# BEPU Evaluation for APR1400 MSLB Accident using Artificial Intelligence

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## 1. INTRODUCTION

APR1400 main steam line break (MSLB) accident is classified as a postulated design base accident. The break can occur either inside or outside the containment as a result of pipe failure. In this paper the plant response during this transient has been simulate using the best estimate thermal-hydraulic code, MARS-KS V1.4. For this work, the MSLB is assumed to occur before the main steam isolation valve (MSIV) on one of two main steam piping lines outside the containment. As a result of the accident, the heat removal by the secondary system is increases, the RCS is excessively cooldown which may in turn increase in core reactivity. Consequently, departure from nucleate boiling (DNB) may occur, causing heat to buildup and the fuel temperature to increase which threatens the fuel integrity. From a safety perspective, this event is considered in the plant design as a design basis accident (DBA) and provisions should ensure that the safety criteria are met.

However, to manage this DBA successfully a number of uncertainties need to be quantified. To survey the impact of variability in possible combinations of initial, boundary and design conditions, a Best Estimate Plus Uncertainty (BEPU) approach is adopted to verify that the safety criteria are met. BEPU is a modern and technically sound approach that utilizes best estimate methodology including an evaluation of the uncertainty in the calculated results (Musoiu, 2019). It provides a more realistic safety margin and helps improve the emergency operating procedures to prevent progression into a severe accident. In this study, uncertainty quantification method using the Wilks' formula is employed to identify the success window with a 95% confidence level and 95% probability.

This work uses the results of the BEPU analysis to provide a database of the thermal hydraulic response to the Artificial Intelligence (AI) algorithm training. AI is used as an alternative data-driven approach to predict the plant response during MSLB accident given the underlying uncertainties.

## 2. METHODOLOGY

This section describes the methodology used in this work and can be divided into two main sub-sections. The first section describes the BEPU analysis using the thermal hydraulic model and the second section describes the artificial neural network model.

### *2.1 Thermal Hydraulic Model for BEPU Analysis*

To model the Main Steam Line Break (MSLB), the first step is to develop a thermal hydraulic model of APR 1400. This is achieved using the realistic thermal hydraulic system code, MARS-KS. The system nodalization used is illustrated in Figure 1. It reflects the main systems and components included in the thermal hydraulic model which are also summarized in Table 1. The turbine is represented as boundary condition using a time dependent volume. Similarly, the containment is represented by a time dependent volume. It is assumed that the core is inintially operating at full power (4,062 MWt), the pressurizer pressure is 16.345 MPa, the core inlet temperature is 563.65 K, two safety injection pumps are in operation, and offsite power is lost concurrent with the reactor trip. The sequences simulated using MARS-KS code as described in the Design Control Document are showed in Table 2.

**Table 1. MSLB Model Systems and Components**

| |
|---|
| **Reactor Coolant System (RCS)** |
| Reactor Pressure Vessel (RPV) |
| 2 Hot Legs |
| 4 Cold Legs and four Reactor Coolant Pumps (RCPs) |
| Pressurizer (PZ) |
| Pressurizer Safety relief Valves (PRSVs) |
| Safety Depressurization System (SDS) |
| **Secondary System** |
| 2 Steam Generators (SGs) |
| Main Feedwater System (MFWS) |
| Main Steam Line (MSL) |
| 6 Secondary Main Steam Safety Valves (MSSVs) |
| 2 Main Steam Line Atmospheric Depressurization Valves (MSL-ADVs) |
| 2 Main Steam Line Isolation Valves (MSLIVs) |
| Turbine Bypass Valve (TBV) |

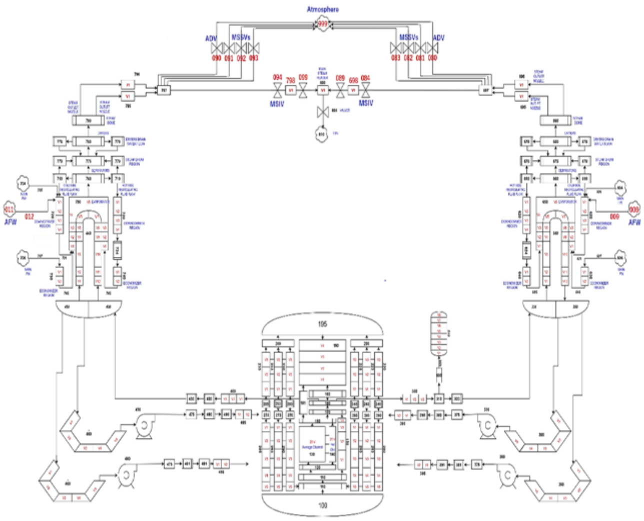

**Figure 1. MARS-KS Nodalization.**

### *2.1.1 Thermal Hydraulic Model Validation*

The steady state calculation was performed, and the model results compare reasonably well to the corresponding values reported in the Design Documents of APR1400 as shown in Table 2. The results of the transient calculations are described in detail in the next section.

**Table 2. Model Validation**

| Parameter | Base Case | DCD |
|---|---|---|
| Core-exit temperature, K | 600.57 | 598.15 |
| Reactor inlet temperature, K | 570 | 563.65 |
| Primary coolant flow rate | 20175 | 20200 |

### *2.1.2 Sequence of events*

Following the reactor trip, shown in Figure 2, the auxiliary feed water system is assumed to be immediately activated to the SGs. The depressurization of the affected SG results in the actuation of an MSIS. Actuation of an MSIS closes the MSIVs, isolating the unaffected SG from blowdown, and closes the MFIVs, terminating the main feed water flow to both SGs. The pressurizer pressure decreases to the point where a safety injections actuation signal (SIAS) is initiated as seen in Figure 3. The SIAS activates the safety injection which in turn introduces boron into the system which causes the core reactivity to decrease. At 30 minutes after the event initiation, the operator follows the emergency procedure, and initiates plant cooldown by manual control of the ADVs. Shutdown cooling is initiated when the RCS reaches 449.85 K (350 °F) and 3.103 MPa (450 psia).

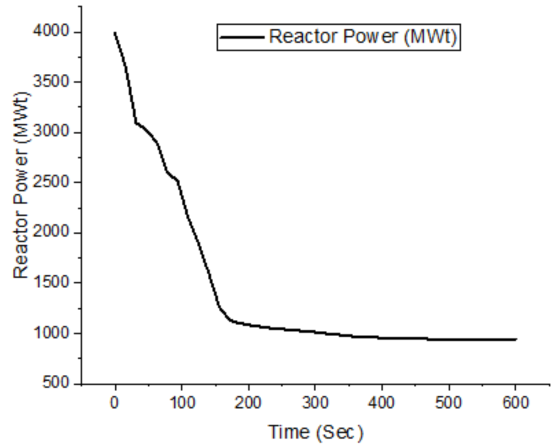


**Figure 2. Reactor Power after Trip Initiation**

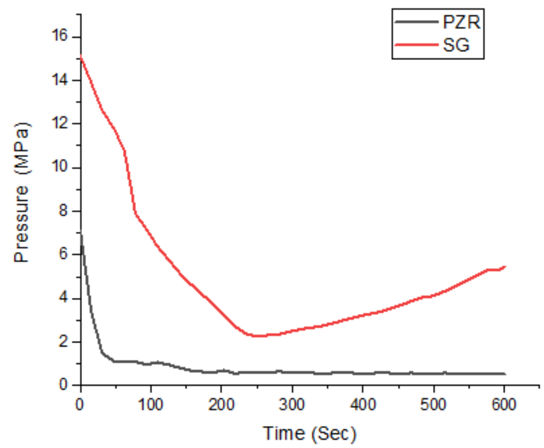


**Figure 3. Steam Generator and Pressurizer Pressure**

### *2.1.3 Uncertainty Quantification*

The thermal hydraulics code is coupled to a statistical tool, DAKOTA, to assess the impact of the uncertainty parameters on the minimum DNB ratio (MDNBR) using Python programming language that provide the communication interface. The model performs the uncertainty propagation, including uncertain parametric sampling, simulation code execution and data extraction, as illustrated in Figure 4. The simulation was conducted using 3 GHz Pentium CPU with 12 cores and Windows 10, with one-sided 5$^{th}$ order Wilks method for uncertainty quantification. 311 cases were generated in 2 days to ensure 95 % probability coverage at 95 % confidence level. 5$^{th}$ order Wilks was selected instead of Monte Carlo sampling because of time limitation and because Wilks 3$^{rd}$ order or higher has been proven in previous studies, for example, by A. de Crécy et al (2008), as a reliable method for sensitivity evaluation.

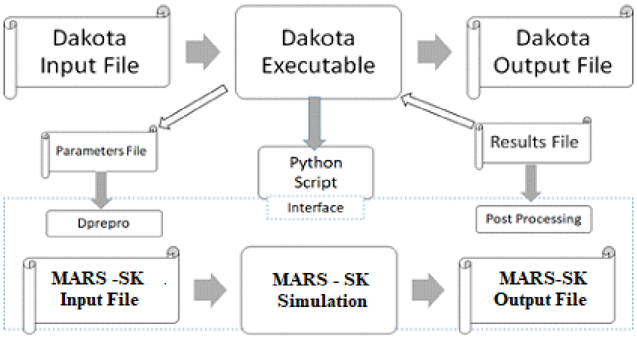


**Figure 4. MARS-DAKOTA Uncertainty Analysis Framework**

The uncertainty analysis is performed using a set of uncertain parameters derived from key phenomena that govern the accident progression as identified in previous studies [Yang et al. (2020), Lee et al. (2003), Castro et al. (2016) and Avramova et al. (2011)]. Subsequently, the uncertainties are propagated through the thermal hydraulic model for uncertainty quantification. A dataset of the system response is generated for randomly selected values of the uncertain parameters that may have great influences on the figure of merit (FoM), which is the DNBR in this paper. The number of runs is calculated by DAKOTA code based on the required confidence level and probability. The probability distribution functions (PDF's) are used in this method to determine the chances of appearance of each parameter over the uncertainty range. Different PDF's are used for different parameters depending on its variation, nature and its estimated distribution. These PDF's will determine which value to be selected for each parameter in each run. Deviation and mean value are needed in order to perform such selection. Based on the available literature, 27 uncertain parameters (UPs) were selected, and the associated distribution, mean values and range have been identified. One UP is assumed to be discrete, 23 UPs are assumed to have a uniform distribution and the rest are assumed to follow a normal distribution as illustrated in Table 3.

With the completion of the uncertainty analysis, a dataset of 311 samples is obtained for the system response. Next, this dataset is used to train and validate the ANN which will be described in the following subsection.

### *2.1 AI Model Development*

The AI model uses an artificial neural network (ANN), as illustrated in Figure 5, mimic the way human neurons behave by processing the information and finding the relation between input and output strictly using a data-driven approach. In this investigation, an ANN model is developed according to the process shown in Figure 6. The model tests several network architectures that are capable of producing good regression performance metrics.

**Table 3. APR 1400 MSLB PIRT**

| No | Parameter | Distribution | Normalized | | | |
|---|---|---|---|---|---|---|
| | | | L | U | Mean | SD |
| 1 | SIT Temprature | Uniform | 0.9 | 1.1 | 1 | 0.05 |
| 2 | Core Decay Heat | Uniform | 0.9 | 1.1 | 1 | 0.05 |
| 3 | Core Conductivity | Uniform | 0.9 | 1.1 | 1 | 0.05 |
| 4 | Core Heat Capacity | Uniform | 0.9 | 1.5 | 1 | 0.15 |
| 5 | Break Area | Uniform | 0.95 | 1.5 | 1 | 0.1375 |
| 6 | Depressurization Valves Discharge Coefficient | Uniform | 0.8 | 1.2 | 1 | 0.1 |
| 7 | Break Discharge Coefficient | Uniform | 0.6 | 1.4 | 1 | 0.2 |
| 8 | Interphase heat transfer Coefficient | Uniform | 0.9 | 1.1 | 1 | 0.05 |
| 9 | Single phase Heat transfer coefficient | Uniform | 0.9 | 1.1 | 1 | 0.05 |
| 10 | Critical flow | Discrete | 50 | 53 | 1 | 0.75 |
| 11 | AFW flow rate | Uniform | 500 | 800 | 1 | 75 |
| 12 | MSIS setpoint | Uniform | 851 | 975 | 1 | 31 |
| 13 | Initial PZR pressure | Uniform | 2000 | 2325 | 1 | 81.25 |
| 14 | Initial SG inventory | Uniform | 0.35 | 0.982 | 1 | 0.158 |
| 15 | Safety injection delay time | Uniform | 20 | 30 | 1 | 2.5 |
| 16 | Initial PZR Liquid Volume | Uniform | 0.219 | 0.6 | 1 | 0.09525 |
| 17 | Flow Rate | Normal | 0.01 | 1.01 | 1 | 0.25 |
| 18 | Power | Normal | 0.15 | 1.15 | 1 | 0.25 |
| 19 | Inlet Temperature | Uniform | 0.15 | 1.15 | 1 | 0.25 |
| 20 | Subchannel Area | Normal | 0.05 | 1.05 | 1 | 0.25 |
| 21 | Nucleate boiling heat transfer coefficient | Normal | 0.24 | 1.24 | 1 | 0.25 |
| 22 | Interfacial drag coefficient (bubbly flow) | Normal | 0.32 | 1.32 | 1 | 0.25 |
| 23 | Interfacial drag coefficient (droplet flow) | Normal | 0.26 | 1.26 | 1 | 0.25 |
| 24 | Interfacial drag coefficient (film flow) | Normal | 0.36 | 1.36 | 1 | 0.25 |
| 25 | Outlet water pressure | Normal | 0 | 0 | 1 | 0 |
| 26 | Fuel pellet diameter | Normal | 0.92 | 1.08 | 1 | 0.04 |
| 27 | Cladding thermal conductivity | Normal | 0.9985 | 1.0015 | 1 | 0.00075 |

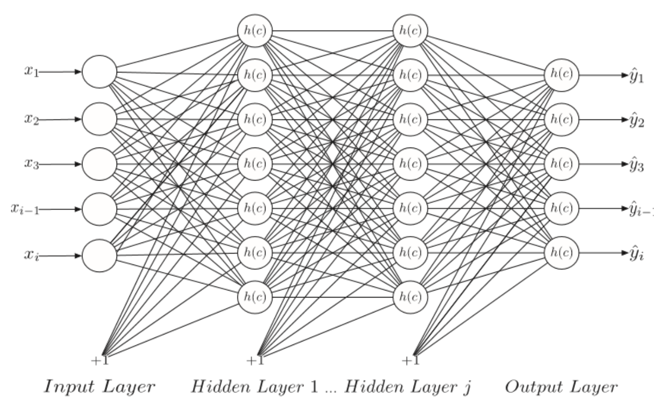


**Figure 5. Neural network representation.**

The ANN model should undergo training, validation, testing and evaluation. Each step is compulsory to ensure the model generated is robust enough to predict the output value with accuracy compared to the known value from the pre-existing database.

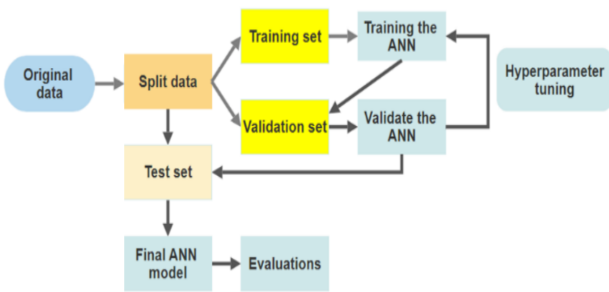


**Figure 6. ANN model development process**

Initially, the data will be split into training and testing subsets. The ANN model will then be trained using the majority of data points before going through the validation process. If the validation is not within a reasonable range, the ANN will be tune by optimizing its hyper-parameters to reach satisfactory regression metrics. The regression metrics used are: mean squared error (MSE), root means square error (RMSE), mean squared logarithmic error (MSLE) and mean absolute error (MAE). Once the metrics reach the lowest achievable value, the ANN model will be tested with the randomly selected unseen data from the database and evaluated by testing regression performance. In this study the ANN architecture used (15:15:15) configuration, which is selected based on the previous literature with 15 neurons for each of the three hidden layers. Each layer is activated using a 'ReLU' function to eliminate the gradient reduction problem and achieve the model generalization (Park, H. et al, 2020). The ANN is train using 1000 epochs to ensure adequate learning process. According to the common practice, the batch size is selected as one for generalization and faster convergence. Table 5 shows the ANN architecture used for making the DNBR predictions.

**Table 4 ANN architecture**

| | |
|---|---|
| **Architecture** | 15 : 15 : 15 |
| **Activation function** | ReLU |
| **Number of epochs** | 1000 |
| **Number of batches** | 1 |
| **initializers** | None |

Once the database of MDNBR is created for a range uncertain parameters, it will undergo feature selection to determine key uncertainty parameters with a strong relationship (positive or negative) with the figure of merit (FoM), in this case MDNBR. Only those uncertain parameters that are strongly correlated with the MDNBR are included in the input of the ANN model to predict the MDNBR for computational efficiency.

## RESULTS

The data set generated from this Wilks 5$^{th}$ order simulation is fed to the AI algorithm to provide training and validation. The AI algorithm should be able to predict the MDNBR value.

## CONCLUSION

The preliminary results of this research shows that APR1400 is robust enough to overcome MSLB accident. This work is part of ongoing effort to use AI in decision making for actions under severe accident conditions.

## ACKNOWLEDGMENTS

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