

BEPU Evaluation for APR1400 MSLB Accident using Artificial Intelligence

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OUTLINES

- INTRODUCTION
- METHODOLOGY
- BEPU MODEL
- ARTIFICIAL INTELLIGENCE MODEL
- RESULTS AND ANALYSIS
- CONCLUSION

INTRODUCTION

APR1400 main steam line break (MSLB)  postulated design base accident

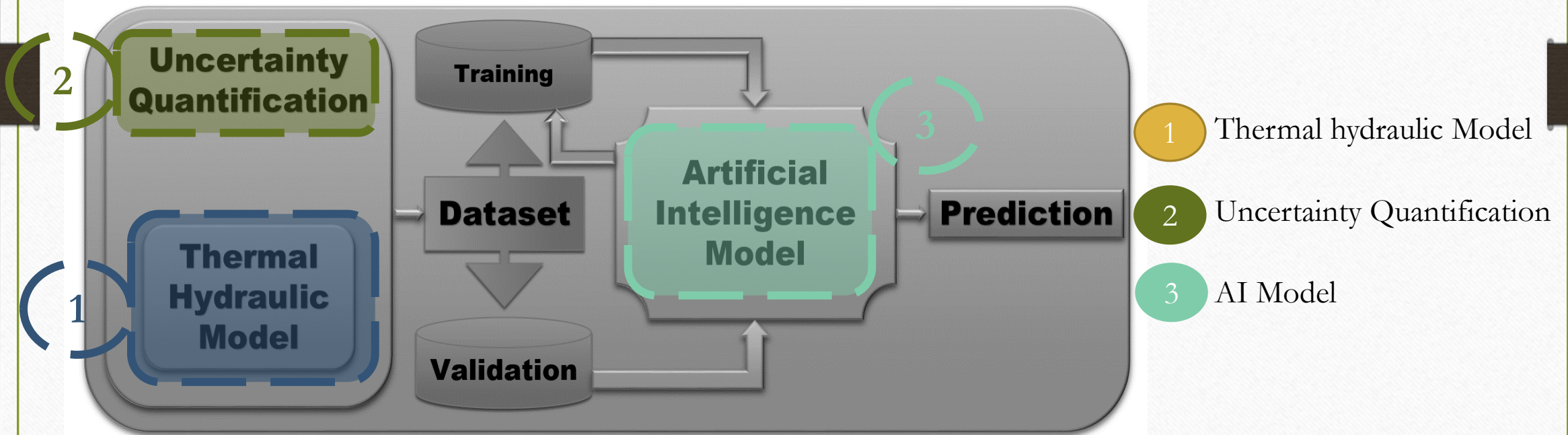
- As a result of the accident, the heat removal by the secondary system is increases.
- The RCS is excessively cooldown which may in turn increase in core reactivity.
- As a result, departure from nucleate boiling (DNB) may occur, causing heat to buildup and the fuel temperature to increase which threatens the fuel integrity.
- AI is used as an alternative data-driven approach to predict the plant response during MSLB accident given the underlying uncertainties.
- The figure of merit (FoM) in this study is the MDNBR.

GOAL AND OBJECTIVES

- Explores the applicability of Artificial Intelligence (AI) to predict the MDNBR during APR1400 MSLB Accident.
- To achieve it :
 - Develop BEPU model to provide a database of the thermal hydraulic response to train an Artificial Intelligence (AI) algorithm.
 - AI model is used as an alternative approach that relies on data-driven models to provide a fast design tool that can predict the MDNBR in APR1400 MSLB Accident.

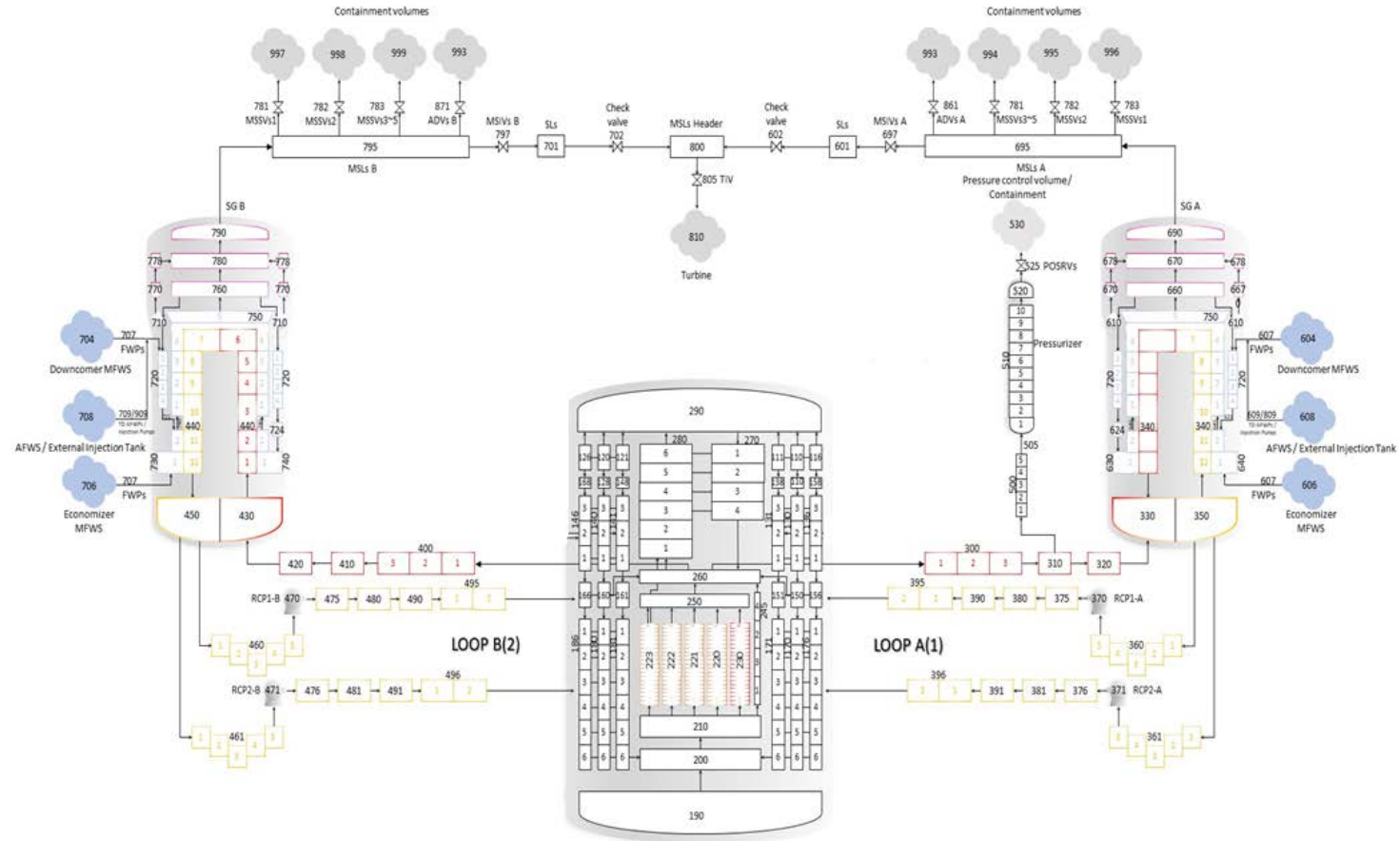
METHODOLOGY

The methodology adopted in this work involves three building blocks:



Thermal hydraulic model development

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)



APR1400 MSLB Systems and Components

APR1400 Nodalization

Thermal hydraulic model development

ACCIDENT SCENARIO



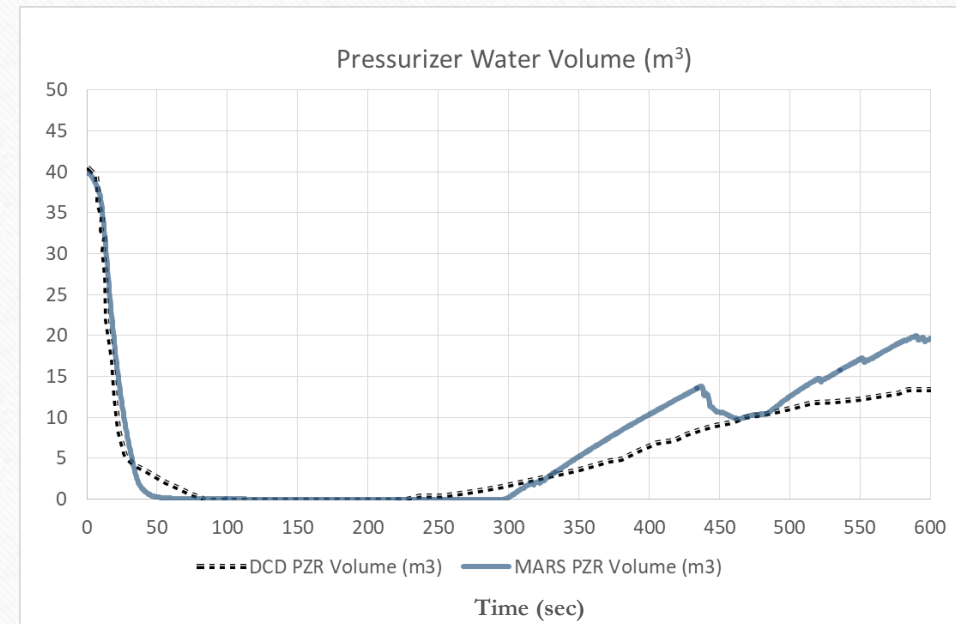
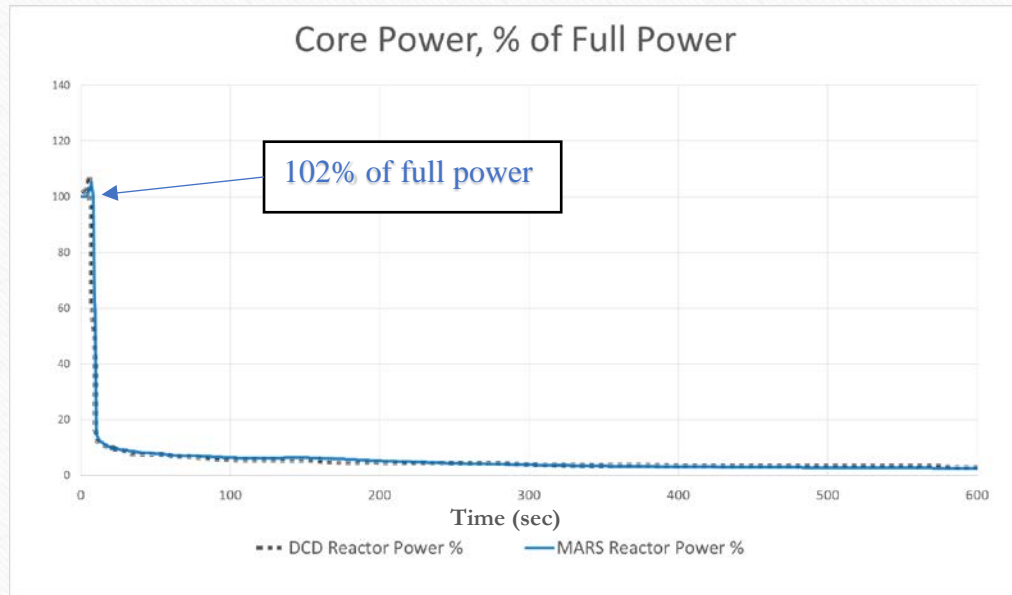
AFWP: Auxiliary Feedwater Pump
RCP: Reactor Coolant Pump
SG: Steam Generator
MSIV: Main Steam Isolation Valve
MFIVs: Main Feedwater Isolation Valve

Thermal hydraulic model development

BASE CASE VALIDATION - Steady State

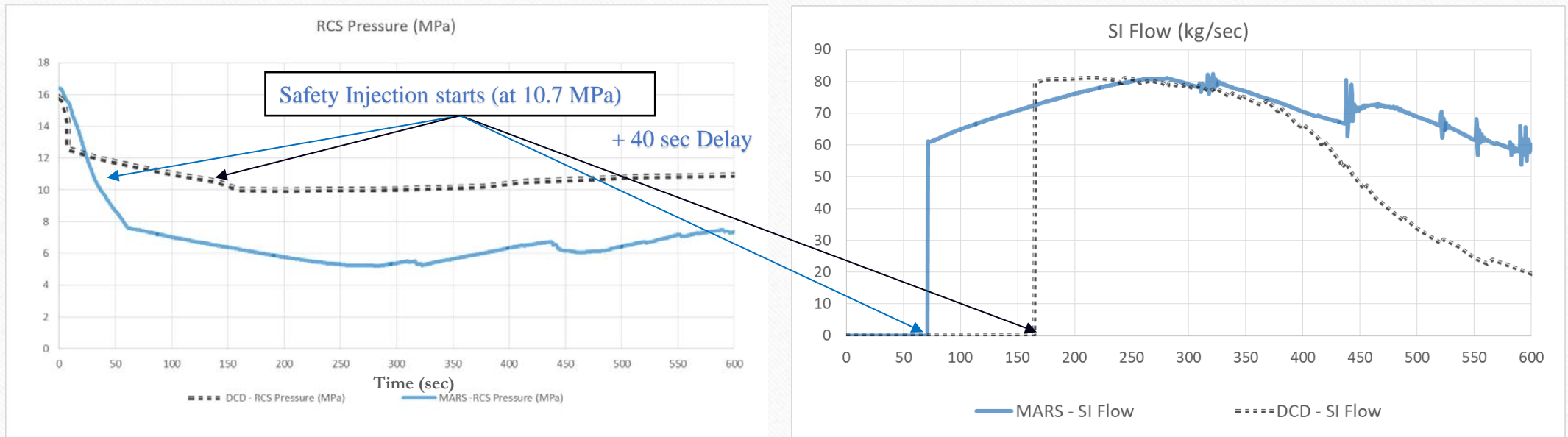
Parameter	Assumptions and Initial Conditions			
	DCD	MARS	Variance	%
Initial core power level, MWt	4,062.66	4,062.66	-	0.0%
Initial core inlet coolant temperature, (°K)	568.15	572.53	4.38	0.8%
Initial core mass flow rate, kg /s	19,344.44	19,668.00	323.56	1.7%
Initial pressurizer pressure, Mpa	16.04	16.40	0.36	2.3%
Initial pressurizer water volume, m3	39.91	39.87	(0.04)	-0.1%
Initial SG liquid inventory per SG, kg	124,113	125,820.00	1,707.00	1.4%
Blowdown fluid	Saturated steam	Saturated steam	-	-
Blowdown area for each steam line, m2	0.119	0.119	-	-
Loss of offsite power	Not assumed	Not assumed	-	-

Thermal hydraulic model development



BASE CASE VALIDATION - Transient

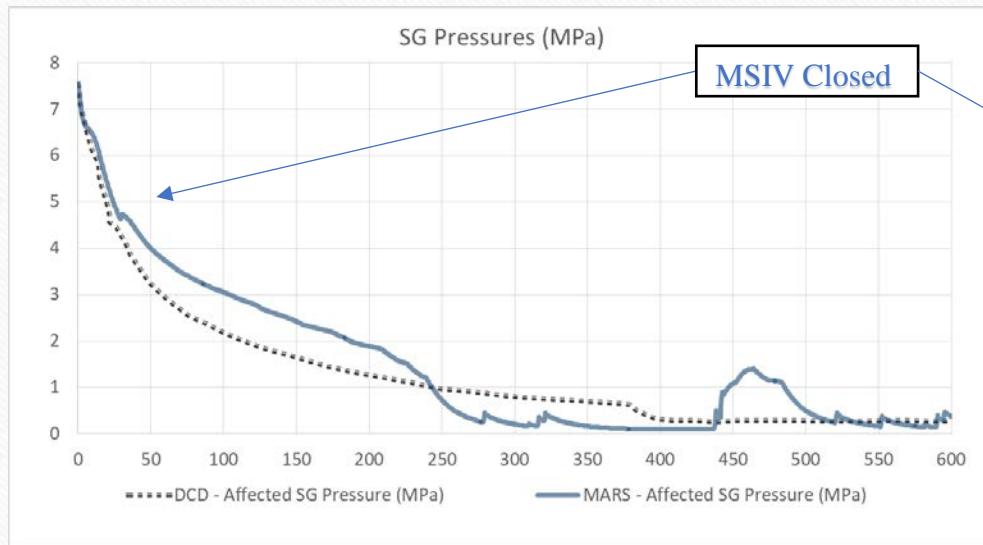
Thermal hydraulic model development



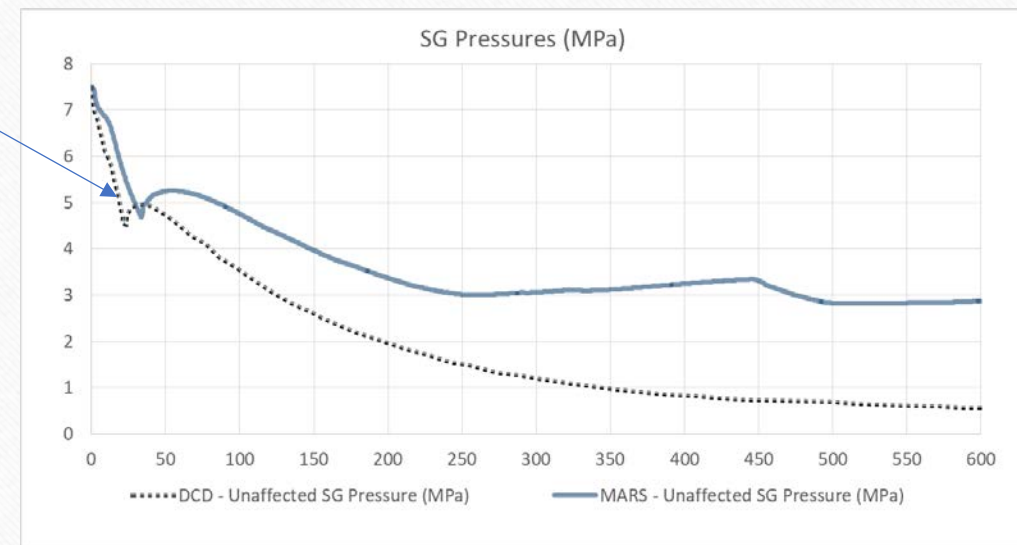
BASE CASE VALIDATION - Transient

Wednesday, December 30, 2020

Thermal hydraulic model development

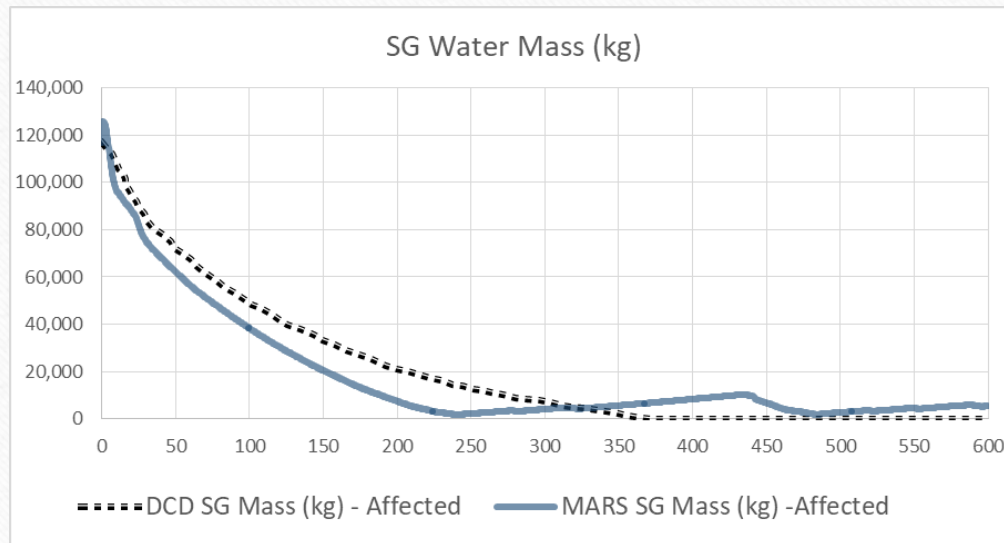


Affected SG

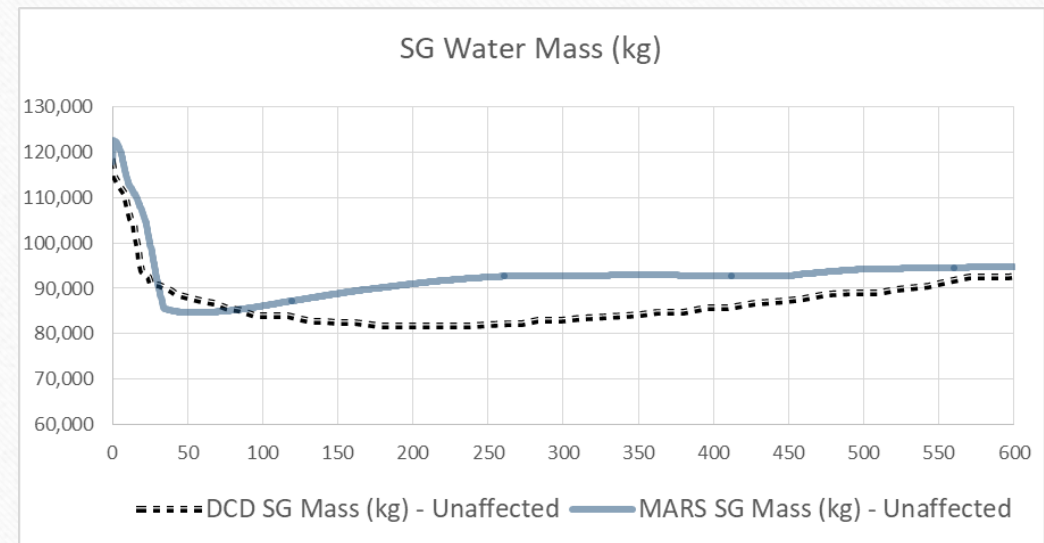


Unaffected SG

Thermal hydraulic model development



Affected SG



Unaffected SG

First Identifying input uncertainties

Second Propagating these uncertainties through a computational model (MARS-KS)

Third Performing statistical assessments on the resulting responses

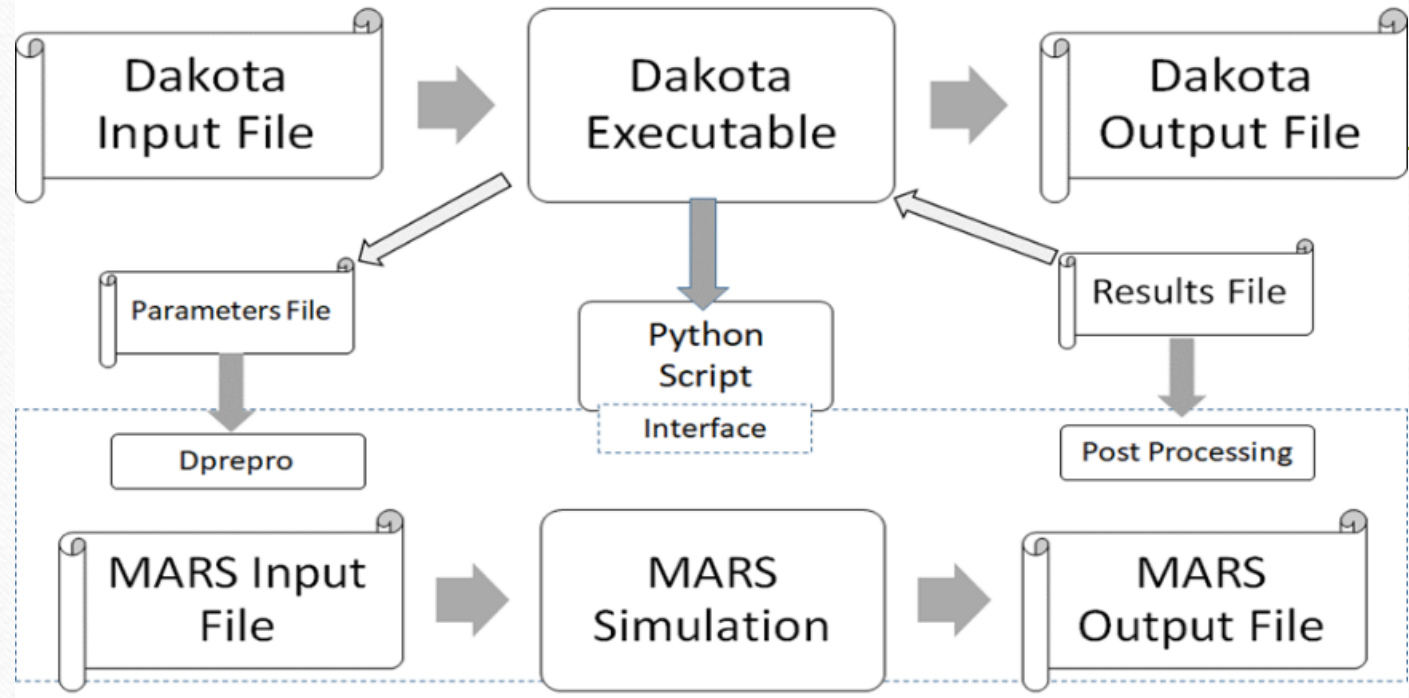
**Development of
uncertainty
quantification
framework**

Uncertainty parameters

No	Parameter	Distribution	Normalized			
			L	U	Mean	SD
1	SIT Temperature	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

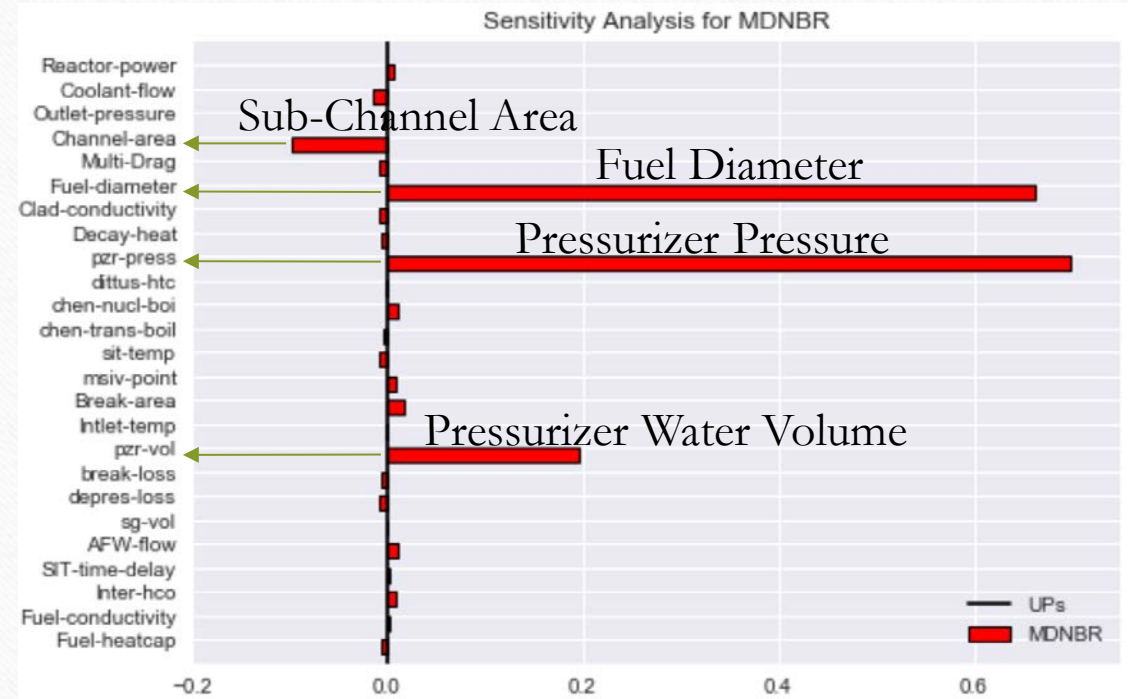
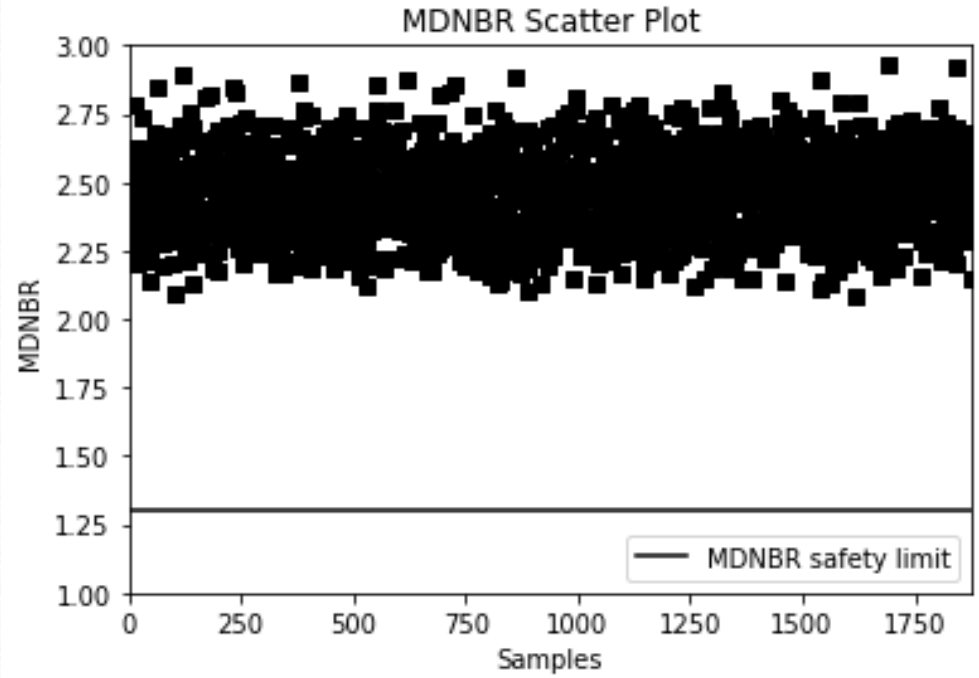
Development of uncertainty quantification framework

1. Yang, Y., Yang, J., Deng, C., Ishii, M., Simulation and Uncertainty Analysis of Main Steam Line Break Accident on an Integral Test Facility. *Annals of Nuclear Energy*, 144, 107565 (2020).
2. C. S. Lee, Y. K. Jin, S. W. Kim, C. J. Choi, S. Y. Lee, and J. T. Seo., Best Estimate Evaluation of Steam Line Break Accident Using Uncertainty Quantification Method. *Proceedings of the Korean Nuclear Society Autumn Meeting* (2003).
3. Castro González, Emilio & Avramova, Maria & Cuervo, D. & Herranz, Nuria., *Thermal-Hydraulic Uncertainty Propagation in a Main Steam Line Break Scenario* (2016).
4. M. Avramova, C. Arenas, K. Ivanov, Extension of BEPU Methods to Sub-channel Thermal-Hydraulics and to Coupled Three-Dimensional Neutronics/ Thermal-Hydraulics Codes, *OECD/CSNI Workshop, Barcelona (Spain)* (2011).

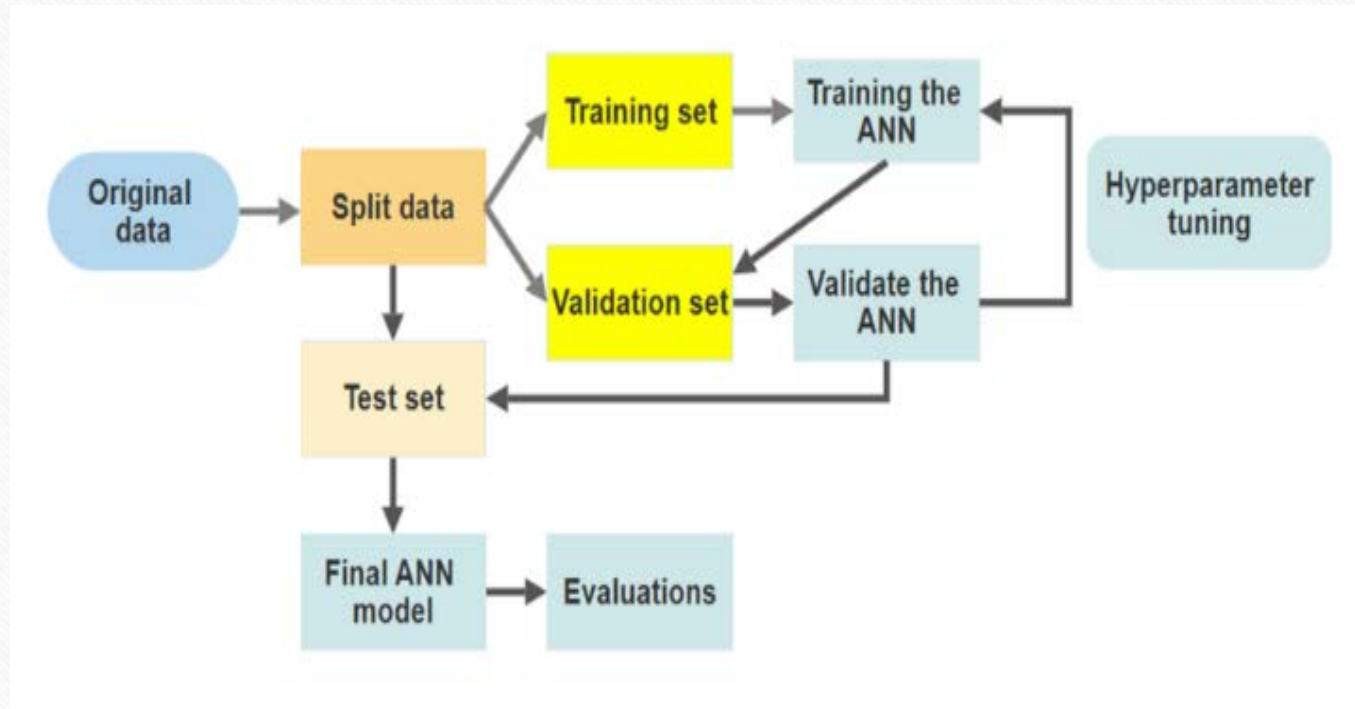


Uncertainty quantification framework

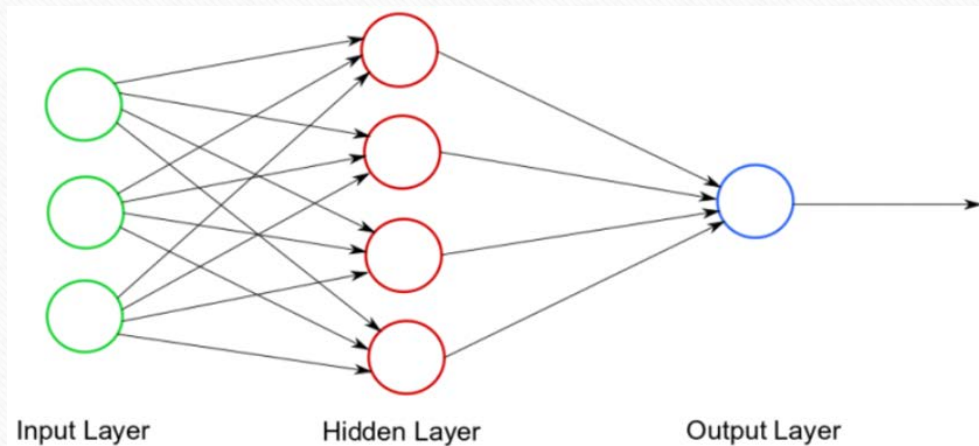
Result of the uncertainty quantification framework



Artificial Intelligence AI Model



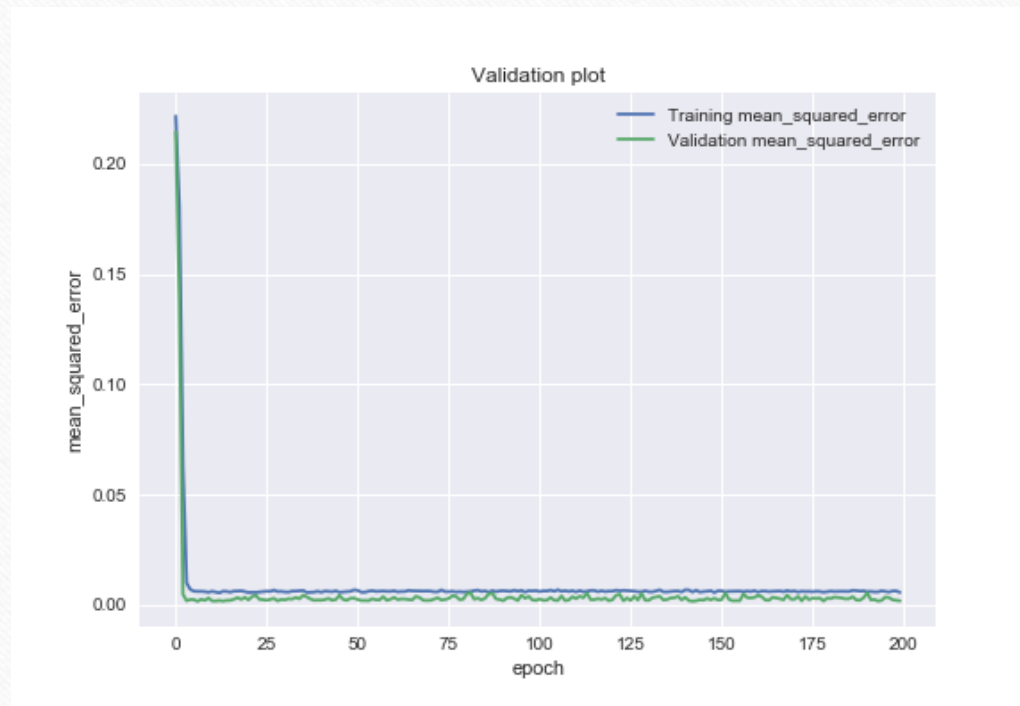
AI MODEL ARCHITECTURE



Hyperparameters dictionary

#	Hyperparameters	Search Boundary
1	Batch Size	2, 4
2	Hidden Layer Neurons	32, 64
3	Dropout Rate	0.6
4	Epochs	200
5	Optimizer	Adam, Nadam, RMSprop,SGD
6	Last Activation	relu, linear
7	Metric	mean_squared_error
8	Loss Function	mean_squared_error

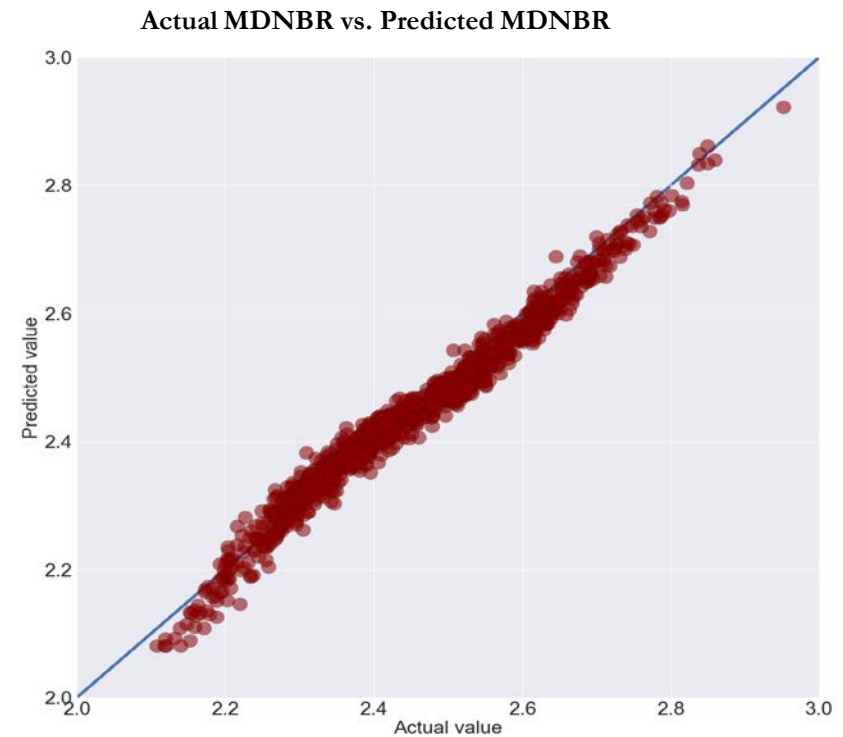
AI MODEL VALIDATION



mean_squared_error	0.004629
val_mean_squared_error	0.000832

Results and Analysis

#	Hyperparameters	Search Boundary
1	Batch Size	4
2	Hidden Layer Neurons	64
3	Dropout Rate	0.6
4	Epochs	200
5	Optimizer	SGD
6	Last Activation	relu
7	Metric	mean_squared_error
8	Loss Function	mean_squared_error



Conclusion

- The results of this research shows that APR1400 is robust enough to overcome MSLB accident.
- AI algorithm is capable of predicting MDNBR of APR1400 MSLB with very low error.
- Although the development of the AI algorithm is time-consuming; but once developed, the prediction can be obtained much faster than conventional deterministic methods.

References

1. Yang, Y., Yang, J., Deng, C., Ishii, M., Simulation and Uncertainty Analysis of Main Steam Line Break Accident on an Integral Test Facility. *Annals of Nuclear Energy*, 144, 107565 (2020).
2. C. S. Lee, Y. K. Jin, S. W. Kim, C. J. Choi, S. Y. Lee, and J. T. Seo,, Best Estimate Evaluation of Steam Line Break Accident Using Uncertainty Quantification Method. *Proceedings of the Korean Nuclear Society Autumn Meeting* (2003).
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Thank You