KINGS KEPCO INTERNATIONAL NUCLEAR GRADUATE SCHOOL

Time-Series Forecasting of NPP Response Undergoing LOCA

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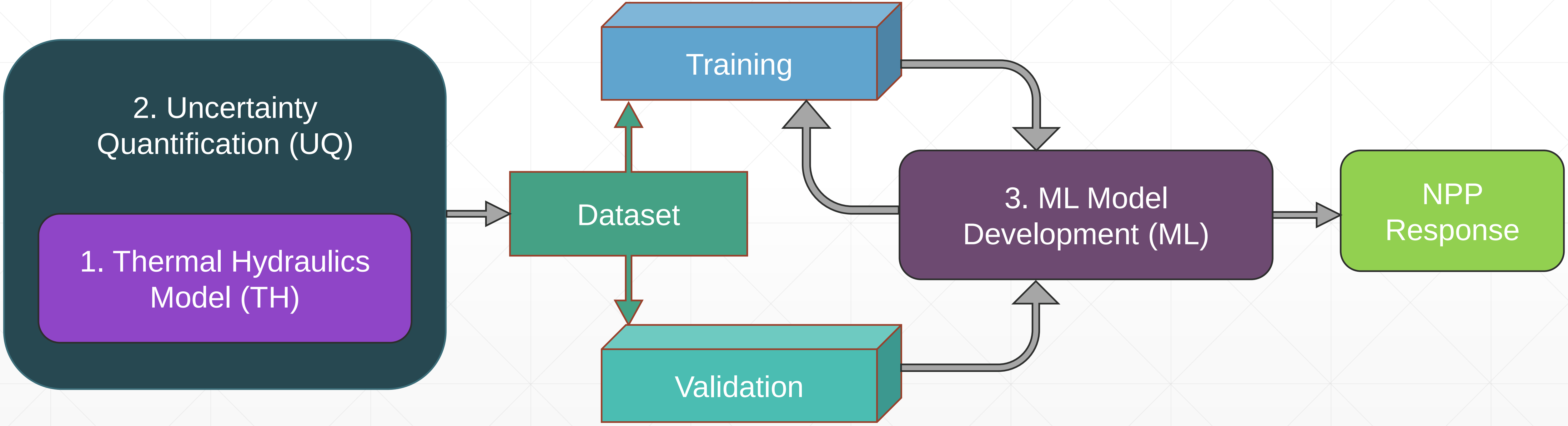
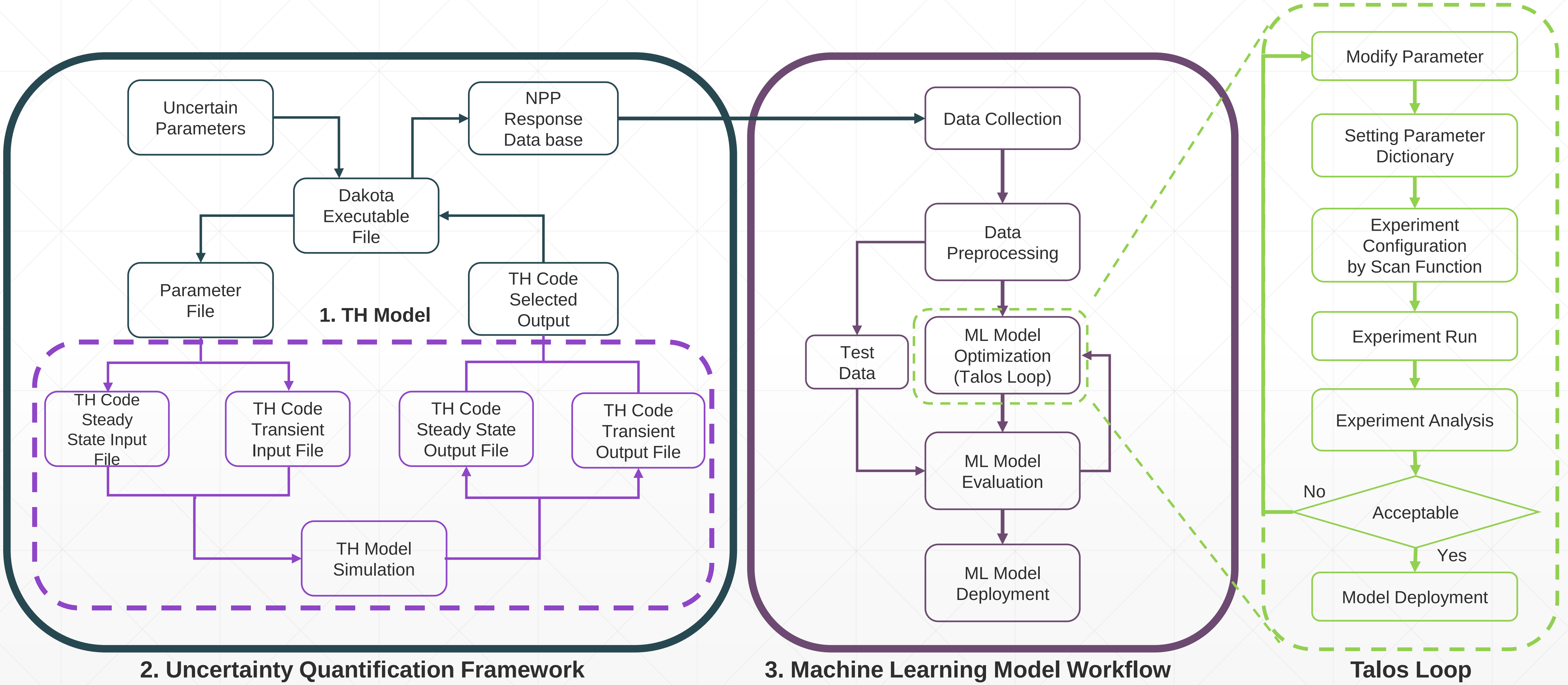
Introduction

- Loss-of-coolant accident (LOCA) – is analyzed for APR-1400 nuclear power plant (NPP) system response using the Best Estimate Plus Uncertainty (BEPU) approach.
- A thermal-hydraulics model of APR-1400 is developed with one-way coupling with point kinetics model using MARS-KS
- Data generation and uncertainty propagation is conducted by coupling MARS with Dakota.
- Machine Learning (ML) is used to predict the real time NPP response using the database created via the uncertainty quantification framework.

Methodology



Methodology



TH

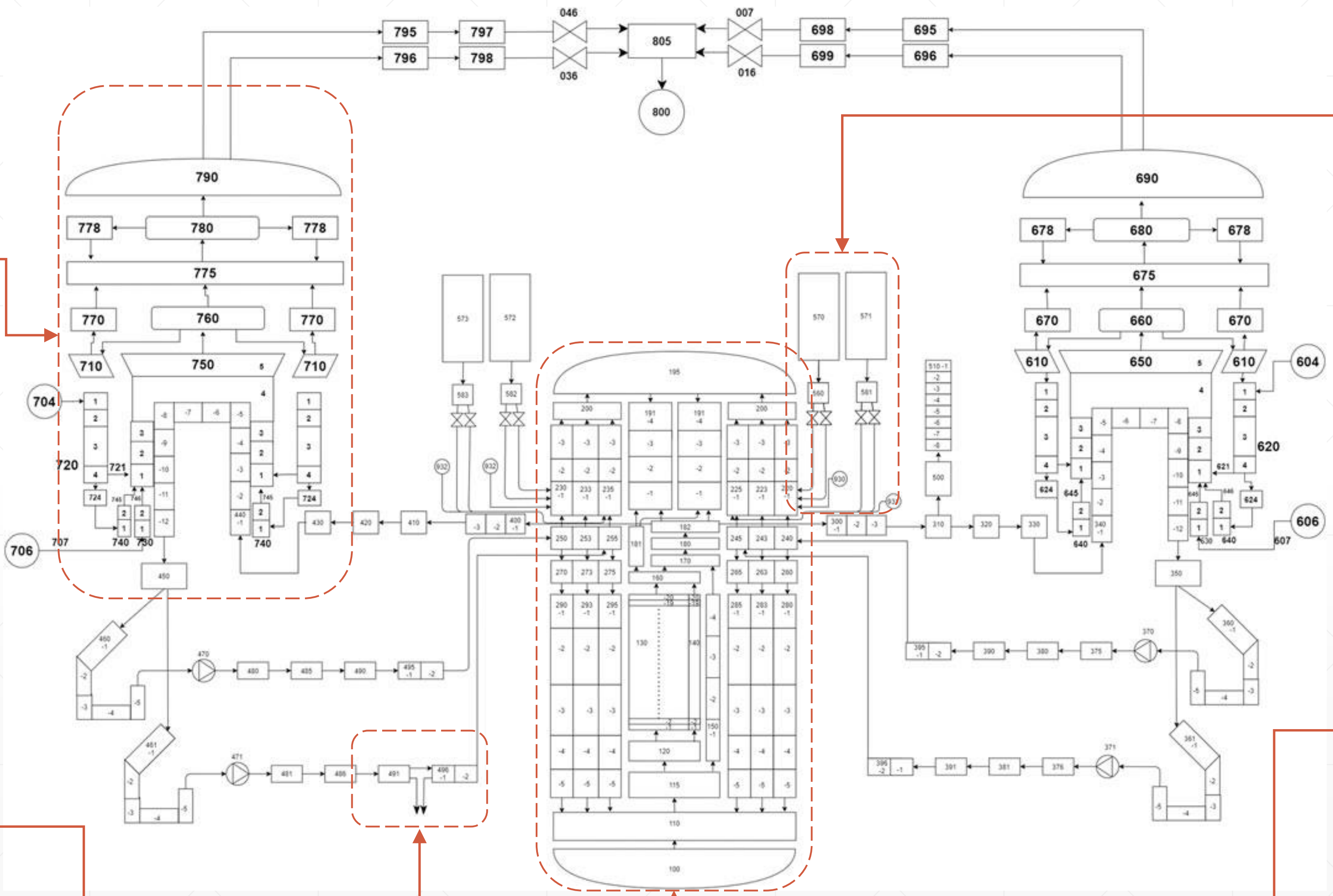
Thermal-Hydraulic Model
APR-1400 Nodalization

Steam Generators (SGs)

- Two SGs - each connected to the RPV via one hot leg and two cold leg
- Heat generated on the primary side is transferred to the SGs via the u-tubes
- The u-tube section is modeled with equivalent heat transfer and pressure drop conditions
- Secondary water is provided by the Main Feedwater System (MFWS) as boundary condition
- Steam generated in the SGs is directed via the main steam line to the turbine modeled as a boundary condition
- Other important components of the SGs are: evaporator, separator, dryer, dome

Break

- 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.



Modelled Safety Injection System (SIS)

- 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.

Reactor Pressure Vessel (RPV)

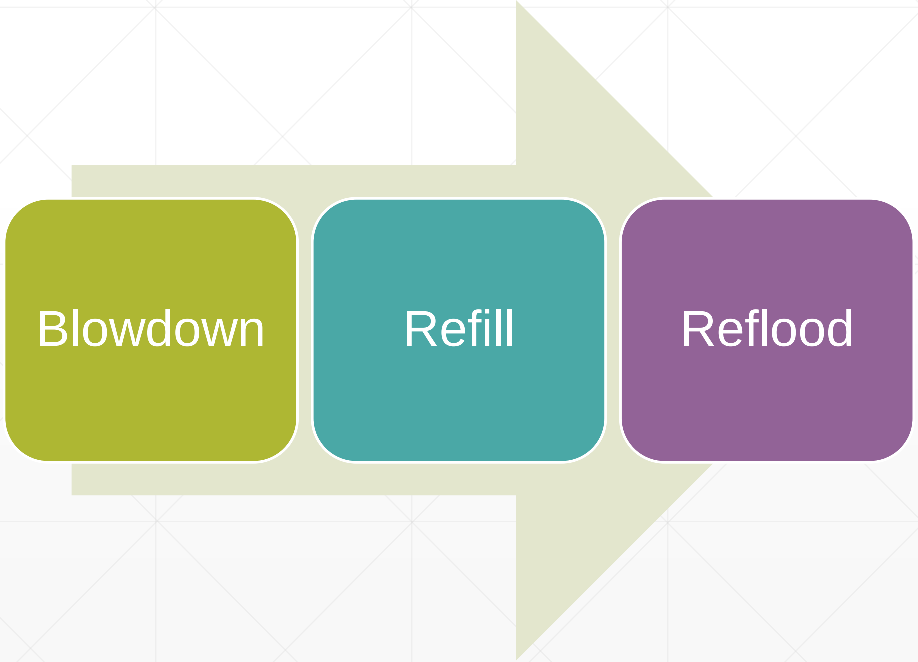
- The core is represented using an average and a hot channel, surrounded by an annular core shroud together with the core bypass
- The core connects to an upper plenum and a lower plenum
- Two hot legs lead the coolant from the RPV to the SGs u-tubes, four cold legs connect the RCPs to the downcomer
- The downcomer is modeled using annulus six components

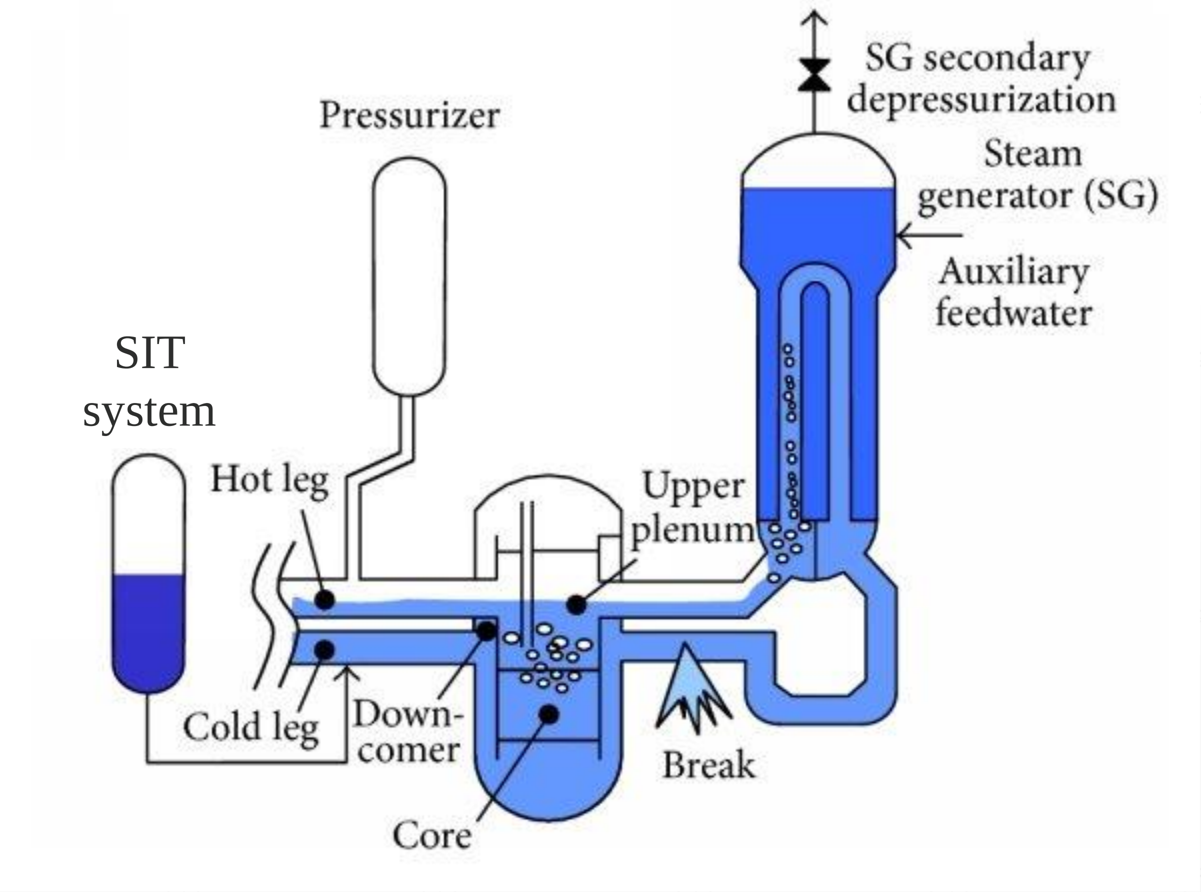
TH

Thermal-Hydraulic Model

Accident Description

- The Loss of Coolant Accident (LOCA) is assumed to result from a double-ended guillotine break of the cold leg after pump discharge. Such an event with a concurrent loss of offsite power (LOOP) is considered to be the most limiting case. The event is not anticipated during the life of the plant.





Thermal-Hydraulic Model
Model Validation*

○ Steady State Validation

Parameters	MARS	DCD	Error (%)
Power (MWt)	4062.66	4062.0	0.0
RCP flowrate (kg/s)	5272.0	5250.0	0.4
Core flowrate (kg/s)	20367.0	20361.0	0.03
Primary pressure (MPa)	15.52	15.51	0.01
Core inlet temperature (K)	564.3	563.8	0.12
Core outlet temperature (K)	598.4	597.1	0.16
Upper head temperature (K)	563.9	584.5	3.53
Pressurizer level (m)	8.22	8.18	0.5
Secondary pressure (MPa)	6.90	6.86	0.58
Hot rod fuel temperature (K)	1988.7	1985.2	0.18

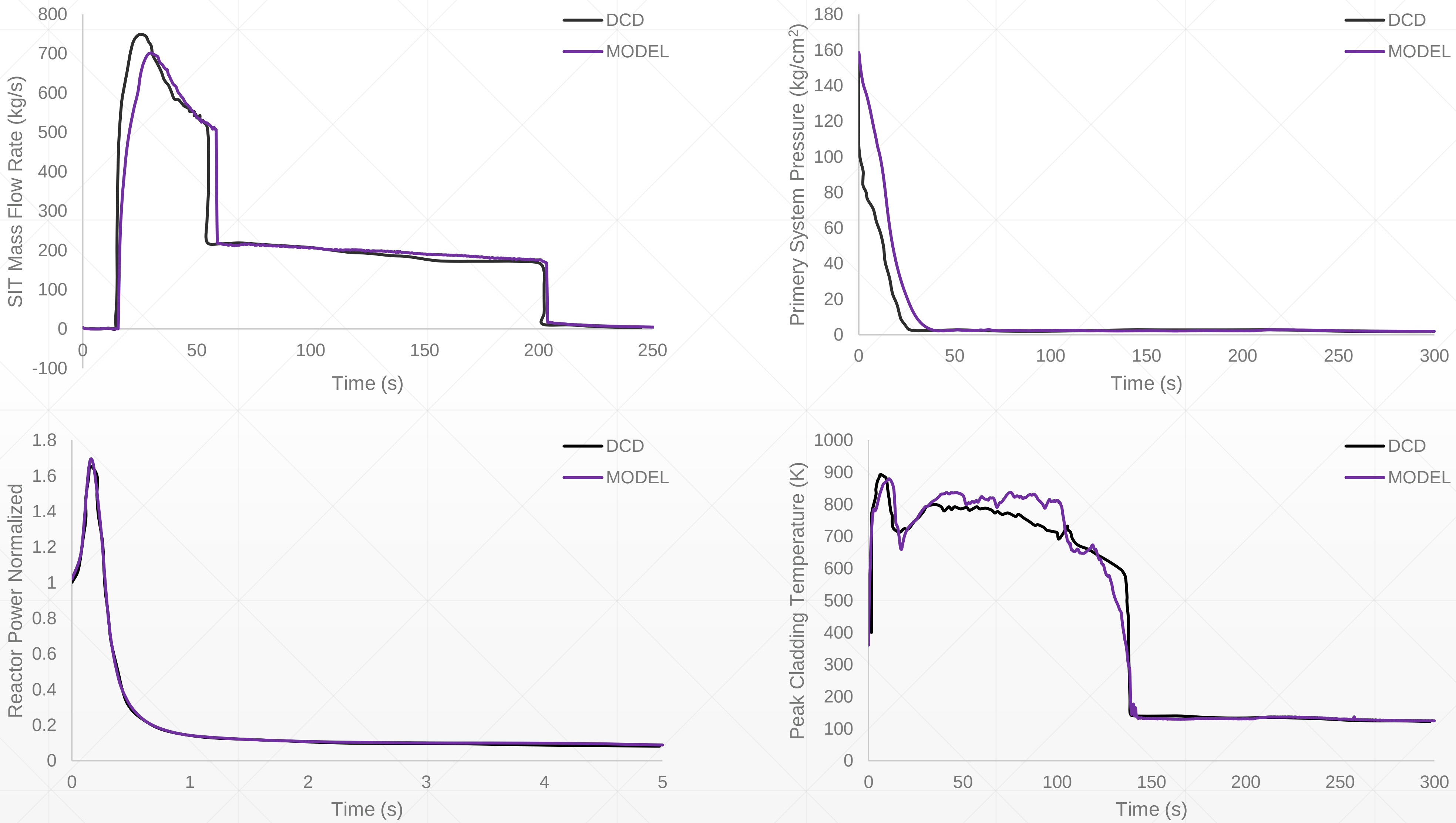
○Transient Validation

EVENT	DCD	MODEL
Break Occurs	0	0
Reactor Trip signal Occurs	6.2	5.8
SI Injection signal Occurs	6.2	5.8
SIT Discharge Begins		
SIT 1 (Broken Cold Leg Side)	14.4	16.0
SIT 2 (Broken Loop Intact Cold Leg Side)	14.4	16.0
SIT 3 (Intact Loop Intact Cold Leg Side 1)	14.4	16.0
SIT 4 (Intact Loop Intact Cold Leg Side 2)	14.4	16.0
Pumped SI Injection	46.2	48.0
SIT Empty Time		
SIT 1 (Broken Cold Leg Side)	201.5	204.0
SIT 2 (Broken Loop Intact Cold Leg Side)	201.5	204.0
SIT 3 (Intact Loop Intact Cold Leg Side 1)	201.5	204.0
SIT 3 (Intact Loop Intact Cold Leg Side 2)	201.5	204.0

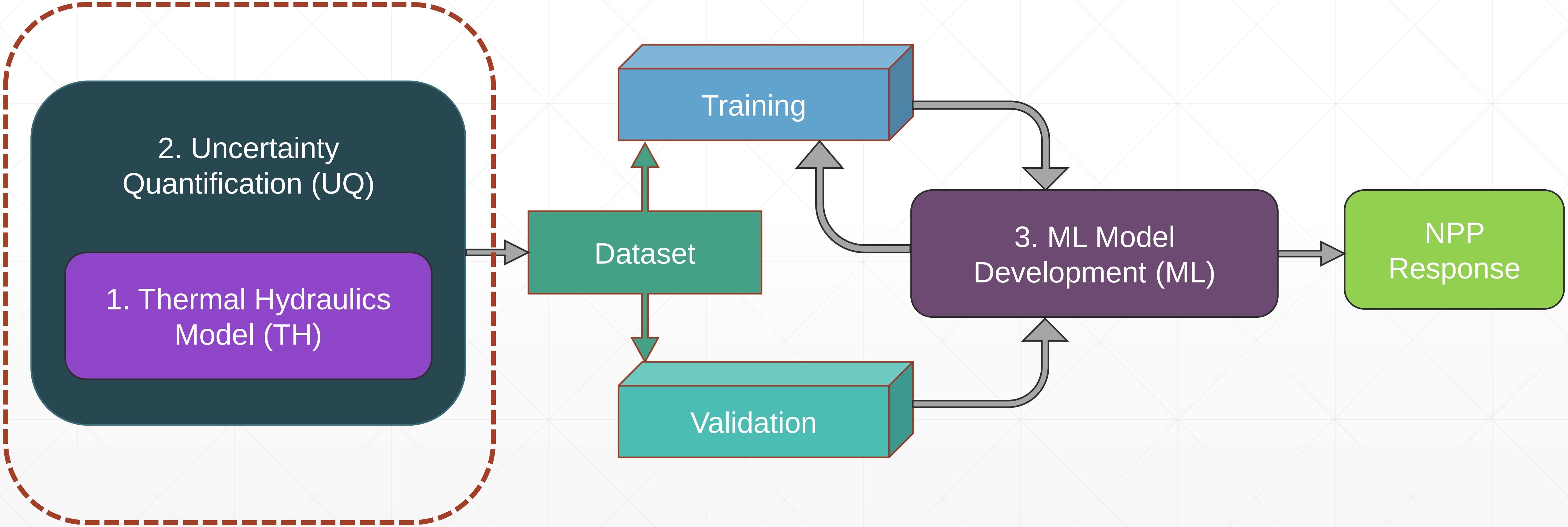
*APR-1400 Design Control Document, Tier 2, Chapter 15, "Loss-of-Coolant Accidents Resulting from the Spectrum of Postulated Piping Breaks within the Reactor Coolant Pressure Boundary" (APR1400-K-X-FS-13002, Revision 0, September 2013)

TH

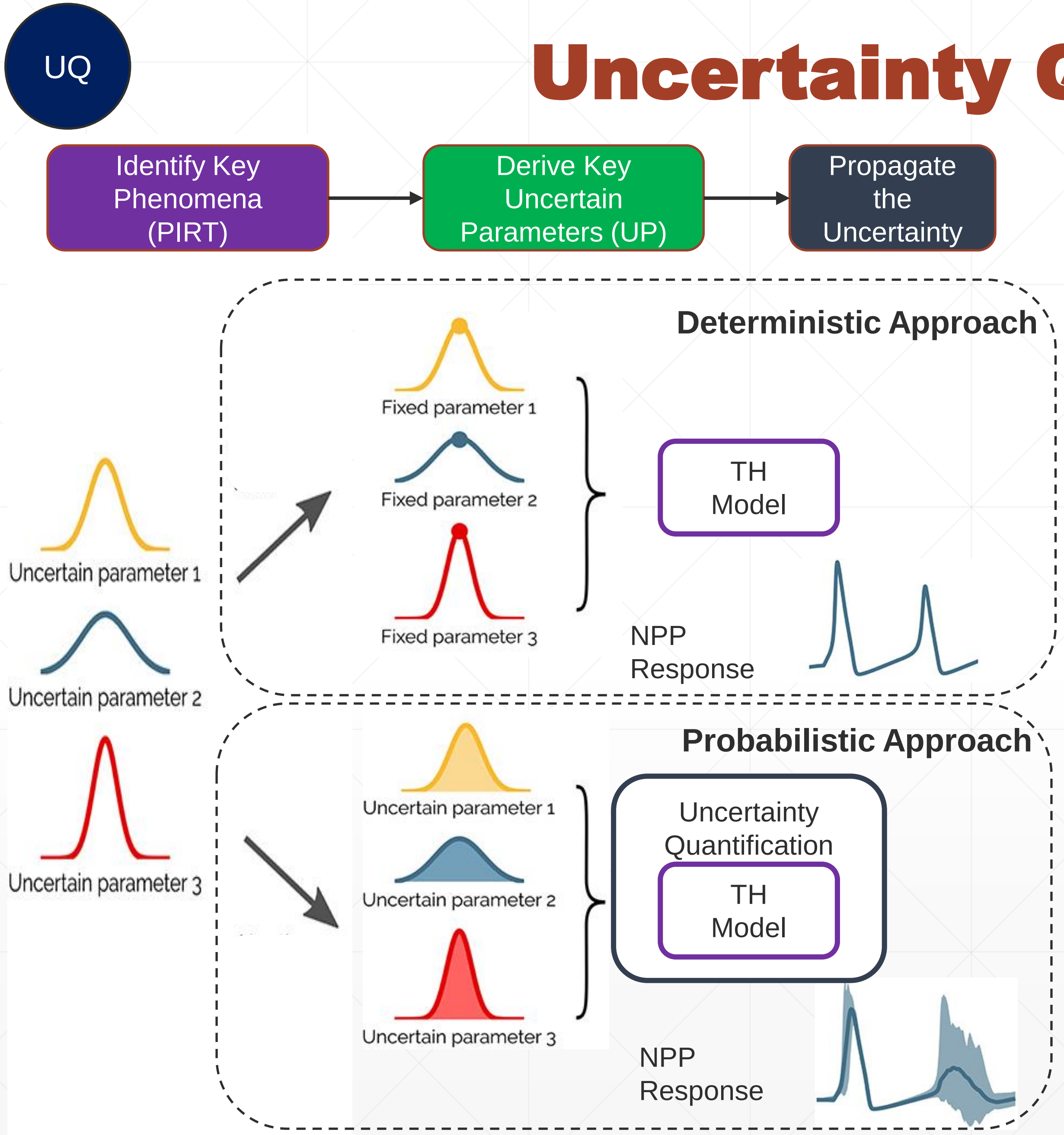
Thermal-Hydraulic Model
NPP Response



Methodology



Uncertainty Quantification*

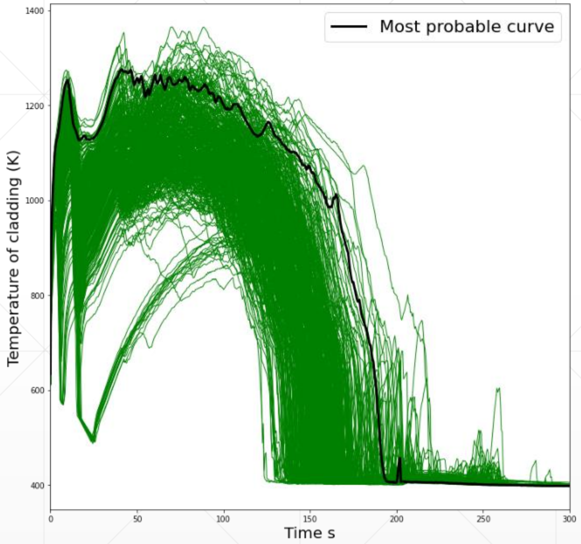


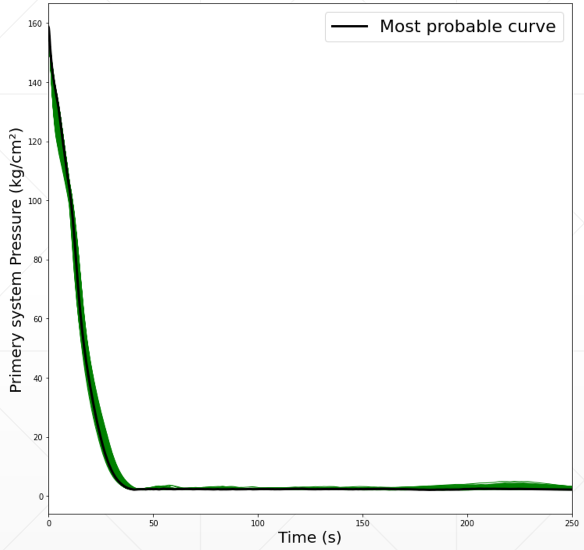
#	Parameter Description	Mean, μ	PDF	Standard deviation, σ	Range, L_{high}-L_{low}
1	Core power	1.0	Normal	0.01	0.98–1.02
2	Groeneveld-CHF	1.0	Normal	0.414	0.173–1.827
3	Chen nucleate boiling HTC	1.0	Normal	0.234	0.553–1.467
4	Transition boiling HTC	1.0	Normal	0.230	0.54–1.46
5	Dittus-Boelter liquid HTC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

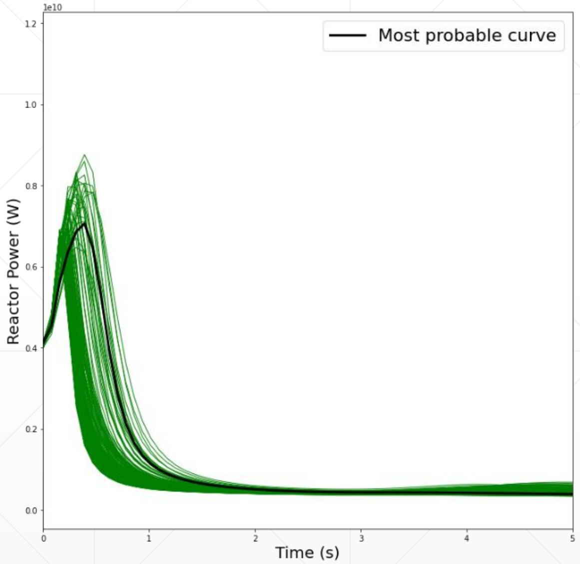
*W. Sallehhudin and A. Diab, "Using Machine Learning to Predict the Fuel Peak Cladding Temperature for a Large Break Loss of Coolant Accident," Front Energy Res, vol. 9, Oct. 2021, doi: 10.3389/fenrg.2021.755638.

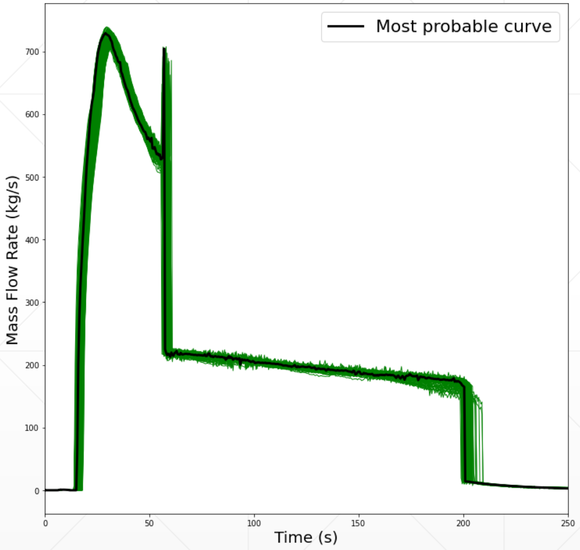
UQ

Uncertainty Quantification









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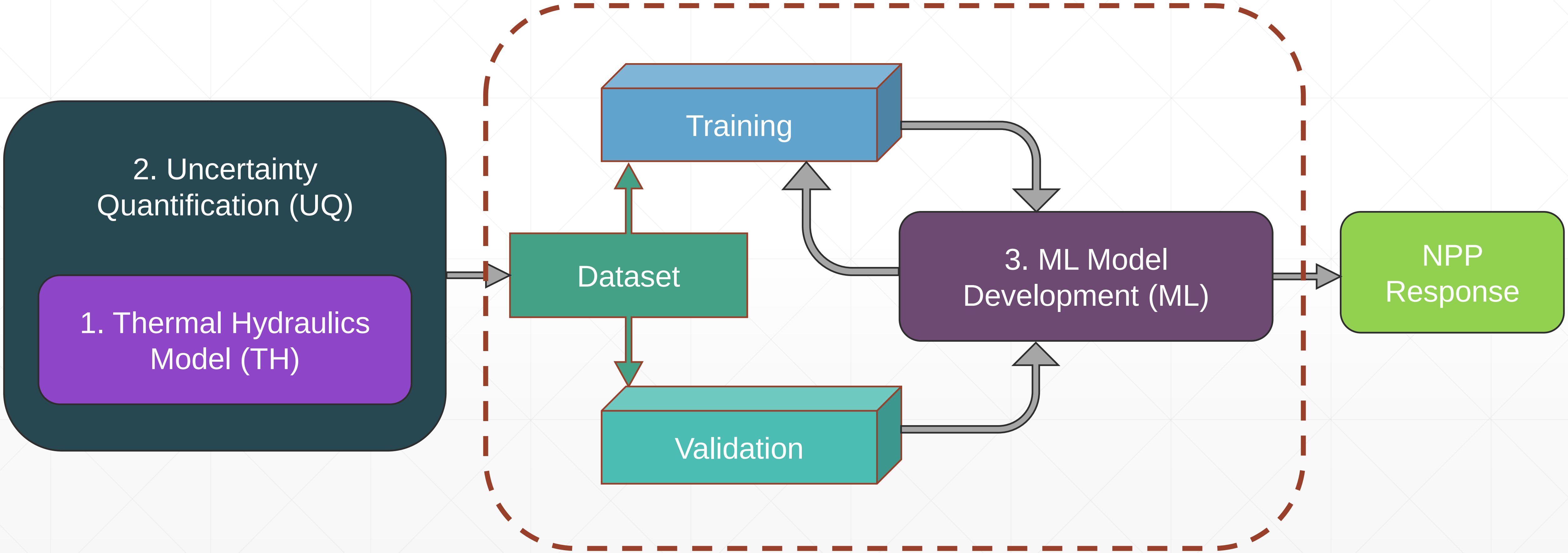
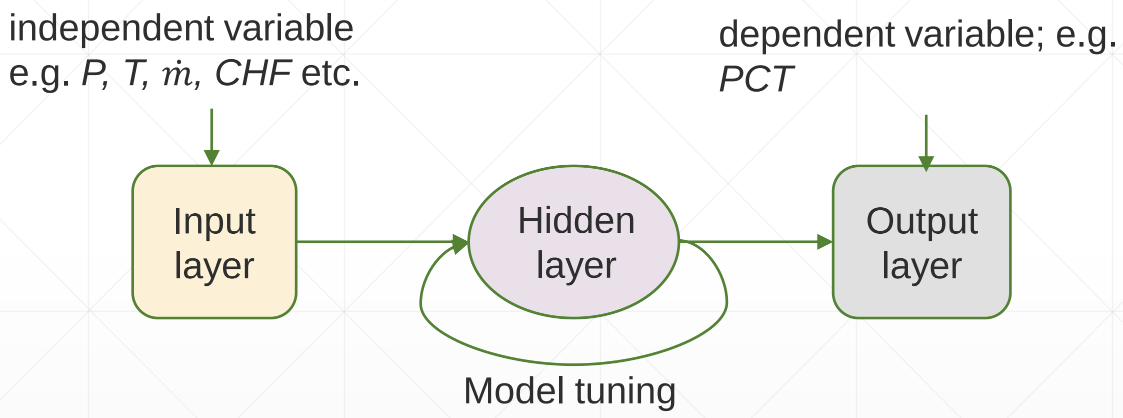
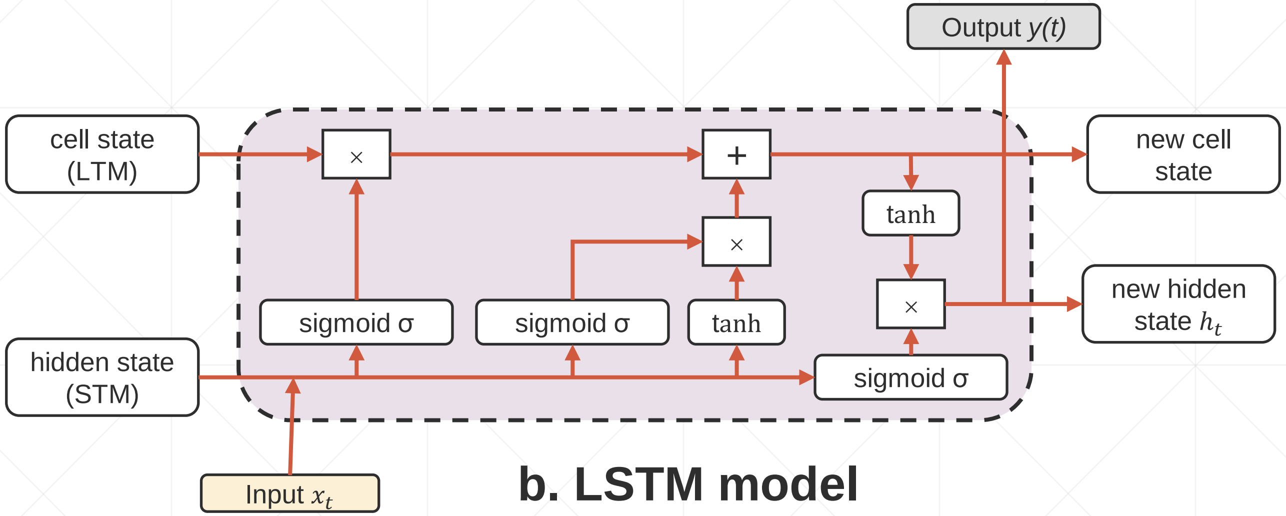


ML

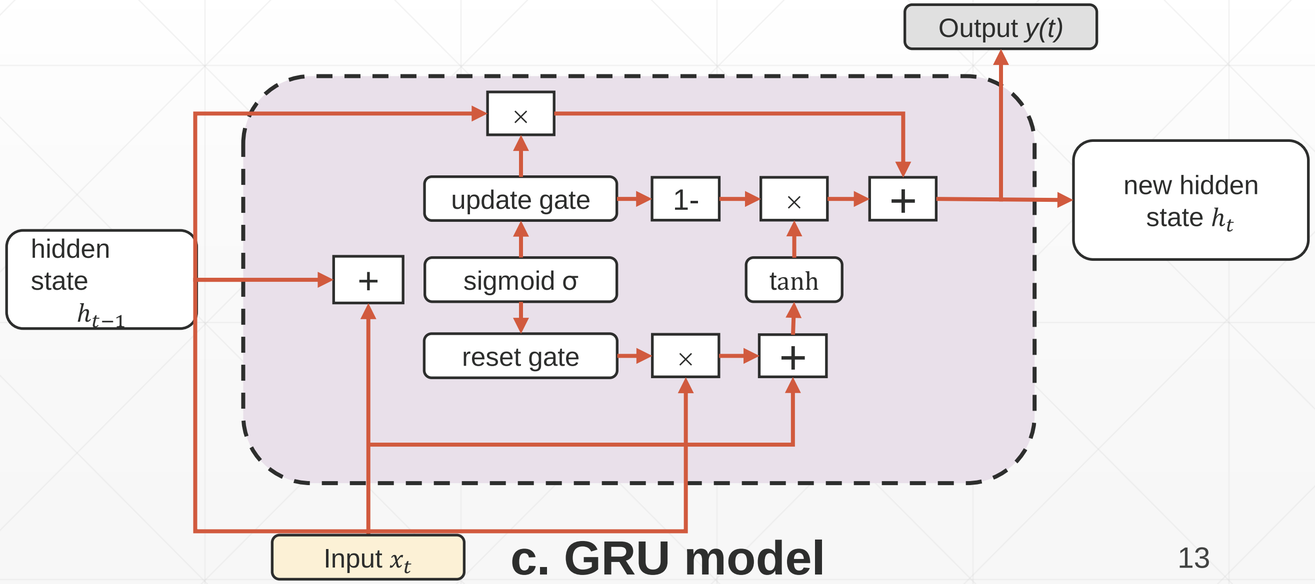
Model Development



a. Simple RNN Representation

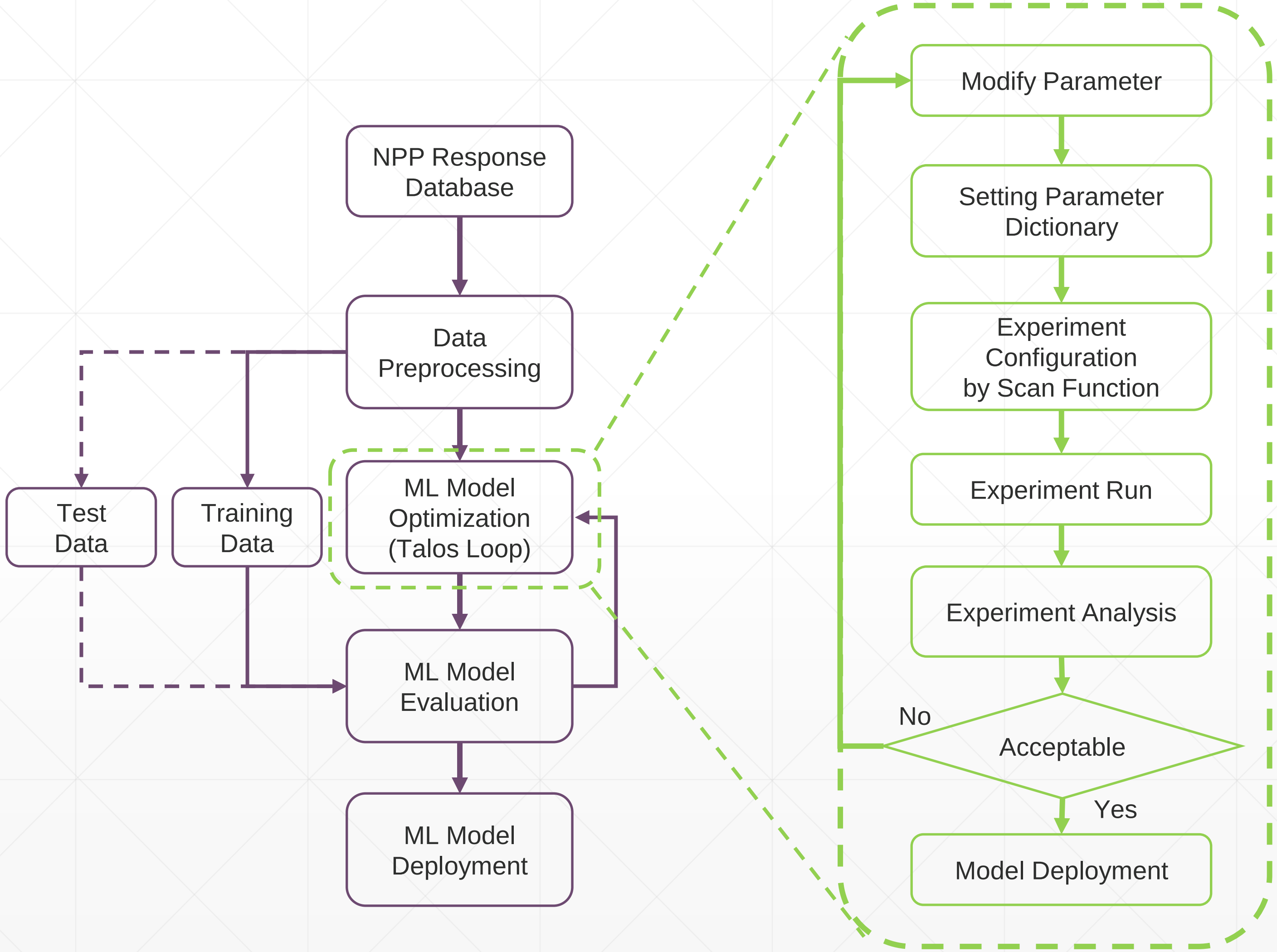


b. LSTM model



c. GRU model

ML Model Development



a. Machine Learning Model Workflow

b. Talos Loop

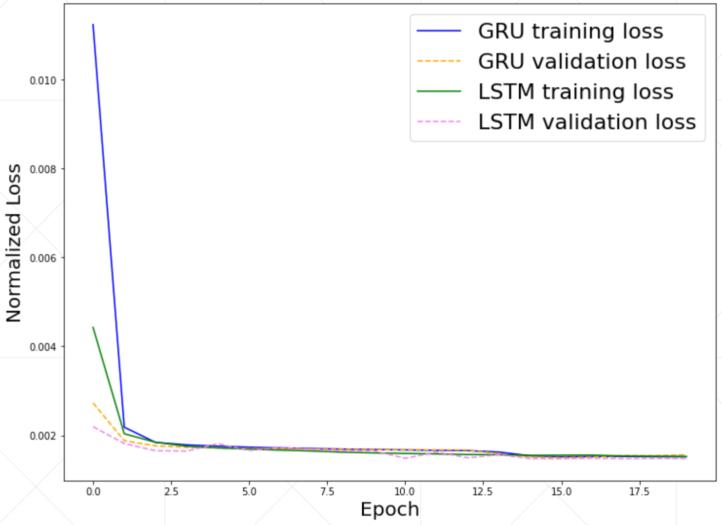
Dictionary & Optimization by Talos

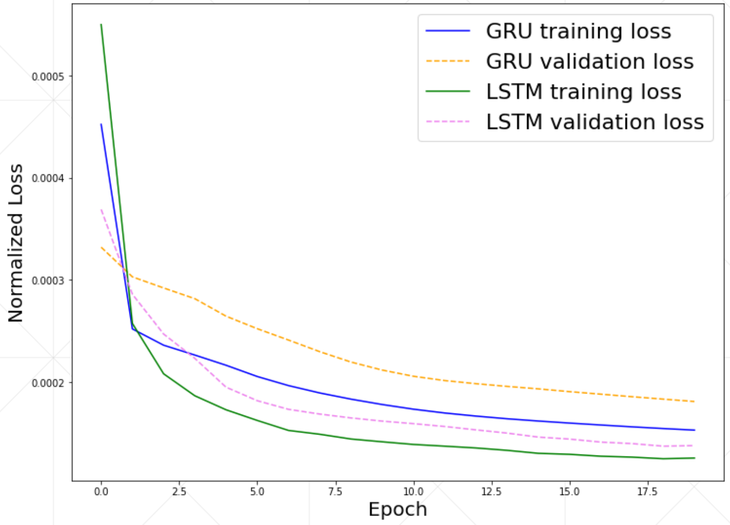
Hyper parameters dictionary	Type	Range	Optimum
Activation function	Categorical	ReLU, Tanh, Sigmoid, Softmax	Relu
Recurrent activation functions		Sigmoid, ReLU, Tanh	Relu
Optimizer		Adam, Nadam, SGD, RMSprop	Adam
Kernel regularizers	Numerical	$1x10^{-4}$, $1x10^{-5}$, $1x10^{-6}$	L1($1x10^{-6}$)
First Neuron		10-50	13
Hidden layers		1-3	1
No neurons hidden lyer		13-100	26
Batch size		64-200	64
Epoch		10-100	20
Dropout		0.01-0.1	0
Learning rate		0.0001-0.01	0.01

ML

ML Model Performance

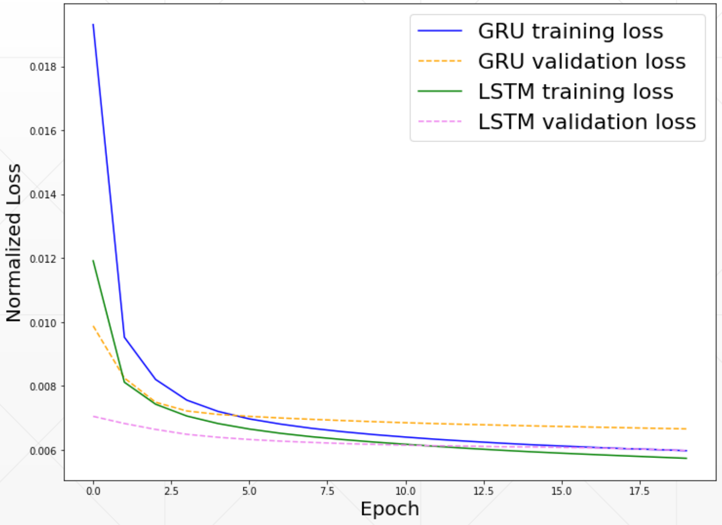
Primary System Pressure

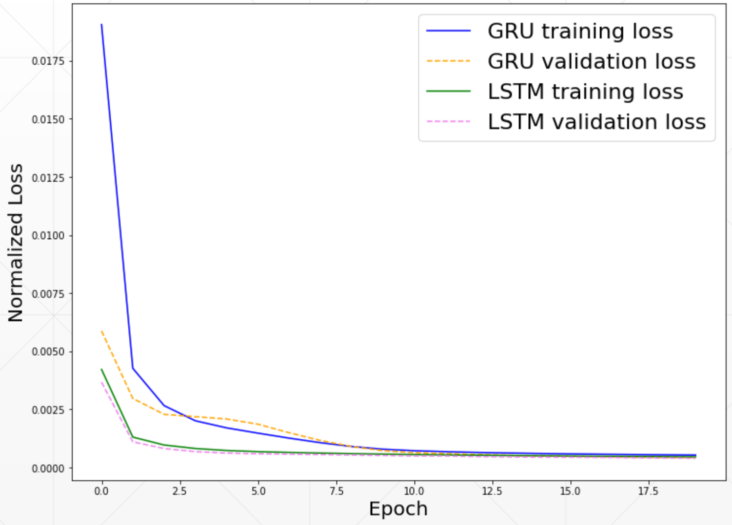




Reactor Power

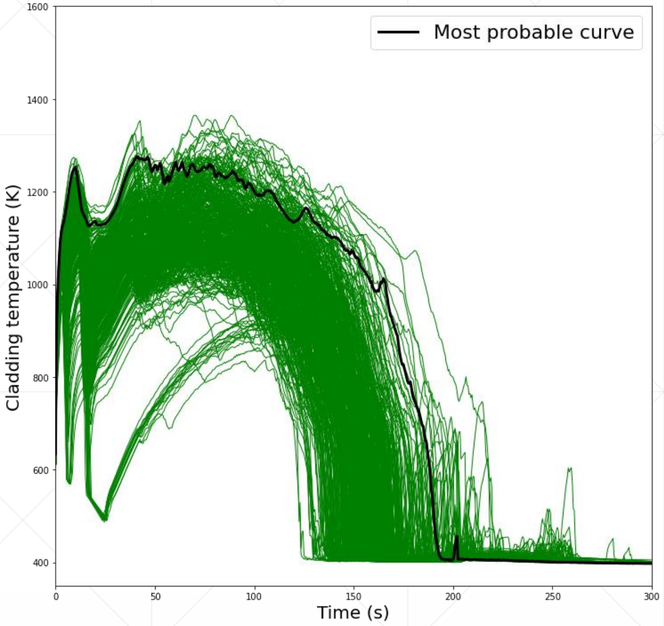
PCT



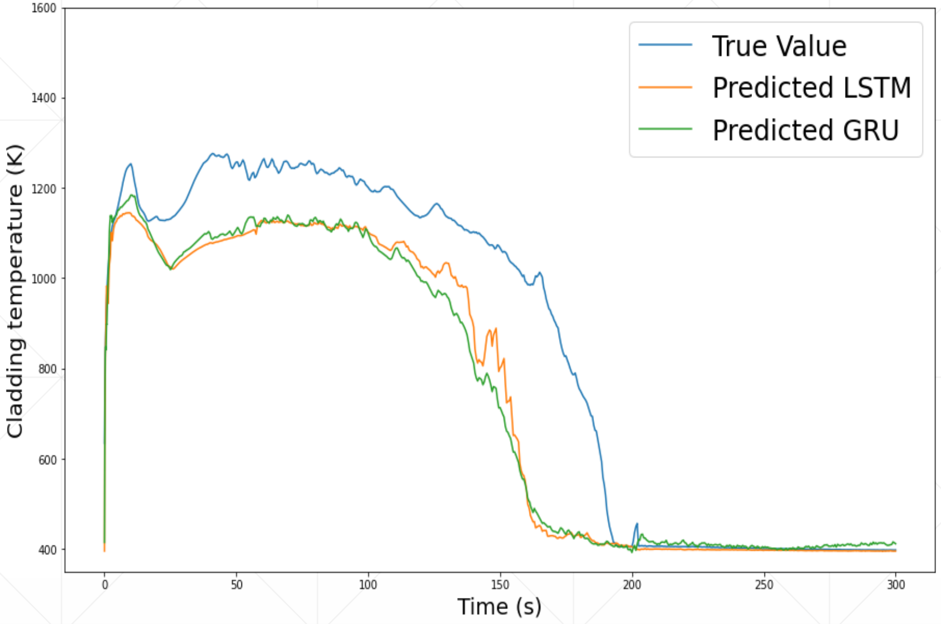


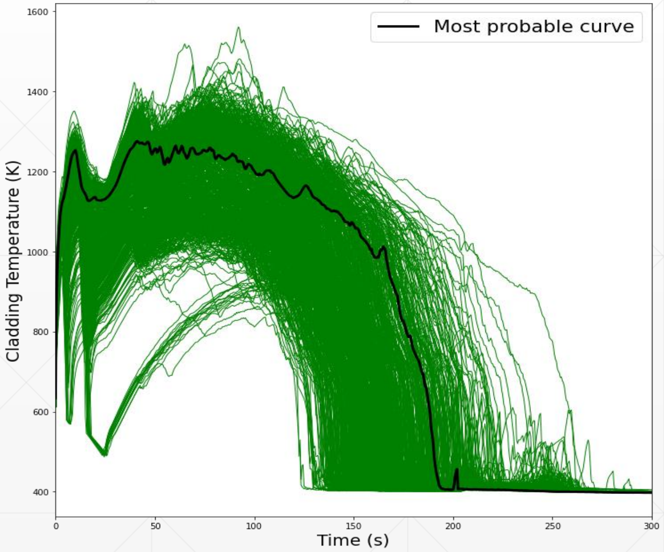
SIT

ML Model Performance

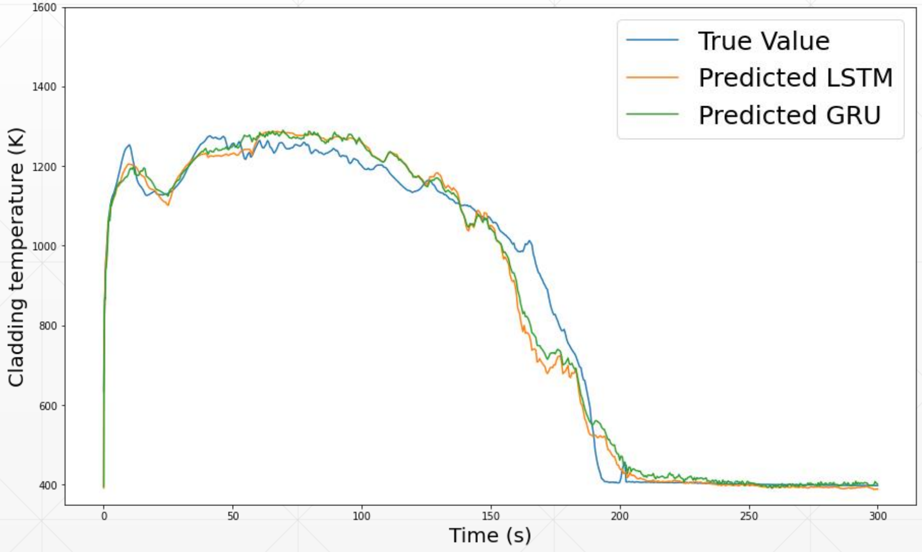


Original dataset





Dataset with over-sampling

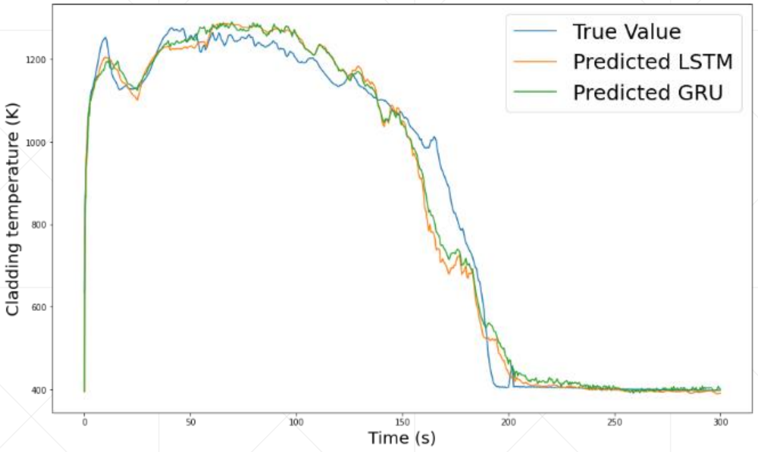


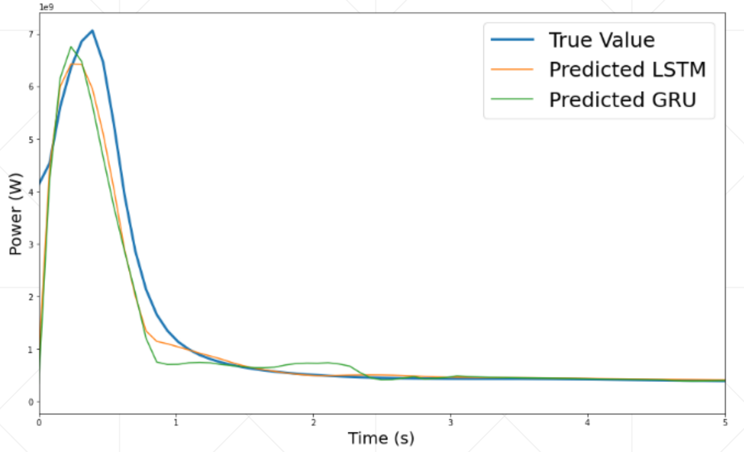
ML

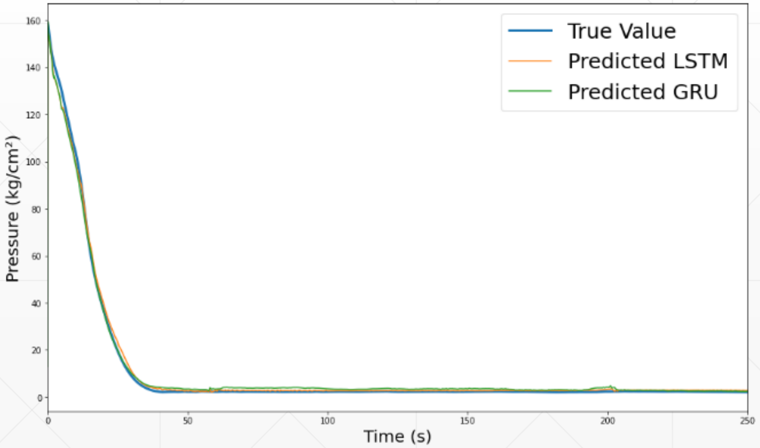
ML Model Prediction Results

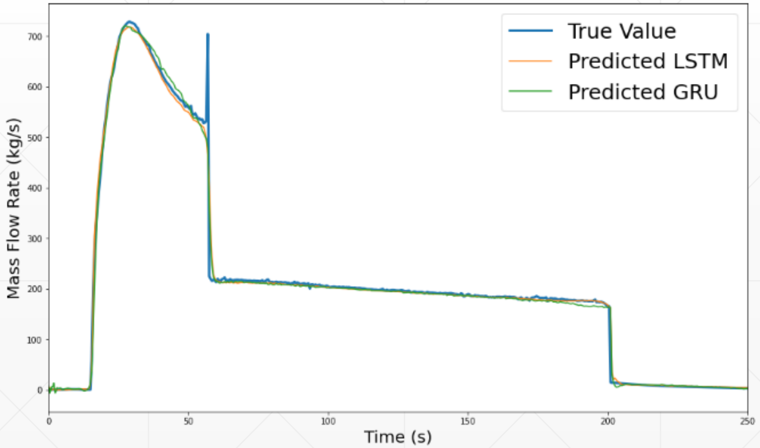
ML MODEL EVALUATION METRICS

Parameter	ML Models	RMSE	MAE	R^2
PCT	GRU	0.043	0.027	0.980
	LSTM	0.047	0.028	0.976
Pressure	GRU	0.039	0.012	0.980
	LSTM	0.039	0.011	0.980
SIT	GRU	0.019	0.007	0.994
	LSTM	0.019	0.005	0.994
Power	GRU	0.012	0.003	0.899
	LSTM	0.011	0.002	0.920









Conclusions

- In this work, the LOCA accident scenario was investigated using a physics-based approach (TH model) and a data-driven approach (ML model).
- An uncertainty quantification framework was developed to assess the uncertainty in the NPP response under the 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.
- Developed Machine learning model predicted NPP response under accident conditions with reasonable accuracy. ML model is currently being tuned to further enhance its performance.
- This research is aimed to serve as a first step towards the development of a real-time aid for operators to expedite the decision-making process under accident conditions.

Thank you!

감사합니다

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