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ON THE USE OF A NEURAL NETWORK TO PREDICT TENABILITY CONDITIONS DURING A FIRE ON A NUCLEAR POWER PLANT CONTROL ROOM

David Lázaro[1], Mariano Lázaro[2], Daniel Alvear[3] and Miguel Ángel Jiménez[4]

[1] Phd, Universidad de Cantabria, Spain (lazarod@unican.es)
[2] Phd, Universidad de Cantabria, Spain
[3] Phd, Universidad de Cantabria, Spain
[4] Phd, Consejo de Seguridad Nuclear, CSN, Spain

ABSTRACT

Fires in nuclear power plants pose a significant risk to both the safety and stability of the facility and the surrounding communities. The control room, housing the staff and equipment crucial for monitoring and controlling the reactor, is particularly critical. A fast and effective response to ensure its functionality during a fire is essential. However, predicting the sustainability conditions in a fire-affected control room proves challenging due to the complexity of the involved physical and thermal processes and more sophisticated and accurate of existing computational models require a high computational cost, rendering them impractical for real-time decision support in emergency situations.

The primary objective of this study is to assess the feasibility of developing a neural network-based model capable of reliably predicting real-time sustainability conditions during a control room fire in a nuclear power plant. The choice of neural networks is motivated by their capacity to process complex data and make accurate predictions. Initially, the model underwent training using simulations generated with the CFAST zone model. The study evaluated the optimal number of simulations for training, laying the groundwork for future enhancements of the model.

The results of this study provide insight into the feasibility of using neural networks for fire risk assessment in nuclear power plants. It was determined that the optimal training dataset comprises 2800 fire simulations.

INTRODUCTION

Computational fire models have been often employed to predict sustainable conditions in nuclear plants for design or planning purposes, but they require definition by expert users. Additionally, more detailed models come with a high computational cost, rendering them impractical for real-time decision support in emergency situations. Simpler fire models, such as zone models, offer faster predictions for specific sustainability conditions, such as temperature and height of the hot smoke layer. Zone models enable the quick modelling of significant larger number of scenarios compared to the analytical models, but their results exhibit greater uncertainty compared to more complex computational fire models like Computational Fluid Dynamics (CFD). Recent efforts have focused on utilizing sophisticated mathematical methods and various artificial intelligence techniques. These approaches aim to reduce the time required for obtaining modelling results without increasing the uncertainty associated with the outcomes.

Lee et al. (2004) and Lee (2009) introduced the GRNNFA (General Regression Neural Network - Fuzzy Adaptive Resonance Theory), a neural network model designed to predict parameters of compartment fires. This model was specifically applied to forecast the location of the hot smoke layer in a

single-compartment fire and was trained using experiments conducted by Steckler et al. (1982). The outcomes demonstrated that the GRNNFA fire model could predict the hot smoke layer's location with minimal computational time and resource requirements. In a related study, Lázaro et al. (2013) presented a GRNN-based neural network model to predict the temperature and height of the hot gas layer in an enclosure. This network allowed for single-step training, using data from 4640 simulations performed with the CFD model Fire Dynamics Simulator (FDS). Following the development and training of the neural network, validation was carried out against two small-scale atrium fire tests (3 x 3 x 1.8/2.2 m). The model yielded comparable results to those obtained with the FDS model but with a significantly reduced computational time—20 seconds versus 5400 seconds. Hodges (2018) and Hodges et al. (2019) have developed a novel approach to predict temperatures and velocities within one or more connected compartments. The model proposes the use of a computational zone fire model combined with a transpose convolutional neural network (TCNN), which allows prediction of the most detailed heat flow field within each compartment. Sun et al. (2023) presented a multi-backpropagation neural network (BPNN) fusion algorithm to predict the ceiling temperature distribution of tunnel fires. Su et al. (2021) used the transposed convolutional neural network (TCNN) to predict the smoke movement in the atrium and the availability of exit times. Buffington et al. (2021) used deep learning for predicting the temporal evolution of temperature, pressure, and smoke in high-rise fires. Finally, as it is referred in the NUREG 7294, that includes the advanced computational tools and techniques with artificial intelligence and machine learning in operating nuclear plants, Worrell et al. (2019) applied machine learning to develop metamodel approximations of a physics-based fire hazard model to improve modelling realism in probabilistic risk assessment without significant computational burdens.

In this study, our primary objective is to address the challenge of predicting tenability conditions in a fire-affected control room of a nuclear power plant. We achieve this by developing a neural network model capable of accurately predicting the real-time gas layer temperature and height within the control room during a fire. In this initial phase, the model underwent training using simulations generated by the zone model CFAST, and we assessed the optimal number of simulations required for effective training.

FIRE SCENARIO

The scenario under consideration in this study reflects a typical control room scenario of a nuclear power plant, with the characteristics defined based on the guidelines outlined in NUREG 1934 (2012). The model's definition of the control room is structured to align with the specifics outlined in NUREG 1934, providing a reference scenario that can be extrapolated to accommodate different control room configurations. In the control room fire scenario outlined by NUREG 1934, the primary control room (MCR) door is assumed to be closed (a typical situation), and the initial ventilation conditions are set to normal or considered off at the onset of the fire. Despite the presence of numerous electrical cabinets within the MCR, as depicted in Figure 1, these are not incorporated into the CFAST model. The focus of the analysis is specifically on the temperature and height of the hot gas layer, excluding considerations for fire propagation between the electrical cabinets. Figure 1 illustrates the geometry of the MCR as per the specifications outlined in NUREG 1934.

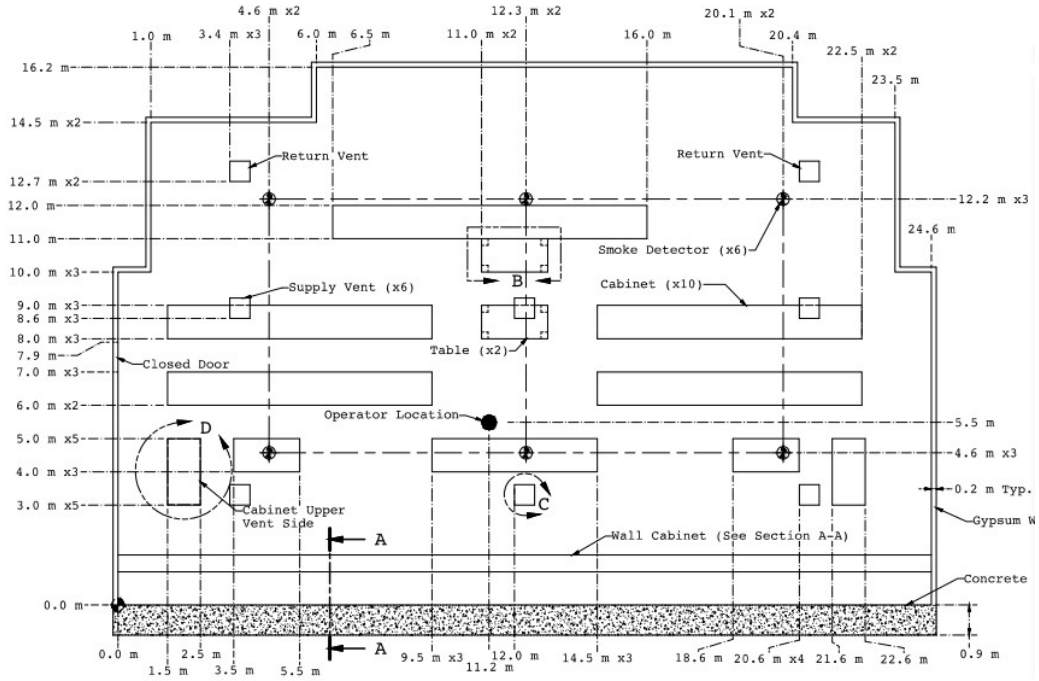

Figure 1 Geometry of the main control room NUREG 1934 (2012).

The main control room's geometry is characterized by a single compartment with a floor area of 369.87 m^2 and a height of 5.2 m. The structural components of the compartment include walls constructed with 1.6 cm gypsum boards supported by steel profiles. The floor is comprised of a 0.5 m thick concrete slab, and the ceiling has a thickness of 0.9 m. The thermal properties of the various materials are derived from NUREG 1805 (2004) and are presented in Table 1.

Table 1 Thermal properties of the materials NUREG 1805 (2004).

Material	Thermal conductivity (W/mK)	Density (kg/m^3)	Specific heat (kJ/kgK)
Concrete	1.6	2400	0.75
Gypsum plasterboard	0.17	960	1.1

Concerning the ignition source, the fire initiates as a result of an electrical failure in the XPE/neoprene cables within a 2.4 m high electrical control cabinet. The fire progresses in accordance with a "t-squared" curve, reaching a maximum value of 702 kW in 12 minutes and then stabilizing for an additional eight minutes, as specified in NUREG/CR-6850 (2005). Table 2, sourced from NUREG 1934, provides the parameters employed to characterize the combustion reaction within the cabinet. Nevertheless, it is important to note that there may be additional ignition sources present in a MCR. Therefore, the model is designed to be flexible and open to considering different HRR peaks. This adaptability ensures a more comprehensive representation of potential fire scenarios within the MCR.

Table 2 Reactivity input data for the electrical cabinet.

Parameter	Value	Reference
Effective Fuel Formula	$C_3H_{4.5}Cl_{0.5}$	XPE/neoprene
Peak HRR	702 kW	NUREG/CR-6850 (2005)
Time to reach peak HRR	720 s	NUREG/CR-6850 (2005)
Heat of Combustion	10300 kJ/kg	Hurley (2016)
CO2 Yield	0.63 kg/kg	Hurley (2016)
Soot Yield	0.175 kg/kg	Hurley (2016)
CO Yield	0.082 kg/kg	Hurley (2016)
Radiative Fraction	0.53	Hurley (2016)
Mass Extinction Coefficient	8700 m^2/kg	Mulholland and Croarkin (2000)

METHODOLOGY

The methodology employed for developing the sustainability conditions prediction model in nuclear power plants, based on neural networks, is outlined below. Additionally, the process for evaluating the size of the training simulations required for network training is detailed.

Integrated system for fire modelling of nuclear power plant fires

The development of the integrated tool for predicting sustainability conditions in the event of fires in nuclear power plants encompasses three primary pillars: i) the stochastic generation of training data, ii) the selection and training of the neural network, and iii) the application of the neural network. Figure 2 illustrates a schematic of the tool, highlighting these key components.

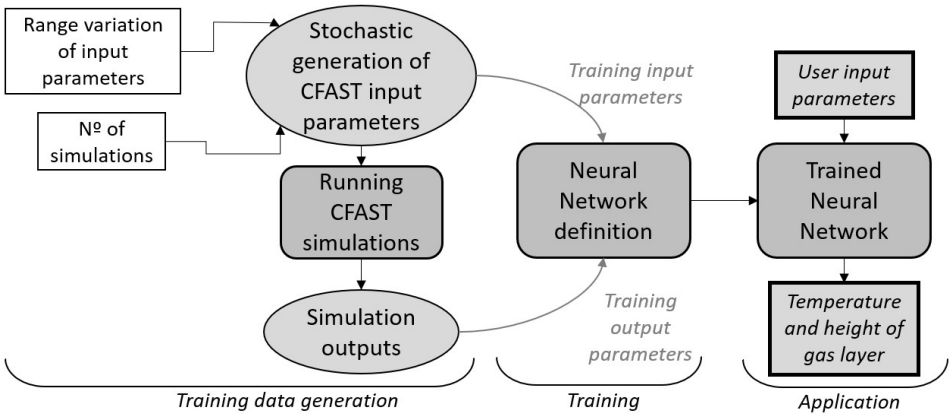

Figure 2 Scheme of the integrated tool.

The stochastic generation of training data serves a dual purpose: firstly, to train the neural network, and secondly, to define the range of scenarios applicable to the neural network model. This module within the tool facilitates the design, execution, and processing of simulations as specified by the user, within the defined range of variation for independent parameters. The number of training simulations used to configure the neural network plays a crucial role in determining the confidence level of the tool's results. The training and application of the neural network constitute an integrated module that can be utilized in conjunction with the training data generation module or independently. The selected neural network undergoes training by automatically processing the outcomes of the stochastic training data generation module. Ultimately, the

tool empowers the user to define a scenario and promptly obtain real-time results for the temperature and height of the hot gas layer, facilitating the analysis of sustainability conditions within the designated MCR.

Neural Network

A pivotal aspect in defining the integrated fire modelling tool for the MCR of a nuclear power plant is the selection of the neural network architecture. The chosen neural network for the current model is a General Regression Neural Network (GRNN), Specht (1991). Noteworthy advantages of this network include its ability to function without the need for predefined nodes and layers, ease of single-step training, and adaptability for retraining as new data becomes available. Additionally, GRNN is able to capture the behaviour of non-linear systems. Even with sparse data in a multidimensional measurement space, the algorithm ensures a smooth transition between observed values. It's worth noting that a limitation of this network lies in its poor extrapolation capability beyond the range of data used in training. Therefore, it is well-suited for the present model where parameters are defined within a specific range.

In MATLAB, this network can be instantiated using the function *newgrnn*. This function directly takes all the training data as inputs, creating the desired neural network and facilitating its training. The GRNN structure in MATLAB consists of a radial base layer and a special linear layer, as illustrated in Figure 3.

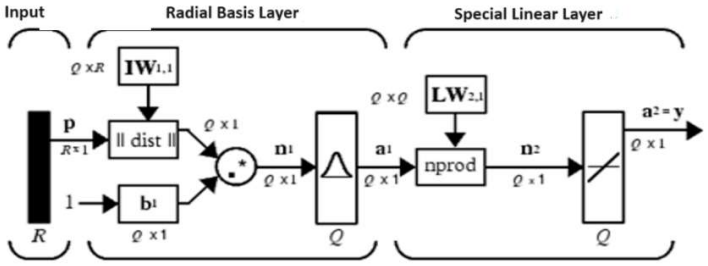

Figure 3 General regression neural network architecture (MATLAB)

Where R is the number of elements in the input vector, Q is the number of neurons in layers 1 and 2, and the number of input/output pairs. The first layer of the GRNN is known as the radial basis layer, functioning akin to a radial basis function network. This layer comprises neurons, each corresponding to a specific input/target pair in the training data. The neurons in this layer act as radial basis functions, computing their output based on the distance between the input vector and their respective weight vectors. The key operation in the radial basis layer involves the calculation of weighted inputs for each neuron. This is achieved by determining the distance between the input vector and the vector of weights associated with each neuron. The spread parameter SPREAD influences the shape and responsiveness of these radial basis functions, providing adaptability to the network. This layer functions similarly to the radial basis *newrbe* network. The bias b^1 is set to a column vector of 0.8326/SPREAD. The spread parameter, denoted as SPREAD, plays a pivotal role in shaping the behaviour of the GRNN. This user-defined parameter determines the distance an input vector must be from a neuron's weight vector to yield a 0.5 response. In essence, SPREAD controls the width of the radial basis functions employed by the network. The user's choice of SPREAD is crucial, as it directly impacts the network's responsiveness to input vectors. A larger SPREAD results in broader regions of influence for each neuron, leading to smoother, more gradual radial basis functions. Conversely, a smaller SPREAD creates sharper, steeper functions. The selection of SPREAD is contingent upon the characteristics of the data and the desired behaviour of the network. The default value, and the one used in this study, for the SPREAD parameter is 1.

Each weighted neuron input is the distance between the input vector and its vector of weights. Each input neuron of the network is the product of its weighted input with its bias. In turn, each output neuron is the input to the network passed through the radial basis layer. If the neuron's vector of weights is equal to the adapted input vector, its weighted input will be 0 and its output will be 1. Following the radial basis layer, the GRNN includes a special linear layer, which plays a crucial role in refining the network's output. Similar to the radial basis layer, the special linear layer comprises neurons, the number of which corresponds to the input/output vectors in the training data. Assuming we have an input vector p that is close to p_i, one of the input vectors among the input/output vector pairs is used in the design of the weights of layer 1.

Stochastic data generation for the training

The stochastic generation of training data serves a crucial role in ensuring a homogeneous definition of input parameters within user-defined ranges for each independent variable. In this study, the CFAST fire computational model, Peacock et al. (2023), has been chosen as the simulation tool for generating the training data. CFAST stands out for its ability to execute a substantial number of simulations within a short timeframe, owing to its efficient computational speed. This model offers considerable versatility, accommodating various typologies of fire scenarios. Additionally, CFAST has undergone extensive validation, Peacock et al. (2023). The robustness of CFAST makes it a suitable choice for generating a diverse and comprehensive dataset, providing a solid foundation for training the neural network model.

For the current analysis, a no-ventilation scenario will be considered. This choice is deliberate to constrain the variation parameters of the model, allowing for a focused examination. Additionally, adopting a no-ventilation condition facilitates a direct comparison of results with those presented in NUREG 1934. Notably, in NUREG 1934, calculations for the height of the hot gas layer were exclusively conducted with CFAST under conditions of no ventilation.

In this approximation, the independent variables subjected to analysis include enclosure dimensions (length, width, and height), ignition Heat Release Rate (HRR) peak, *soot_yield*, and *CO_yield*. The specified ranges of variation for these independent variables are detailed in Table 3. This comprehensive selection of independent variables ensures a thorough exploration of the parameter space, allowing for a robust evaluation of the neural network model's performance.

Table 3 Range of variation of the independent variables for training simulations.

Parameter	Minimum value	Maximum value
HRR peak (kW)	100	3000
Length (m)	4.5	50
Wide (m)	4.5	50
Height (m)	2	8
Soot_yield	0.01	0.4
CO_yield	0.01	0.2

The stochastic generation of each of the parameters is based on the following equation:

$$P_i = P_i^l + rand \cdot \left(P_i^u - P_i^l\right) \tag{1}$$

Where P_i is the stochastic value generated for each i independent variable, P_i^l is the minimum value for the i independent variable, P_i^u is the maximum value for the i independent variable, and *rand* produces a random number comprised between 0 and 1.

An essential consideration in creating the training data for a neural network is the judicious selection of the training sample size, denoted by the number of simulations used. In this study, the optimal size of the training sample has been systematically investigated by employing seven training datasets, each characterized by a different number of CFAST simulations. The training process involved distinct neural networks, each exposed to varying numbers of CFAST simulations: 1000, 2000, 2500, 2700, 2800, 3000, and 6000 simulations. This approach allows for a nuanced exploration of the impact of training sample size on the neural network's performance. The variation in the number of simulations provides valuable insights into the network's ability to generalize and make accurate predictions across different scenarios. Subsequent analysis and comparison of the results obtained from these diverse training datasets will contribute to determining the optimal training sample size for robust and reliable neural network performance in predicting sustainability conditions in the specified nuclear power plant scenario.

The MATLAB-based function responsible for generating CFAST input files, inputting stochastically obtained independent variables, and executing simulations has been developed. The use of MATLAB allows to integrate it with the neural network, *newgrnn*. From the simulations, the extracted dependent variables include the temperature and height of the hot gas layer. These variables are recorded at regular intervals within the time span [0 s:60 s:2400 s], resulting in a dataset comprising 41 temperature points and 41 height points for each simulation.

Figure 4 illustrates the schematic representation of the training input and output matrices, where *n* signifies the number of simulations conducted to train the network. For every set of training data, two distinct neural networks have been established. The first network, as depicted in Figure 4, is designed to predict the Upper Gas Layer Temperature (TGL). Simultaneously, another network is configured to forecast the Height of the Upper Gas Layer (HGL). In the latter case, the temperature matrix is substituted with the height matrix during the training process. This dual-network approach facilitates the comprehensive training of the model to accurately predict both temperature and height dynamics in response to varying input parameters.

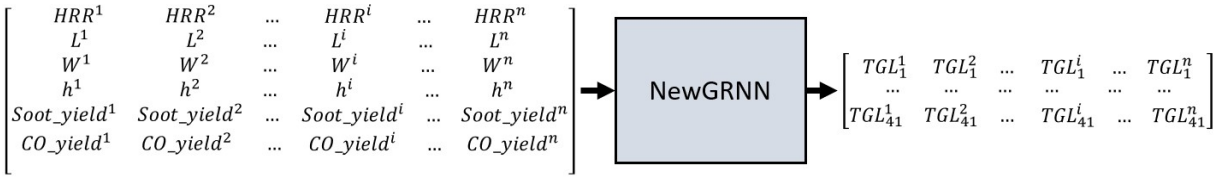

Figure 4 Diagram with input and output matrices of the *NewGRNN* training network.

Results evaluation.

To assess the influence of the seven training datasets analysed in the study, the Root Mean Square Error (RMSE) was calculated in comparison to the original simulations executed in CFAST, as specified by the U.S. Nuclear Regulatory Commission in NUREG 1934 (2012). The evaluation was conducted using the following equation:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(E_i - M_i)^2} \tag{2}$$

Where n is the total number of time instants of the MLR curves, E_i is the result of the experimental MLR at time instant i, and M_i is the result of the simulated MLR at time instant i. The squared error is computed rather than the simple error in our analysis. This choice ensures that the error is consistently

positive. By adopting this approach, a perfect approximation corresponds to an error of 0, providing a clearer understanding of the accuracy and deviation of the predictions from the original CFAST simulations.

RESULTS

To characterize the MCR as outlined in NUREG 1934, the model takes into account the input parameters listed in Table 4. These parameters serve as the foundational elements for accurately representing and simulating the MCR scenario within the defined framework.

Table 4 Independent variables to define the control room.

Parameter	Input value
HRRpeak (kW)	702
Length (m)	4.5
Wide (m)	4.5
Height (m)	2
Soot_yield	0.01
CO_yield	0.01

Once the model is designed, and the training data are available, the results obtained from various trained AI models are compared with the MCR CFAST simulation defined in NUREG 1934. The difference between the AI models is the number of training simulations employed for each. Named in the figures as "AI *i*" are presented the results of the AI model trained with *i* simulations, as an example, "AI 1000" represents the AI model trained with 1000 simulations. Figures 5 and 6 depict the comparison of the TGL and HGL obtained with the proposed AI models versus the CFAST model.

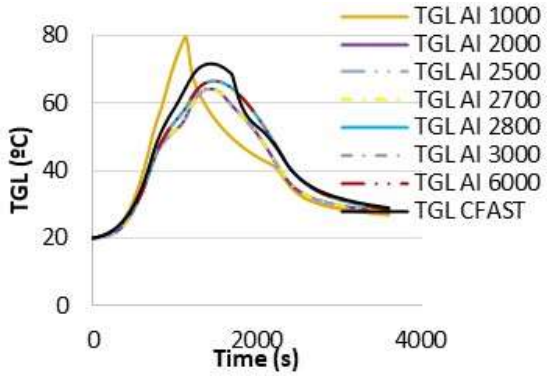

Figure 5 Comparison of the upper layer temperature in the AI model and in CFAST.

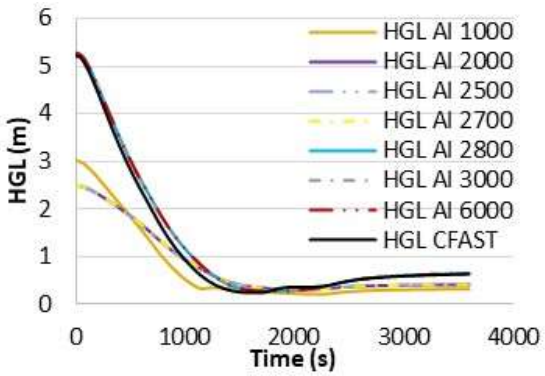

Figure 6 Comparison of the upper layer height in the AI model and in CFAST.

The AI models demonstrate a commendable ability to approximate results obtained with CFAST, the model with which they were trained, especially in the prediction of the upper layer height.

In addition to comparing the curves, Figures 7 and 8 showcase the RMSE comparison for the TGL and the HGL results among different neural networks and the CFAST simulation outlined in NUREG 1934. Notably, scenarios with more than 2800 training simulations yield the closest approximation to CFAST results. In this specific case, the RMSE for TGL is 2.6 ºC, and for HGL, it is 0.13 m. These results signify the effectiveness of the neural networks, particularly when trained with an ample dataset, in achieving accurate predictions comparable to CFAST simulations.

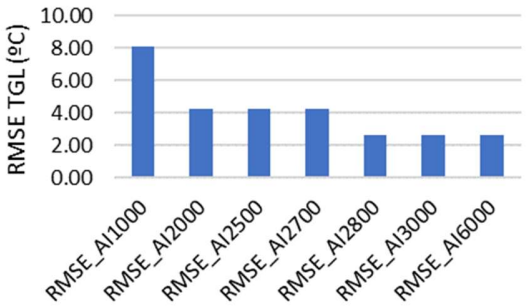

Figure 7 Comparison of the TGL of the temperature results of the different neural networks with respect to the results of the simulation included in NUREG.

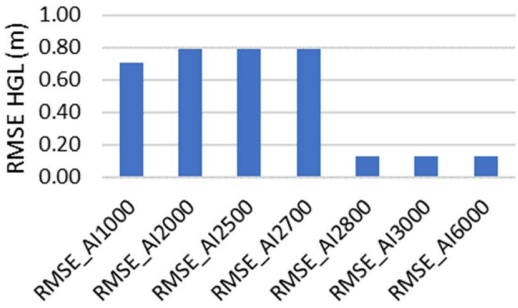

Figure 8 Comparison of the RMSE of the HGL results of the different neural networks with respect to the results of the simulation included in NUREG.

CONCLUSIONS

In conclusion, this study has successfully explored the feasibility of employing artificial intelligence, specifically neural networks, for predicting fire dynamics in nuclear power plant control rooms. The developed models, trained with CFAST simulations, showcase a promising capacity to approximate results compared to the established CFAST model described in NUREG 1934. The comparison of upper layer temperature and height reveals the proficiency of the AI models in capturing the dynamics of fire scenarios.

The evaluation of RMSE highlights those models with over 2800 training simulations yield the closest approximation to CFAST results, underscoring the importance of dataset size in achieving reliable predictions. Notably, the achieved RMSE values of 2.6 ºC for TGL and 0.13 m for HGL signify the effectiveness of the trained neural networks in providing accurate predictions, offering valuable insights for practical applications.

Nevertheless, in order to perform a first analyse of the feasibility of employing artificial intelligence to predict tenability conditions during a fire, we have studied the reproduction of the zone model CFAST results, whose already enable the quick modelling of significant larger number of scenarios. The demonstrated capability of the AI models to provide accurate approximations suggests potential enhancements through training with more complex computational fire models like FDS. This extension could further improve accuracy and broaden the applicability of the models, enabling real-time predictions of fires in nuclear power plants. Incorporating additional parameters such as the ignition source location or ventilation system, and exploring new inputs like ventilation details and thermal properties of walls, represent avenues for future research.

In summary, the findings from this study present a significant step toward leveraging artificial intelligence for fire risk assessment in nuclear power plants, paving the way for enhanced safety measures and decision-making capabilities in emergency scenarios.

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en centrales nucleares", and for the research project SUBV-18/2022 “NUCLEVS - Validación, calibración y aplicación de modelos de propagación de incendios en escenarios reales de Centrales Nucleares”.

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