Identification of Flex Strategy Success Window for Extended SBO using BEPU and AI

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1. INTRODUCTION

The Fukushima accident was initiated by an earthquake followed by a Tsunami which resulted in a Station Blackout (SBO) for an extended period of time due to the devastation and failure to restore AC power. This drew the industry's attention to the importance of enhancing the existing plants' coping capabilities with an extended SBO as a possible risk. A SBO occurs as a result of loss of all offsite power together with the loss of all on-site power due to failure of the Emergency Diesel Generators (EDGs) (Lee et al., 2014). As a result of loss of all AC power sources during an extended SBO, the main motor driven feedwater pumps are lost. The Turbine Driven Auxiliary Feedwater Pumps (TD-AFWPs) pickup but are eventually lost within 8 hours when the batteries become unavailable. After the battery depletion, the secondary heat removal is lost and the plant undergoes a severe accident, unless proper mitigation strategies are implemented.

A number of mitigation strategies have been proposed to enhance the plant's coping capability. These are reflected in a set of high level candidate actions to guide the staff to mitigate the accident and minimize its consequences. FLEX strategies have been proposed to enhance the plant's coping capabilities with extended design conditions and beyond design basis accidents. It involve three phases: firstly, installed equipment will be utilized; secondly, portable onsite equipment and consumables need to be utilized for the transition phase until further off-sire resources are available to sustain the required functions and provide long-term cooling. The successful implementation of FLEX requires a controlled and systematic approach to transition to mobile equipment providing protection, access and connections for the portable equipment to enable key safety functions to be maintained despite a postulated extended loss of normal AC power and loss of normal access to the ultimate heat sink.

However, the effectiveness of this strategy relies on a number of uncertainties that need to be quantified before they can be deemed successful. This necessitates conducting a significant number of simulations to survey possible combinations of initial, boundary and design conditions, which may be time consuming. Therefore This work, builds on a previous work by the second author (Ricardo and Diab, 2019) where the Best Estimate Plus Uncertainty (BEPU) approach is implemented. It 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 of FLEX strategy 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 train an Artificial Intelligence (AI) algorithm. AI is used as an alternative approach that relies on data-driven models to provide a fast design tool that can predict the success window of the mitigation strategy. This paper attempts to explore the possibility of using AI to predict the success window of FLEX strategy for APR1400.

2. METHODOLOGY

This section describes the methodology followed 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

The first step is to develop a thermal hydraulic model of APR 1400 under SBO scenario. This is achieved using the realistic thermal hydraulic system code, MARS-KS. The system nodalization used is illustrated in Fig.1 reflects the Reactor Coolant System (RCS) which consists of Reactor Pressure Vessel (RPV), two Hot Legs, four Cold Legs and four Reactor Coolant Pumps (RCPs). A Pressurizer (PZ) is connected to the Hot Leg and at its top, Pressurizer Safety relief Valves (PRSVs) and Safety Depressurization System (SDS) were modelled to simulate release of RCS coolant in case of depressurization. On the secondary side, two Steam Generators (SGs) whose water level is automatically controlled via the Main Feedwater System (MFWS). The steam from the SGs is directed to the turbine through the Main Steam Line (MSL). Six Secondary Main Steam Safety Valves (MSSVs), two Main Steam Line Atmospheric Depressurization Valves (MSL-ADVs), two Main Steam Line Isolation Valves (MSLIVs) and Turbine Bypass Valve

(TBV) are modelled on the MSL connected to the upper head of the SGs. The MSSVs prevent over pressurization of the SG automatically, TBV is used to isolate the Turbine and the ADVs are used to depressurize the SGs by the operator. The turbine, is represented using a time dependent volume as boundary condition. Similarly, the containment is represented by a time dependent volume.

2.1.1 Base Case

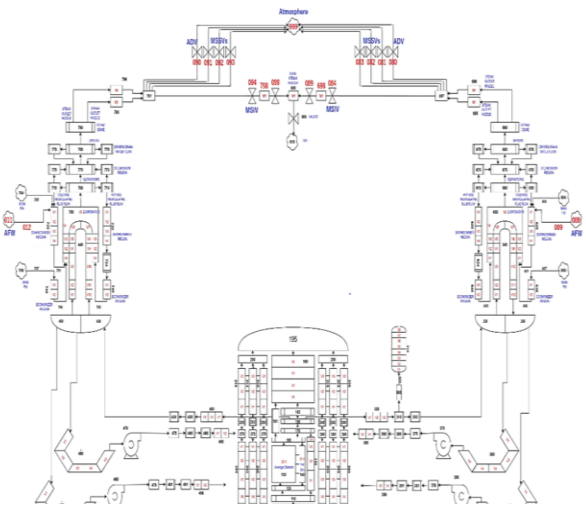

Figure 1 : MARS-KS Nodalization

A base case was simulated for an SBO initiated from the nominal reactor conditions. The steady state calculation was performed, and the model results compared to the corresponding values reported in the Design Documents of APR1400 as shown in Table 1.

Table 1 : APR 1400 Steady State

Parameter	SBO Model	DCD [16]
Reactor Power (MWth)	3983	3983
Primary Pressure (MPa)	15.5	15.5
Secondary Pressure (MPa)	6.9	6.9
Hot leg temperature (K)	598	597
Cold leg temperature (K)	566	564
RCS seal leakage flow rate per pump (kg/s)	1.325	N/A
RCS mass flow rate (kg/s)	20,992	20,992

When an SBO occurs, the reactor is shut down and the TDAFWPs start automatically. After 3 seconds the RCP seal leakage occurs as a result of seal failure due to loss of component cooling, which further challenges the plant. After 8 hours the battery is lost, at which time, the turbine drive auxiliary water pumps (TDAFWPs) are lost.

To enhance the plant's coping capability, the FLEX strategies should be implemented. Within 30 minutes, the operator opens the atmospheric dump valve (ADV) to create a flow path to cool down the system according to the emergency operating procedures (EOPs). Subsequently, the mobile FLEX pumps are connected to the primary and secondary system, within 2 hours, for external water injection into the primary system and secondary systems, respectively. However, they are not able to inject water into the system unless the system pressure reaches the pump shutoff pressure.

The FLEX strategy is considered successful if the system copes with the accident for a mission time of 72 hours. A severe accident can be avoided if the battery lasts up to 8 hours which allows enough time for the FLEX equipment to be aligned. However, injection is achieved only if the system pressure drops below the shutoff head of the mobile pumps which are 1.2 MPa and 0.23 MPa, respectively.

2.1.2 Model for BEPU Analysis

The thermal hydraulics code is coupled to a statistical tool, DAKOTA, to assess the impact of the uncertainty parameters on the performance metrics that reflect the success of the FLEX strategy using Python programming language to provide the communication interface as shown in Fig 2. 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 (Kang et al., 2013, Kozmenkov et al., 2017 and Lee et al., 2014) and shown in Table 2. Subsequently, the uncertainties are propagated through the thermal hydraulic model for uncertainty quantification.

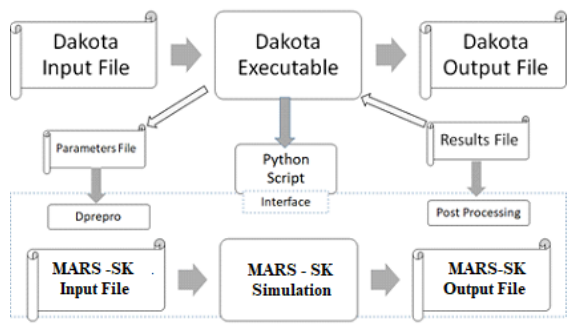

Figure 2 : Uncertainty Analysis Framework

A dataset of the system response is generated for randomly selected values of the uncertain parameters represented a priori by range and distribution. The safety metric for this problem is the peak cladding temperature. A peak cladding temperature (PCT) of 1477K, corresponds to a core exit temperature of 922K indicates the onset of a severe accident and is used to transition to the severe accident management guidelines (SAMG). Therefore, a PCT less than 1477K is indicative of the success of the Flex strategy. Figure 4 shows the PCT value during the base case transient.

Table 2 : SBO PIRT

Uncertain Parameters	Range	Distribution
Reactor Power	0.98-1.02	Normal
Decay Heat Power	0.92-1.08	Uniform
Fuel Heat Capacity	0.98-1.02	Normal
Fuel Thermal Conductivity	0.90-1.10	Normal
Initial PZR Pressure	0.974-1.026	Uniform
Set point for pressurizer relief valve	0.982-1.017	Normal
Initial Secondary Pressure	0.974-1.026	Uniform
Multiplier for liquid Dittus-Boelter correlation	0.85-1.15	Uniform
Multiplier for Chen nucleate boiling model	0.8-1.2	Uniform
Multiplier for vapor Dittus-Boelter correlation	0.8-1.2	Uniform
Initial total mass flow	0.95-1.05	Uniform
Total moment of inertia for RCPs	0.8-1.2	Normal
Initial coolant inventory in SITs	0.88-1.12	Uniform
Initial pressure in SITs	0.93-1.23	Uniform
Initial coolant temperature in SITs	0.93-1.23	Uniform
Initial temperature in the mobile pumps	0.94-1.06	Uniform

With the completion of the uncertainty analysis, a dataset of 2500 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.

2.2 AI Model Development

The AI algorithm utilizes the artificial neural network (ANN) technique which has been proven successful for various health monitoring and optimization studies in a number of disciplines including nuclear power plant accident diagnostics.

The ANN mainly consists of an input layer, one or more hidden layers, and an output layer as shown in Fig. 3. Each layer includes multiple processing units called artificial neurons that are connected to each to form the structure of the network. The network is assembled using a combination of transfer functions, constrained within a number of hidden layers than can be used to model the data by deducing the mathematical function that reflects the statistical correlation between the inputs and output performance metric. Information from the input layer is propagated forward to estimate the output by iteratively setting appropriate weight factors that reflect the strengths of the relationship between the output and input parameters via weight factors. Next, the error between the estimated output and pre-existing output is back propagated to adjust the weight factors.

During the training phase, the AI model is tuned and optimized using the database provided by the thermal hydraulics model. Subsequently, the AI model is validated against the remaining sub-set (test data). The developed model can be used to provide a reliable prediction tool to verify the emergency operating procedures and ensure the successful implementation of the mitigation strategy.

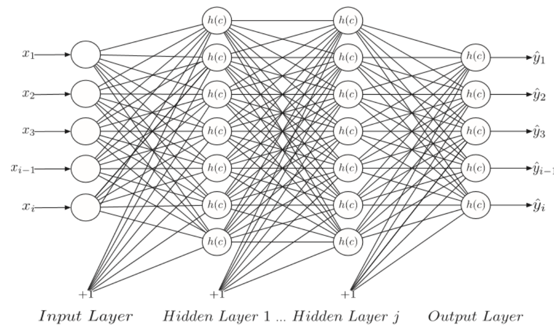

Figure 3 : Neural network representation

RESULTS

The success window of FLEX strategy strongly depends on the time gap between injection time using FLEX portable pumps and the time at which the Turbine Driven Auxiliary Feedwater Pump (TDAFWP) stops. The PCT is less than 1477K when Flex pumps start within 1 hour of the accident. However, the chances for PCT to exceed 1477 K increase when the injection using FLEX portable pumps is delayed. On the other hand, when stops earlier (for example, if the battery depletion time is less than 8 hours), the chances of PCT to reach or exceed 1477K is higher. With that said, for all tested cases the failure of FLEX strategy is very rare as illustrated by Figure 4.

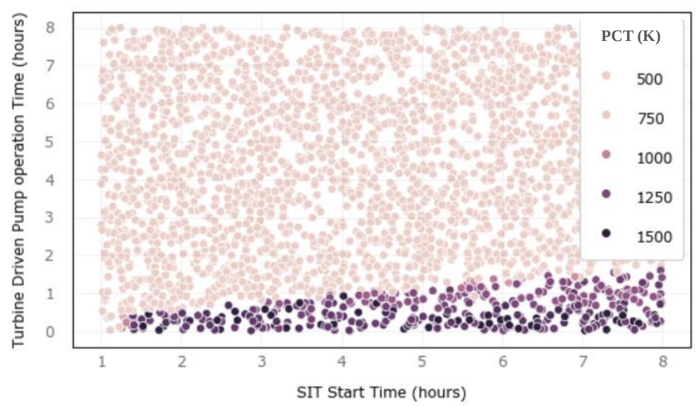

Figure 4 : Success Window for Flex Strategy

The data set generated from this Monte Carlo simulation is fed to the AI algorithm to provide training and validation. For the AI algorithm, this is a classification problem. It should be able to identify the cases where the strategy succeeded and those cases where the strategy failed. However, sometimes, success cases are confused as failed cases and vice a versa. Figure 5 shows the confusion matrix which summarizes the degree of success of the AI algorithm in predicting successful cases as successful and failed cases as failed. The AI model can accurately classifies the successful cases as illustrated by the Confusion Matrix in Fig. 5. The true success predictions are 1519 out of 1873 cases.

However, as mentioned earlier, the failure of FLEX strategy is rare and represents only 2% of the simulated cases which produces imbalanced dataset. An imbalanced dataset gives poor accuracy for the minority subset of the data that used to train the AI algorithm, therefore under-sampling and over-sampling techniques were used to balance the data. To improve the accuracy and avoid overfitting, Monte Carlo sampling was used to generate a large database. After splitting the data for training the algorithm, under-sampling is applied on the success cases from the training set by selecting a number of success cases randomly. Also oversampling is applied on the failed cases in the training dataset by duplication the failed cases and selecting a number of failed cases randomly. These two techniques increase the fraction of failed cases and produce balanced dataset, which lead to increase the accuracy of the model in predicting the success (0.95) and failure (0.77) of operators action to implement the FLEX strategy as shown in Table 3.

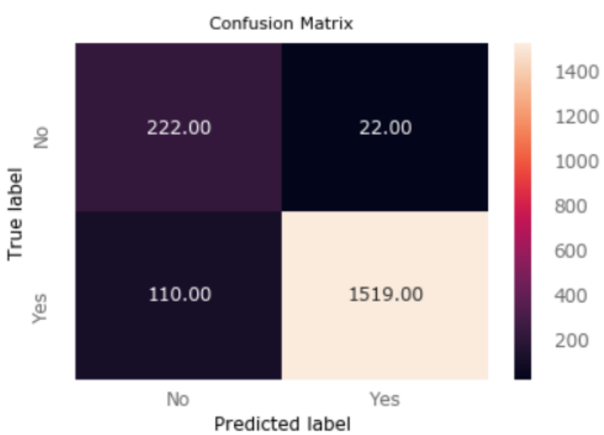

Figure 5 : Confusion Matrix

Table 3 : Prediction Accuracy using f1-Score

	Precision	Recall	F1-Score	Support
Fail	0.6687	0.9098	0.7708	244
Success	0.9857	0.9325	0.9584	1629
Overall accuracy			0.9295	1873

CONCLUSION

The results of this research shows that APR1400 coping capability for extended SBO is enhanced using the FLEX strategy with extremely low failure rate. This confirms the effectiveness of the emergency operating procedures as evidenced by the successful time window for operator action using BEPU analysis. Moreover, the AI algorithm is capable of predicting the success window of implementing the FLEX strategy with acceptable accuracy. However, because of the high reliability of FLEX strategy, the failed cases were limited causing an unbalanced dataset. To overcome the unbalanced dataset, a larger data set is needed. Accordingly, under-sampling and oversampling techniques need to be applied. This work is part of an ongoing effort to use AI in the decision-making process regarding the implementation of high-level candidate actions during severe accident mitigation.

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