An Approach Based on the Regression between Radiological Source Term and Consequence for Effective and Efficient Risk Assessments of NPPs

Jiyeong SEO[1], Sung-yeop KIM[2*], Jaehyun CHO[3*]

[1] *Chung-Ang University, Heukseok-ro 84, Dongjak-gu, Seoul, 06974, Republic of Korea,* sjy9442@cau.ac.kr
[2] *Korea Atomic Energy Research Institute, Daedeok-daero 989-111, Yuseong-gu, Daejeon, 34057, Republic of Korea,* sungyeop@kaeri.re.kr
[3] *Chung-Ang University, Heukseok-ro 84, Dongjak-gu, Seoul, 06974, Republic of Korea,* jcho@cau.ac.kr

EXTENDED ABSTRACT

1. Introduction

Following the Fukushima Daiichi nuclear disaster, the accurate prediction of offsite radiological consequences from severe nuclear accidents has emerged as a critical aspect of risk-informed safety management. Level 3 Probabilistic Safety Assessment (PSA), which evaluates radiological impacts on surrounding populations, relies heavily on computational tools such as MACCS [1]. However, these tools require considerable computational time and resources, limiting their application in real-time analysis and large-scale scenario evaluations.

This study presents a deep learning-based surrogate model, referred to as the *Accident Consequence Estimator*, which estimates population-weighted individual risk (PWIR) from time-dependent radiological source term data. The model is designed to provide fast and reliable consequence predictions, enabling timely emergency response and informed decision-making[2, 3].

2. Methods

2.1 Dataset and Preprocessing

The model was trained using 658 severe accident scenarios for the OPR1000 reactor generated by MAAP5. Each scenario includes time-series release data for 25 major radionuclides and the peak time of core exit temperature (CET), which was added as an additional input feature. To reduce computational load and preserve temporal patterns, the data were downsampled and encoded with positional vectors, resulting in a final input shape of (1097, 39).

The output data represent PWIR, a scalar metric quantifying cancer fatality risk based on MACCS simulations. Each input scenario corresponds to a single normalized PWIR value, forming an output shape of (658, 1). Both input and output data were scaled using min-max normalization to improve model convergence and training stability.

2.2 Model Architecture

The model utilizes a 1D Convolutional Neural Network (Conv1D) with causal padding and dilation to capture multiscale temporal features. It includes five convolutional layers followed by pooling, flattening, and three fully connected layers (Dense), with a dropout layer (rate = 0.38) applied to prevent overfitting. Ensemble learning was used by averaging outputs from ten independently trained models.

2.3 Training Strategy

The model was trained using the Adam optimizer (initial learning rate: 0.00012) with early stopping and ReduceLROnPlateau scheduling. The dataset was split into training (63.75%), validation (21.25%), and test sets (15%) to ensure generalization and robustness.

3. Results

3.1 Predictive Performance

Model performance was assessed by comparing predicted PWIR values to MACCS-based reference values across 98 test scenarios. The model achieved a mean squared error (MSE) of approximately 0.0002. Visual inspection of predictions showed accurate trend capture with minor deviations, as confirmed in Figure 1, which presents 20 randomly selected test scenarios.

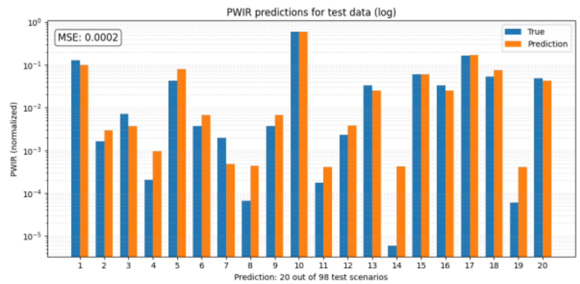

FIGURE 1. PWIR predictions for 20 out of 98 test scenarios

3.2 Application Study: SAG Effectiveness

An application study was conducted using five configurations of Severe Accident Guideline (SAG) strategies applied to the STC5-SBO scenario. Among the strategies, SAG-02 (RCS depressurization) had the most significant impact, reducing PWIR by 26.3%. The combination of SAG-02 and SAG-03 (RCS injection) yielded the highest overall mitigation (27.3%), whereas SAG-01 (SG injection) alone or in combination with SAG-02 showed limited additional benefit, as confirmed in Figure 2.

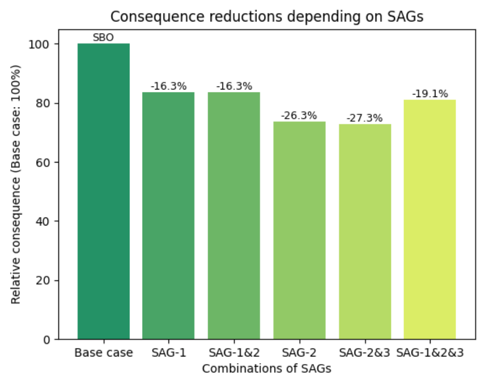

FIGURE 2. PWIR(Consequence) reductions depending on SAGs

4. Discussion and Conclusions

The proposed deep learning model demonstrated high accuracy and efficiency in estimating offsite radiological consequences from source term data. Its performance enables real-time risk assessment, supporting emergency decision-making processes. The application study highlighted the varying effectiveness of SAG strategies and the potential non-additivity of combined actions, emphasizing the need for scenario-specific optimization in severe accident management.

Future research will focus on expanding the model's applicability to other reactor types and integrating uncertainty quantification for enhanced safety planning.

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