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Application of Machine Learning for a Real-Time NPP Response Prediction under Uncontrolled CEA Withdrawal Accident Conditions

Felix Isuwa Wapachi [a] and Aya Diab [a,b,†]
[a]Department of NPP Engineering, KEPCO International Nuclear Graduate School, Republic of Korea.
[†]First Author Email: wapachi.felix@ntc.nigatom.org.ng | fisuwa@yahoo.com
[b]Mechanical Power Engineering Department, Faculty of Engineering, Ain Shams University, Egypt
[†]Corresponding Author Email: aya.diab@kings.ac.kr | aya.diab@eng.asu.edu.eg

1. Introduction

With the current advances in computation power, data science, and artificial intelligence, Machine Learning (ML) has been penetrating many fields including nuclear safety. ML can play a significant role in maintaining the safety of nuclear power plants while simultaneously minimizing the possibility of human error, particularly it can be used to expedite the decision-making process under nuclear plant accident conditions.

In fact, ML is increasingly being used to predict nuclear accident scenarios. To mention but a few, Neural-based long short-term memory (LSTM) in comparison to DNN was used to forecast a loss of coolant accidents scenario Radaideh et al., (2020); similarly, Bae et al., (2021), performed a real-time prediction of the nuclear power plant parameter trends following operator actions and recently Alketbi and Diab, (2020) used DNN to identify the success window of FLEX strategy under an extended station blackout.

In this work, a time series meta-model is proposed based on a data-driven approach rather than the conventional physic-base counterpart to map the relationship between the power plant real-time parameters to its response under reactivity insertion accident condition and hence forecast the future plant response using Recurrent Neural Networks (RNN), namely: the Long-Short-Term-Memory (LSTM), Gated Recurrent Unit (GRU) and a series combination of convolutional neural network (CNN) with LSTM for deep learning time series forecasting.

Although a number of accident scenarios have been predicted and/or analyzed using machine learning expert algorithms, there exist limited applications to predict NPP transient responses under reactivity-initiated accident conditions. This research intends to support the development of a real-time aid for operators to expedite the decision-making process under more severe accident conditions.

The chosen scenario is a Control Element Assembly (CEA) withdrawal concurrent with Loss of Offsite Power (LOOP) and the power plant of choice is APR1400. The presumed transient of uncontrolled CEAs withdrawal may occur as a result of a single failure in the Control Element Drive Mechanism Control system (CEDMCS), reactor regulating system (RRS), or with regards to operator error concurrent with the Loss of Offsite Power (LOOP) (APR-1400 Design Control Document Tier 2, 2018). Operating at nominal power condition, the reactor undergoes uncontrolled withdrawal at the speed of 76.2 cm per minute with an equivalent reactivity insertion rate of 0.315×10^{-4} Δρ/s which in turn induces an increase in the core power and heat flux with a corresponding increase in the Reactor Coolant System (RCS) temperature and pressure. It is important to also note that the reactor at the above set conditions will experience asymmetrical distribution of core power, leading to intense thermal stress in the region of CEA withdrawal and consequently, the specified acceptable fuel design limits (SAFDL) on departure from nucleate boiling ratio (DNBR) and fuel centerline melt temperatures might be approached which will eventually lead to the reactor protection system (RPS) signaling on Variable Overpower (VOP), Low DNBR, High Local Power Density (HLPD) and or High Pressurizer Pressure (HPP) and hence reactor trip.

A substantial amount of time series database is required to train and test the time series ML expert algorithm. This database can be acquired through the development of an uncertainty quantification framework by coupling DAKOTA software with the best estimate thermal hydraulics system code, MARS-KS. The database generation can thus be obtained using the best estimate plus uncertainty quantification (BEPU) methodology.

In recent years, the best estimate plus uncertainty quantification (BEPU) methodology has been applied to analyze reactivity-initiated accidents (RIA) by Dokhane et al., (2022b); Gorton and Brown, (2020); (Marchand et al., 2018), loss coolant accident (LOCA) by Radaideh et al., (2020) Queral et al., 2015; Mazgaj et al., (2022); Chen et al., (2022), and more recently, station blackout (SBO) by Ghione et al., (2017); Alketbi and Diab, (2020). The BEPU methodology starts with the Phenomena Identification and Ranking Table (PIRT) established by Marchand et al. (2018), and Zhang et al., (2011) for RIA. Next, key uncertain parameters are derived and propagated using the Monte-Carlo approach and the Latin Hypercube Sampling technique to generate a statistically significant database of the thermal-hydraulic NPP response, which was then used to train, test, and validate the RNN ML model. The details of the developed models will be described in the next section.

2. Methods and Results

This section delineates the methodology applied to achieve the set goal as discussed in section 1. The overall scope of the work consists of the development of three main building blocks: thermal-hydraulic model, uncertainty quantification framework, and machine learning model with the ultimate goal of predicting the NNP response for the accident scenario under consideration. Figure 2.1 depicts the overall research methodology.

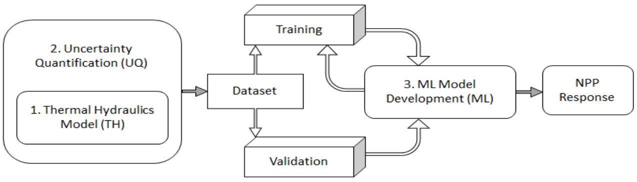

Figure 2.1 Research Methodology

2.1 Thermal-Hydraulic Model

The thermal-hydraulic model development necessitates building a system nodalization for APR1400 key systems and components relevant to the selected accident scenario as shown in Figure 2.2. The primary side consists of the reactor pressure vessel (RPV), a pressurizer (PRZ), two loops with four cold legs (CLs) and two hot legs (HLs) connected to the steam generators. The secondary side includes a detailed representation of the two steam generators (SGs), four main steam lines together with associated valves (MSSV, MSIV, and ADV). From either side of the loop, the primary coolant flows from the RPV through the SG u-tube section via a single HL, where the heat is transferred to the secondary feed-water, and then back to the RPV via the two CLs. Each cold leg hosts a single reactor coolant pump (RCP) that forces the flow of coolant in the primary circuit. On one of the hot legs, the PRZ is connected to compensate for pressure drop or build-up in the primary system. Four Pilot Operated Safety Relief Valves (POSRV) are connected to the pressurizer to protect the primary side against over-pressurization. The reactor core is represented using an average channel by lumping 240 fuel assemblies and a hot channel representing the hottest fuel assembly. Both the average channel and the hot channel is discretized using 20 vertical nodes. The turbine is modeled as a boundary condition. The safety injection system (SIS) is modeled to represent the emergency core cooling system (ECCS) of the APR1400.

Figure 2.3 depicts the thermal-hydraulic predictions of the key NPP system responses which are cross-validated against results reported in the APR-1400 Design Control Document Tier 2, (2018) with reasonable agreement.

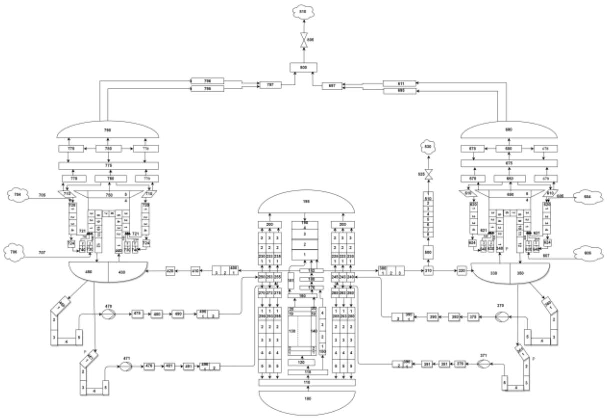

Figure 2.2. APR1400 Nodalization

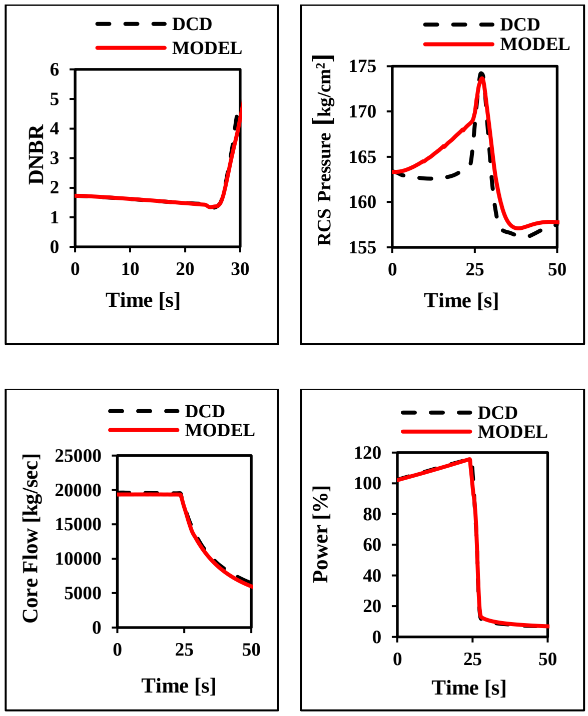

Figure 2.3 Thermal Hydraulic Model Validation

2.2 Uncertainty Quantification

An uncertainty quantification (UQ) framework was developed by coupling the best estimate system code, MARS-KS, and the statistical tool, DAKOTA, via a python interface. Dakota is an open-source statistical tool developed by the Sandia National Laboratory. It can be used for optimization, sensitivity analysis, and uncertainty quantification Adams et al. (2020).

The coupling of MARS-KS and DAKOTA permits the propagation of the uncertain parameters using the non-parametric Monte Carlo random propagation technique. It is important to note that in the DAKOTA tool the Latin Hypercube Sampling (LHS) was used as is commonly better than the simple random sampling (SRS) technique.

The UQ process considers the system response under the different initial, boundary, and operating conditions, as well as thermo-physical properties, and manufacturing tolerances as listed in Table 2.1. Figure 2.4 shows the result of the uncertainty quantification of the departure from nucleate boiling ratio (DNBR), RCS pressure, core flow rate, and core power respectively

Table 2.1: Uncertain Parameters

PIRT	Uncertainty parameter (unit)	μ	σ	PDF	min	max
Fuel Manufacturing Tolerances	Cladding outside diameter (mm)	9.40	0.01	Normal	9.38	9.42
	Cladding inside diameter (mm)	8.26	0.01	Normal	8.24	8.28
	Fuel theoretical density (kg/m^3 at 20°C)	10970	50	Normal	10870	11070
	Fuel porosity (%)	4	0.5	Normal	3	5
	Cladding roughness (μm)	0.1	1	Normal	10^{-6}	2
	Fuel roughness (μm)	0.1	1	Normal	10^{-6}	2
	Filling gas pressure (MPa)	2.0	0.05	Normal	1.9	2.1
thermal-hydraulic initial and boundary conditions	Coolant pressure (MPa)	15.500	0.075	Normal	15350	15650
	Coolant inlet temperature (°C)	280	1.5	Normal	277	283
	Coolant velocity (m/s)	4.00	0.04	Normal	3.92	4.08
Core Power	Injected energy in the rod (J)	30000	1500	Normal	27000	33000
	Full width at half maximum (ms)	30	5	Normal	20	40
thermo-physical properties and key heat transfer models	Fuel thermal conductivity model	1.00	5%	Normal	0.90	1.10
	Clad thermal conductivity model	1.00	5%	Normal	0.90	1.10
	Fuel thermal expansion model	1.00	5%	Normal	0.90	1.10
	Clad thermal expansion model	1.00	5%	Normal	0.90	1.10
	Clad yield stress	1.00	5%	Normal	0.90	1.10
	Fuel enthalpy/heat capacity	1.00	1.5%	Normal	0.97	1.03
	Clad-to-coolant heat transfer	1.00	12.5%	Normal	0.75	1.25

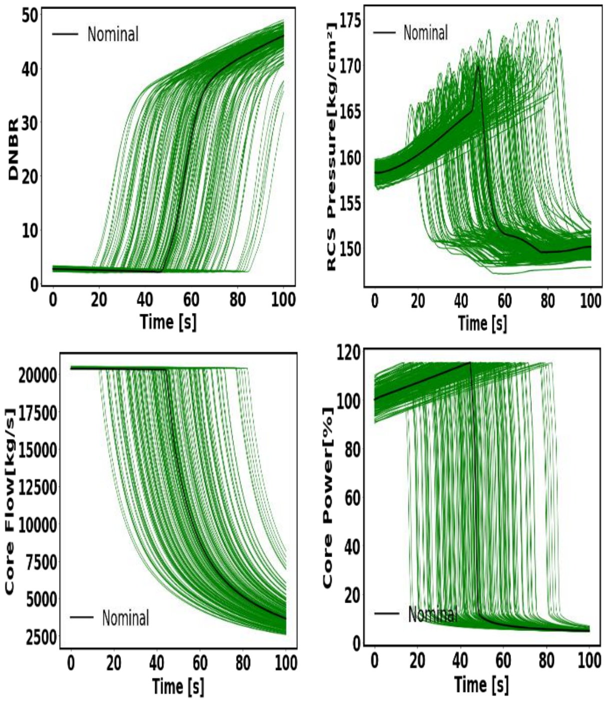

Figure 2.4 Uncertainty Quantification Results

2.2.1 The 2σ Bound and Most Probable Response

Wilks' fifth order was used to guarantee the 95% probability with a 95% confidence level, a criterion commonly required by the US NRC [6]. For the fifth order Wilk's sampling technique a minimum of 181 samples is required to satisfy the 95/95 criterion. At such a tolerance limit, the most probable value of DNBR, RCS pressure, core power, and core flow rate would be the fifth in the rank of the most critical case for each. Accordingly, for the RCS pressure, that would correspond to the fifth highest pressure response whereas it would be the fifth lowest response for DNBR. Figure 2.3 depicts the nominal response (in solid black) most probable system response (in dotted red), along with the 2σ uncertainty bound (in green).

2.3 Machine Learning Model

The Autonomio Talos tool (2019) was used to help develop and optimize the machine learning meta-model for the prediction of NPP responses under reactivity-initiated accident. Multivariate time series data of the NPP response is required to train and validate the machine learning model. This database is obtained using the UQ framework as discussed in the previous section. The three different RNN models learn the trend from the NPP response sequences and make a prediction based on the changing weight and bias.

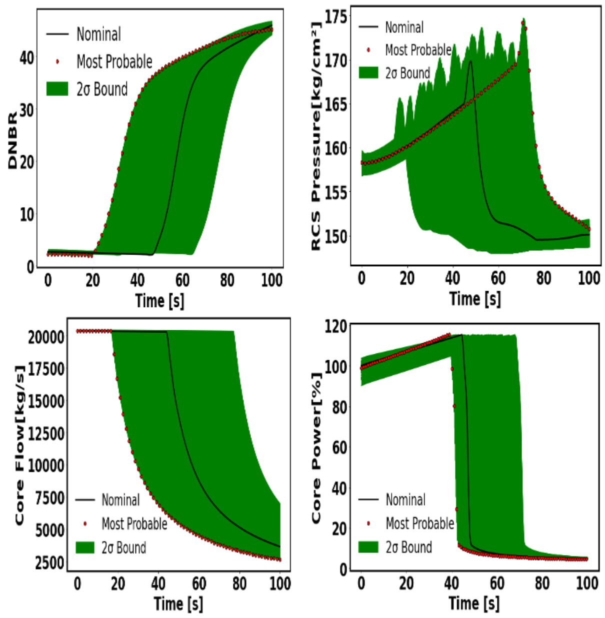

Figure 2.5 Uncertainty Quantification

However, before feeding the database into the three different RNN models, it is necessary to preprocess the data. The preprocessing is done by normalization or scaling to minimize the bias as a result of too big or too small data range by specifying a finite range of 0 to 1 using the MinMax scaler function.

Forecasting the outputs at a given time step t, involve the use of static features plus the outputs of the previous Z time steps as predictors. The total number of predictors or the lookback will consist of the number of features in addition to the number of outputs multiplied by the preceding time steps. Each chunk of the output time series will become an input feature for the next chunk and so on. With the transformed array the input array is no longer static but rather time-dependent. Z which represents the lookback is usually optimized to determine how many previous time steps are required by the RNN model to best predict the next time step output. This supervised form of transformation is repeated for all sequences/samples in the dataset.

In this research 181 samples were used with input dimension of (32522, 10, and 9). The numbers of features passed to the model are nine (9), with a lookback of 10 in this case, the outputs of the first 10 time steps are deleted and become input features for the next step. Using the transformed first time step the ML model can predict the NPP response for t = 11 using time steps from 1 to 10, similarly, for time step t = 12, can be predicted using the time steps from 2 to 11, and so on until t = 32522s. The maximum possible time step that can be predicted is t = 32512s. Therefore, the size of the transformed output array becomes (32512, 9). The dimension of the input array (32522, 9), is transformed from a two (2) dimension static array to a three (3) dimension series or sequence array. Figure 2.4 shows the ML model prediction results. Clearly, all models predict the NPP response with reasonable accuracy. However the CNN+LSTM model has the additional benefit of computational efficiency.

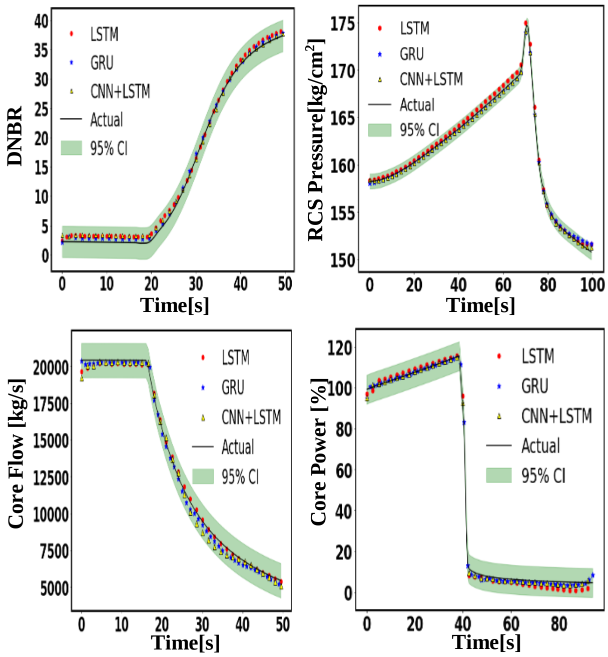

Figure 2.6 Machine Learning Predictions with 95% Confidence Level

3. Conclusions

The uncontrolled CEA withdrawal at power accident scenario was simulated using the thermal hydraulics best estimate code, MARS-KS. Validation of key system parameters (reactor power, RCS temperature, and pressure, SG pressure, minimum DNBR, etc.) was conducted and found to be in close agreement with the conservative analysis reported in the DCD. Once the APR-1400 NPP system response was validated, the nominal conditions were used instead of the conservative assumptions to conduct the BEPU analysis using the uncertainty quantification framework developed using DAKOTA to assess the uncertainty in the NPP response under different initial, boundary, and operating conditions, as well as thermo-physical properties, and manufacturing tolerances. The generated database is used to train the ML model which is based on RNN; specifically, GRU, LSTM, and CNN+LSTM. The GRU and LSTM models have comparable performance. However, the model combining CNN and LSTM outperformed the other approaches at a reduced computational time.

Acknowledgments

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