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Development of Effective Bi-Fidelity Surrogate Model for Disposal Holes

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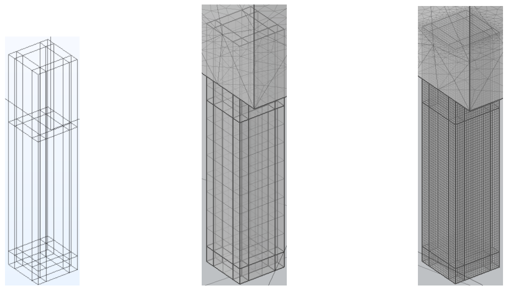
1. Introduction

Conducting Total System Performance Assessment (TSPA) [1] for the disposal system, encompassing thousands of disposal holes containing spent nuclear fuel and their geological surroundings over a span of more than 100 thousand years, is an arduous task, particularly due to the immense computational demand involved in numerical analysis. One of the most challenging aspects is the substantial computational load, primarily stemming from internal components, especially disposal hole. In this research, we aim to address this challenge by developing a bi-fidelity surrogate model to efficiently reduce the computational effort. The core principle of the bi-fidelity surrogate model involves analyzing data from a model with coarse meshes and correcting it using results from a model with fine meshes. For accomplishing this, we employed machine learning techniques. As a result, our study significantly reduces the computational burden required for conducting TSPA for disposal system, while simultaneously yielding higher accuracy results.

2. Methods and Results

In this section, we aim to provide a brief explanation of the bi-fidelity surrogate model for the disposal system that we intend to develop in this study. This model primarily focuses on the disposal hole, where a significant computational load is required. The bi-fidelity surrogate model was developed using machine learning techniques, and its applicability to the TSPA was verified through a numerical example.

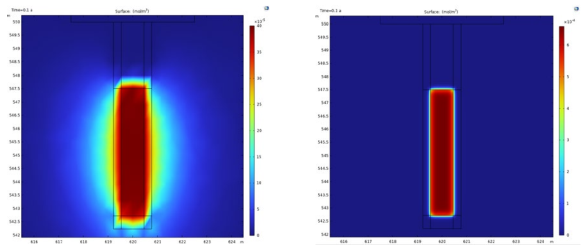
The shape and features of the disposal hole are depicted in Fig. 1(a). While the conventional disposal hole typically takes on a cylindrical shape, for the purpose of validating the feasibility of the bi-fidelity surrogate model, we simplified it to a rectangular shape. In this study, our aim is to utilize the results from a model with coarse meshes to correct the analysis outcomes obtained from a model with fine meshes through the employment of the bi-fidelity surrogate model. To achieve this objective, we divided the disposal hole into two distinct models, as depicted in Fig. 1(b) and (c).



(a) shape (b) modeled with coarse meshes (c) modeled with fine meshes

Fig. 1 Descriptions of disposal hole

When performing the TSPA using two models with coarse and fine mesh, and comparing the concentrations of radionuclides, the results are illustrated in Fig. 2. It is evident that significant discrepancies arise in the analysis outcomes due to differences in mesh size.



(a) Coarse meshes (b) Fine meshes

Fig. 2 TSPA results at disposal hole using COMSOL

To address this issue, this study aims to develop a bi-fidelity surrogate model using machine learning techniques. We have chosen to employ the ResNet [2], which is simple yet widely utilized to conduct regression. Additionally, we have developed a machine learning architecture using 3D convolution networks because of the data format.

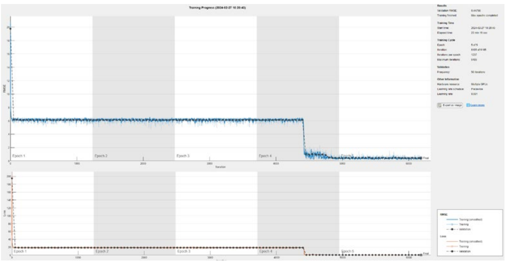


Fig. 3 Training progress using MATLAB

The training was conducted using MATLAB, as depicted in Fig. 3. Before training, 10% of the entire dataset was separated for validation. Upon comparing the predicted results for the validation data, as shown in Fig. 4, it was observed that the R2-error was 0.9986, indicating a high level of accuracy.

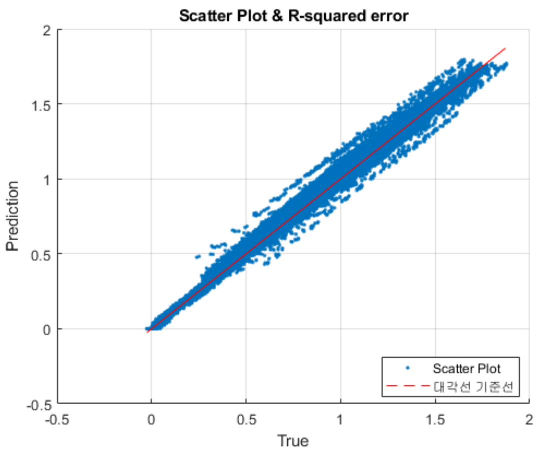


Fig. 4 Scatter plot and R2-error for validation data set

To assess the effectiveness of the developed bi-fidelity surrogate model, we conducted the TSPA for disposal system modeled with coarse and fine meshes. Simultaneously, we utilized the developed bi-fidelity surrogate model to correct the results of coarse meshes.

When comparing the computation times, it was observed that using a fine mesh resulted in approximately 15 times longer compared to the coarse mesh. In addition, when employing the bi-fidelity surrogate model to correct the coarse mesh, an additional 1.5 times computation time was required compared to the coarse mesh. Comparing this to the fine mesh, it was found to be approximately 10 times shorter.

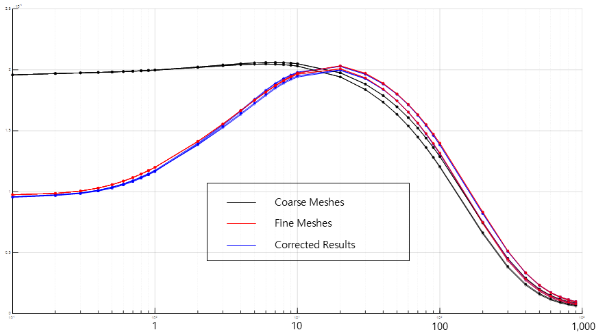


Fig. 5 Comparison among coarse, fine, and corrected results

The concentrations of radionuclides for each analysis are depicted in Fig. 5. It can be observed that the black solid line represents the results from the coarse mesh, while the red solid line represents results from the fine mesh. Subsequently, the blue solid line depicts the results corrected using machine learning techniques based on the coarse mesh results. Consequently, it can be observed that the corrected results using the developed bi-fidelity surrogate model almost perfectly mimic those of the fine mesh.

3. Conclusions

In this study, our aim was to develop a bi-fidelity surrogate model to correct results obtained from analysis modeled using a relatively efficient but less accurate coarse mesh. Through examples, it was demonstrated that the developed bi-fidelity surrogate model effectively enhances analysis while achieving higher accuracy. In a near future, we intend to extend this methodology to apply to a wider range of problems.

REFERENCES

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