Peak Cladding Temperature Prediction using Deep Learning

Osama Sharif Al-Atawneh[1, *] and Aya Diab[1, 2, †]

[1]*Nuclear Engineering Department, KEPCO International Nuclear Graduate School, Ulsan, South Korea*
[2]*Mechanical Power Engineering Department, Faculty of Engineering, Ain Shams University, Cairo, Egypt*
[*] *First Author Email: usamah.alatawneh99@outlook.com*
[†]*Corresponding Author Email: aya.diab@kings.ac.kr | aya.diab@eng.asu.edu.eg*

INTRODUCTION

Traditionally nuclear thermal hydraulics and nuclear safety relied on numerical simulations to predict the system response of a nuclear power plant either under normal operation or accident condition. However, this approach may sometimes be rather time consuming particularly for design and optimization problems. To expedite the decision-making process data-driven models can be used to deduce the statistical relationships between inputs and outputs rather than solving physics-based models. Compared to the traditional approach, data driven models can provide a fast and cost-effective framework to predict the behavior of highly complex and non-linear systems where otherwise great computational efforts would be required.

The objective of this work is to develop an AI algorithm to predict the peak fuel cladding temperature as a metric for the successful implementation of FLEX strategies under extended station black out. To achieve this, the model requires to be conditioned using a database created using the thermal-hydraulic analysis code, MARS-KS [1]. In the development stage, the model hyper-parameters are tuned and optimized using the Talos tool.

METHODOLOGY

The methodology can be best described by dividing the work into two parts: generating a database for the thermal hydraulic response and developing the AI algorithm.

Accident Scenario and Thermal Hydraulic Model

A station blackout (SBO) is an accident scenario where all the plant's alternating current electric power sources are lost. This renders many of the safety systems unavailable which may lead to inventory loss, core uncover and threaten the plant's integrity. Accordingly, many utilities have adopted the diverse and flexible strategies (FLEX) to enhance the coping capability of their advanced nuclear reactors.

The peak cladding temperature (PCT) is an important metric that can be used to assess the success of the FLEX strategies. If the PCT is maintained well below 1477K, the fuel integrity can be assured. However, the success window of FLEX implementation relies on various initial and operating conditions that may be uncertain at the time of the accident. This work builds on a previous work [2] by the second author, where a best estimate plus uncertainty (BEPU) analysis was performed to analyze a station blackout for APR1400 nuclear reactor to ensure the successful implementation of the emergency operating procedures. A model of the plant is used to generate the system response using the realistic multi-dimensional thermal hydraulic system code MARS-KS V1.4. The SBO model assumptions are:

- FLEX equipment is aligned at 2 hours.
- RCP seal leakage is 21 gpm.
- Battery power is guaranteed for 8 hours.
- Feed and bleed are performed on the secondary side.
- Safety injection pump is unavailable.
- Shutdown cooling pump is unavailable.
- Auxiliary charging pump is unavailable.
- Motor driven auxiliary feed water pump is unavailable.

The impact of various uncertain parameters on the PCT was assessed by building a framework coupling the thermal hydraulic code, MARS-KS and the statistical tool, Dakota [3], using python programming language. The uncertain parameters were identified based on the phenomena identification and ranking table (PIRT) developed by Kang et al. [4] and on the uncertainty analysis performed by Kozmenkov et al. [5] and by Lee et al.

A total of 16 parameters were identified as key uncertain parameters affecting the PCT. These uncertain parameters are summarized in Table I. A partial rank correlation was used to examine the independency of the uncertain parameters. Next, the uncertain parameters were sampled and propagated into the developed thermal hydraulic model, using Dakota to produce the minimum number of samples that ensures the USNRC 95 percent probability and 95 percent confidence requirements.

Spearman's correlation was applied to measure the degree of correlation between the input parameters and PCT. The accident can be divided into two main phases before and after FLEX implementation. To cut down the learning curve for the AI algorithm, three parameters were identified for every phase, as the main parameters impacting the PCT, as will be shown later in this paper. A database of those key parameters and the PCT was therefore generated for training the AI algorithm as described in the next section.

Table I: Uncertain Parameters

Symbol	Physical Parameter
P_1	Reactor Power
P_2	Fuel Heat Capacity
P_3	Fuel Thermal Conductivity
P_4	Total Moment of Inertia for RCP
P_5	Set Point for Pressure Relief Valve
P_6	Decay Heat
P_7	Steam Generator Initial Pressure
P_8	Pressurizer Initial Pressure
P_9	Multiplier for Liquid Dittus-Boelter Correlation
P_{10}	Multiplier for Chen Correlation
P_{11}	Multiplier for Vapor Dittus-Boelter Correlation
P_{12}	Initial Total Mass Flow
P_{13}	Initial Coolant Inventory in SITs
P_{14}	Initial Pressure in SITs
P_{15}	Initial Temperature in SITs
P_{16}	Initial Temperature from Mobile FLEX pumps

It is worth noting that, a sensitivity study revealed that not all of the variables of the thermal hydraulic model were strongly impacting the peak cladding temperature. Hence, to cut down the training time for the AI model, only three input features were selected given their strong connection with the output as evidenced by their high correlation coefficients with the target variable. The features selection was based on the results of Spearman's correlation that was selected because of the nonlinearity of the data. Those features are reactor power (P1), initial pressurizer level (P8), and the multiplier for vapor Dittus-Boelter correlation (P11) as clarified below.

Artificial Neural Network

In this work, an artificial intelligence algorithm is developed using and artificial neural network (ANN) to accurately predict the peak cladding temperature, a performance metric to indicate the success of the FLEX strategy in enhancing the plant's capability to cope with a station blackout.

An ANN architecture is composed of a layer of inputs, one or more hidden layers, and an output layer as shown in Fig. (1). Within these layers are neurons, mathematical activation functions and weighing factors that help the AI algorithm deduce the correlation between the output and various inputs.

For complex nonlinear problems, like the problem at hand, the accurate prediction of the relationship between the inputs and output necessitates a deep network structure. For deep learning, the neural network is therefore based on multiple layers that parametrize the data transformation via weights. The objective of the deep neural network is to find the right values of these weights that will correctly map the given inputs to the corresponding output.

For the problem at hand, the output layer includes the parameter to be predicted by the AI algorithm, the peak cladding temperature in this case. The peak cladding temperature is chosen since it provides an indication for the successful implementation of the FLEX strategy. On the other hand, the input layer includes the NPP initial and operating conditions as well as key parameters that reflect the most relevant physical phenomena underlying a station blackout scenario. These are reactor power, decay heat

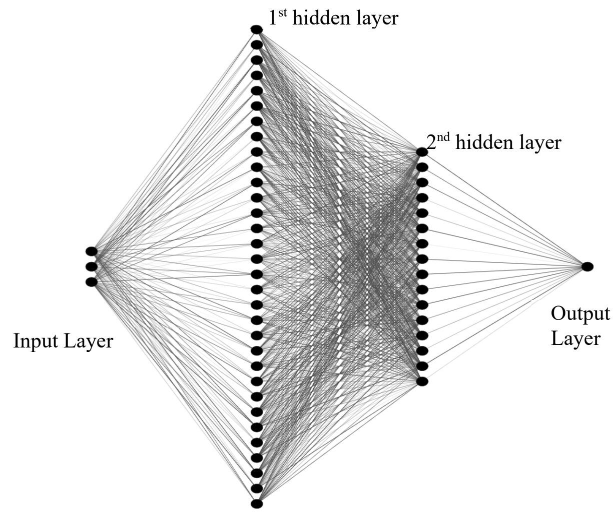

Fig. 1. Deep Learning Model

power, fuel heat capacity, fuel thermal conductivity, initial pressurizer level, set point for pressurizer relief valve, initial secondary pressure, multiplier for liquid Dittus-Boelter correlation, multiplier for Chen nucleate boiling model, multiplier for vapor Dittus-Boelter correlation, initial total mass flow, total moment of inertia for RCPs, initial coolant inventory in safety injection tanks (SITs), initial pressure in SITs, initial coolant temperature in SITs, and initial temperature in the mobile pumps. These parameters will dictate the value of peak cladding temperature depending on the relative correlation strength with the outputs as reflected by the assigned weights.

The main component in any layer within the neural network is the neuron. As shown in Fig. 2, the information passed to any neuron, transformed using a weight and a bias according to equation (1).

The transformed information is passed to the next neuron in the next layer after calculating it based on the activation function. The neuron's output is calculated by equation (1):

$$\Sigma(weight \times input + bias) = activation \quad (1)$$

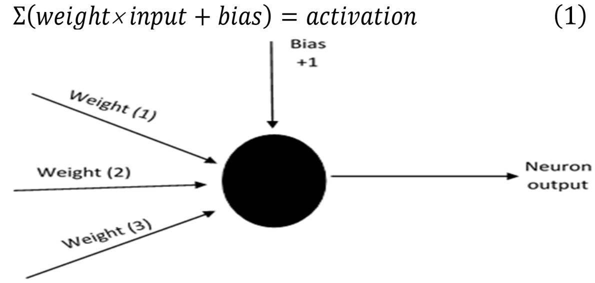

Fig. 2. Neuron, Weight and Bias

This process is known as forward propagation by which the model estimates the peak cladding temperature as output. Forward propagation uses a function to compute the output of each neuron that is passed to other neurons in next layers, this function is actually called activation function or transfer function [6].

However, the prediction process is not complete without comparing the estimated peak cladding temperature to the known value from the pre-existing database. This is achieved when the forward propagation is complemented by a backward propagation step to compute the value by which the weights should be altered to minimize the error between estimated and the known output values of the peak cladding temperature.

As previously mentioned, the objective of deep learning is to find the appropriate weight associated with every neuron in the network relative to the weights of other neurons. This process is conducted by monitoring an object function (also known as the loss function).

This step entails the calculation of a prediction error after completing a forward propagation step, followed by the calculation of the gradient of error function relative to the weights through a backward propagation step, and using the chain rule from output layer to the input layer to calculate the derivatives of the error (loss) function with respect to the weights of the model in each layer. So, the derivative of the loss function with respect to model's parameters as shown in equation (2).

$$\frac{\partial\, loss}{\partial\, \text{Weight}} = \frac{\partial\, loss}{\partial\, \text{pred.output}} * \frac{\partial\, \text{pred.output}}{\partial\, \text{Wieght}} \qquad (2)$$

This derivative is actually the slope of the object function, and determines the degree by which the weights should be changed to minimize the value of the loss function which is called loss. Hence, minimizing the loss value yields a conditioned model with high accuracy of prediction.

This process is applied to all neurons within the network to evaluate the performance before the weights are adjusted for another iteration, as explained by Fig. 3. For simplicity let's suppose that we only have one input, one hidden neuron, and one output.

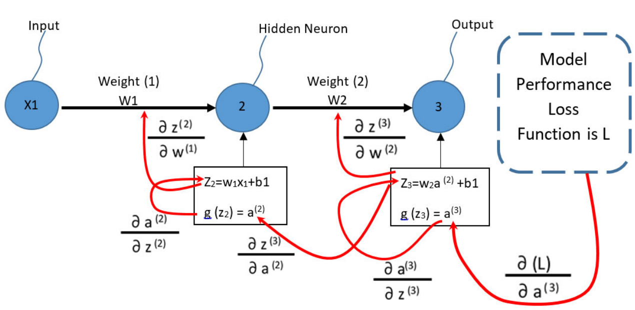

Fig. 3. Deep Learning Mechanism

Minimizing the loss function is the objective of the learning process and it is done via the optimization algorithm in such a way that the weights are updated iteratively until the output is predicted with the acceptable accuracy.

One of the most important optimization algorithms is the so-called gradient descent algorithm. The algorithm starts by assigning random values to the model parameters and then it computing the loss function and its gradient (derivative) with respect to those parameters at a given point.

At very point (parameter) the slope is evaluated until the slope vanishes. This process is actually controlled by the learning rate which determines how big a step the algorithm requires to reach the global minimal from the initializing point.

OPTIMIZATION

This is the most time-consuming process, which can be significant depending on the parameters size and the searching method used. Different search methods are available, the grid search method is the most time consuming since it considers all the values defined in the search space. For computational efficiency, the random search approach that was therefore selected [7]. The random search method was implemented through the Talos tool [8]. More than 1500 models were tested by defining a search space for parameters selection as shown in Table II. The best model is composed of one input layer, two hidden layers with 32 neurons (16 neurons in each layer) and an output layer. The input layer includes 3 parameters selected using Spearman's correlation.

Table II: Parameters used in Talos Tool

Parameter	**Range/Descriptors**
Learning rate	(0.001, 10, 10)
Neurons	[4, 8, 16, 32, 64, 128]
Hidden Layers	[0, 1, 2,3]
Batch Size	(5, 50, 5)
Epochs	[100, 500, 1000]
Dropout	(0, 0.5, 5)
ANN's architecture	[brick, funnel, triangle]
Optimizer	[Adam, Nadam, RMSprop, SGD]
Loss Functions	[mean_squared_logarithmic_error, mean_squared_error]
Activation Functions	[relu, elu]
Kernel Initializer	[normal, uniform]
Last activation	[linear]

The selection was based on their high correlation values with the peak cladding temperature as shown in Figure (4).

RESULTS

A Monte Carlo simulation with a sample size of 924 runs was generated using random seeding for a total of 16 input variables representing the input features and one representing the output variable (PCT) to be predicted by the neural network. As mentioned earlier, a sensitivity study was conducted to assess the key parameters the impact the PCT the most for every phase of the accident: before and after FLEX implementation. For brevity, the discussion will be limited to the first phase of the accident, i.e. before FLEX implementation. For this phase, three input features (namely, reactor power: P_1, pressurizer initial pressure: P_8, and multiplier for vapor Dittus-Boelter correlation: P_{11}) were selected due to their high correlation coefficient with the target variable (PCT: P_{17}). This is depicted in Figure (4). The developed AI algorithm was trained to learn the inherent knowledge about the NPP system undergoing a station blackout, by processing the data set prepared using the thermal hydraulics system code, MARS-KS. During the training process, the interneuron connection strengths so called weights are tuned to store the salient features that characterize the data by minimizing the loss function.

Once trained, the model is tested using an unseen sub-set of the pre-existing database to validate its ability to accurately predict the PCT based on a set of initial and operating conditions.

The PCT predicted values were compared to the values obtained from the thermal hydraulic model. The prediction results are in reasonable agreement with the known values for PCT as shown in Figure (5).

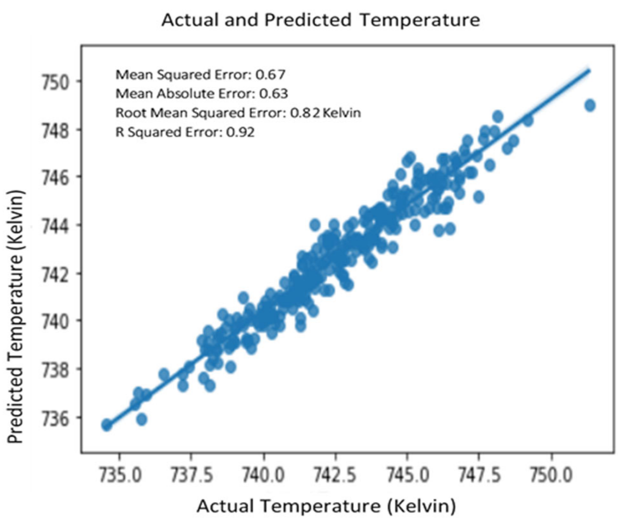

Fig. 5. AI Model Prediction versus the Known PCT Values

CONCLUSION

In this work, a realistic best estimate plus uncertainty simulation of the NPP response to a station blackout was generated using MARS-KS code coupled with Dakota. This database was used to train an AI algorithm developed to predict the peak cladding temperature as an important safety metric to assure the fuel integrity under the accident condition and hence used to assess the success of the FLEX strategy. The deep learning model was able to predict the PCT with reasonable accuracy. As a continuation of this work, the model will be generalized to explore the reliability of its prediction under different accidents conditions.

ACKNOWLEDGMENTS

This research was supported by the 2020 Research Fund of the KEPCO International Nuclear Graduate School (KINGS), Republic of Korea.

REFERENCES

[1] KAERI, "MARS Code Manual," KAERI/TR-2812/2004 Korea Atomic Energy Research Institute, Daejeon, 2009.

[2] J. Ricardo Tavares de Sousa, Aya Diab "Best Estimate Plus Uncertainty Analysis for SBO", Presented at the 2019 ANS Winter Meeting & Expo, 2019.

[3] B.M. Adams, L.E. Bauman, W.J. Bohnhoff, K.R. Dalbey, M.S. Ebeida, J.P. Eddy, M.S. Eldred, P.D. Hough, K.T. Hu, J.D Jakeman, J.A. Stephens, L.P. Swiler, D.M. Vigil, and , T.M. Wildey, "Dakota, A Multilevel Parallel Object Oriented Framework for Design Optimization, Parameter Estimation, Uncertainty Quantification, and Sensitivity Analysis: Version 6.12 User's Manual," Sandia Technical Report SAND2020-5001 (2020).

[4] K. H. Kang, C. H. Song, B. D. Chung, K. D. Kim, S. W. Lee, K. Y. Choi, B. J. Yun, J. J. Jeong, Y. S. Bang, Y. H. Ryu,H. G. Kim, C. J. Choi, C. H. Ban, S. K. Sim, "Development of a Phenomena Identification ranking Table (PIRT) for a Station Blackout (SBO) Accident of the APR1400", Transaction of the Korean Nuclear Society Autumn Meeting, Gyeongju (2013).

[4] Y. Kozmenkov, M. Jobst, S. Kliem, F. Schaefer and P. Wilhelm, "Statistical analysis of the early phase of SBO accidents for PWR," Nuclear Engineering and Design, pp.131-141 (2017).

[6] W. Rodgers, *Artificial Intelligence in a Throughput Model Some Major Algorithms*, 1st ed. CRC Press, 2020.

[7] J. Bergstra, Y. Bengio, "Random Search for Hyper-Parameter Optimization," Journal of Machine Learning Research 13 (2012) 281-305.

[8] Autonomio Talos [Computer software]. (2019). Retrieved from http://github.com/autonomio/talos.

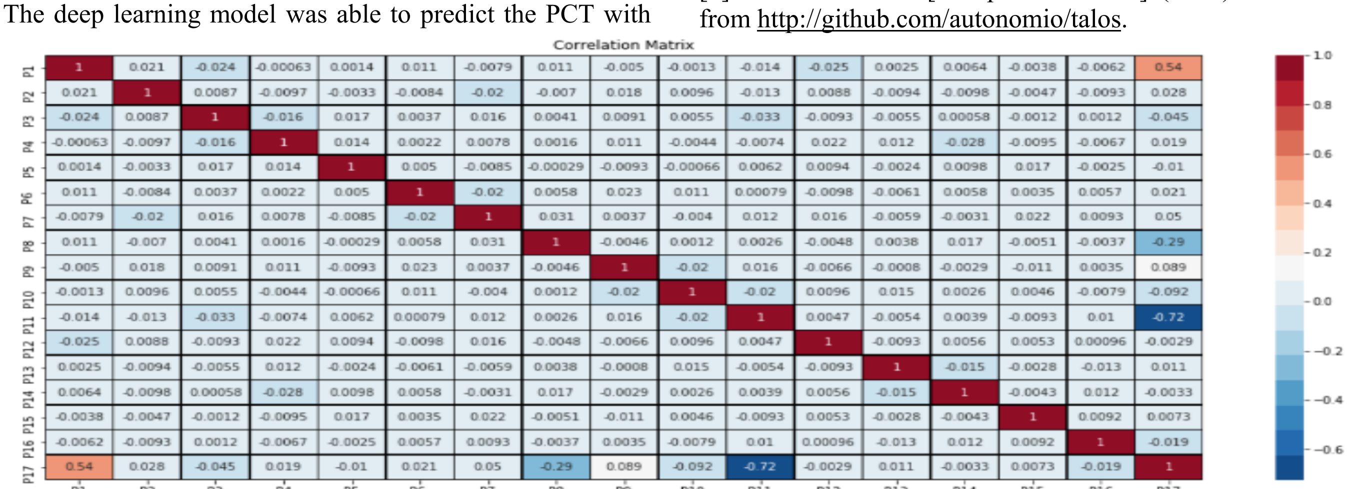

Fig. 4 Spearman's Correlation Matrix