Prediction of Evacuation Time in Ventilated Main Control Room during Fire using CFAST Simulations and Machine Learning Model

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1. Introduction

Effective emergency response strategies are essential in minimizing the devastating impact of nuclear power plant fires, which can cause significant loss of life and property damage. A crucial aspect of fire emergency response is timely evacuation of a space from a fire. This study presents a novel approach for evacuation time of a ventilated main control room using machine learning. The aim is to predict evacuation variables which is necessary for effective abandonment of the main control room (MCR). The proposed methodology combines consolidated model of fire growth and smoke transport (CFAST) simulations and machine learning model to predict evacuation time under different fire scenarios based on initial fire conditions. The model is trained on a dataset generated through CFAST simulations specific to nuclear power plant conditions and validated. The results demonstrate that the machine learning model can accurately predict the time required for meeting evacuation criteria based on initial fire conditions of the main control room when the fire first broke out. This study provides a useful tool for fire safety design and evacuation planning in nuclear power plants, ensuring the safety of personnel during a main control bench board fire. The primary focus of our study was on hot gas layer temperature as the key factor in determining evacuation criteria, given its importance in predicting the spread of fire and potential hazards to occupants. While smoke can also be a critical factor in ensuring the safety of occupants during evacuation, our study was limited by the availability of data and resources primarily centered on temperature measurements.

2. Overview of the MCR model

The main control bench board (MCB), which contains numerous electrical enclosures shaped like a horseshoe and has all of its walls closed except for the ventilation area, is depicted in Fig. 1 from the top view. The height of the MCB consisting of 11 panel boards (PB) is 2.9 m. The floor area of the compartment has been taken from the previous study [1] which is given by 21.4 m x 18.4 m. The thickness of concrete walls is 0.4 m. The overall flow rate through the 24 supply vents, each measuring 0.4 m x 0.4 m, is 7.08 m^3/s. The flow rate through the four each exhaust valves, which are 1.0 m x 0.6 m in size, is 1.00 m^3/s. The door condition was examined in three different circumstances: (i) closed door all time, (ii) closed door and then open after 10 minutes, and (iii) open door all time. The door is assumed to open at 10 minute after a fire is started. Since the operators (target) often stand close to the operator console, it was presumed that they were situated in the middle of the MCR. With reference to the SFPE Handbook, loose leakage area condition was taken into consideration in this investigation [2].

Fig.1. Top view of the reference MCR

2.1 Fire Scenario and evacuation criteria

PB-10 is considered as the main source of ignition when ventilation is in operation, leading to the propagation of fire to adjacent panel boards PB-09, PB-08, and PB-07 in approximately 10 minutes. If a fire occurs in one MCB panel, it has the potential to spread to neighboring MCB panels, resulting in malfunction or failure of safety systems connected to them. In each MCB panel, there was XLPE/Neoprene cable having a chemical composition of $C_3H_{4.5}Cl_{0.5}$. The input parameters according to NUREG-1805 [3], SFPE Handbook and NUREG-1934 [4] are mentioned in Table I. The peak heat release rate (HRR) value of a single panel is assumed to be 400 or 702 kW, according to NUREG/CR-6850 [5]. To avoid operators from losing habitability and leaving the MCR, the hot gas layer temperature (HGLT) should not go beyond 95°C according to NUREG-6850. This criteria should be satisfied to prevent operators from loss of habitability and abandon the MCR.

Table I. Input parameters for CFAST model analysis

Input parameters	Values
HRR (kW)	400 and 702
Fire propagation time (minute)	10
Ventilation height (m)	2.2
Fire source height (m)	0.9
Leakage area ratio (m^2/m^2)	3.5×10^{-4} (Loose)
Door conditions	Closed, Closed-Open and Open
Ventilation flow rate (m^3/s)	1.00
Ambient temperature (°C)	20
Effective fuel formula	$C_3H_{4.5}Cl_{0.5}$
Heat of combustion (kJ/kg)	10,300
CO_2 yield (kg/kg)	0.63
CO yield (kg/kg)	0.082
Soot yield (kg/kg)	0.175
Radiative fraction	0.53

2.2 Machine learning

To predict the duration time required for the HGLT to exceed 95°C in the ventilated main control room during a fire outbreak, this study employed a Multi-Layer Perceptron (MLP) model with input variables such as heat release rate (HRR), fire propagation time, ventilation height, flow rate, height of fire, ambient temperature, leakage area ratio, and door condition. Table II presents the eight input variables used for training the MLP model. These input variables represent the initial fire conditions of the MCR in the CFAST analysis. We preprocessed the categorical data variables of door condition and leakage area ratio into one-hot encoding values, resulting in 12 input variables of the MLP model. The output variable is the duration of time taken for the HGLT to exceed 95°C in the CFAST simulation. We created the CFAST dataset through 11,340 CIFAR simulations, which represent all possible combinations of input variables.

The MLP is a type of neural network that consists of one or more hidden layers between the input and output layers. Each hidden layer consists of multiple neurons that use activation functions to introduce non-linearity into the model, allowing for a better understanding of the relationship between the input and output variables. We used the MLP model with a single hidden layer containing of 32 neurons and gaussian error linear units activation function. The input layer consists of 12 neurons to take in 12 input variables, while the output layer has one neuron to output the time taken for HGLT to first reach 95°C. The model was trained using a CFAST dataset, which was prepared by normalizing and removing some missing data points, and subsequently divided into 90% training and 10% testing subsets. The MLP was trained to minimize the loss function known as residual sum of squares between actual and predicted values using the backpropagation algorithm and the Adam optimization method.

Table II: Input variables for training the MLP.

Input Variables	Values
Peak HRR	400, 702
Propagation Time	10, 15
Door Condition	Closed, Closed-open, Open
Height of Fire	0, 0.45, 0.9
Ventilation Height	2.2, 2.7, 3.2
Flow Rate	1.0, 1.25, 1.5, 1.75, 2, 2.25, 2.5
Leakage Area Ratio	Tight, Loose, Very Loose
Ambient Temperature	20, 25, 30, 35 and 40

3. Results and discussions

3.1 CFAST simulation results

Fig. 2 displays the changes in target output parameters of CFAST, HGLT, at a height of 1.8 meters above the floor, in response to various input parameters including peak HRR and door conditions when the fire propagation time is 10 minute and ventilation flow rate of 1.00 m^3/s with loose leakage area condition at ambient temperature of 20°C. The study has revealed that the closed-door condition results in the highest values for the HGLT. In the closed-door condition, the HGLT is significantly higher compared to when the door is open. At peak HRR of 400 and 702 kW, the maximum values for HGLT are 119°C and 189°C, respectively, for the closed-door condition.

Table III provides an overview of the changes in the abandonment time, which refers to the duration at which the evacuation criteria meet the relevant standards, for a peak HRR of 400 and 702 kW. The results indicate that the HGLT at HRR of 400 kW takes longer to meet the relevant criteria compared to that at HRR of 702 kW. Furthermore, the change in door conditions from closed-door to open-door condition caused a delay in the abandonment time from 1630 to 1746 seconds, by 116 seconds for HGLT at HRR= 400 kW, and from 1118 to 1123 seconds, by 5 seconds, at HRR= 702 kW.

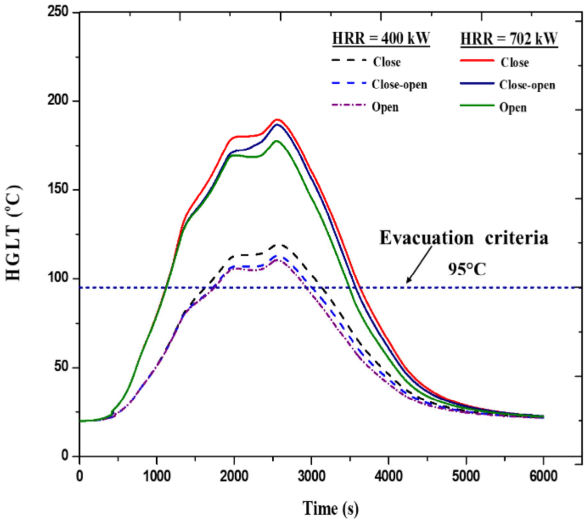

Fig. 2. Variations of HGLT with respect to different door conditions

Table III. Abandonment time of MCR fire scenario for different door conditions

Fire scenario Flow Rate =1.00 m^3/s, T_∞ = 20°C, 10 min, loose leakage area **(Door conditions)**	**Abandonment Time (s) HGLT**	
	HRR = 400 kW	**HRR = 702 kW**
Closed door	1630	1118
Closed-Open door	1728	1122
Open door	1746	1123

3.2 Prediction results

To evaluate the performance of the model, we utilized R^2 score, also known as the coefficient of determination. It indicates how well the predictions made by a machine learning model fit the actual data. It ranges from 0 to 1, with 1 indicating a perfect fit and 0 indicating that the model provides no improvement over using the mean value of the output variable. A higher R^2 score indicates a better fit of the model to the data. For pairwise comparisons, we conducted five repeated experiments with different seeds and reported the mean of R^2 score.

The average R^2 scores of the MLP model for the training and testing data over five repeated experiments are 0.98 and 0.97, respectively, demonstrating the model's prediction ability to accurately predict evacuation times based solely on the initial fire conditions without overfitting the training data. Fig. 3 depicts the MLP model's predictive performance in terms of evacuation time using testing data. The x-axis represents the predicted value obtained using the MLP model, while the y-axis indicates the actual time taken for the HGLT to reach 95°C during a fire. Each blue dot represents the prediction result for a single fire scenario, and most of the blue dots show a perfect match between the predicted and actual values, indicating excellent predictive performance. The performance of the MLP model is slightly less accurate when predicting abandonment times between 2,000 and 3,500 seconds compared to other time intervals. After examining the training data, we observed that the number of data points in this interval is relatively small compared to others. Therefore, we believe that the model's performance in this group can be improved with more data.

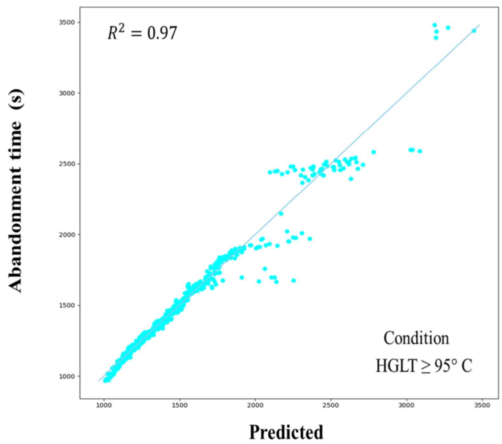

Fig. 3. Example of visualizing the prediction results of the MLP model.

4. Conclusions

During CFAST simulation, the closed-door condition produces the highest values for the HGLT. Specifically, the HGLT is considerably higher in the closed-door condition compared to when the door is open, highlighting the importance of effective evacuation strategies. The use of machine learning algorithms to predict the necessary evacuation time in the event of a fire in critical facilities such as the MCR of nuclear power plants is an effective approach that can significantly improve fire safety. By applying the six-step process of data collection, data preprocessing, feature selection, model selection, model training, and model evaluation to the CFAST dataset, we were able to accurately predict the time required for the evacuation criteria to be met for the first time after the outbreak of a fire in the MCR. The average R^2 score of 0.97 indicates that our model provides a highly accurate fit to the data, and can therefore be relied upon to make precise predictions. This approach has the potential to significantly improve fire safety in the MCR of nuclear power plants.

ACKNOWLEDGMENTS

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