Evacuation Time Modeling for Fire Incidents within the Nuclear Power Plants Using Self- and Semi-Supervised Learning Algorithms

Geonhui Jang[a], Sumit Kumar Singh[b], Saerin Lim[a], Jinsoo Bae[a], Jongkook Heo[a], Yu Zhang[b], Weon Gyu Shin[b], Seoung Bum Kim[a]

[a]School of Industrial and Management Engineering, Korea University, Seoul, Republic of Korea

[b]Department of Mechanical Engineering, Chungnam National University, Daejeon, Republic of Korea

1. Introduction

The main purpose of this study is to predict evacuation time during fire emergencies within nuclear power plants with consolidated fire and smoke transport (CFAST) simulations. Our approach leverages the CFAST simulator in conjunction with the deep neural networks for prediction.

While it is easy to generate initial fire conditions, it is time-consuming and expensive to feed these inputs into CFAST because of their computational complexity. Therefore, considering the initial input fire conditions as unlabeled data and the set containing the evacuation time as labeled data, we explore self- and semi-supervised methodologies that can achieve good prediction performance even under the circumstance of a small amount of labeled data.

The present study shows that the results of semi-supervised methodologies trained with large unlabeled, and few labeled data are better than those trained solely with labeled data.

2. Data Preprocessing

We first generate various initial fire conditions as shown in Table I. To build an evacuation time prediction model using deep learning, we then use the CFAST simulator with these fire conditions and collect fire simulation results. However, the CFAST simulator provides sequential measurements of room and fire, rather than a single evacuation time. Consequently, we set three evacuation initiation criteria as follows:

(1) temperature inside MCR exceeds 95℃,
(2) heat flux of the fire exceeds 1kW/m^2, and
(3) optical density of the smoke exceeds 3m^(-1).

We define the evacuation time as the time point when at least one of the three criteria is met and transform the fire simulation results into evacuation time data. Finally, we create a dataset comprising pairs of initial fire conditions and corresponding evacuation times to train deep learning models.

Input Variables	Training States	Testing States
Peak HRR	400, 702	702
Propagation Time	10, 15	10
Door Condition	Closed, Closed-open, Open	Closed, Closed-open, Open
Height of Fire	0, 0.45, 0.9	0, 0.3, 0.45, 0.6, 0.9
Ventilation Height	2.2, 2.7, 3.2	2.2, 2.5
Flow Rate	1.0, 1.25, 1.5, 1.75, 2, 2.25, 2.5	1.0, 1.1
Leakage Area Ratio	0.03, 0.26, 0.73	0.26
Ambient Temperature	20, 25, 30, 35, 40	20, 22, 25, 27, 30, 32, 35, 37, 40

Table I. Initial condition variables and their states

3. Methodologies

We used supervised learning, semi-supervised learning, and a combination of these learning algorithms to evaluate prediction performance of evacuation time.

1. Self-supervised Learning Methods: focuses on extracting task-agnostic features and enhancing generalization capacity during the pre-training phase using unlabeled data.

- **Denoising Auto-Encoder**: trained to reconstruct the original input from its latent vector by using a perturbed version of the original input with Gaussian noise.

2. Semi-supervised Learning Methods: combines both labeled and unlabeled data during training to enhance performance in target tasks, such as regression or classification.

- **Pseudo-Label**: improves data efficiency by assigning labels with maximum probability from unlabeled data and predicts the same label for both the original and noisy unlabeled samples for model's robustness.
- **Mean Teacher**: generates consistent outputs for unlabeled data through the exponential moving average update even in the face of noise perturbations.
- **Virtual Adversarial Training**: enhances the robustness by encouraging the model to be consistent in the presence of virtual adversarial (opposite to optimize) noise applied to unlabeled data.

3. Combination of Self- and Semi-supervised Learning Methods

- **Value Imputation and Mask Estimation (VIME)**: reconstructs original features from corrupted data and identifies which parts of tabular data are corrupted. Then, they are trained to produce consistent predictions across multiple instances of corrupted data and predict labels of a small amount of labeled data.

4. Experiments and Results

The above five self- and semi-supervised learning models and the supervised learning model using only labeled data were trained with the preprocessed data of initial fire conditions and evacuation time. The evaluation results of the trained models are shown in Table II.

Number of Training Data		Method					
		Supervised Learning	Self-supervised Learning	Semi-supervised Learning			Self + Semi Supervise Learning
Labeled Data	Unlabeled Data	Neural Network	Denoising Auto-encoder	Pseudo-Label	Mean Teacher	VAT	VIME
308	3,080	0.03 (0.32)	0.36 (0.10)	0.35 (0.16)	0.38 (0.19)	0.23 (0.20)	**0.49 (0.27)**
615	3,080	0.43 (0.21)	0.63 (0.09)	0.63 (0.13)	0.57 (0.18)	0.60 (0.16)	**0.70 (0.12)**
1,540	3,080	0.60 (0.06)	0.69 (0.07)	0.67 (0.06)	0.66 (0.10)	0.66 (0.11)	**0.77 (0.04)**
3,079	3,080	0.55 (0.06)	0.64 (0.04)	0.64 (0.04)	0.62 (0.06)	0.61 (0.06)	**0.81 (0.01)**

Table II. Average and standard deviation (in parentheses) of R^2 on testing dataset across five runs. The best results are in bold.

Figure 1 shows the evacuation time prediction results of the neural network and VIME. K (%) represents the ratio of labeled data to the number of unlabeled data. VIME, which benefits from additional training using unlabeled data, enhances the predictive performance of the neural network. These advantageous attributes of VIME further underscore the practicality of using unlabeled data as a solution to address the scarcity of labeled data.

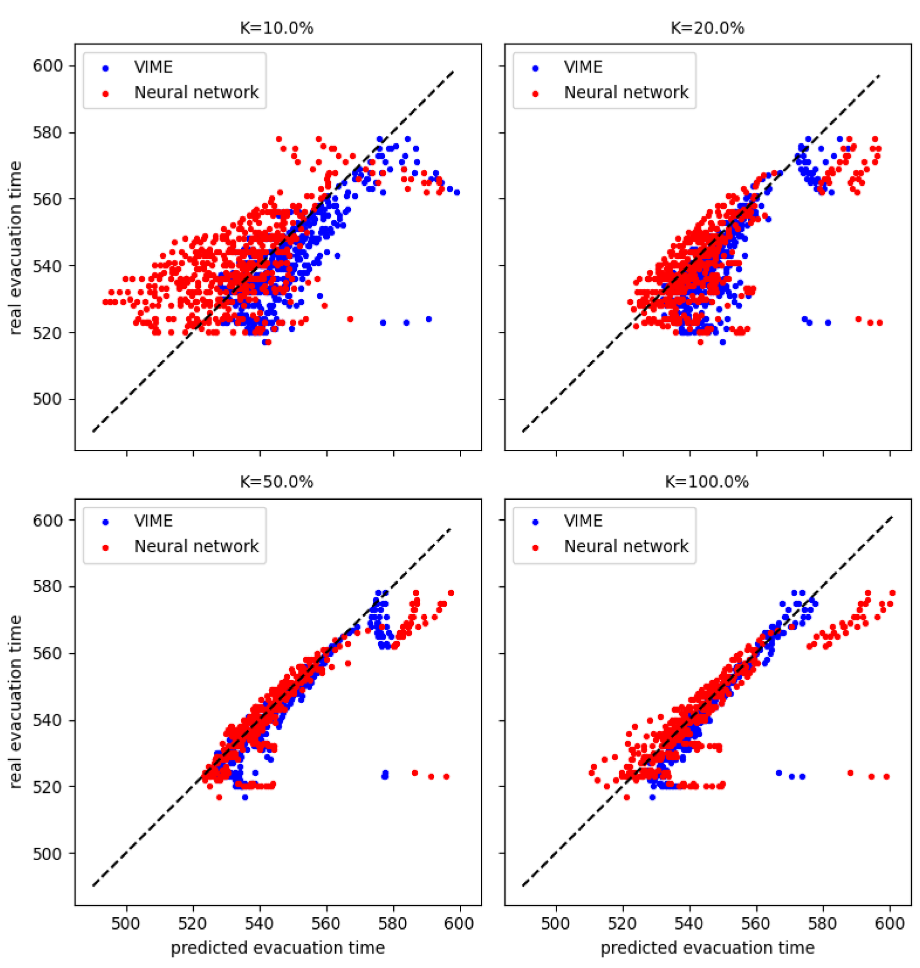

Fig. 1. Prediction results of the neural network and VIME.

5. Conclusions

This study demonstrates that evacuation time prediction through self- and semi- supervised learning can be achieved by using combinations of basic initial fire conditions without the need for prediction of extensive state sequence using a simulator.

The research findings are not limited to MCR within nuclear power plants and applicable to other high-risk environments across various industries.

We envision the continued development of this robust evacuation time prediction framework through future research endeavors, contributing to the enhancement of nuclear safety.

Contact Email: csleivear1@korea.ac.kr, sbkim1@korea.ac.kr