Identification of FLEX Strategy Success Window using BEPU and AI

Korean Nuclear Society (KNS)

2020 Fall Conference

Salama Alketbi and Aya Diab

Nuclear Safety and Thermal hydraulics Lab

Department of Nuclear Power Plant

KEPCO International Nuclear Graduate School,

Republic of Korea (KINGS)

OUTLINES

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

INTRODUCTION

- **Fukushima accident revealed the vulnerabilities of:**
    - **The operational nuclear power plants**
    - **The existing approaches used to cope with an extended station blackout SBO**

- **Diverse and Flexible Strategies to provide and maintain core cooling under SBO conditions are needed.**

SBO: Station Blackout

GOAL AND OBJECTIVES

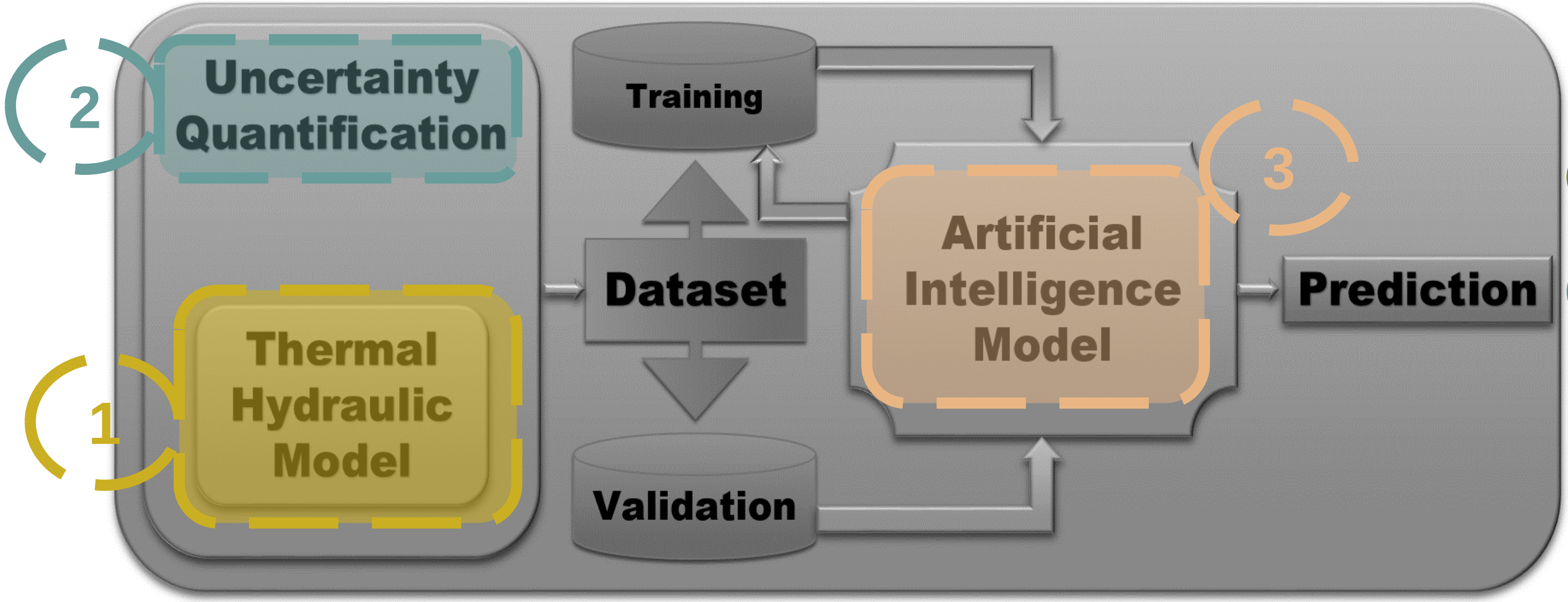
- Explores the applicability of Artificial Intelligence (AI) to identify the success window of FLEX strategy for extended SBO. To achieve it :

    - 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 success window of the FLEX strategy.

METHODOLOGY

The methodology adopted in this work involves three building blocks:

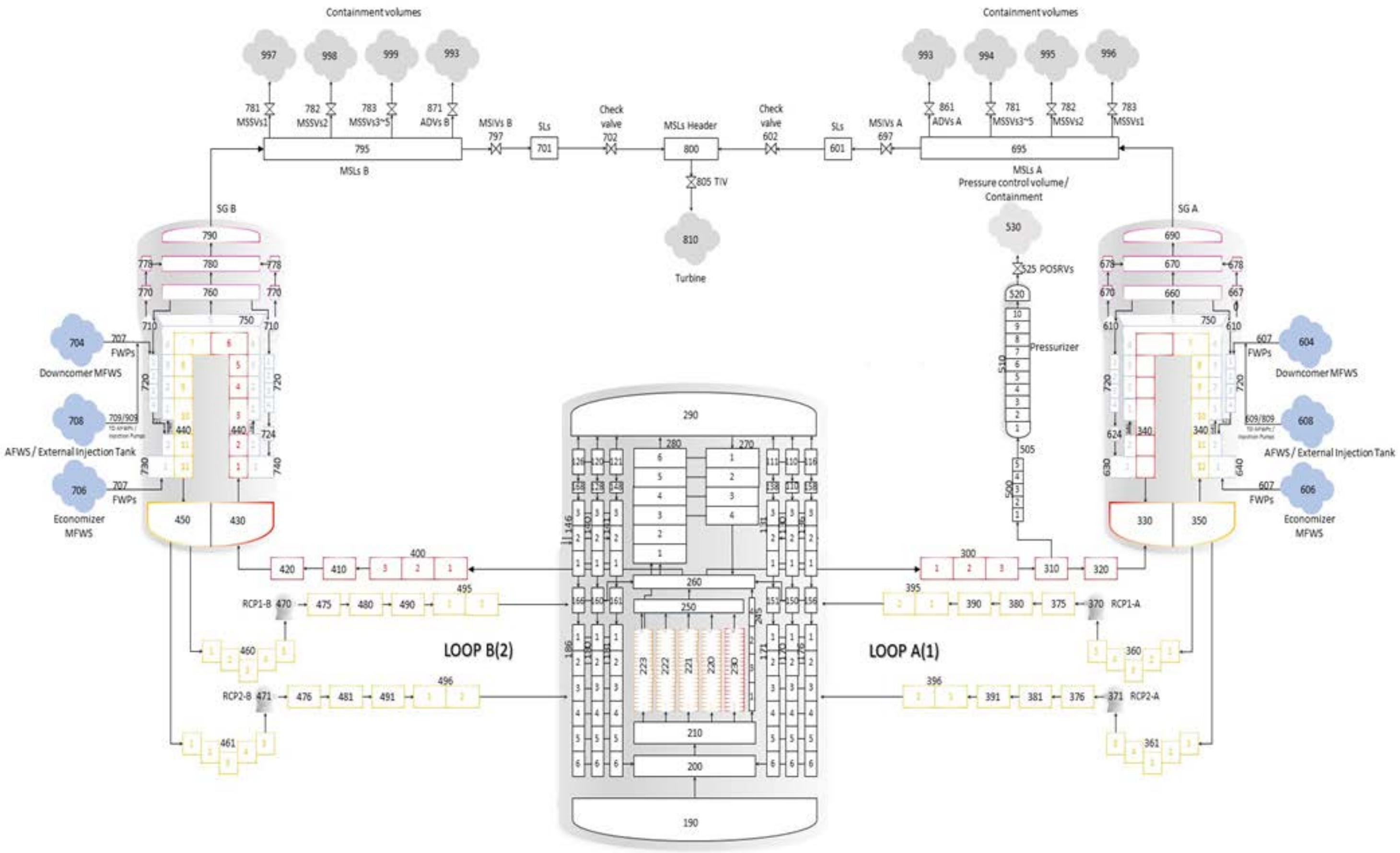


1. Thermal hydraulic Model
2. Uncertainty Quantification
3. AI Model

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 SBO Systems and Components



APR1400 Nodalization

Thermal hydraulic model development

ACCIDENT SCENARIO

At 00:00h

- Station blackout occurs
- Reactor shutdown
- TDAFWPs start

At 00:03h

- The RCP seal leakage occurs

At 00:30

- Operator opens the atmospheric dump valve (ADV)

At 02:00

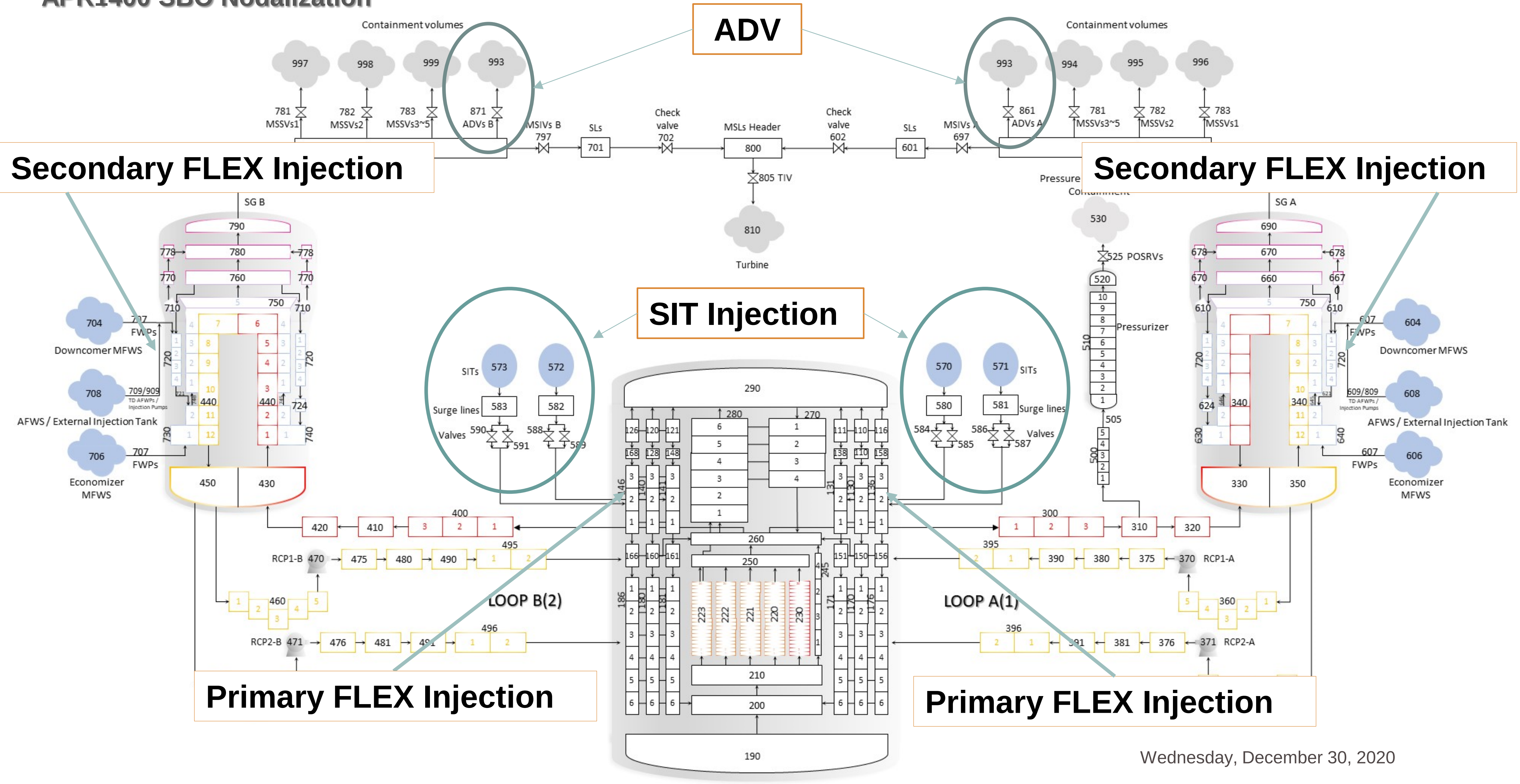
- FLEX pumps aligned
- FLEX pumps start injection when shutoff pressure reached

At 08:00h

- Batteries are lost
- TDAFWPs stop
- FLEX strategy assumed successful if the system copes with the accident for a mission time of 72 hrs

TDAFWP: Turbine Driven Auxiliary Feedwater Pump
RCP: Reactor Coolant Pump

APR1400 SBO Nodalization

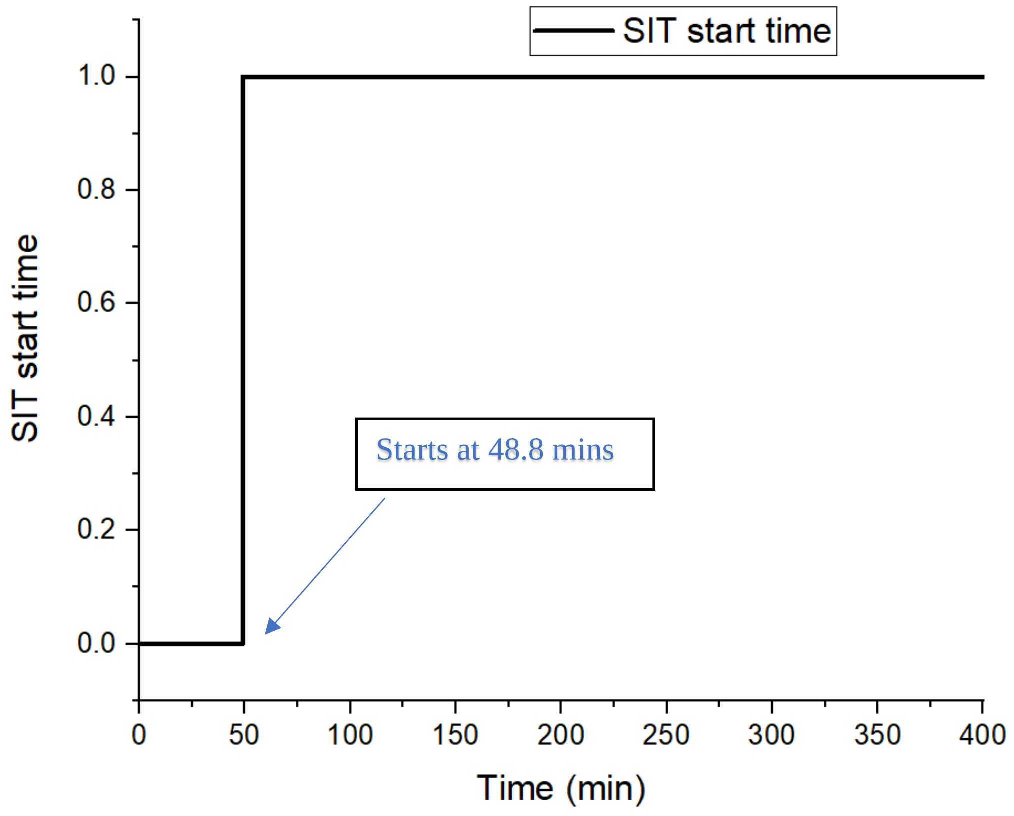


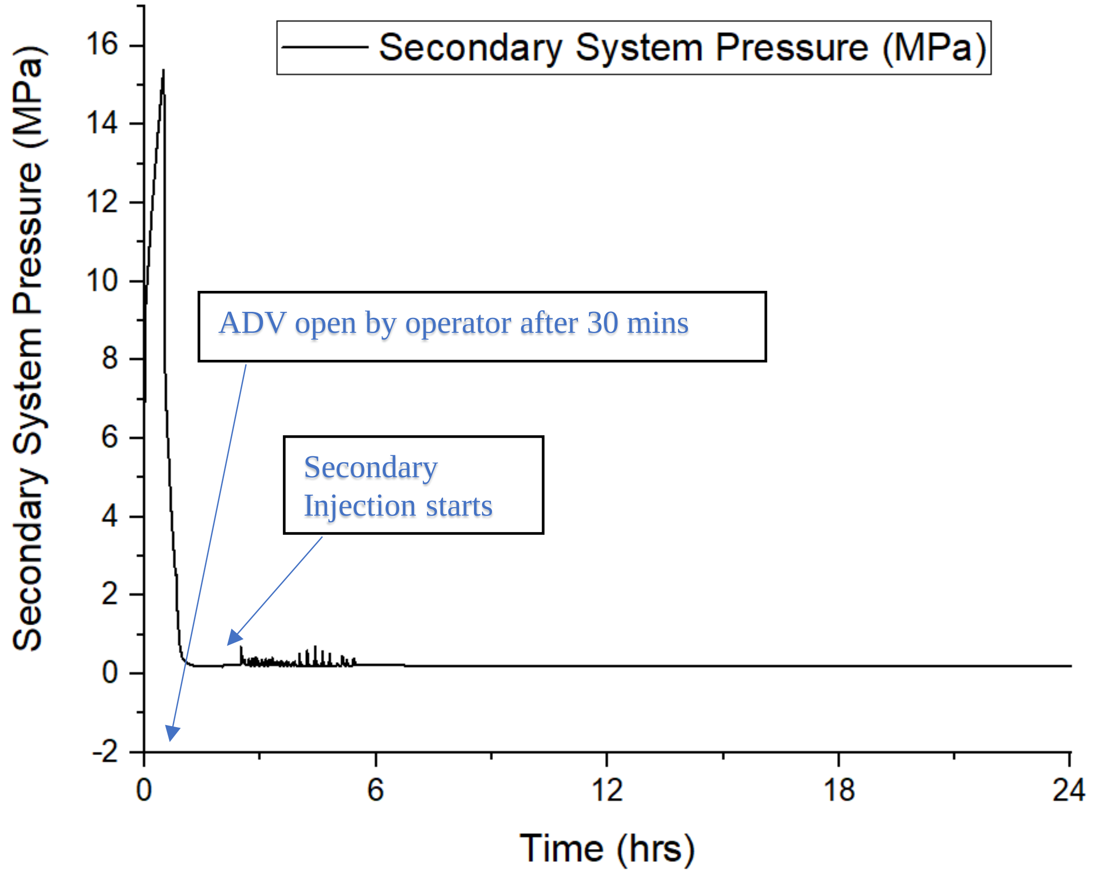
Thermal hydraulic model development

BASE CASE VALIDATION - Steady State

Parameter	DCD	SBO Model
Reactor Power (MWt)	3,983.00	3,983.00
Primary Pressure (MPa)	15.50	15.50
Secondary Pressure (MPa)	6.90	6.94
Hot Leg Temperature (K)	597.00	598.63
Cold Leg Temperature (K)	564.00	565.93
RCS Mass Flowrate (kg/s)	20,992.00	20,995.00

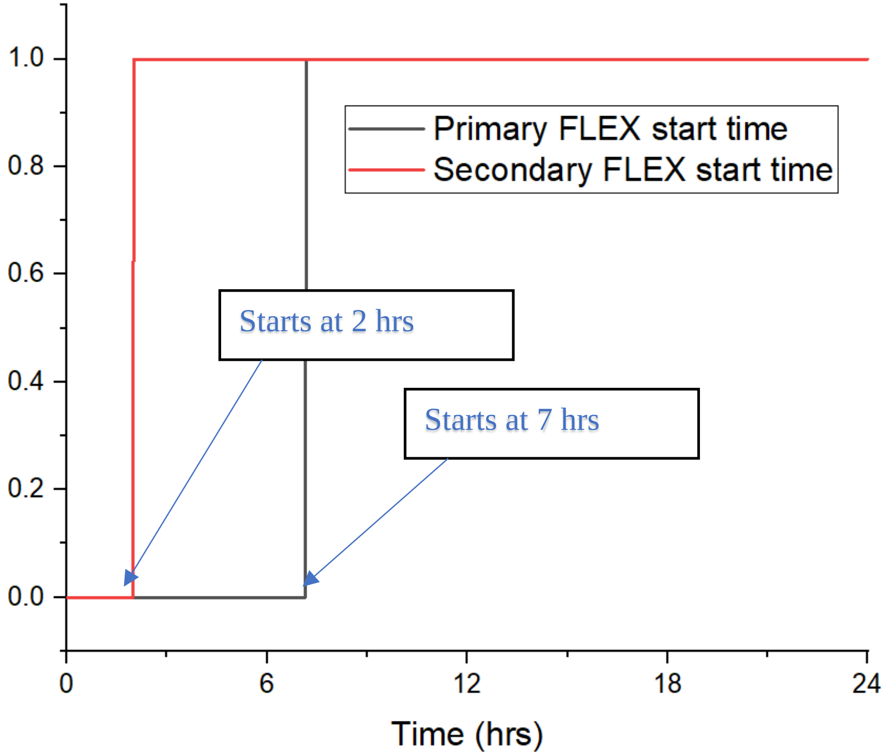
Thermal hydraulic model development





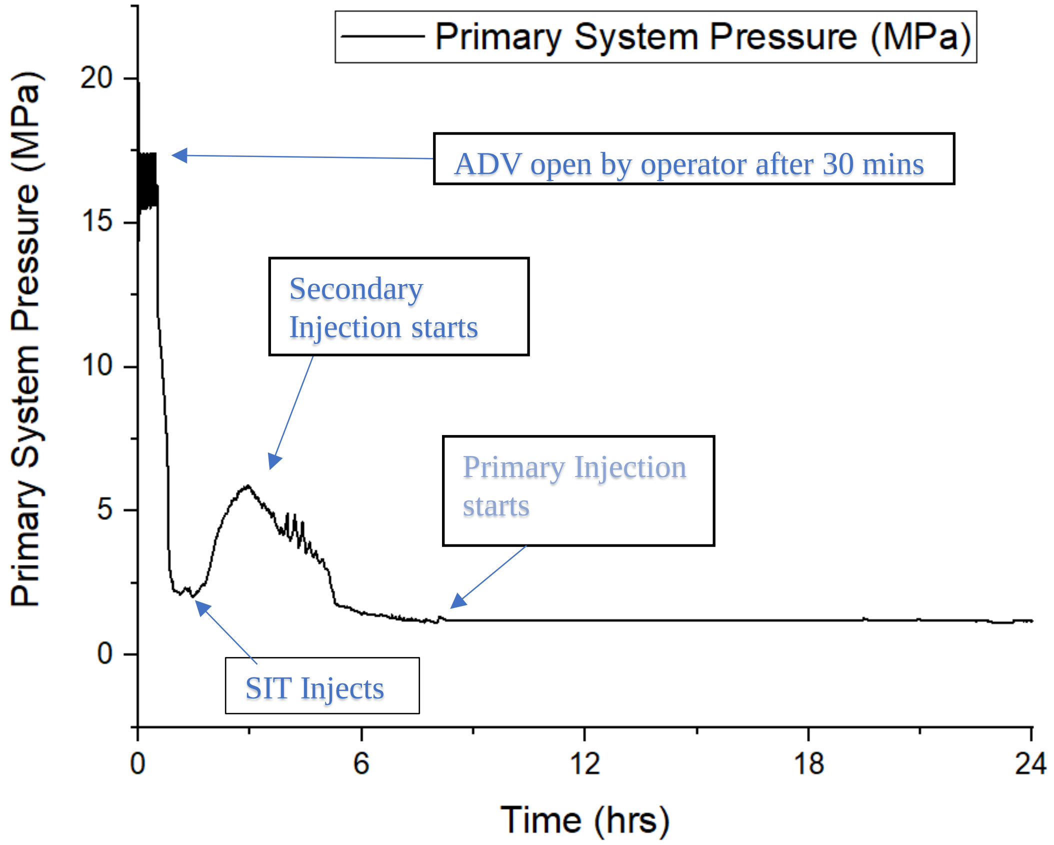
BASE CASE VALIDATION - Transient

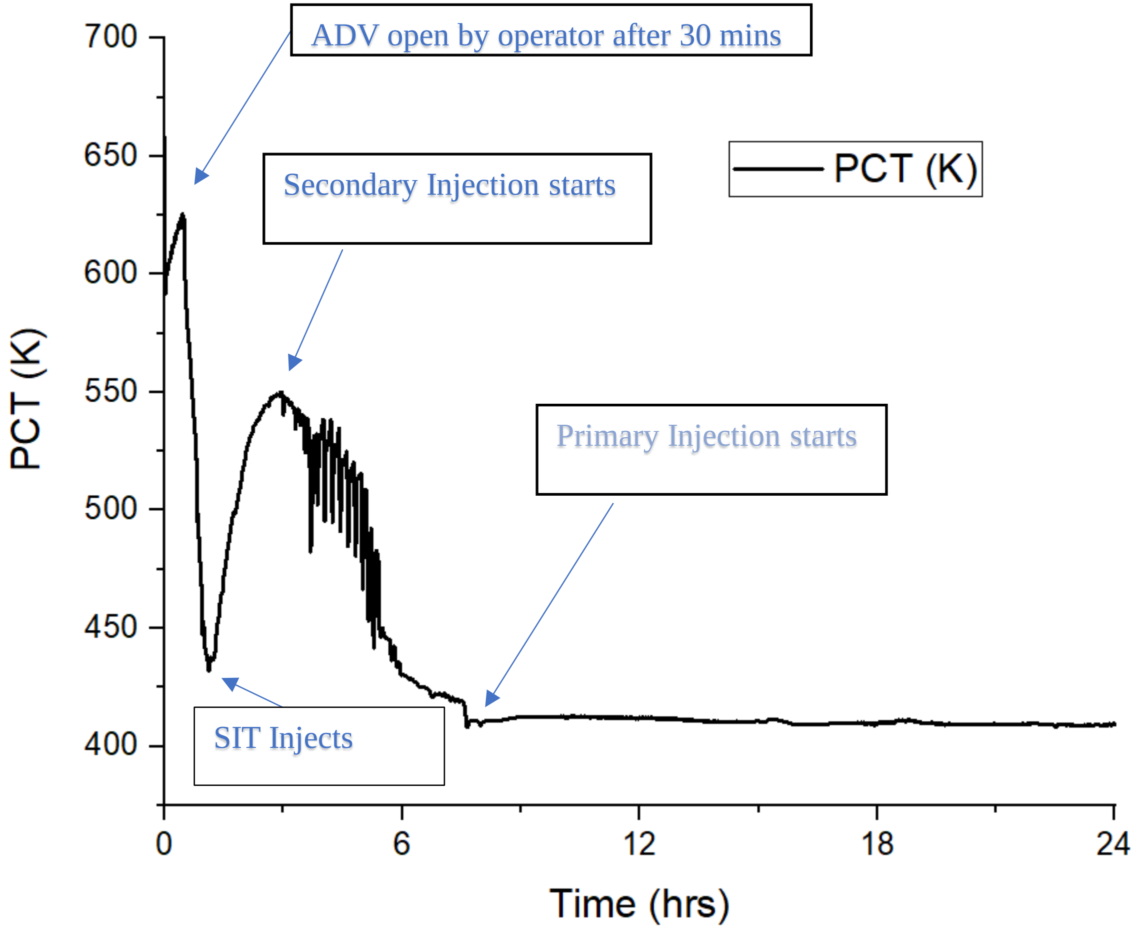
Thermal hydraulic model development



BASE CASE VALIDATION - Transient

Thermal hydraulic model development





BASE CASE VALIDATION - Transient

Development of uncertainty quantification framework

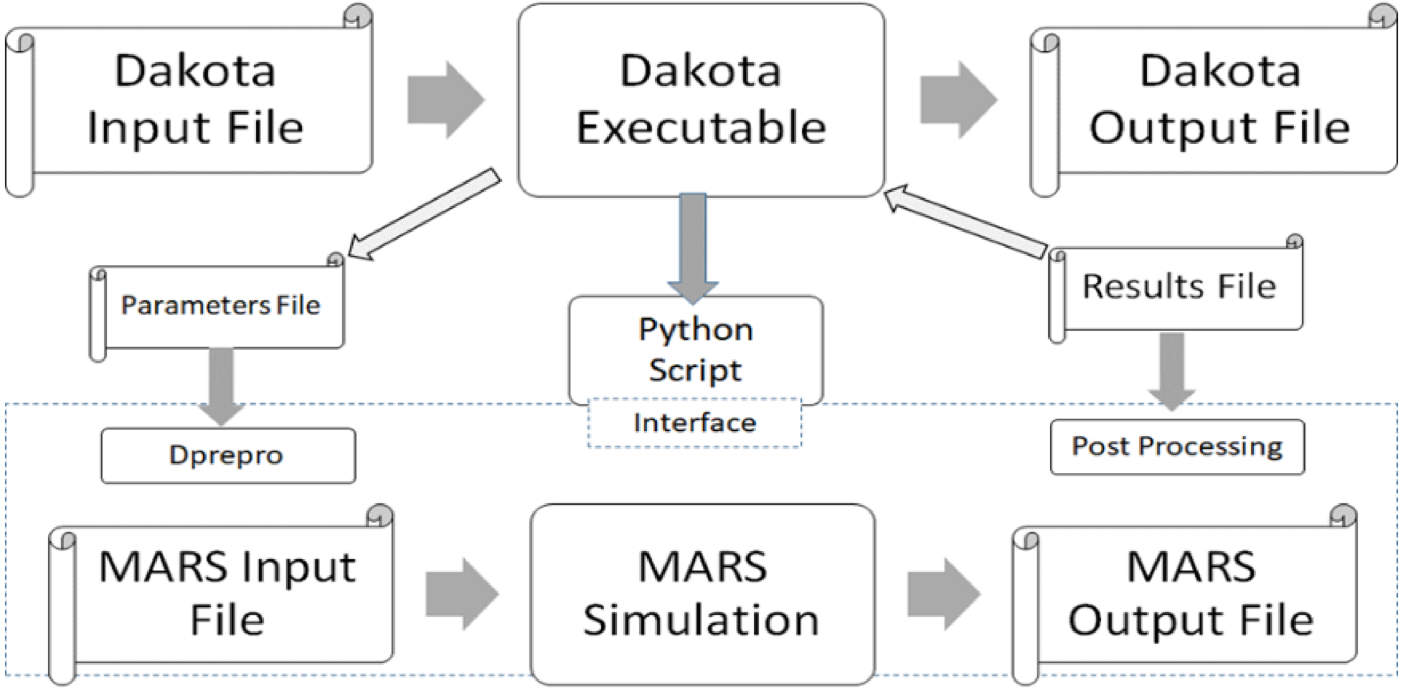
First	**Identifying input uncertainties**
Second	**Propagating these uncertainties through a computational model (MARS-KS)**
Third	**Performing statistical assessments on the resulting responses**

Uncertainty parameters

Phenomenon	Uncertain Parameters	Range	Distribution
Core Thermal Power	Reactor Power	0.98-1.02	Normal
	Power of Decay Heat	0.92-1.08	Uniform
Accumulation of Energy (Primary System)	Capacity of Fuel Heat	0.98-1.02	Normal
	Fuel Thermal Conductivity	0.90-1.10	Normal
Pressure Control (Primary and Secondary Systems)	Initial PZR Pressure	0.974-1.026	Uniform
	POSRV Set-point	0.982-1.017	Normal
	Initial Secondary Pressure	0.974-1.026	Uniform
Removal of Heat /Transfer (Primary and Secondary Systems)	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
Flow of coolant (Primary System)	Initial Total Mass Flow	0.95-1.05	Uniform
	Total Moment of Inertia of RCPs	0.8-1.2	Normal
Coolant Injection by ECCSs (Primary System) and Mobile Pumps (Primary and Secondary Systems)	Initial Inventory of Coolant in SITs	0.88-1.12	Uniform
	Initial Pressure in SITs	0.93-1.23	Uniform
	Initial Temperature of Coolant in SITs	0.93-1.23	Uniform
	Initial Temperature in the Mobile Pumps	0.94-1.06	Uniform
	TDAFWP stop time (hour)	0 - 8	Uniform
	FLEX pumps alignment time (hour)	1 - 8	Uniform
	Seal Leakage rate (gpm)	0 - 120	Uniform

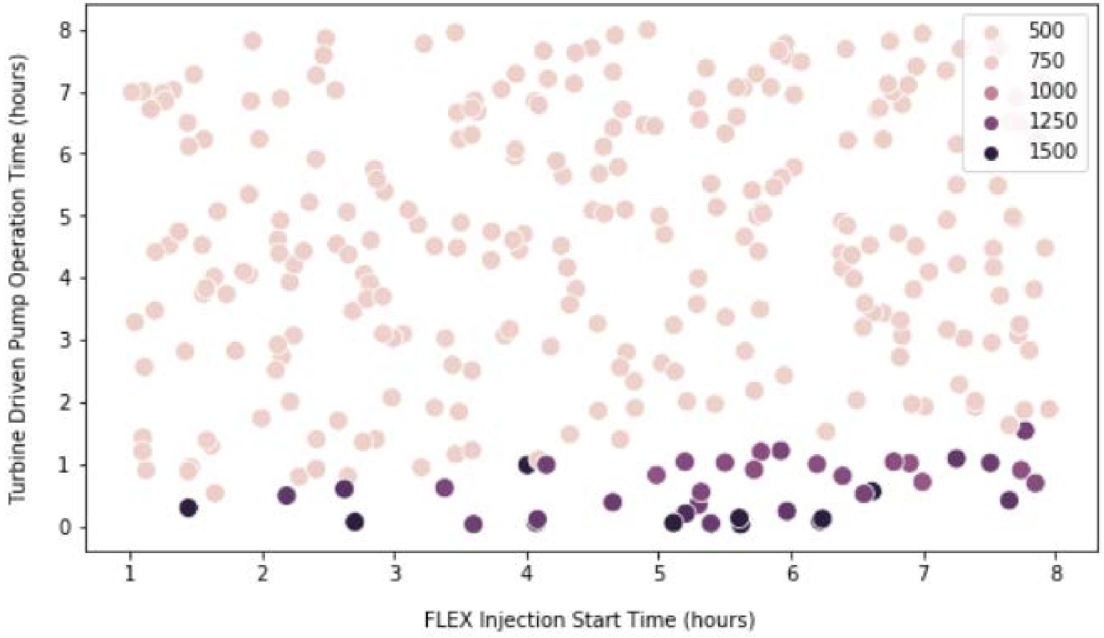
K. H. Kang, "Development of a Phenomena Identification ranking Table (PIRT) for a Station Blackout (SBO) Accident of the APR1400"

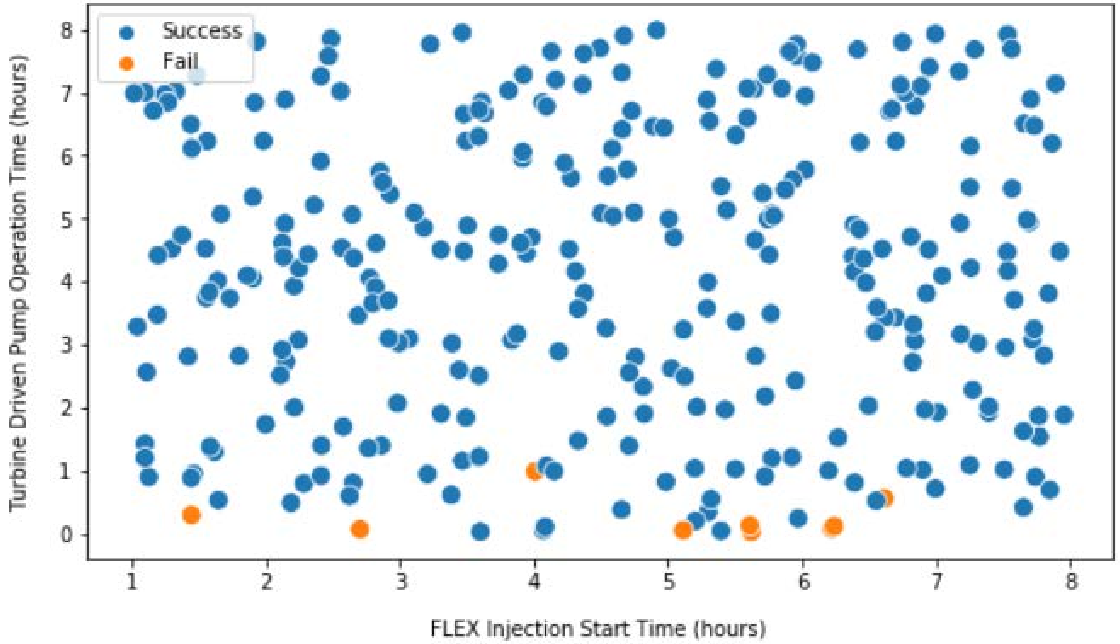
Development of uncertainty quantification framework



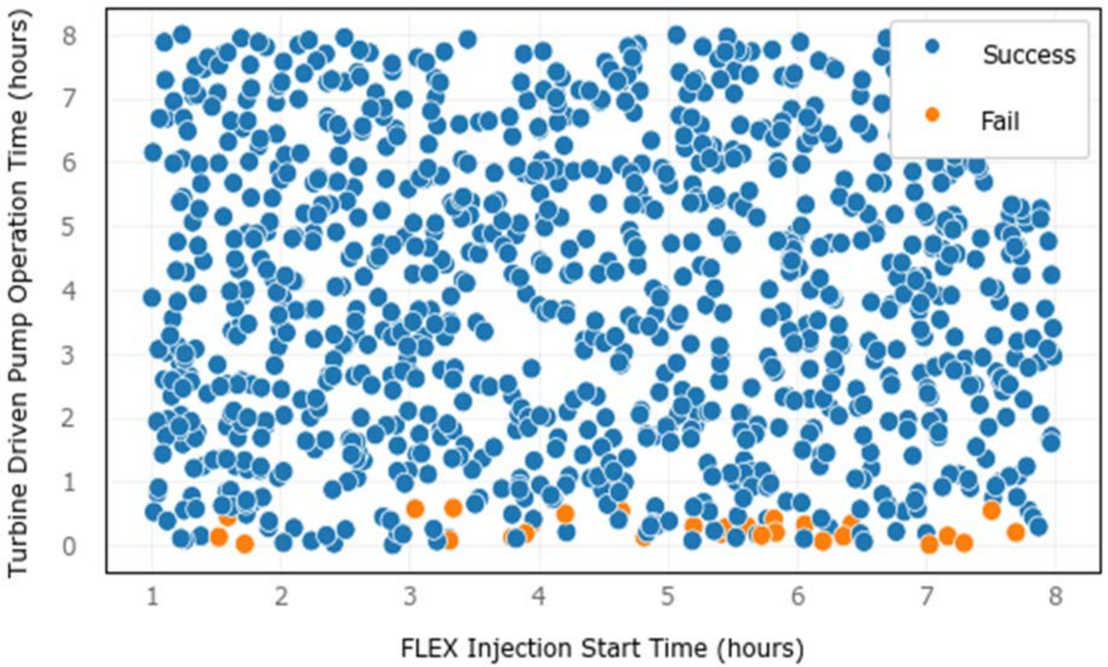
Uncertainty quantification framework

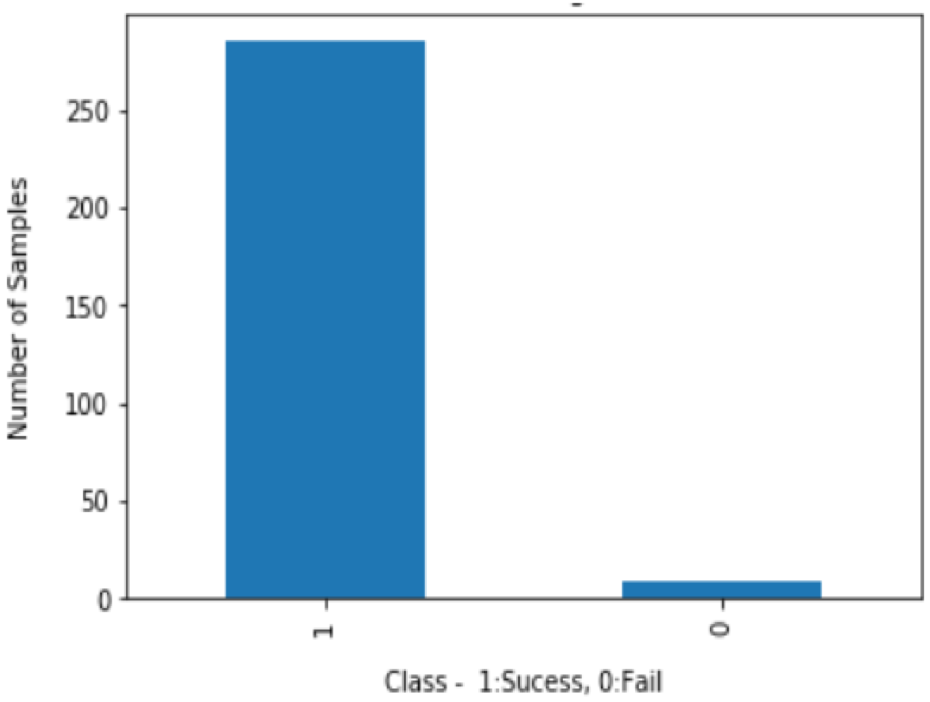
Result of the uncertainty quantification framework



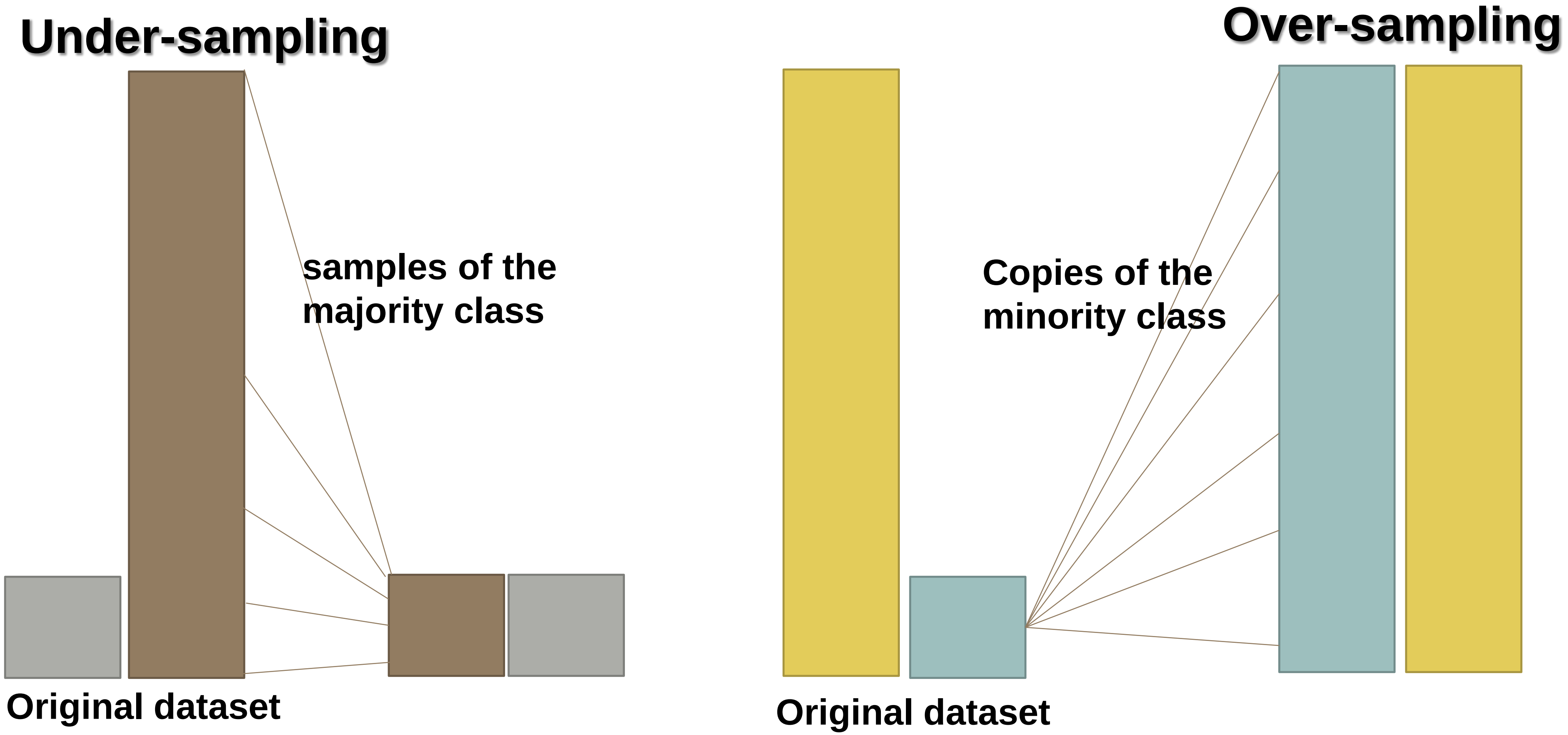


Artificial Intelligence AI Model

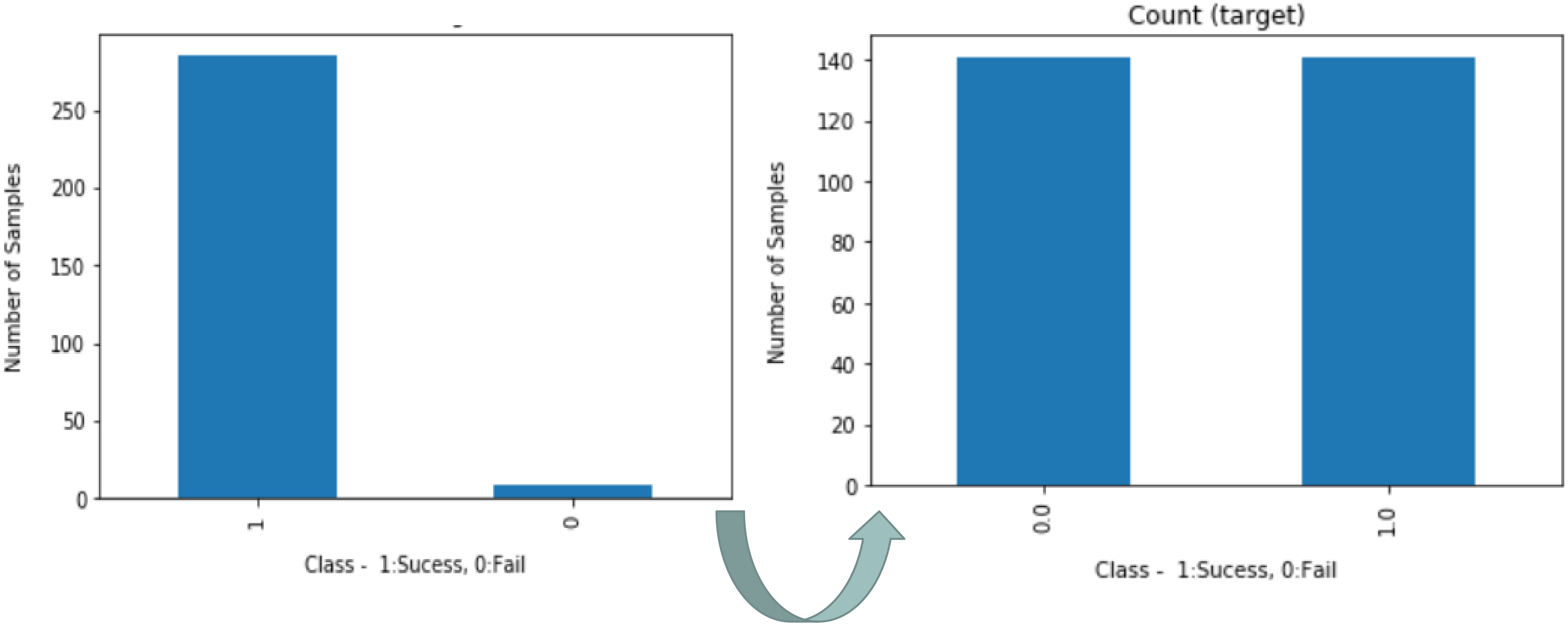




over-sampling and under-sampling



over-sampling and under-sampling



AI MODEL ARCHITECTURE

Hyperparameters dictionary

#	Hyperparameters	Search Boundary
1	Activation	elu
2	Batch size	4,8,16
3	Hidden Layer Neurons	16,32,64
6	Dropout rate	0.0 – 0.4
7	Epochs	200
8	Optimizer	Adam, Nadam
9	Last Activation	Sigmoid

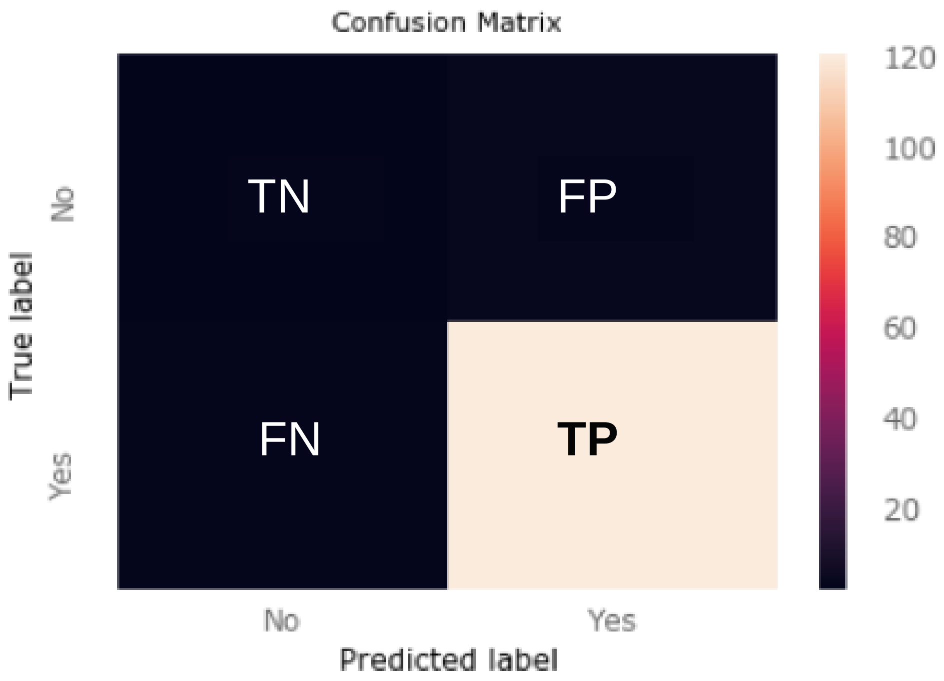
AI MODEL VERIFICATION

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)}$$

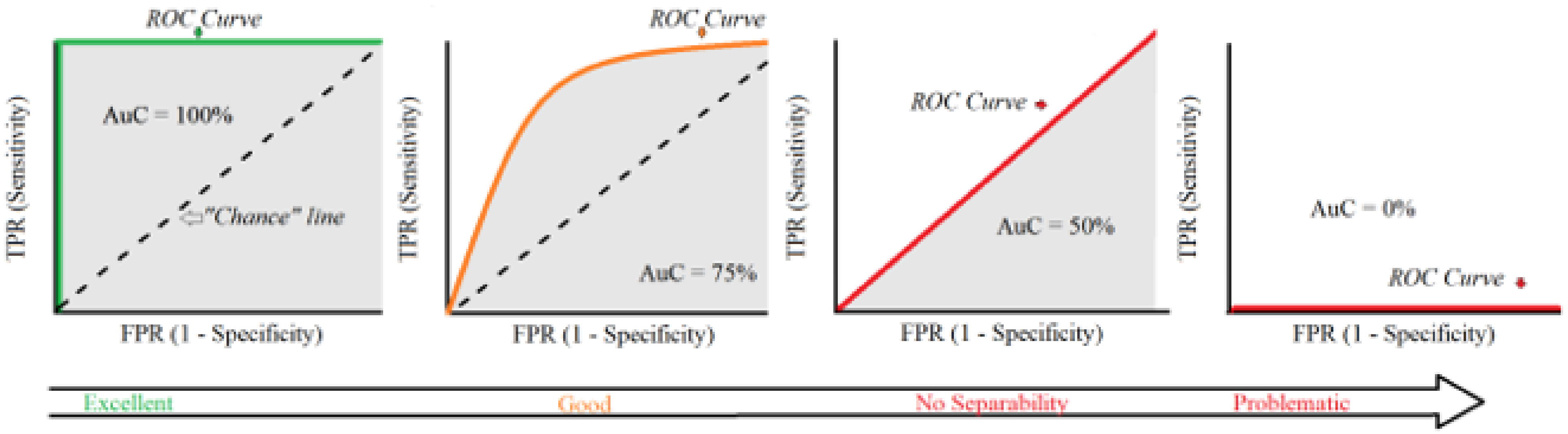
$$Precision = \frac{TP}{(TP + FP)}$$

$$Recall = \frac{TP}{(TP + FN)}$$

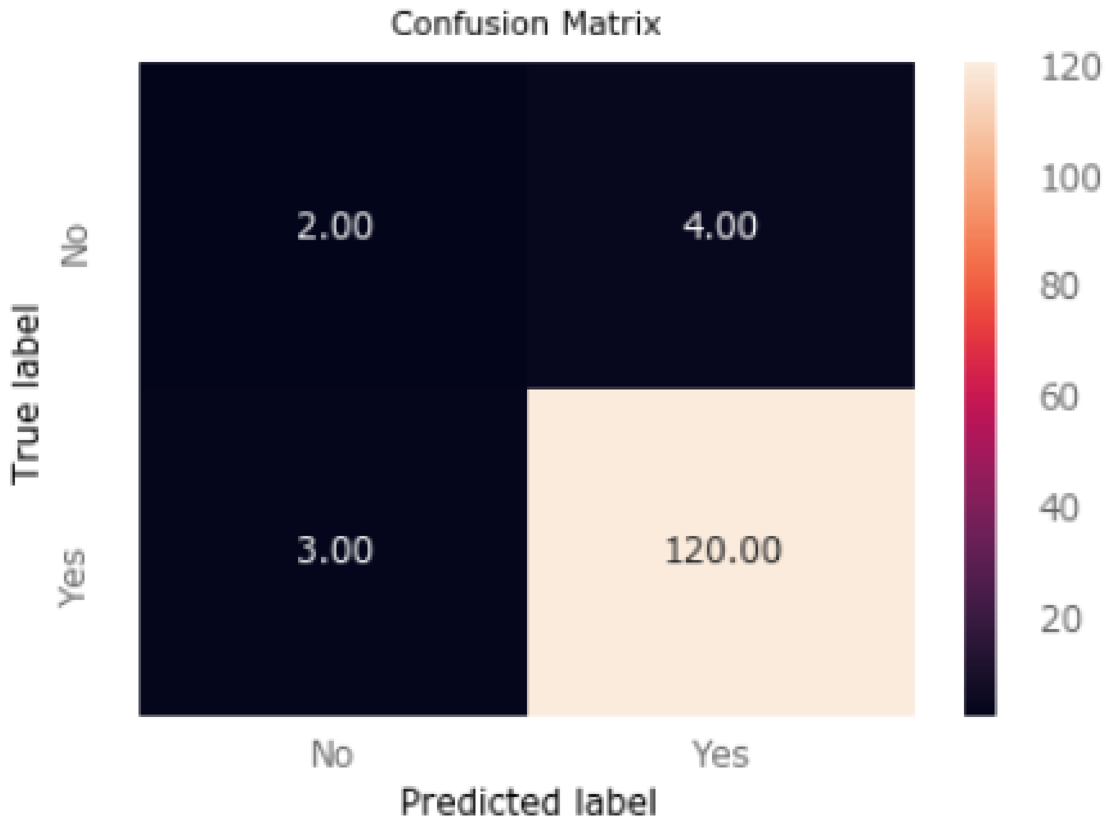
$$F1\ \text{Score} = 2\frac{Precision \times \text{Re}call}{Precision + \text{Re}call}$$



AI MODEL VERIFICATION

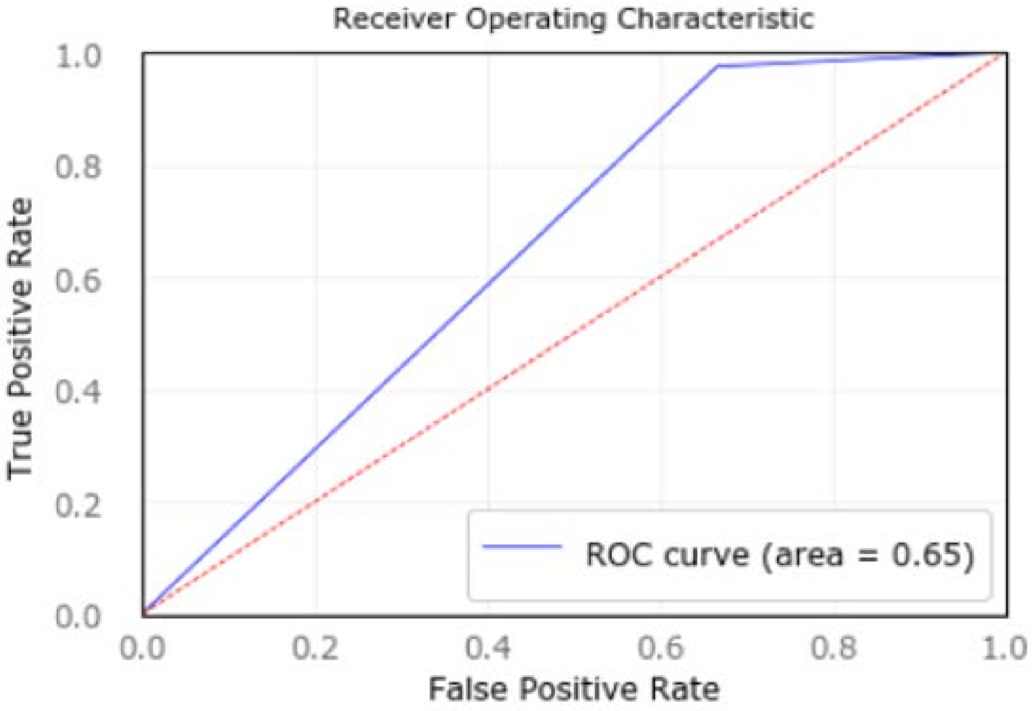


Results and Analysis (Exp-1)



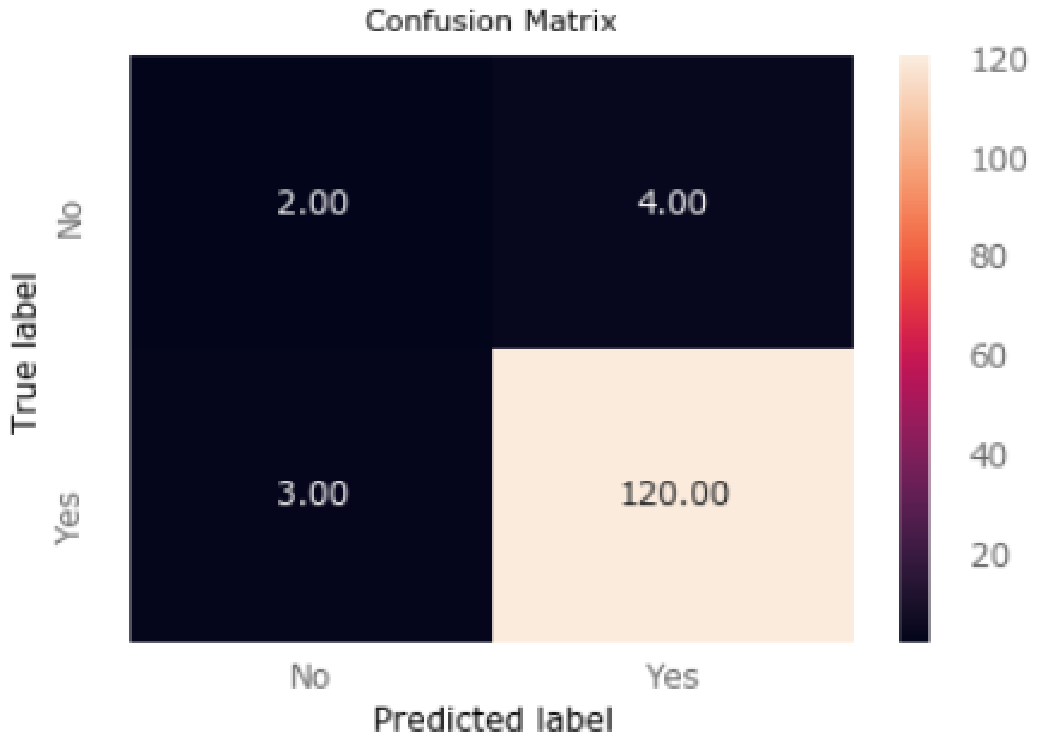
Class	Samples Count
FP	4
FN	3
TP	120
TN	2

Results and Analysis (Exp-1)

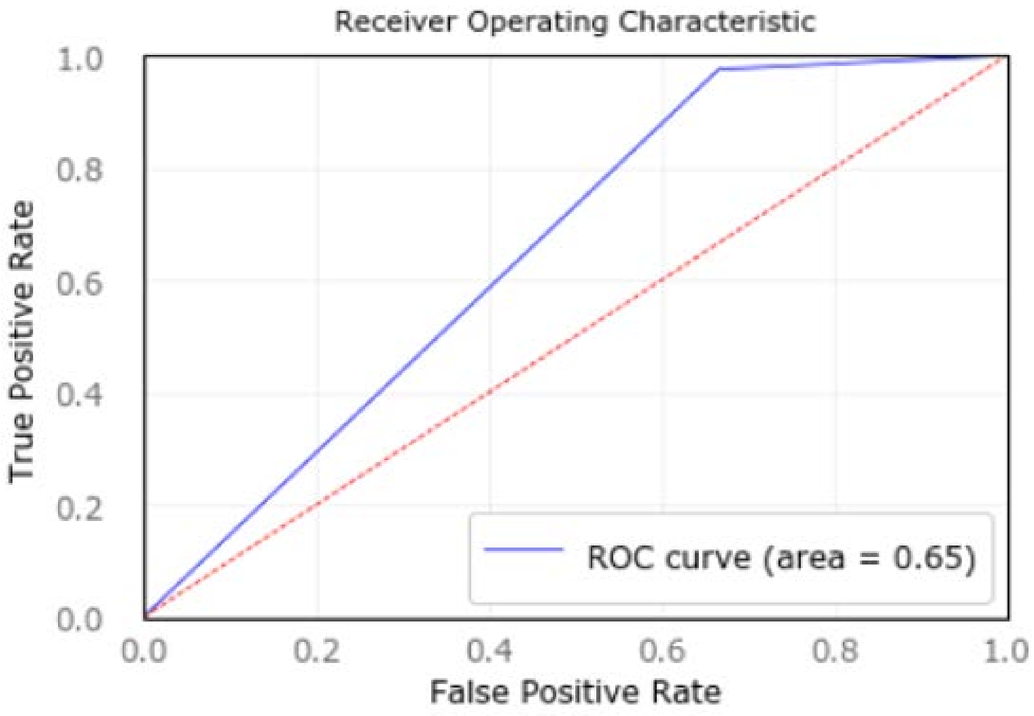


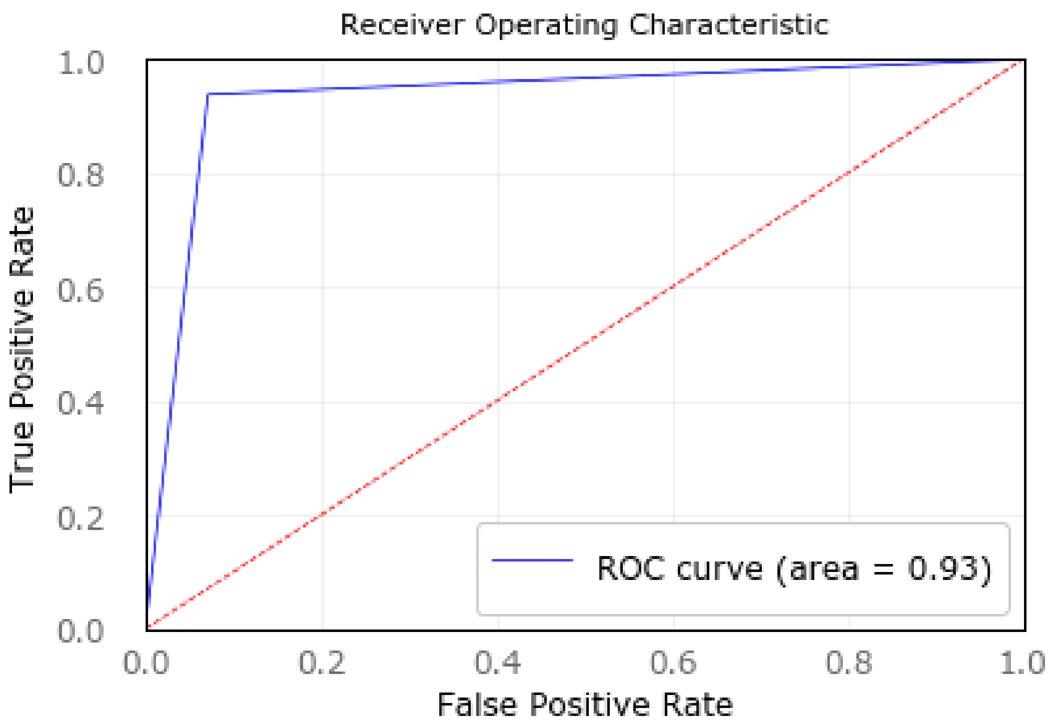
Metric	Success	Fail
Precision	0.9978	0.3023
Recall	0.9383	0.9286
F1-Score	0.9671	0.4561
Overall Accuracy	0.938	

Results and Analysis (EXP-1 vs. Exp-2)



Results and Analysis (EXP-1 vs. Exp-2)



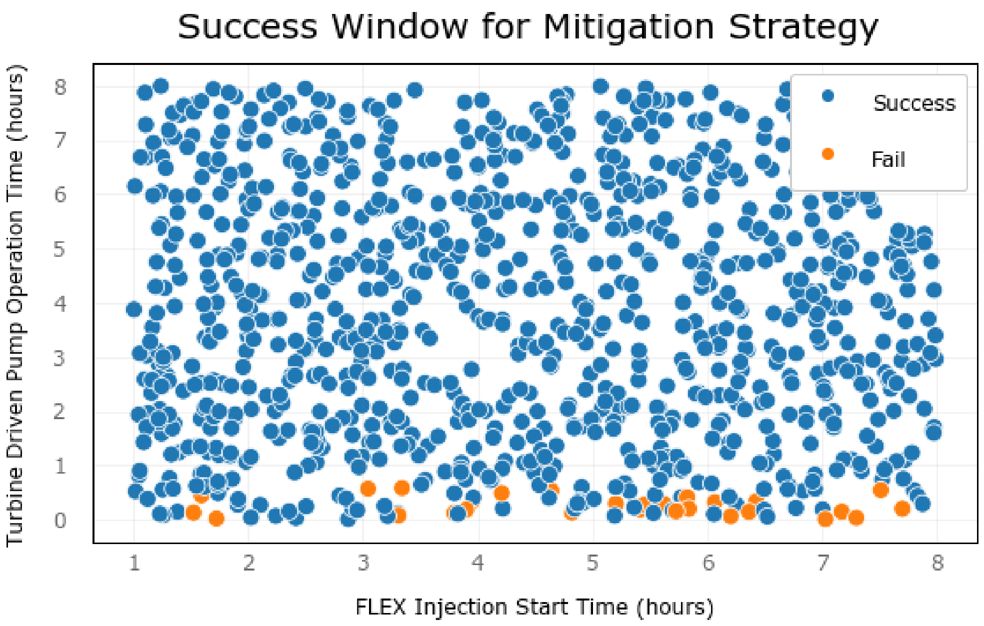


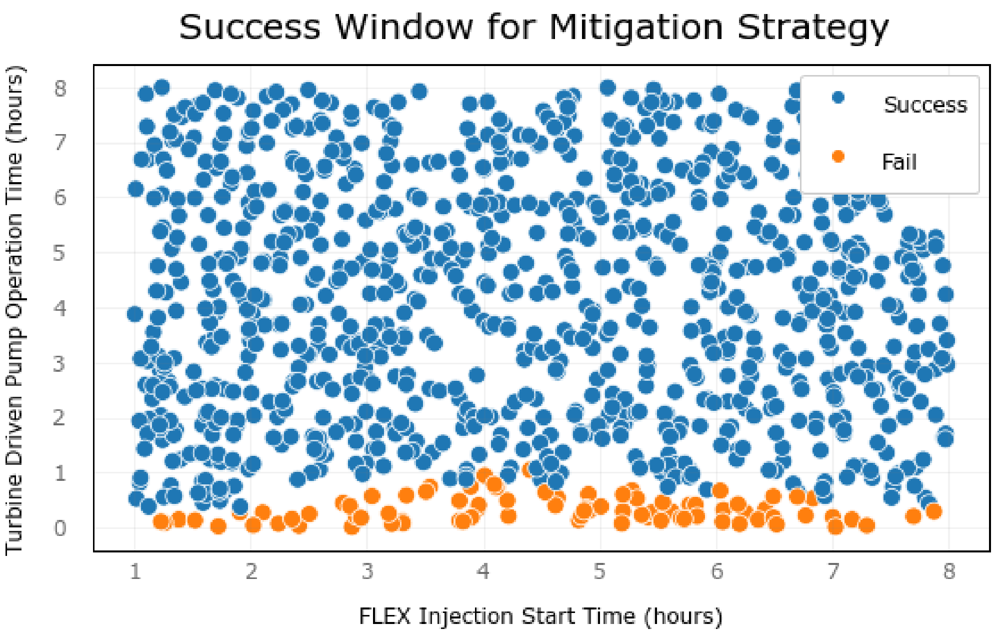
Metric	Success	Fail
Precision	0.968	0.4
Recall	0.976	0.333
F1-Score	0.972	0.364
Overall Accuracy	0.946	

Metric	Success	Fail
Precision	0.9978	0.3023
Recall	0.9383	0.9286
F1-Score	0.9671	0.4561
Overall Accuracy	0.938	

Results and Analysis (EXP-1 vs. Exp-2)

Results and Analysis (Actual vs. Exp-2)





Conclusion

- This work proves the capability of APR14000 to withstand extended station blackout accident scenario by using the FLEX strategy.
- AI algorithm is capable of predicting the success window of implementing the FLEX strategy with acceptable accuracy.
- Because of the high reliability of FLEX strategy, the accuracy of predicting the failed cases was limited due to an unbalanced dataset.
- To overcome the unbalanced dataset, a larger data set is needed. Accordingly, under-sampling and oversampling techniques need to be applied.
- Although the development of the AI algorithm is time-consuming; but once developed, the prediction can be obtained much faster than conventional deterministic methods.
- AI model useful in expediting the decision-making process under severe accident conditions.

References

1. J. Ricardo Tavares de Sousa, Aya Diab "Best Estimate Plus Uncertainty Analysis for SBO", Presented at the 2019 ANS Winter Meeting & Expo, 2019.
2. K. H. Kang, C. H. Song, B. D. Chung, K. D. Kim, S. W.Lee, K. Y. Choi, B. J. Yun, J. J. Jeong, Y. S. Bang, Y. H. Ryu,H. G. Kim, C. J. Choi, C. H. Ban, S. K. Sim, "Development of a Phenomena Identification ranking Table (PIRT) for a Station Blackout (SBO) Accident of the APR1400", Transaction of the Korean Nuclear Society Autumn Meeting, Gyeongju (2013).
3. Y. Kozmenkov, M. Jobst, S. Kliem, F. Schaefer and P. Wilhelm, "Statistical analysis of the early phase of SBO accidents for PWR," Nuclear Engineering and Design, pp.131-141 (2017).
4. Lee, S. W., Hong, T. H., Seo, M. R., Lee, Y. S., & Kim, H. T. (2014). Extended station blackout coping capabilities of APR1400. Science and Technology of Nuclear Installations, 2014.
5. 14. M. Mohan Raju, R. K. Srivastava, Dinesh C. S. Bisht, H. C. Sharma, and Anil Kumar (2011). Development of Artificial Neural-Network-Based Models for the Simulation of Spring Discharge. Hindawi Publishing Corporation, 2011, 1-11.
6. P. Anvesh, S. Abhilash (2019). Application Of Hyperparameter Optimized Deep Learning Neural Network For Classification Of Air Quality Data. International Journal of Scientific & Technology Research, Volume 8(11), 1435-1443.

Thank You