare core region set into 0.

For training ViT models, corresponding output datasets need for the input datasets. The input datasets were executed using ST/RK to calculate Cycle Lengths and Peaking Factors for each loading pattern. The output values were normalized from 0 to 1, with 0 representing 0 and the maximum values for each parameter being 600 days and 7.0.

It is commanding to acknowledge that this study employs a dataset of 110,000 samples, which may constrain the performance due to the small dataset size. Future research and larger datasets may be needed to apply the model for practical applications.

2.2 Model Training and Evaluation

After data preparation, the ViT model was trained using the generated loading pattern images. The dataset was partitioned into training, validation, and testing subsets, having 90K, 10K, and 10K samples, respectively. The training subset eases the learning process for the ViT model, while the validation subset supplies an evaluation of the performance at each stage. The testing subset shows the results of the ViT training.

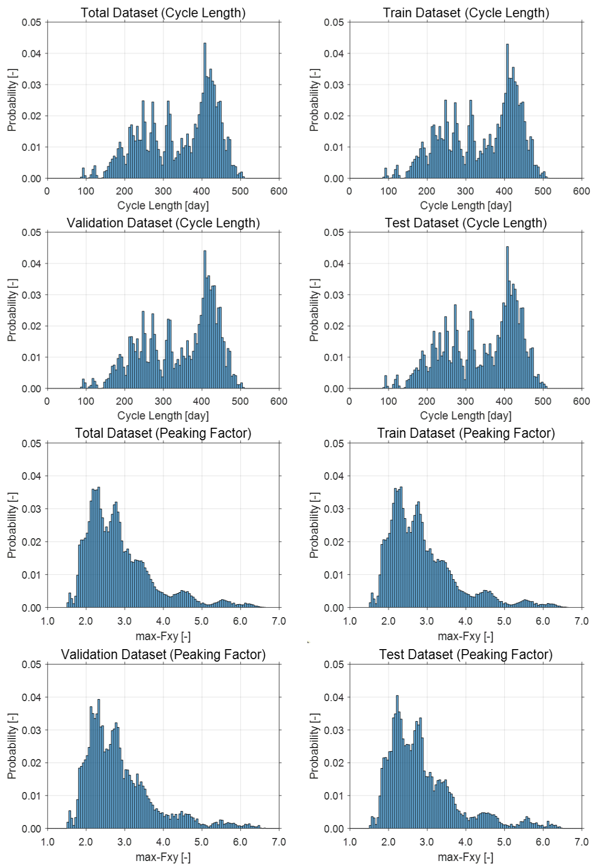

Fig. 4. Distribution of Cycle Length and Peaking Factor from the Loading Pattern dataset. The size of the datasets is 110K, 90K, 10K, and 10K separately.

The optimization process for the ViT model focused on minimizing the discrepancies between predicted and actual values of Peaking Factors and Cycle Lengths. The trained ViT model shows the following characteristics: an input image is 128x128 pixels, divided into 8x8 pixel patches. Each pixel stands for a pin. Each patch transforms into a vector of 256 dimensions. Other parameters of the model are presented in Table I. The optimization process employed the Mean Squared Error (MSE) loss function.

Table I: Hyperparameters of the Vision Transformer.

Attention heads	4
Encoder layers	3
Feed Forward layer dimension in Encoder	128
Training steps	1,000 (Cycle Length) 100 (Peaking Factor)

4. Results and Conclusions

In this study, we proved the potential of using the ViT model for estimating loading patterns in OPR1000 nuclear power plants. During the training phase, the MSE showed a decreasing trend in Cycle Length and Peaking Factor prediction. However, the MSE values plateaued, suggesting the limitations of training the given model.

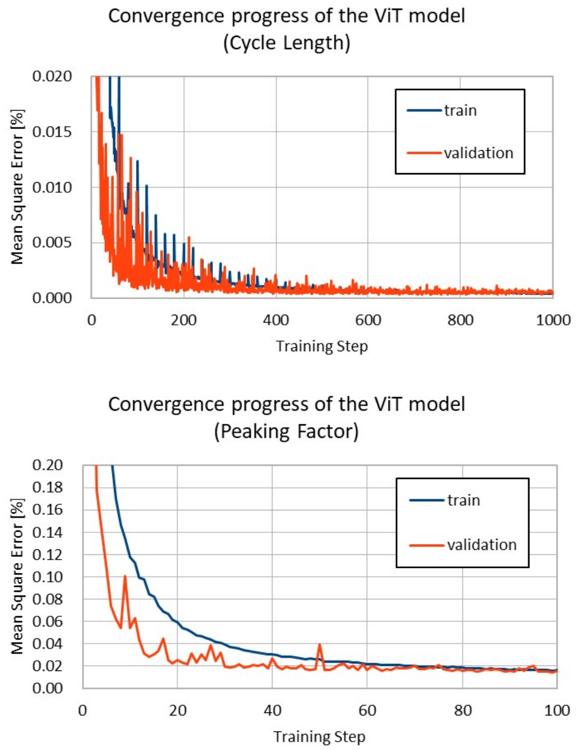

Fig. 5. MSE convergence progress predicting Cycle Length and Peaking Factor. The Peaking Factor model shows low performance than Cycle Length. It postulates that the Peaking Factor model requires further optimization to improve prediction accuracy.

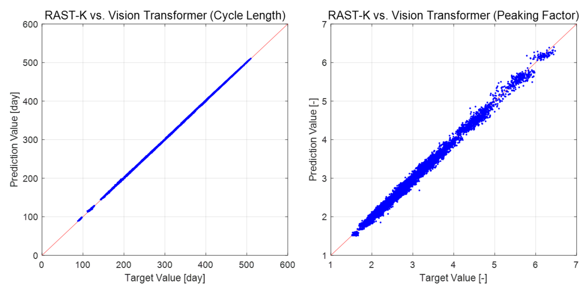

Fig. 6. ViT prediction compared with ST/RK calculation. The red line stands for identical prediction and calculation results.

Table II: Root Mean Square (RMS) and Maximum Relative Error of the parameters between ST/RK calculation and ViT prediction.

Parameter	RMS of Rel. Err. [%]	Max. of Rel. Err. [%]
Cycle Length	0.36	3.75
Peaking Factor	3.92	16.29

Despite the difference in the dataset, the ViT model shows comparable prediction accuracy to the CNN model [3] while having a significantly low training step size, even with an identical dataset size. This finding underscores the potential of the ViT model. Two or more strategies, such as data augmentation and regularization techniques, can be implemented to enhance the ViT model performance. These methods involve changing input datasets, mitigating overfitting, and improving the model accuracy even with limited datasets [8]. By integrating these techniques into the ViT model, more exact and reliable results for predicting Peaking Factors and Cycle Lengths in loading patterns can be achieved.

In summary, our research emphasizes the ViT model's potential for predicting Peaking Factors and Cycle Lengths in nuclear power plant operations, particularly in the context of the OPR1000. Comparisons with traditional methods and CNN models are planned for future research. Moreover, more investigation and validation are needed to apply the model for practical applications within the nuclear industry.

Future research will focus on the application of visualization techniques to help better understanding and interpretation of the model's predictions. This could include interactive visualizations that allow users to examine the influence of various input parameters on the model's output. For example, the optimization of loading patterns using the simulated annealing method in conjunction with ViT screening could be a potential application.

REFERENCES

[1] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. Kaiser, and I. Polosukhin, Attention Is All You Need, arXiv preprint, arXiv:1706.03762v5, 2017.

[2] A. Dosovitskiy, L. Beyer, A. Kolesnikov, D. Weissenborn, X. Zhai, T. Unterthiner, M. Dehghani, M. Minderer, G. Heigold, S. Gelly, J. Uszkoreit, and N. Houlsby, AN IMAGE IS WORTH 16X16 WORDS: TRANSFORMERS FOR IMAGE RECOGNITION AT SCALE, arXiv preprint, arXiv:2010.11929v2, 2021.

[3] H. Jang, H. Shin, D. Kim, H. Lee, Application of Convolutional Neural Network to Fuel Loading Pattern Optimization by Simulated Annealing, Transactions of the Korean Nuclear Society Virtual Autumn Meeting, Dec.17-18, 2022.

[4] S. K. Lee, et. Al., Nuclear Design Report for Yonggwang Unit 3, Cycle 1, Korea Atomic Energy Research Institute (KAERI), Sep 1995.

[5] C. S. Yoo, et. Al., Nuclear Design Report for Yonggwang Nuclear Power Plant Unit 3 Cycle 2, Korea Atomic Energy Research Institute (KAERI), Jan 1996.

[6] A. Steiner, A. Kolesnikov, X. Zhai, R. Wightman, J. Uszkoreit, L. Beyer, How to train your ViT? Data, Augmentation, and Regularization in Vision Transformers, arXiv preprint, arXiv:2106.10270v2, 2022.