Responses to Reviewer's Comments and a Summary of the Revisions.
("Evacuation Time Modeling for Fire Incidents within the Nuclear Power Plants Using Self- and Semi-Supervised Learning Algorithms.")
(23A-093)

We thank you for your thorough evaluation and helpful suggestions and comments. We have revised the manuscript and incorporated all your comments into our revised manuscript. These revisions are summarized in our point-by-point responses to your itemized comments. All changes made in the revised manuscript have been highlighted in blue. We hope that this revised version addresses all concerns raised in your review.

1. The paragraph in Sec. 1 should be properly partitioned (one paragraph is too long).

Response: Section 1 has been partitioned into three short paragraphs for improved readability.

2. Please explain in more detail about the methods used in this paper.

Response: Thank you for your suggestion. We have included a more detailed explanation of the self- and semi-supervised learning methods used for our works in Section 2.2.

Optional. Consider adding a simple illustration to explain the unsupervised learning methods.

Response: Thank you for your considerate suggestion. We have added an illustration that provides an overview of self-and semi-supervised learning in Section 2.2.

3. Please explain why R2 decreases except for the VIME method even though the number of the labeled data increases from 1,540 to 3,079.

Response: Thank you for your careful reading and findings. We have mentioned the reason for the decrease in performance despite the increased labeled data from the perspective of model complexity, and have also added a potential solution to address this issue in the third paragraph of Section 3.2.

4. The reviewer agrees that this approach is effective in conditions where label data are difficult to obtain. However, this level of R2 does not seem to provide sufficient accuracy to predict the evacuation time in practice. Please briefly describe the limitations of this study or future works in the conclusion section.

Response: We appreciate your recognition of the effectiveness of our approach and value your comment. In the Conclusions section of our paper, we have addressed the study's limitations and proposed future avenues to address these challenges.

5. Describe as Table I:, Table II: instead of Tables 1 and 2.

Response: The requested modification has been made.

6. Explain why the input variables in Table I(1) were selected and the appropriateness of their values. For example, MCR is a place where operators are located, and ambient temperatures of 30, 35, and 40 degrees are unrealistic.

Response: Thank you for your thoughtful consideration. We have addressed the selection of input variables and the appropriateness of their values in the second paragraph of Section 2.1.

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

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1. Introduction

In recent years, deep learning techniques have evolved to solve various problem situations, and data collection through simulation is also developing accordingly. 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. The main control room (MCR) of nuclear power plants needs to be managed essentially in emergency situations to prevent subordinate damage. Our approach leverages the CFAST simulator in conjunction with the deep neural networks for prediction.

However, a challenge arises when integrating the simulation outcomes into conventional deep learning methods. While it is easy to generate initial fire conditions, it is time-consuming and expensive to feed these inputs into such physics-based simulators because of their computational complexity. Fewer labeled data are better for such costly conditions, thus we explore self- and semi- supervised methodologies that can achieve good prediction performance even under the circumstance of a small amount of labeled data, frequently encountered in reality.

In this study, the input variable is a combination of eight initial conditions, such as heat release rate or fire propagation time in the MCR. The output variable is the minimum time required to achieve the first of the three critical evacuation criteria. Considering that initial fire conditions can be easily created in almost seconds, we consider the initial input variables as unlabeled data, while the set containing the evacuation time as 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 and Related Works

2.1 Data Collecting and Preprocessing

To build an evacuation time prediction model using deep learning, we use the CFAST simulator. We first generate various initial fire conditions based on the nuclear power plant fire modeling analysis guidelines [1]. Table I shows the initial fire conditions that we used. We then simulate the CFAST with these fire conditions and collect fire simulation results. However, it is noted that the CFAST simulator provides the room and fire measurements over time, rather than providing evacuation time. Consequently, we set three evacuation initiation criteria as follows: (1) temperature inside MCR exceeds 95℃, (2) heat flux of the fire exceeds $1\mathrm{kW/m^2}$, and (3) optical density of the smoke exceeds $3\mathrm{m^{-1}}$. We define the evacuation time as the time point when at least one of the three criteria is met. We then 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.

Table I: Initial condition variables and their states.

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

The selection of input variables in fire simulations is driven by a paramount concern for safety. While the ambient temperatures of 30, 35, and 40 degrees might seem extreme for an MCR, it is important to clarify that these values are intentionally chosen to evaluate the evacuation response under worst-case conditions. Our aim is to rigorously test the evacuation time model and fire protection systems to ensure operator safety in the most challenging scenarios. These extreme temperatures are not intended to simulate routine conditions but rather to challenge the system's ability to ensure operator safety during abnormal events.

2.2 Self- and Semi- supervised learning

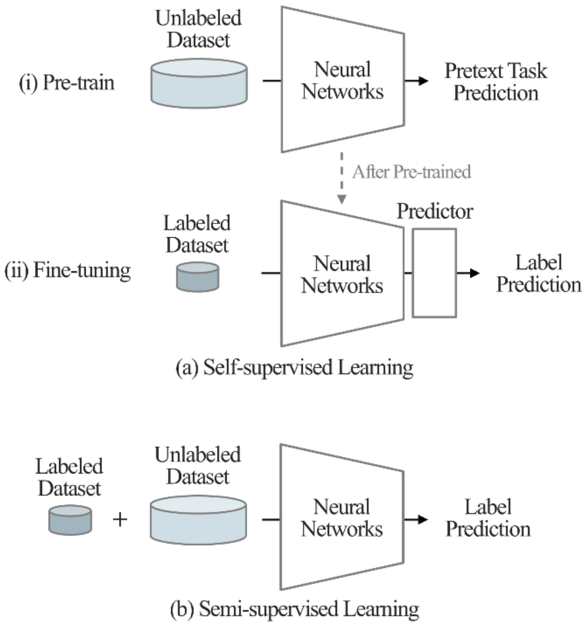

Fig. 1. A schematic overview of self- and semi-supervised learning methods.

Traditional deep learning models require enough labeled data to ensure high performance. Nevertheless, it is challenging to acquire a large number of labeled data in real-world scenarios. In contrast, the collection of unlabeled data is comparatively inexpensive. Consequently, many studies seek to leverage large pools of unlabeled data to enhance the performance of deep learning models. These efforts typically fall within two principal categories: (1) self-supervised learning, and (2) semi-supervised learning. Figure 1 illustrates the overall process of these two methodologies. Self-supervised learning focuses on extracting task-agnostic features and enhancing generalization capacity during the pre-training phase using unlabeled data. After that, the neural networks undergo fine-tuning for a specific task, using the knowledge acquired from the pretext task to enhance their performance. The most fundamental cornerstone of self-supervised learning lies in autoencoder-based approaches. Especially, denoising autoencoder is trained to reconstruct the original input from its latent vector by using a perturbed version of the original input with Gaussian noise. In the process of compressing noisy data to a lower-dimensional representation and subsequently reconstructing it, the encoder component of the autoencoder learns the underlying patterns and relationships between initial condition variables.

Semi-supervised learning directly combines both labeled and unlabeled data during training to enhance performance in target tasks, such as regression or classification. Specifically, in semi-supervised learning, unlabeled data are used to enhance consistency or minimize entropy in improving the neural network's robustness. Pseudo-Label [2] improves data efficiency by assigning labels with maximum probability from unlabeled data. It enhances the neural network's robustness by ensuring that the model predicts the same label for both the original and noisy unlabeled samples. Mean teacher method [3] facilitates the generation of consistent outputs for unlabeled data through the exponential moving average update, even in the face of diverse perturbations and temporal discrepancies across training epochs. It trains the neural networks to minimize the mean squared differences for consistency regularization between the outputs of the student model and the teacher model under stochastic conditions. Finally, the student model can learn the various information from the unlabeled data, and the predictive performance of the model can be further generalized. Virtual adversarial training (VAT) [4] enhances the robustness of the model by encouraging the model to be consistent in the presence of virtual adversarial noise applied to unlabeled data. Virtual adversarial noise intentionally transforms the samples in the opposite direction of what the model should learn, making the learning process challenging. By minimizing the error between the predictions of the original and noisy samples by virtual adversarial noises, the model can maintain reasonable predictive performance even in harsh conditions.

3. Methods and Experiments

3.1 Methods

The present study aims to use and compare self- and semi- supervised learning methods for predicting evacuation time in fire hazards with varying input conditions. However, these approaches are mainly focused on unstructured data such as images. In contrast, our study uses structured tabular data. To address this, we propose using the value imputation and mask estimation (VIME) method [5], which combines the self- and semi- supervised learning, specifically designed for tabular data. In VIME, neural networks reconstruct original features from corrupted data and are trained to identify which parts of tabular data are corrupted. These self-supervised learning techniques enable the neural networks to learn the underlying tabular data representations more effectively and improve their ability to denoise and extract meaningful information. Afterward, they are trained to produce consistent predictions across multiple instances of corrupted data and predict labels of a small amount of labeled data. In these semi-supervised approaches in VIME, the neural networks are trained to maintain consistency on corrupted data and accurately predict labeled data.

3.2 Experiments

In real-world fire scenarios, deep learning models may confront fire scenarios that were not previously included in their training dataset. As a consequence, evaluating the model's capacity for generalization becomes imperative because it indicates its robustness in effectively performing with unseen data. To effectively verify the model's generalization performance, we ensure that the fire scenarios present in the testing dataset differ from those encountered during the training phase. This deliberate distinction aims to assess the model's ability to extrapolate its learned patterns to unforeseen situations, thus confirming its reliability under diverse conditions. Table I shows the eight input variables and their corresponding states for both the training and testing datasets of the deep learning models. To simulate real-world fire scenarios, the testing dataset includes several new states that the model did not encounter during the training phase.

To evaluate the performance of the deep learning model, we used the R^2 score, indicating the degree to which the model's predictions align with the actual data. The R^2 score ranges between one, representing an excellent prediction match, and negative infinity, which indicates the poorest possible performance. We conducted five repeated experiments with different random seeds for pairwise comparisons. Table II presents the average and standard deviation of R^2 results of five repeated experiments for the labeled data at four different rates. To examine the performance across varying quantities of labeled data, we conducted experiments for four cases based on the number of training labeled data. These cases correspond to the labeled data rates of 10%, 20%, 50%, and 100%, relative to the total number of unlabeled data.

In a scenario with four different labeling rates, we compared the performance of six methods. It can be seen that the neural network model trained solely on labeled data exhibited inferior performance compared to all self- and semi- supervised learning techniques, regardless of the labeled data ratio. This suggests that the incorporation of additional unlabeled data has proven effective in alleviating the limitations posed by a scarcity of labeled data. Among all self- and semi- supervised methodologies, VIME consistently demonstrated good predictive performance. This outcome shows the specialization of VIME for evacuation time modeling within tabular data. When the number of labeled training data increased from 1,540 to 3,079, we observed a marginal decrease in performance, except for VIME. This can be attributed to the current complexity of the predictive model, which may not be optimally suited for effectively learning from the increased number of labeled data points (3,079). Therefore, we believe that enhancing the model's performance can be achieved through an increase in its capacity and the acquisition of more labeled data. In the case of exceptional performance with VIME, it suggests that incorporating self- and semi-supervised learning techniques enables the neural networks to adapt well to the larger labeled dataset.

Figure 2 illustrates the prediction results for evacuation time using testing data obtained from the neural network and VIME, with each result associated with one of the four labeled data ratios. The *x*-axis represents the predicted evacuation time obtained from the model, and the *y*-axis indicates the actual evacuation time. Each dot represents a prediction result for an individual fire scenario. When the ratio of labeled data is as low as 10%, which represents the smallest amount used for training, the predictive performance of the neural network tends to be poor. In contrast, VIME, which benefits from additional training using unlabeled data, enhances the predictive performance of the neural network. For cases where K is greater than or equal to 20%, it becomes evident that within the range of actual

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

Number of Training Data		Method					
		Supervised Learning	Self-supervised Learning	Semi-supervised Learning			Self + Semi supervised Learning
Labeled Data	Unlabeled Data	Neural Network	Denoising Autoencoder	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)**

evacuation times between 560 and 580, the neural network's performance relatively deteriorates, whereas VIME's predictive performance remains superior. These advantageous attributes of VIME further serve to underscore the practicality of using unlabeled data as a solution to address the scarcity of labeled data.

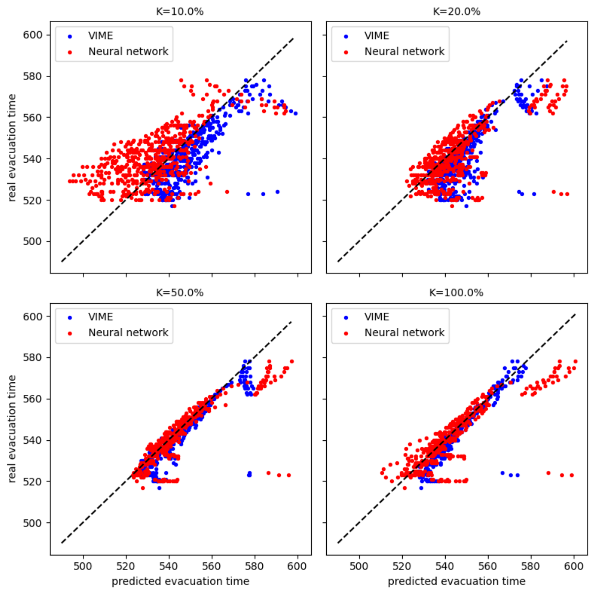

Fig. 2. Four examples of visualizing the prediction results of the neural network and VIME. K (%) represents the labeled data rates relative to the number of unlabeled data.

4. 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. However, the current model's accuracy, as indicated by R^2 values, may not yet meet the stringent requirements of real-world applications. To further enhance the model's precision, our future efforts will entail exploring more specialized neural network architectures and data augmentation strategies specifically designed for tabular data. We envision the continued development of this robust evacuation time prediction framework through future research endeavors, contributing to the enhancement of nuclear safety.

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