Development of meta-modeling considering dynamic features of multi-unit accidents

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Abstract: The multi-unit issues of nuclear power plants (NPPs) have emerged during the construction and operation phases since the Fukushima Daiichi accident. This changing environment has enabled the probabilistic safety assessment (PSA) in Korea to broaden its scope from focusing solely on single units to encompassing multi-unit or site assessments. Until now, Korea's multi-unit risk assessment has been based on the traditional single-unit PSA. This approach struggles to accurately capture the complex dynamics inherent in multi-unit accident scenarios. Extensive computational efforts have been required to analyze thermal-hydraulic (TH) codes, representing a significant challenge in precisely modeling multi-unit accident progression. To address the long computation times associated with TH codes, we propose the development of a meta-modeling utilizing deep learning technology, which has show exceptional capabilities in various fields. By implementing this meta-model, we can significantly reduce the computation timed required for TH codes by effectively incorporating the characteristics or multi-unit scenarios. This method facilitates a more realistic and precise analysis and evaluation of multi-unit risk, enabling the identification of critical vulnerabilities within multi-unit NPPs. Ultimately, this purpose in formulating strategies that markedly enhance the overall safety and risk assessment of multi-unit or site.

Keywords: Meta-model, deep learning, multi-unit PSA, dynamic PSA

1. INTRODUCTION

The Fukushima Daiichi accident has brought the importance of multi-unit issues in nuclear power plants (NPPs) to the forefront. This shift in focus has expanded the scope of probabilistic safety assessment (PSA) in Korea from solely focusing on single units to encompassing multi-unit or site assessments. However, the current approach to multi-unit risk assessment in Korea, which is based on traditional single-unit PSA, struggles to accurately capture the complex dynamics inherent in multi-unit accident scenarios [1, 2]. Complex dynamic accident scenarios between multi-unit NPPs lead to a multifaceted progression of accidents, which is challenging to adequately reflect using existing methods.

To overcome limitations and enhance the accuracy of multi-unit risk assessment, the development of innovative technologies is crucial. While various techniques have been developed, their application to real-world NPP-level PSA models remains hindered by the extensive time and effort required for thermal-hydraulic (TH) simulations, among other significant challenges. To comprehensively address the dynamic features of multi-unit PSA, a method capable of resolving the following aspects is necessary:

- The timing and sequence of various events occurring in each unit
- The availability and success/failure times of systems and components in each unit
- The availability and performance of human and organizational factors as the accident progresses

The timing and sequence of events in each unit are not predetermined, making it difficult to analyze using event trees. The variability in the state of systems and components under multi-unit scenarios is similar to the research in dynamic PSA. However, the dynamic approach requires numerous simulations, and its application is practically impossible to perform in its entirety. In this paper, we suggest the introduction of a meta-model to address this challenge [3].

The term "meta-model" is similar to the surrogate model, which is designed to capture the essential behavior of the original model (real state) while reducing computational requirements. In this study, we have developed a meta-model with the primary objective of identifying core damage or OK as an early stage of introducing meta-modeling. The developed meta-model is able to classify the occurrence of core damage based on the conditions of dynamic accident scenarios. To create dynamic accident scenarios and training data for the meta-model, we analyze loss of offsite power (LOOP) and station blackout (SBO) scenarios that can lead to multi-unit accidents. The data used in this study were generated by the Modular Accident Analysis Program (MAAP) 5 code, which enables the analysis of physical phenomena associated with severe accidents at NPPs.

The meta-model is based on deep learning, which is one of the artificial neural networks and has shown remarkable achievements recently. The data used in this paper have the characteristic of small input size; thus, to achieve accurate results with small input size, we have employed a combination of 1D convolutional neural networks and an adapted Inception architecture. The developed architecture includes inception-n for capturing narrow feature regions, inception-w for capturing wide feature regions, and inception-a for focusing on important features.

After this chapter, the paper is constructed as follows: Chapter 2 describes creating dynamic accident scenarios, Chapter 3 presents the developed model structure, Chapter 4 discusses the results of the developed model, and finally, the conclusion is described.

2. DYNAMIC ACCIDENT SCENARIOS FOR SECURING DATA

In this section, the dynamic accident scenario for securing data to develop meta modeling is explained. The dynamic scenario is established in associated with operating time sampling of electrical component and mechanical components during loss of offsite power (LOOP) and station black out (SBO). A LOOP accident occurs when the reactor is shutdown due to damage to the offsite grid or switchyard, and power supply to power plant is eliminated. That is, it refers to an accident where the reactor is shutdown due to electrical issues in the transmission grid or switchyard, resulting in a loss of power, which in turn triggers the start-up of the associated emergency diesel generators (EDG). The SBO accident covers the all accident which is occurring two EDGs failure after the LOOP. Because the LOOP and the SBO are possible to occur multi-unit accident, these accidents are considered in this paper. Analyzing sequence of the LOOP and the SBO, component list affecting to dynamic accident scenario as below Table 1. In addition, the Figure 1 shows the flow diagram by considering dynamic scenario for LOOP and SBO.

Table 1. Component list of dynamic accident scenario

Variables	**Description**
EDG	Emergency Diesel Generator
Offsite Power	Offsite Power
AAC DG	Alternate AC Diesel Generator
AFW-TDP	Turbine Driven Auxiliary Feedwater Pump
AFW-MDP	Motor Driven Auxiliary Feedwater Pump
HPSI	High Pressure Safety Injection
PSV	Pressurizer Safety Valve Reclose
RCP-Seal	Reactor Coolant Pump Seal Leakage
CSR	Containment Spray Recirculation

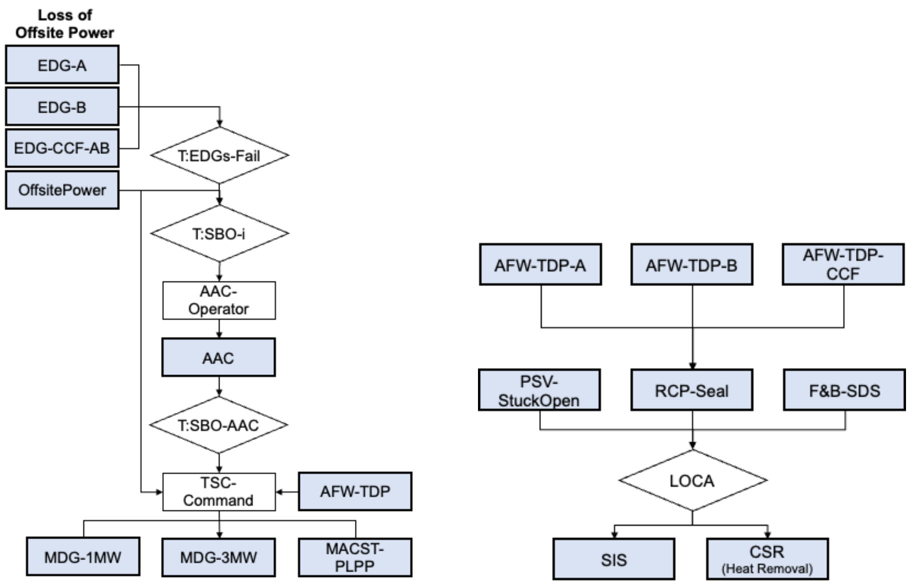

Figure 1. Flow diagram to dynamic scenario for LOOP and SBO

The operation times of the variables excluding PSV and RCP-Seal in Table 1 were randomly sampled between 0 and 72 hours. This provides a simple example to understand how to create a dynamic accident scenario. Assuming that the random sampling is selected as shown in Table 2. The operation time of the electrical system and the associated components should overlap. Consequently, in the case of HPSI and CSR, the actual operation time spans from 13.842 to 29.126 hours, during which they are operated once. Additionally, they operate twice more from 63.32 to 72 hours. For AFW-TDP, the activation period is from 4.193 to 8.193 hours. These instances serve as thermal-hydraulic (TH) input conditions for the simulation, however, in the operation times may vary depending on the system's operating environment. For example, the actual injection time of HPSI can differ based on the pressure in the primary side. Therefore, the sampled times generated above represent the available operation times rather than the actual operation times.

Table 2. Simple example for dynamic accident scenario

Variables	Sampling Operation Time
EDG	On time: 0, Off time:4.193
Offsite Power	On time: 64.32, Off time: 72
AAC DG	On time: 10.474, Off time: 29.126
AFW-TDP	On time: 0, Off time: 8.193
AFW-MDP	On time: 12.142, Off time: 12.142
HPSI	On time: 13.872, Off time: 72
PSV	Success PSV reclose
RCP-Seal	No RCP seal leakage
CSR	On time: 13.842 Off time: 72

The input features for predicting core damage were considered insufficient, we augmented the model input by incorporating additional event tree (ET) sequences. This approach combines traditional PSA methodologies with machine learning techniques, providing a more comprehensive representation of potential accident progressions. The dataset consists of 10,000 dynamic accident scenarios, each analyzed using the MAAP 5 code. The simulation time extends to 72 hours, which is time for PSA considering severe accident, with simulation time step of 50 seconds (72hours/50seconds). The normal code step is 5,180 steps while scenarios below 5,119 steps are truncated (about 5% of total number of simulation). The ratio of training, validation and test is 80%, 10% and 10%, respectively. The output of model represents the core state, evaluated using peak cladding temperature (PCT) as metric of core state. Core damage is defined as occurring when the PCT exceeds 1,255 K. This threshold is consistent with established safety criteria in nuclear engineering.

3. META MODEL

This chapter describes the characteristics of the developed model. The main feature of the developed model is its ability to predict core status with relatively small input. A convolutional layer is a fundamental building block in convolutional neural networks (CNNs), primarily used for feature extraction from input data. It applies a series of filters (kernels) that slide over the input, performing element-wise multiplication and summing the results to produce feature maps. These feature maps capture spatial hierarchies and patterns, making convolutional layers highly effective in tasks like image and signal processing.

In 1D convolution, the convolutional operation is applied along a single spatial dimension, making it particularly useful for processing sequential data such as time series or language. By applying 1D convolutions, the network can generate various combinations of the input features, effectively capturing local dependencies and patterns within the data. This ability to explore diver feature combinations enhances the model's capacity to learn meaningful representations, crucial for tasks such as sequence classification, signal processing, and language modeling.

To achieve this, we adopted the inception structure, which has shown exceptional performance in image recognition models. The Inception architecture is a powerful and innovative neural network model that effectively learns complex patterns through multi-scale feature extraction, efficient parameter utilization, and flexible structure design [4]. This approach allows the network to capture intricate data representations across various scales, optimize computational resources, and adapt to diverse problem domains, making it a versatile and high-performing solution for complex machine learning tasks.

The developed structure consists of three types: inception_n, inception_s, inception_w, and inception_a. The characteristics of each structure are as follows and illustrated from Figure 2 to Figure 5:

a) inception_n
- Suitable for capturing features in narrow regions
- Uses 1x1, 3x3 convolutions and average pooling

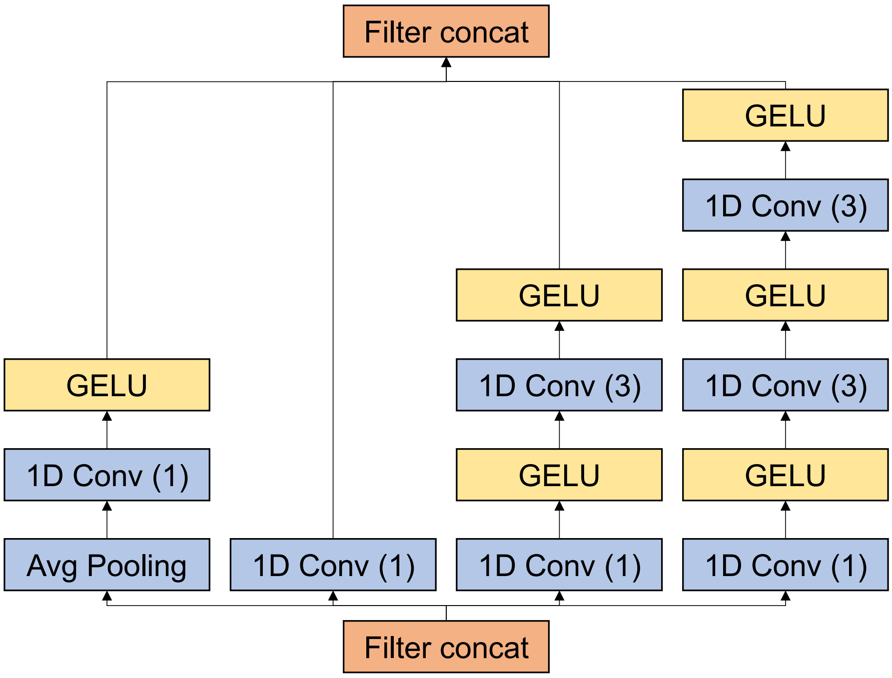

Figure 2. The architecture of inception_n

b) inception_s
- Suitable for capturing features in narrow regions
- To avoid gradient vanishing, the output channel is half of inception_n

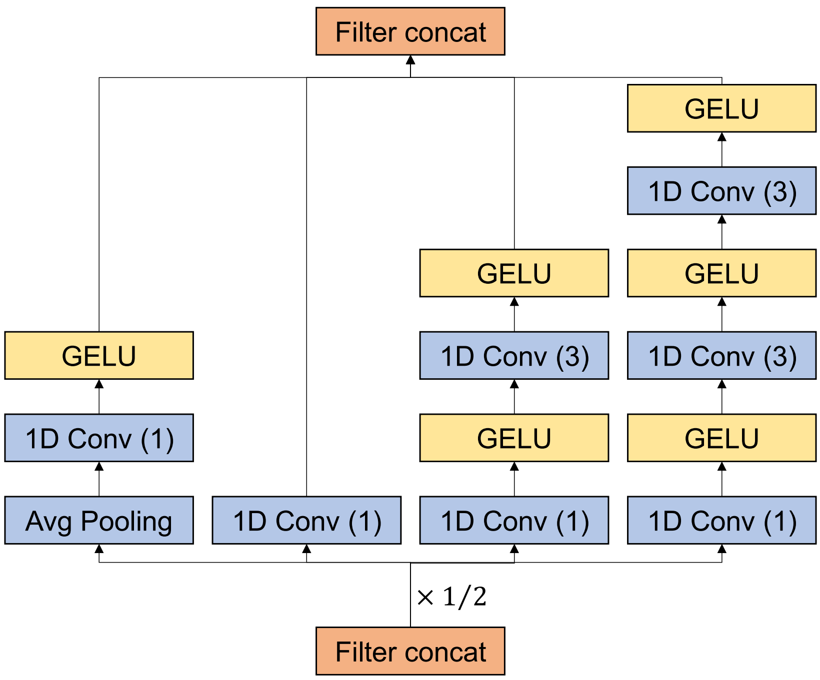

Figure 3. The architecture of inception_s

c) inception_w (w)
- Suitable for capturing features in wider regions
- Uses larger kernel sizes such as 15x15 and 17x17

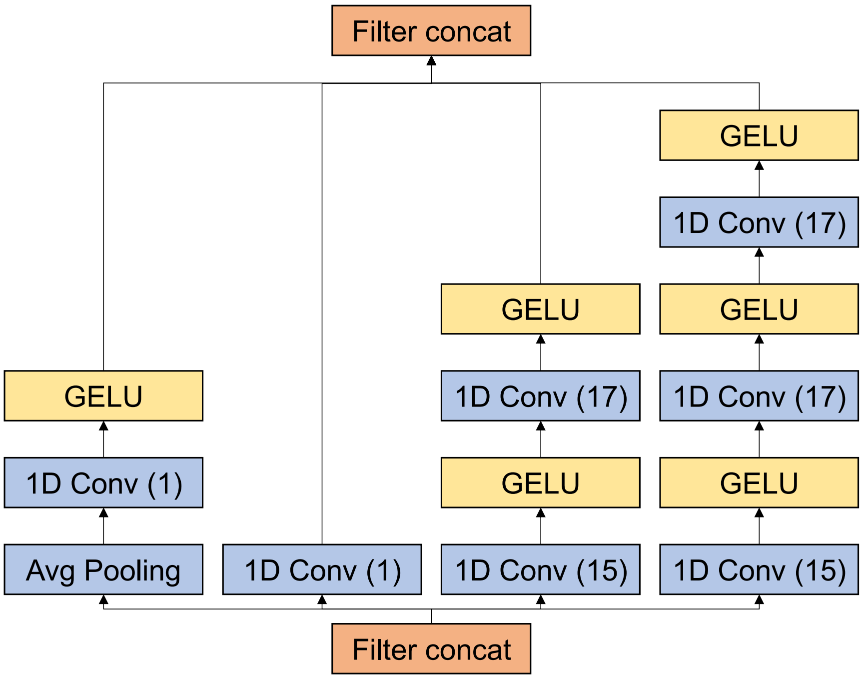

Figure 4. The architecture of inception_w

d) inception_a
- Adds self-attention mechanism to the inception_n structure
- Helps capture global context information

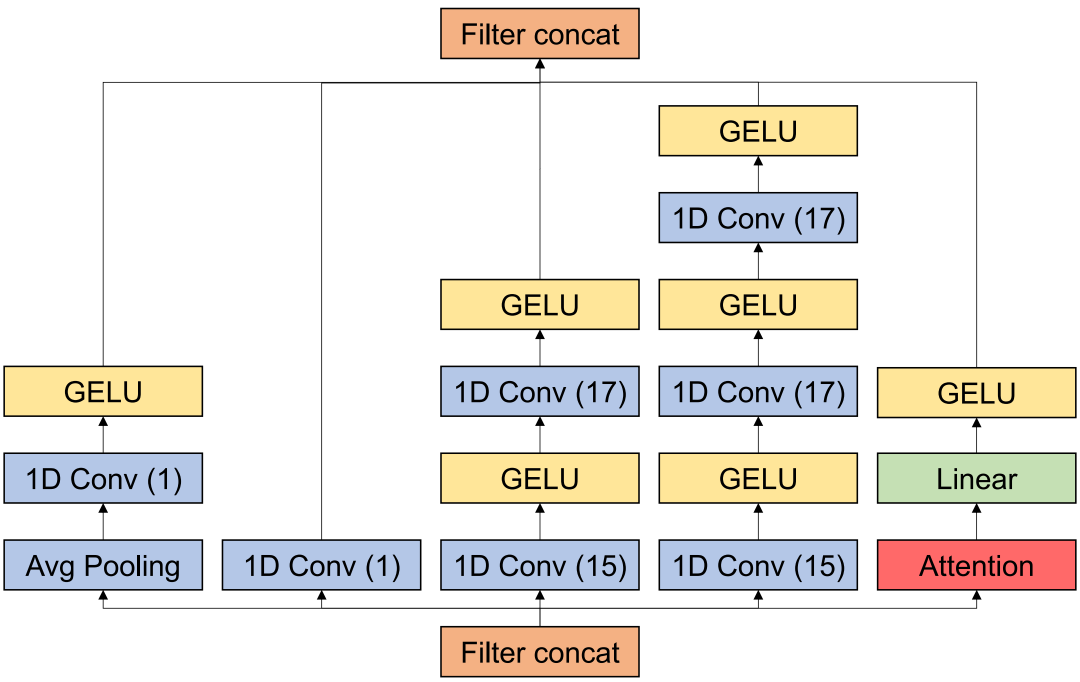

Figure 5. The architecture of inception_a

In the inception_a (a) module, the self-attention mechanism, a key feature of the transformer architecture, has become fundamental to many recent deep learning models [5]. It utilizes multiple attention mechanisms in parallel to extract information from various perspectives. This approach has significantly contributed to performance improvements across diverse deep learning tasks.

Additional features of the model include the use of the Gaussian Error Linear Unit (GELU) activation function to increase non-linearity [6], and the implementation of batch normalization and residual connections to enhance learning stability [7]. The developed model is capable of extracting features at various scales and can emphasize important features through the attention mechanism.

Through extensive experimentation with various hyperparameters and performance testing, the final structure of the model consists of three repeated blocks, each followed by a fully connected layer. The structure can be described as follows:

(1) Three repeated blocks, each comprising:
  - Inception_s (s)
  - Inception_n (n)
  - Inception_n (n)
  - Batch Normalization (b)
  - Inception_a (a)

(2) After the three blocks, a fully connected layer with 1024 units is added.

This can be represented compactly as: 3 × [s-n-n-b-a] + FC(1024). This structure balances different inception modules and incorporates regularization techniques to achieve optimal performance.

4. RESULTS

The performance of the developed deep learning model was evaluated and compared with traditional machine learning methods using the same dataset. The results are presented in a confusion matrix, as shown in Figure 2.

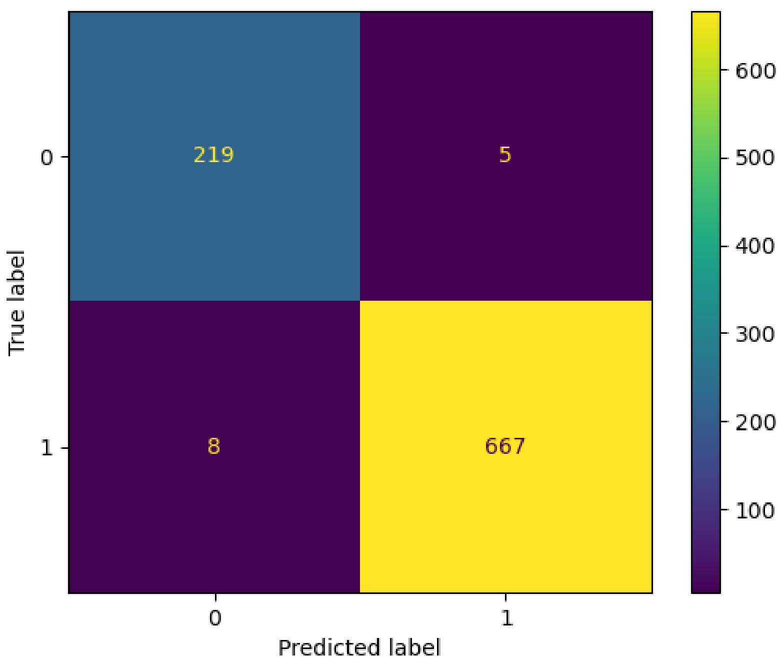

Figure 2. The confusion matrix of developed model.

The 0 means the OK and 1 means the core damage in the confusion matrix, thus, row indicates true value and column indicates predicted value. The confusion matrix displays the model's predictive performance, with 219 true negatives, 667 true positives, 5 false positives, and 8 false negatives. This visual representation helps in understanding the model's classification accuracy across different classes. the developed deep learning model demonstrated performance across all metrics in Table 3:

Table 3. Model Performance of developed model

Metrics	Value
Accuracy	98.55 %
Precision	99.26 %
Recall	98.82 %
F1 Score	99.04 %

To benchmark the model's performance, it was compared against several established machine learning algorithms, all of which underwent hyperparameter optimization to ensure fair comparison. The results of these comparisons are as follows in Table 4:

Table 4. Compared model performance

Metrics	Value
Random Forest	87.52 %
Linear Regression	58.35 %
Support Vector Machine	75.28 %
Gradient Boosting	80.87 %
Fully Connected Layer	74.83 %

6. CONCLUSION

This study presents a novel approach to multi-unit PSA through the development of a meta-model utilizing deep learning techniques. By combining 1D convolutional neural networks and a modified Inception architecture, our meta-model effectively predicts core damage states based on dynamic accident scenarios.

The meta-model demonstrates exceptional performance, achieving an accuracy of 98.55% in classifying core damage states. Furthermore, it exhibits superior performance compared to traditional machine learning algorithms, including Random Forest, Linear Regression, Support Vector Machine, and Gradient Boosting.

In future research, we intend to employ the meta-model to investigate multi-unit effects. Additionally, we plan to develop a regression model that can better reflect the time-series characteristics of a wider range of accident scenario outcomes, taking into account the specific attributes of the model. This advancement will further enhance our ability to analyze and predict complex nuclear safety scenarios.

Acknowledgements

This work was supported by the National Research Foundation of Korea (NRF), funded by the Ministry of Science and ICT (No.RS-2022-00143695)

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