Time-Series Forecasting of NPP Response Undergoing LOCA

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1. Introduction

Modern Nuclear Power Plants (NPPs) are developed with safety as the main priority. During normal operation, operators in the Main Control Room (MCR) continuously monitor a myriad of Nuclear Power Plant (NPP) parameters in order to keep them within their nominal conditions. Under accident conditions, MCR operators should comprehend the current plant dynamics in real-time. This includes accident diagnosis following an emergency situation for which timing and precision are key to the decision-making process to keep the NPP safe.

However, under accident conditions, the operators are exposed to stressful conditions and may need to take split-second decisions. To expedite the decision-making process and simultaneously minimize the possibility of human error, a machine learning (ML) prediction model is proposed using a multi-step artificial neural network. The ML model is trained to mimic the most accurate NPP system response generated using a physics-based model for a set of initial operating and boundary conditions. The main goal of this research is to develop an ML model for real-time prediction of NPP response under accident conditions to help operators in the MCR expedite the decision-making process [1]. Some of the most challenging conditions for the operators are the Loss of Coolant Accident (LOCA) alongside with an extended Station Blackout (SBO) which could potentially lead to a core meltdown [2] as evident by the Fukushima Daichii accident. As a starting point of this research, we start by considering the large break loss of coolant accident (LBLOCA) as a bounding accident scenario.

ML is actively being sought for the development of digital twins [3], as well as the autonomous control of nuclear power plants in an attempt to avoid the possibility of human errors [4]. For example a ML model has been developed by implementing a neural network along with the backpropagation algorithm to help in mitigating a Loss of Feedwater (LOFW) accident in multi-application small light water reactor [5]. A fast running model Conditional Auto-Encoder (CAE), known as an auto-associative neural network (AANN), can predict the pressure as well as Peak Cladding Temperature (PCT) in ARP1400 under a Small Break LOCA (SBLOCA) scenario [6]. Similarly, an ANN model that can also support the implementation of the diverse and flexible coping strategy (FLEX) has been developed for an extended SBO [7], [8]. Previously, artificial neural networks (ANNs) like deep learning neural networks (DLNNs), and the convolutional neural networks (CNNs) have been explored to predict the critical heat flux (CHF) of water flowing in reactor vessel channels [9] without solving the underlying physics. In the wake of the accident at the Fukushima Daiichi NPP researchers explored the use of codes like MELCOR and MAAP to simulate the core behaviour under severe accident conditions, and use the generated databases to develop and train ML models capable of predicting the NPP response at a fraction of the time needed using conventional methods and hence serving as an aiding tool for the decision-making process [10]. ML models have also been used to predict the diffusion and transport of radioactive materials in the atmosphere [11].

Since accident prevention is a top most priority for MCR operators, Korea Hydro & Nuclear Power Co., Ltd. (KHNP) developed an early warning system at the headquarters in Gyeongju. The system monitors and diagnoses 24 nuclear power plants in real-time and uses ML to detect slight fault symptoms of equipment in advance which allows the operators to prevent or prepare for failure and hence minimize losses caused by unplanned maintenance [12]. Currently, engineers from the Central Research Institute (CRI) KHNP are working on developing of ML model that will predict NPP response for an accident scenario.

Given the potential benefits of artificial intelligence (AI) at large and specifically of machine learning, this study builds on the work of Sallehhudin and Diab [13], and follows the work of Radaideh [14] to develop a time-series forecasting ML model capable of predicting the NPP real-time response for APR1400 undergoing a LBLOCA.

2. Methodology

This section describes the methodology applied in this work which involves three basic steps namely the development of a thermal-hydraulic model, an uncertainty quantification framework and a machine learning model. For the machine learning model to predict the NPP response, it is necessary to generate a large enough database using the thermal hydraulics model which in turn is driven by the uncertainty quantification framework as illustrated in Figure 1.

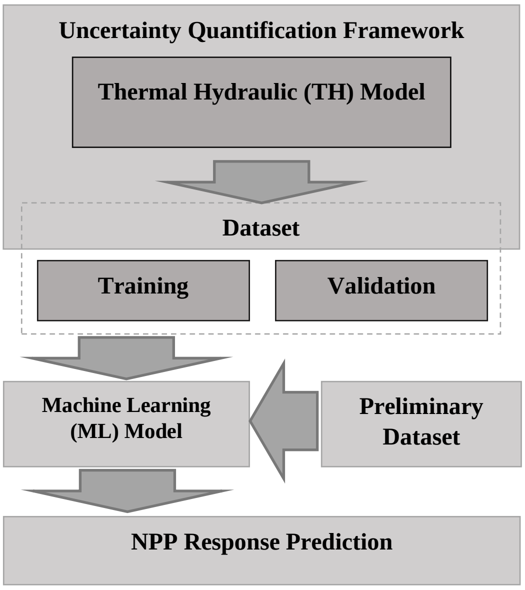

Figure 1. Data Processing Flowchart

2.1. Thermal- Hydraulic Model

The thermal-hydraulic model is developed in MARS-KS system code version 1.4, to simulate the nuclear power plant response under LBLOCA conditions [13]. The nodalization shown in Figure 2 contains key systems and components of APR1400: the Reactor Coolant System (RCS) with a reactor pressure vessel (RPV), hot legs, cold legs, reactor circulating pumps (RCPs), pressurizer (PRZ) and two steam generators (SGs) along with main steam lines and safety valves. The core inlet and outlet nozzles, downcomer, and lower and upper plenum as part of the reactor vessel are modelled as well. The reactor core is represented using an average channel and a hot channel, each is discretized using 20 vertical nodes.

The Emergency Core Cooling System (ECCS) of the APR1400 is represented by modelled Safety Injection System (SIS). The entry location of SIS is the upper annulus. The SIS contains two systems components the Safety Injection Tanks (SITs) and the Safety Injection Pumps (SIPs). The SITs tanks are connected to the upper annulus using valves divided into two parts representing the operation of the fluidic device. In accordance with the conservative assumption of APR1400 Design Control Document (DCD) for LBLOCA evaluation, two out of four SIPs are available during the accident.

For conservatism, the negative reactivity insertion due to the control rod insertion is not taken into consideration due to the APR1400 DCD conservative assumption.

The LOCA is represented as two trip valves connected to the cold leg after pump discharge. When a double-ended guillotine break is initiated, flow is directed from the vessel and cold leg to the time-dependent volumes attached to each valve.

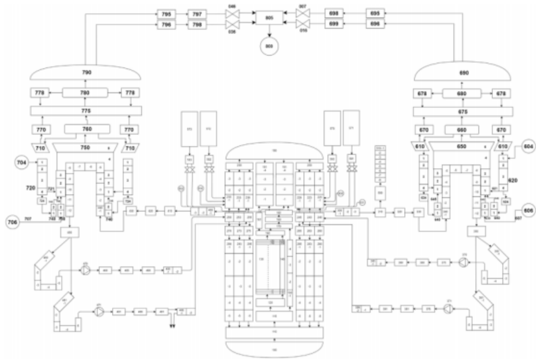

Figure 2. APR1400 Nodalization for the LBLOCA Thermal-Hydraulic Model [12]

2.2. Data Generation

The Best Estimate Plus Uncertainty (BEPU) methodology is applied by propagating key uncertain parameters into the thermal-hydraulics model as listed in Table 1. These uncertain parameters are derived from the Phenomena Identification and Ranking Table (PIRT) developed for LBLOCA scenario [13].

To automate the process of uncertainty quantification, the Uncertainty Quantification (UQ) framework, is developed by loosely coupling the statistical tool, DAKOTA [15], to the thermal-hydraulic system code, MARS-KS, via a Python script. The Monte Carlo (MC) random sampling technique along with the Latin Hyper-Cube method is used to define a combination of input parameters that scan the spectrum of all possible initial and boundary conditions for the thermal-hydraulics model.

DAKOTA then passes the uncertain parameters to the MARS-KS code by reading and writing text files in the developed framework. The uncertain parameters are written into the steady state and transient MARS-KS input files and output files from MARS-KS calculations are passed back to the DAKOTA results file. A Python script is responsible for the input preparation, data exchange between Dakota and MARS-KS, as well as the output post-processing before passing the sample into the data frame as shown in Figure 3.

The Latin Hypercube Sampling (LHS) method was used to cover the distribution with fewer samples and hence reduce the computational burden of conventional Monte Carlo techniques such as the bootstrap [17].

Table 1. Normalized Uncertain Parameters [13]

#	Parameter Description	Mean, μ	Standard deviation, σ	Range, L_{high}-L_{low}
1	Core power	1.0	0.01	0.98–1.02
2	Groeneveld-CHF	1.0	0.414	0.173–1.827
3	Chen nucleate boiling HTC	1.0	0.234	0.553–1.467
4	Transition boiling HTC	1.0	0.230	0.54–1.46
5	Dittus-Boelter liquid HTC	1.0	0.196	0.607–1.393
6	Dittus-Boelter vapor HTC	1.0	0.196	0.607–1.393
7	Film boiling HTC	1.0	0.287	0.426–1.574
8	Break discharge coefficient	1.0	0.115	0.77–1.23
9	Decay heat	1.0	0.033	0.934–1.066
10	Gap conductance	1.0	0.289	0.421–1.579
11	SIT actuation pressure(MPa)	1.0	0.025	0.949–1.051
12	SIT water inventory (m^3)	1.0	0.046	0.907–1.093
13	SIT loss coefficient	1.0	0.20	0.6–1.4
14	Pressurizer pressure (MPa)	1.0	0.113	0.77–1.23
15	Fuel thermal conductivity	-	-	0.847–1.153
16	Pump two phase head multiplier	-	-	0.0–1.0
17	Pump two phase torque multiplier	-	-	0.0–1.0
18	SIT water temperature (K)	-	-	0.955–1.045
19	SIP (IRWST) water temperature (K)	-	-	0.936–1.064

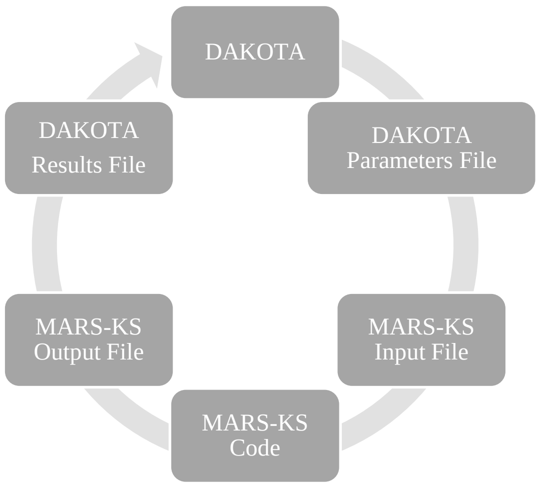

Figure 3. Uncertainty Propagation Framework Coupling MARS-KS and DAKOTA [16]

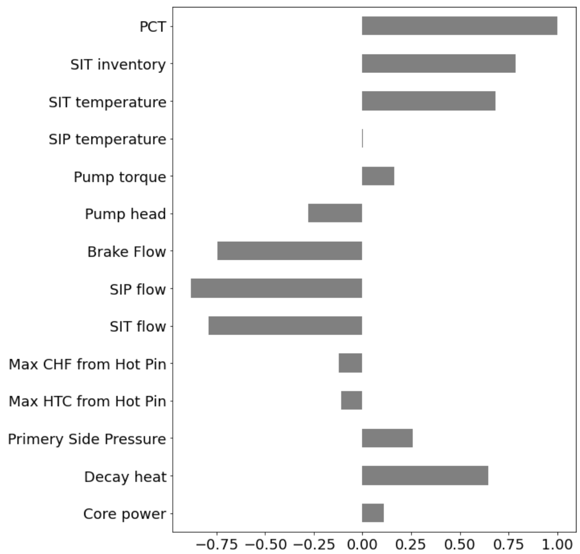

Figure 4. Parameter Correlation Coefficient with the Peak Cladding Temperature

For LBLOCA accident scenario, PCT is one of the most important parameters used as a safety acceptance criterion. Based on the PIRT, the most relevant uncertain parameters that dictate the NPPs response have been identified and used for accurate prediction of the PCT. A list of the correlation coefficient of those key system parameters with PCT is shown in Figure 4. The most influential parameters are SIP, SIT flow, break flow, SIT temperature, and decay heat.

2.3. Machine Learning Model

In contrast to the previous work by Sallehhudin and Diab [12] where an Artificial Neural Network (ANN) was used for the prediction of PCT for different initial and boundary conditions, this research is aimed at predicting the development of the cladding temperature over time as the accident progresses. For this class of problems, time series forecasting based on Recurrent Neural Network (RNN) is the most effective. Two different RNNs are used in this study, namely:

- Long Short Term Memory (LSTM)
- Gated Recurrent Unit (GRU)

The developed RNN models use historical observations (in this case 5 seconds of simulation time represented by 10 data points), for the prediction of the next data point of the NPP response [18].

To tune the ML models to the data at hand, the Talos optimization tool was used to arrive at the best combination of optimized hyper-parameters. The hyper-parameters dictionary is listed in Table 3.

Table 1. List of Hyper-Parameters

Number of neurons in 1st layer	13, 25, 50
Number of neurons in a final layer	1
Number of hidden layers	1, 2, 3
Optimizer	Adam, Nadam, SGD, RMSprop
Activation functions	ReLU, Tanh, Sigmoid, Softmax
Recurrent activation functions	Sigmoid, ReLU, Tanh
Dropout	0, 0.1, 0.2
Batch size	64, 100, 200
Number of iterations	15, 20, 35
Kernel regulariser l1	1×10^{-4}, 1×10^{-5}, 1×10^{-6}

3. Results and Discussion

The MARS-KS thermal-hydraulic model, prepared with uncertainty parameters was run within DAKOTA Uncertainty Quantification framework multiple times until a statistically representative sample size was achieved. The size of the database obtained by DAKOTA is 3469 samples as shown in Figure 5. Following the USNRC rule [19] of 95% probability and 95% confidence level, the most probable PCT curve was identified. The sample represented by this curve was dropped from the training dataset and saved for validation of the model at a later stage.

From a safety perspective, the ML model accuracy is most important at the higher end of the range of PCT observed. To enhance the prediction accuracy, the oversampling technique was applied by replicating 200 samples including the highest PCT. This oversampling method, increases the chances of the model being trained to predict PCT in the upper range of the dataset.

After training the different RNN models, they were used to predict the most probable sample. The results of the prediction can be seen in Figure 6. The performance of the two RNN models is further assessed by comparing the mean absolute error, root mean squared error, and coefficient of determination as listed in Table 4. Comparing GRU, and LSTM models, the LSTM model outperforms the GRU by a small margin.

Clearly, further tuning is needed for better prediction since both models are under-predicting the actual value of PCT. One way to improve the prediction is to train the model using a larger dataset which is currently being generated.

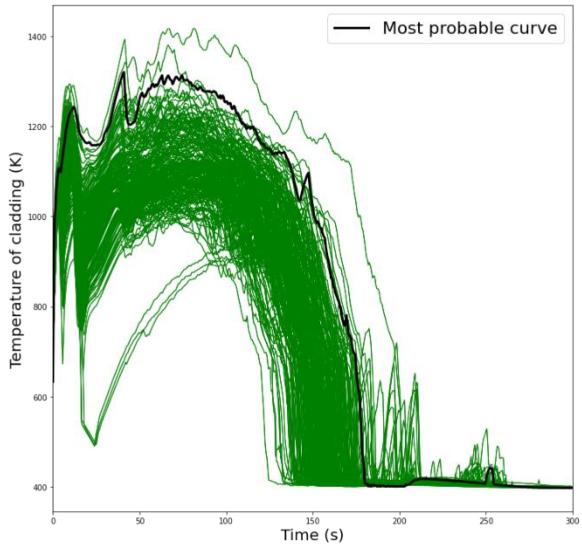

Figure 5. PCT Database

Table 4. ML Model Evaluation Metrics

	RMSE	MAE	R^2
GRU	40	28	0.989
LSTM	35	25	0.992

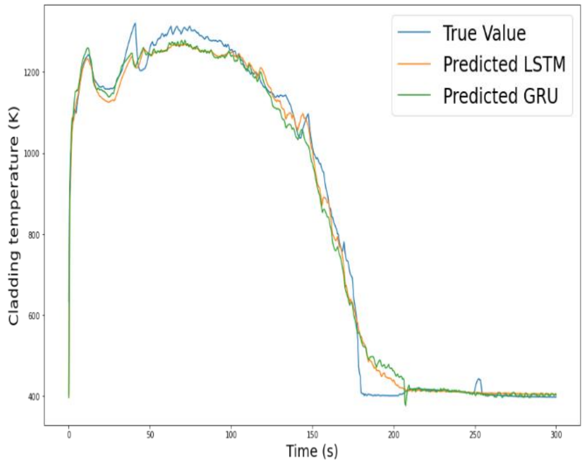

Figure 6. ML Models Prediction of the Most Probable PCT

4. Conclusion

Machine Learning can be a useful tool for the prediction of the critical NPP parameters during accident conditions. The calculations showed that the best-performing LSTM model is capable of predicting PCT with reasonable error, but for accurate prediction, a bigger dataset is required and the models need further tuning to improve their performance.

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