Deep-learning for Guided Simulation of Scenarios for Dynamic Probabilistic Risk Assessment

22. 06. 27

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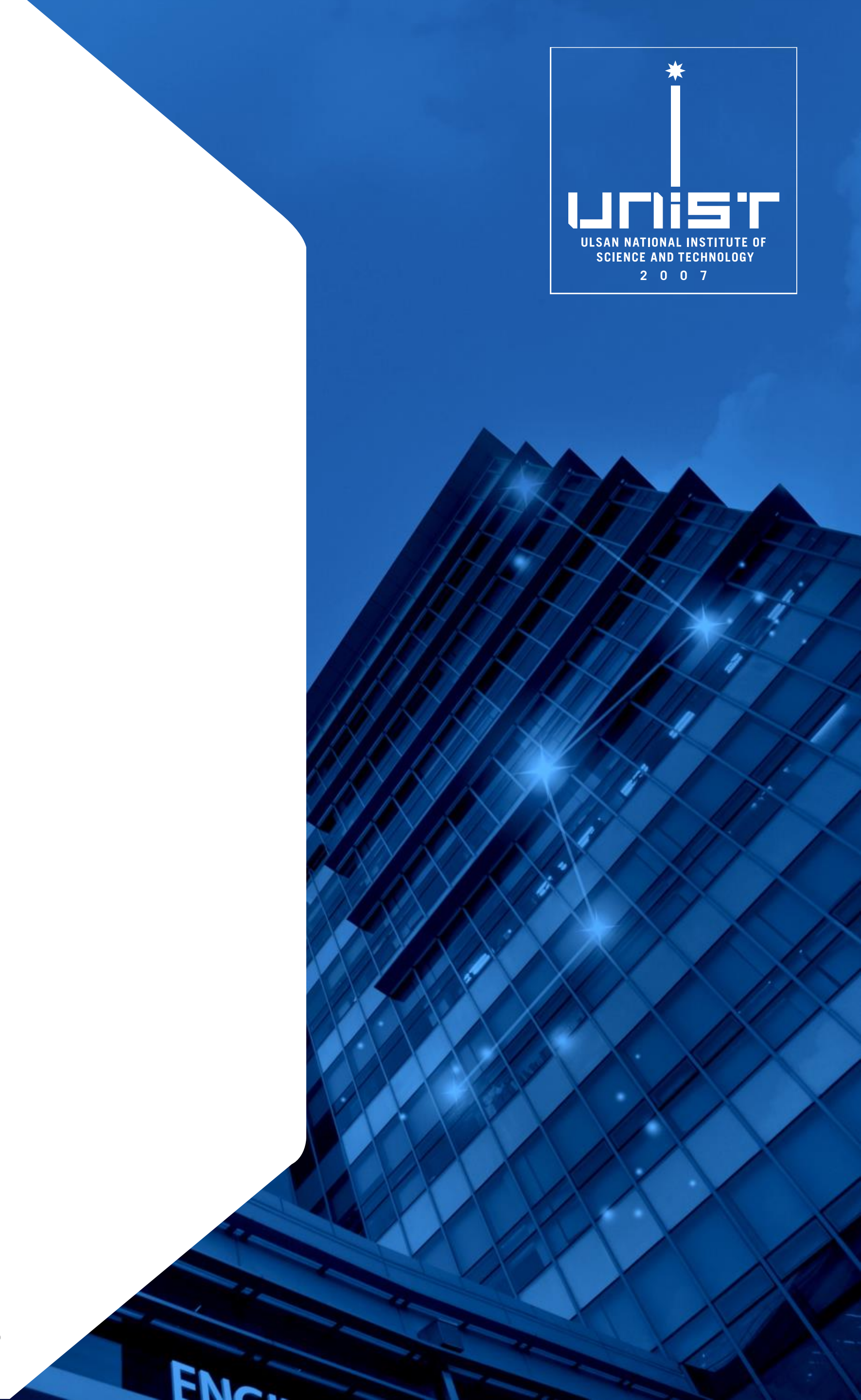
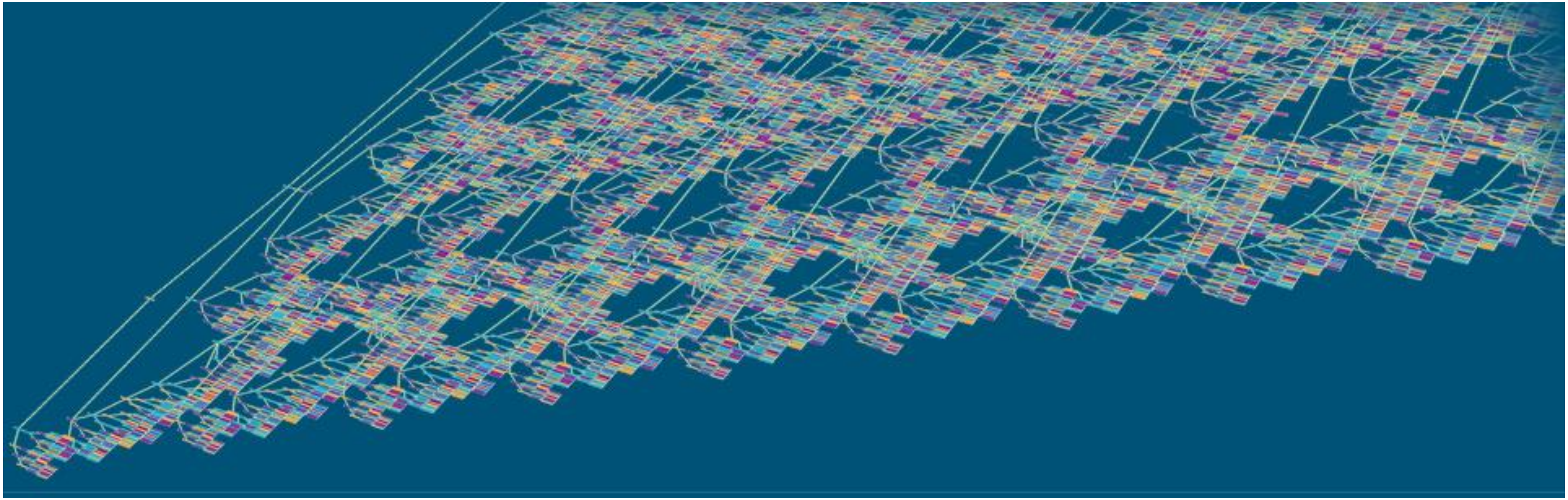


01 Introduction

Practical challenge of simulation-based DPRA

- **<u>An enormous number of scenarios</u>**
  - ✓ Considering dynamic behavior → A scenario in a static PRA is divided into several scenarios.
  - ✓ Each scenarios should be analyzed by TH code runs. → High computational cost

[1]



[1] ADAPT – Dynamic Event Tree Generation and Analysis

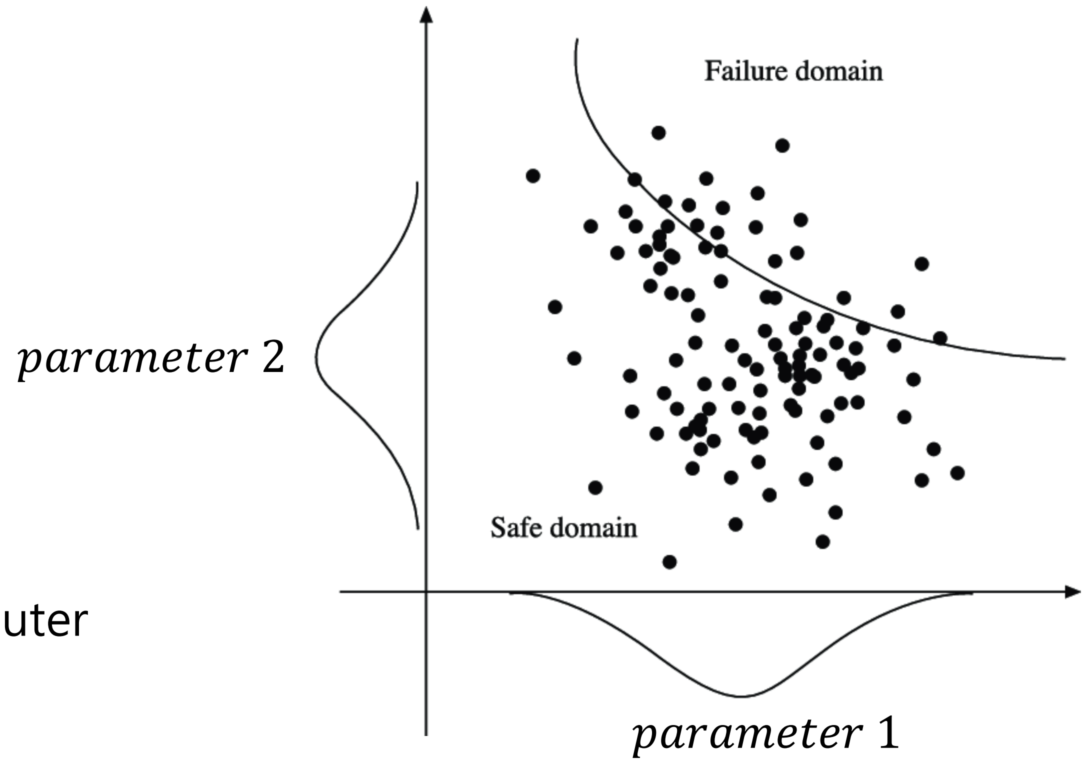
Structural reliability

- **<u>Monte Carlo Simulation (MCS)</u>**
  - ✓ Stochastic sampling of parameters
  - ✓ $P_f = (\#\ of\ failure\ scnarios)/(\#\ of\ tatla\ scenarios)$

- If a system failure is a rare event,
  - ✓ **<u>An enormous number of scenarios</u>** are required.
    - e.g., $P_f = 1 \times 10^{-4} \rightarrow At\ least\ 10{,}000\ scenarios$

- Each scenarios should be analyzed by complex computer codes. → High computational cost

- To tackle this problem, **<u>surrogate models</u>** are widely used.



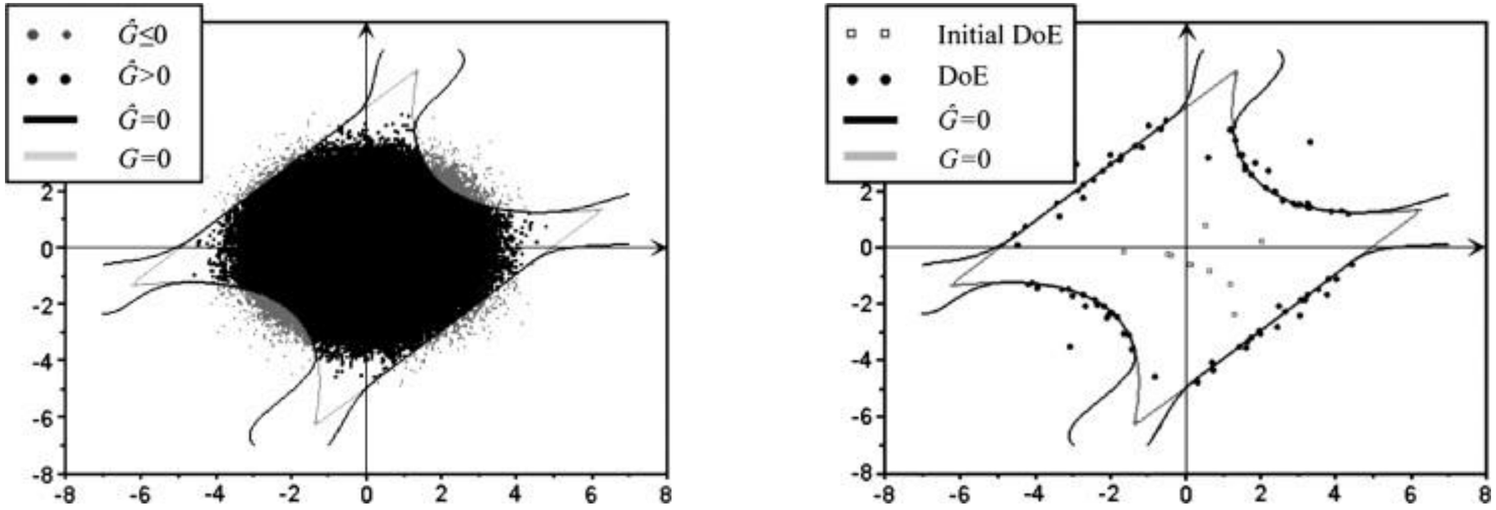
$$\rightarrow P_f = \frac{(The\ number\ of\ failure\ scenarios)}{(The\ number\ of\ total\ scenarios)}$$

An Active learning reliability method combining Kriging and MCS (AK-MCS)

- MCS without evaluating the whole scenario population.
- Success/failure of each scenario is predicted by a **surrogate model** based on **a few simulated scenarios.**

- Surrogate model : A kriging model (i.e., Gaussian process regression)
- A few simulated scenarios
  - ✓ AK-MCS iteratively samples and simulates **the scenarios close to a limit surface.**
    - ▪ **Surrogate model can locate a limit surface**.

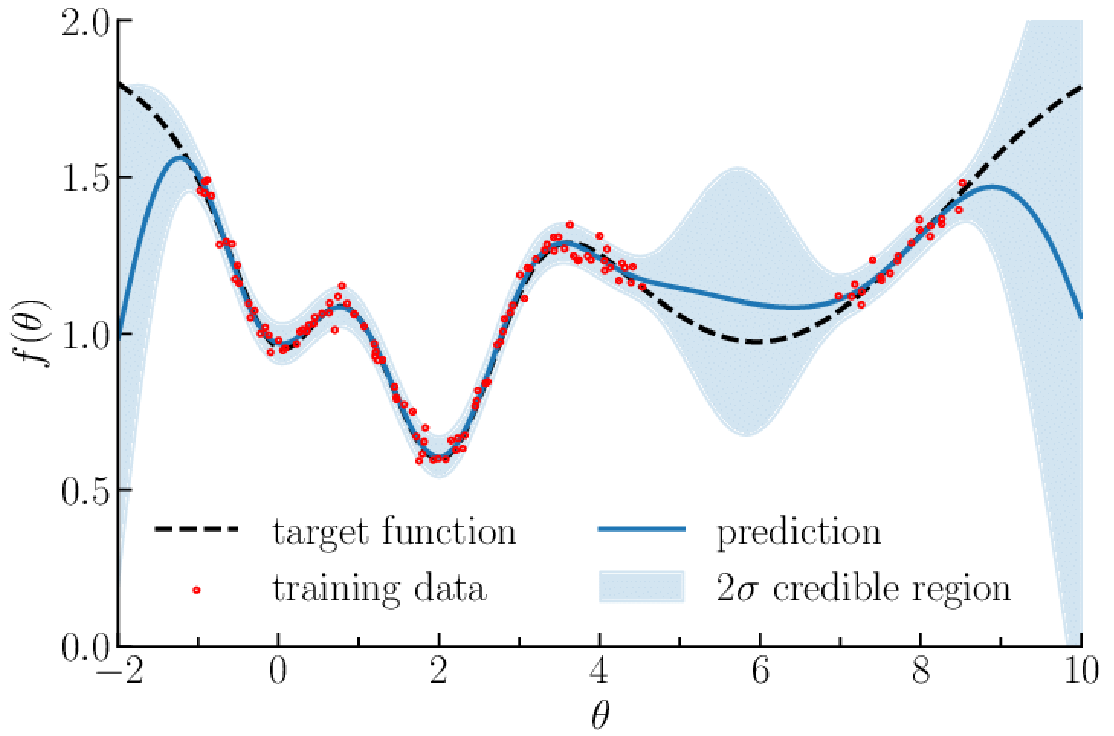
[1]



[1] B. Echard, et al., AK-MCS: An active learning reliability method combining Kriging and Monte Carlo Simulation (2011)

Specialty of AK-MCS

- Predictive uncertainty
  - ✓ Gaussian process regression : prediction + predictive uncertainty
  - ✓ The scenarios sampling efficiency can be improved by prioritizing the scenarios with not only closeness to the limit surface **<u>but also high predictive uncertainty.</u>**
    - Meticulous searching of limit surface



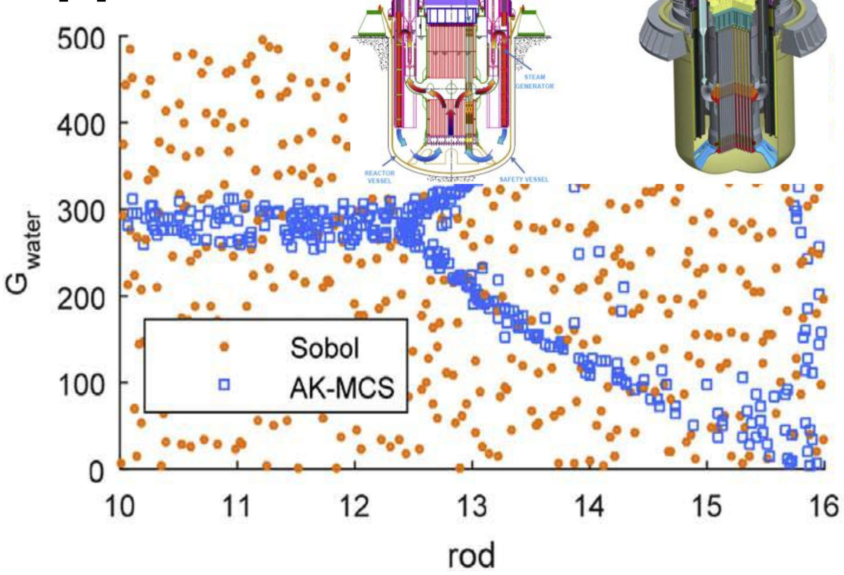
01 Introduction

AK-MCS for dynamic PRA

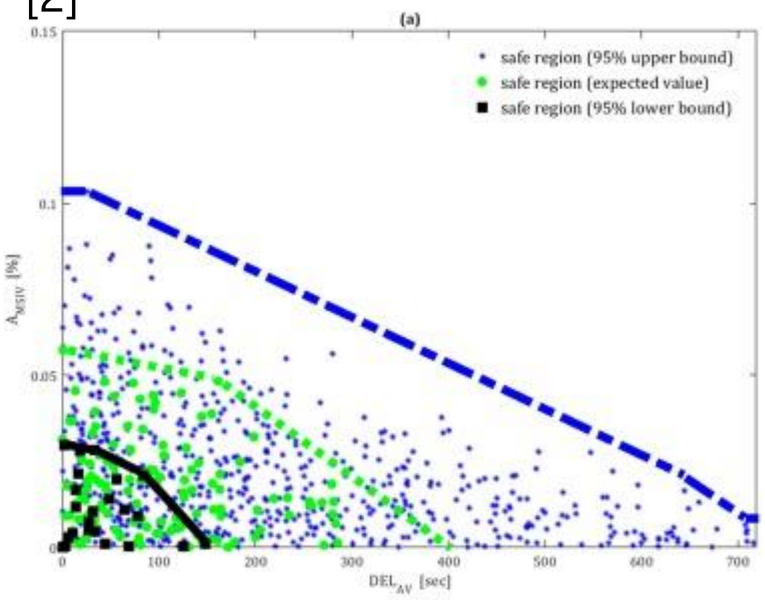
AK-MCS for NPPs

- Failure identification of
  - ✓ Lead Fast reactor
  - ✓ Passive safety system

[1]



[2]



AK-MCS for dynamic PRA

- It can minimize the number of simulations by locating a decision boundary.
- However, **<u>different surrogate model should be employed</u>**.
  - ✓ Scenarios of dynamic PRA has their probability (↔ Monte Carlo simulation).
  - ✓ Limit surface with more than thousands of adjacent scenarios
    - ▪ Gaussian process has a cubic time complexity $O(n^3)$ where n is the size of the training data sets.

[1] Turatia, E. Zio, et al., Adaptive simulation for failure identification in the Advanced LFR European demonstrator (2018).
[2] L. Puppo, E. Zio, et al., Failure identification in a nuclear passive safety system by Monte Carlo simulation with adaptive Kriging (2021).

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Novel algorithm for dynamic PRA

- Scenarios of dynamic PRA has their probability (↔ Monte Carlo simulation).
- Therefore, limit surface should be meticulously located by adjacent scenarios.
  - ✓ The number of adjacent scenarios can be more than thousands.

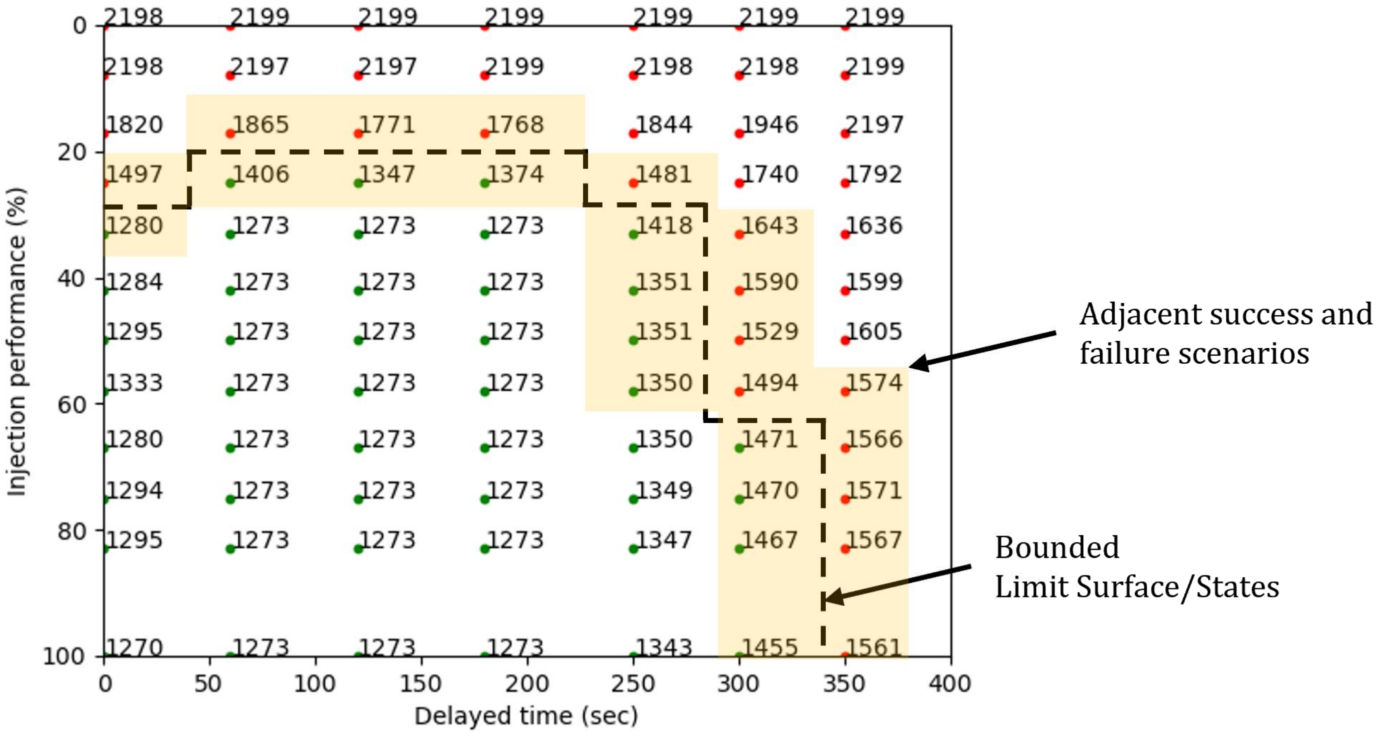
- Novel algorithm should be able to address more than thousands scenarios
  - ✓ **Deep-learning model**
- Novel algorithm needs to keep the advantages of AK-MCS (i.e., predictive uncertainty).
  - ✓ **Monte Carlo dropout (MC dropout)** and **U-learning function**

- Deep-SAILS
  - ✓ Deep-learning based Searching Algorithm of Informative Limit Surface/Scenarios/States

02 Deep-SAILS

Informative scenarios

- The scenarios where the consequence is success or failure by a narrow margin.
  - ✓ locating the limit surface/states
  - ✓ Reasonable assumption about success or failure of remaining scenarios



- Example
  - ✓ LB LOCA
    - ▪ x-axis : ESFAS delayed time
    - ▪ y-axis : SI
    - ▪ 1478K is success criterion.
  - ✓ The scenarios in the yellow shaded area

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Deep-SAILS

- Deep-learning based Searching Algorithm of Informative Limit Surface/Scenarios/States
  1. Simulation of informative (i.e., close to the limit surface) scenarios
  2. Consequence prediction for remaining scenarios with surrogate model
     → Identification of scenario success/failure with minimized simulations.

- Iterative algorithm
  1) Estimates limit surface
     ✓ Predicts a critical parameter (e.g., PCT) of whole scenarios.
     ✓ **Deep-learning model**
  2) Samples the scenarios close to the limit surface
     ✓ Consider closeness and prediction uncertainty together
     ✓ **Monte Carlo dropout** (MC dropout) and **U-learning function**
  3) Simulates the sampled scenarios, updates the deep-learning model, and locates limit surface

SAILS across a sea of dynamic scenarios…

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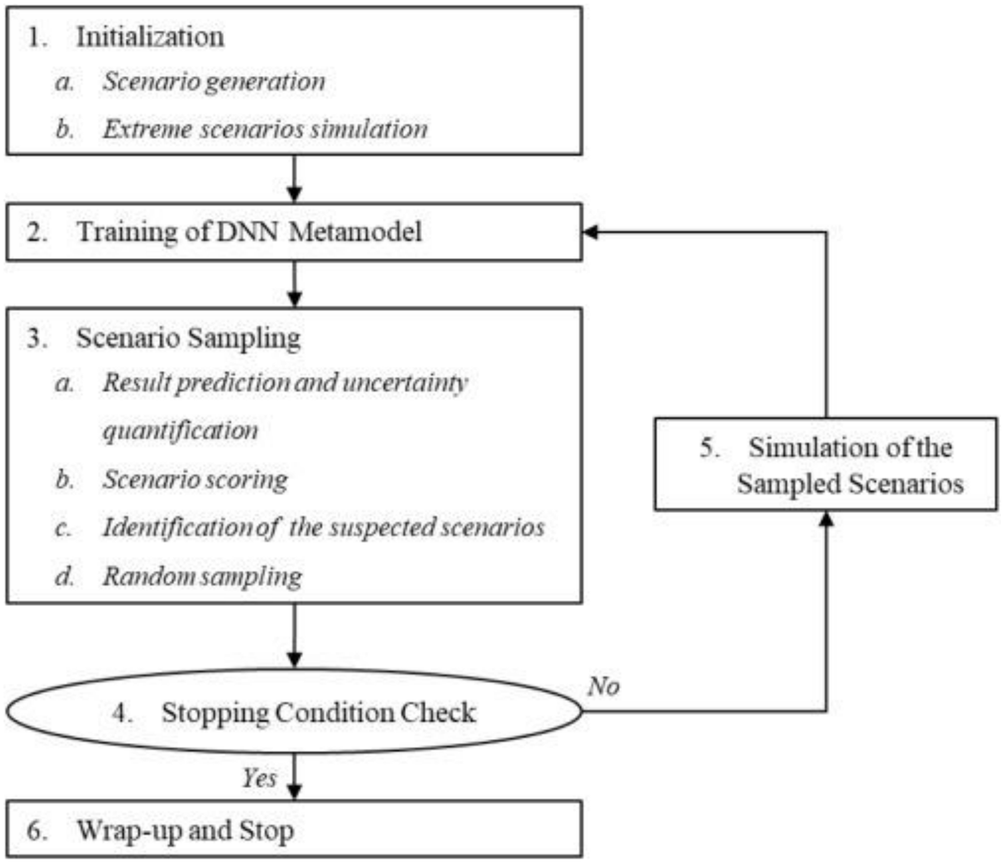
Detailed Algorithm

1. Initialization
   - ✓ Generation of a population of scenarios
   - ✓ Preferential simulation of extreme scenarios
     - Extreme scenarios are the scenarios configured by the maximum and minimum values of each parameter.

2. **Deep-learning model** training
3. **Scenarios sampling** (details in following slides)

4. Stopping condition
   - ✓ The proportion of already simulated scenarios out of the sampled one.

5. Simulation of the sampled scenarios



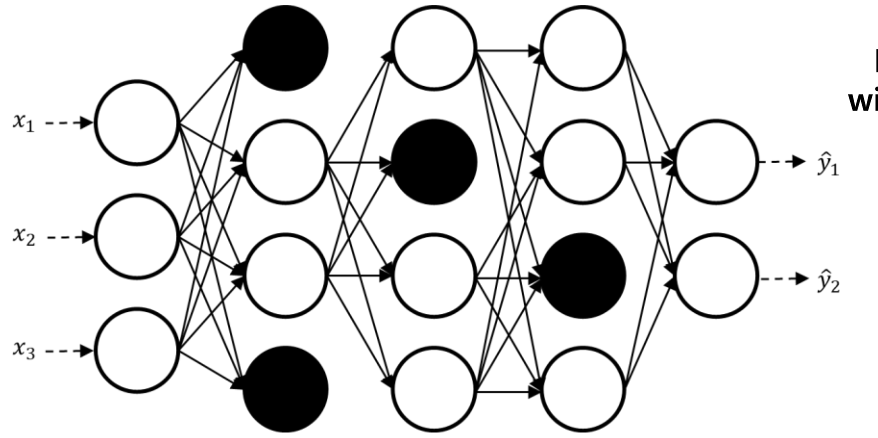
02 Deep-SAILS
Scenarios sampling

3. Scenario Sampling
   a. *Result prediction and uncertainty quantification*
   b. *Scenario scoring*
   c. *Identification of the suspected scenarios*
   d. *Random sampling*

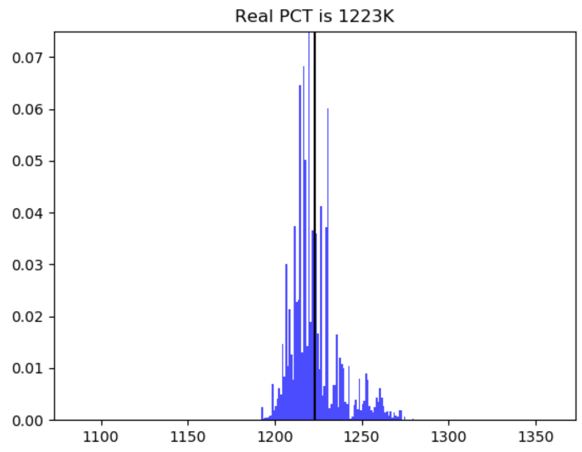
Consequence prediction and predictive uncertainty quantification

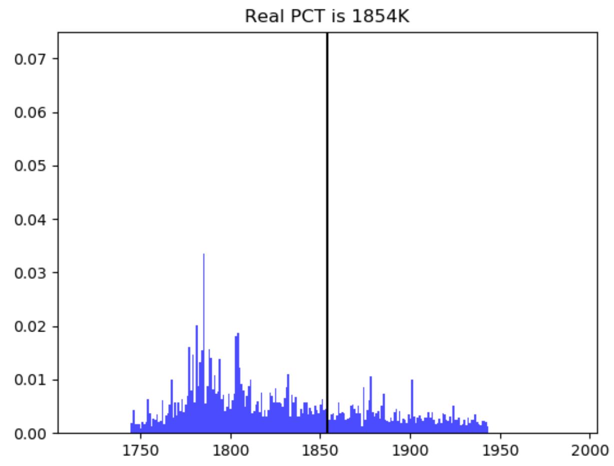
- **Monte Carlo dropout**
  - ✓ Multiple inferences with different dropout configuration.
    - **Means and variance** can be interpreted as **the prediction and uncertainty**, respectively.

- Deep-SAILS predicts consequences of each scenario multiple times with a random dropout configuration.
  - ✓ Acceleration through efficient program and high-performance devices is necessary.
    - (Case study utilized TensorFlow 2.7 with CUDA, RTX3080 GPU, and I7-10700K processor)



Multiple inferences with different dropout configurations





3. Scenario Sampling
   a. *Result prediction and uncertainty quantification*
   b. *Scenario scoring*
   c. *Identification of the suspected scenarios*
   d. *Random sampling*

Scenario Sampling with U-learning function

- Deep-SAILS scores each scenario by the ***U-learning function*** [1].

PCT prediction

PCT criterion (i.e., 1478 K)

$$U(X_i) = \frac{|\hat{y}_i - a|}{\sigma_{\hat{y}_i}} = \frac{|G(X_i)|}{\sigma_{\hat{y}_i}}$$

Variance
(from MCDO)

  ✓ This function gives a lower score for the scenarios where the estimated consequence…
    - are **closer to the failure condition** (i.e., the numerator)
    - have **higher uncertainty** (i.e., the denominator)

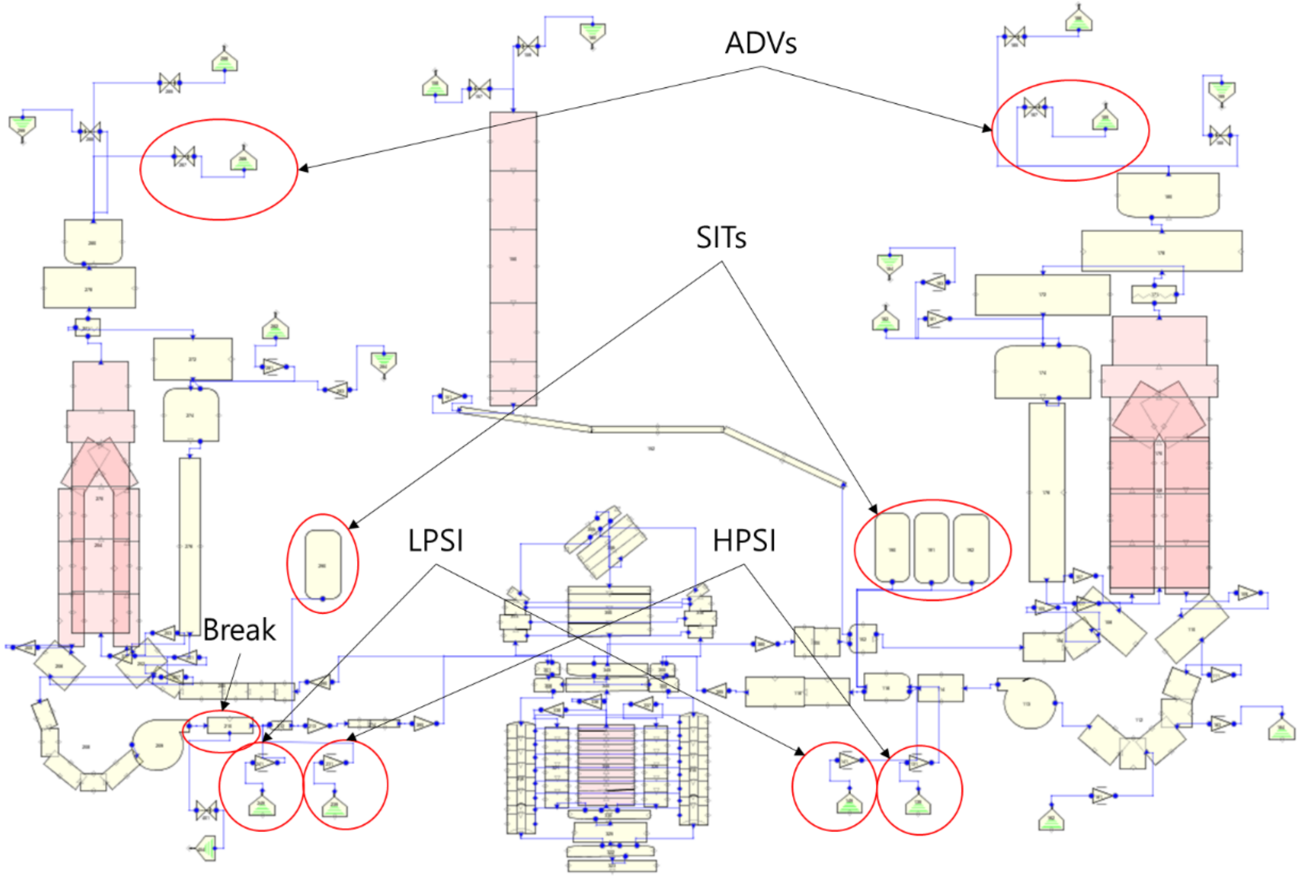
- The suspected scenarios : $U(X) < D$
  ✓ D is the range of suspicion and critical algorithm hyperparameter
- Random sampling among the suspected scenarios
  ✓ Exploration

[1] B. Echard, et al., AK-MCS: An active learning reliability method combining Kriging and Monte Carlo Simulation (2011)

03 Case study

TH system

- Zion NPP, WH-4 loop PWR, 1000MWe
- Assuming only SITs, LPSI, HPSI, and the SHRS via ADVs



Metric

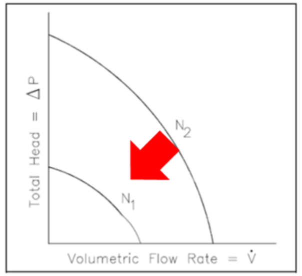
- Classification error rate

		Predicted result		Simulation result	
		Success ($\hat{a}$)	Failure ($\hat{b}$)	Success (A)	Failure (B)
True result	Success (a)	$a\hat{a}$	$a\hat{b}$	aA	
	Failure (b)	$b\hat{a}$	$b\hat{b}$		bB

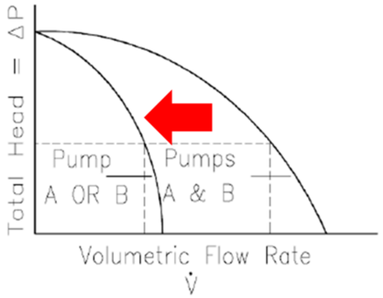
$$Classification\,error\,percentage = \frac{a\hat{b} + b\hat{a}}{a\hat{a} + a\hat{b} + b\hat{a} + b\hat{b} + aA + bB} \times 100$$

Case study (1) : SB-LOCA

- 10,143 scenarios
  - ✓ HPSI performance : **pump performance % = (Conservatively) flow rates %**



1 pump degradation in 1 train



2 pump in 2 train

Parameter	Unit	Uncertain domain	Discretization
HPSI actuation time	min	(0, 60)	21 (0, 3, 6, 9, 12, 15, 18, 21, 24, 27, 30, 33, 36, 39, 42, 45, 48, 51, 54, 57, 60)
ADV open time	min	(0, 60)	21 (0, 3, 6, 9, 12, 15, 18, 21, 24, 27, 30, 33, 36, 39, 42, 45, 48, 51, 54, 57, 60)
HPSI performance	%	(0, 100)	23 (100, 92, 88, 83, 79, 75, 71, 67, 63, 58, 54, 50, 46, 42, 38, 33, 29, 25, 21, 17, 13, 8, 0)

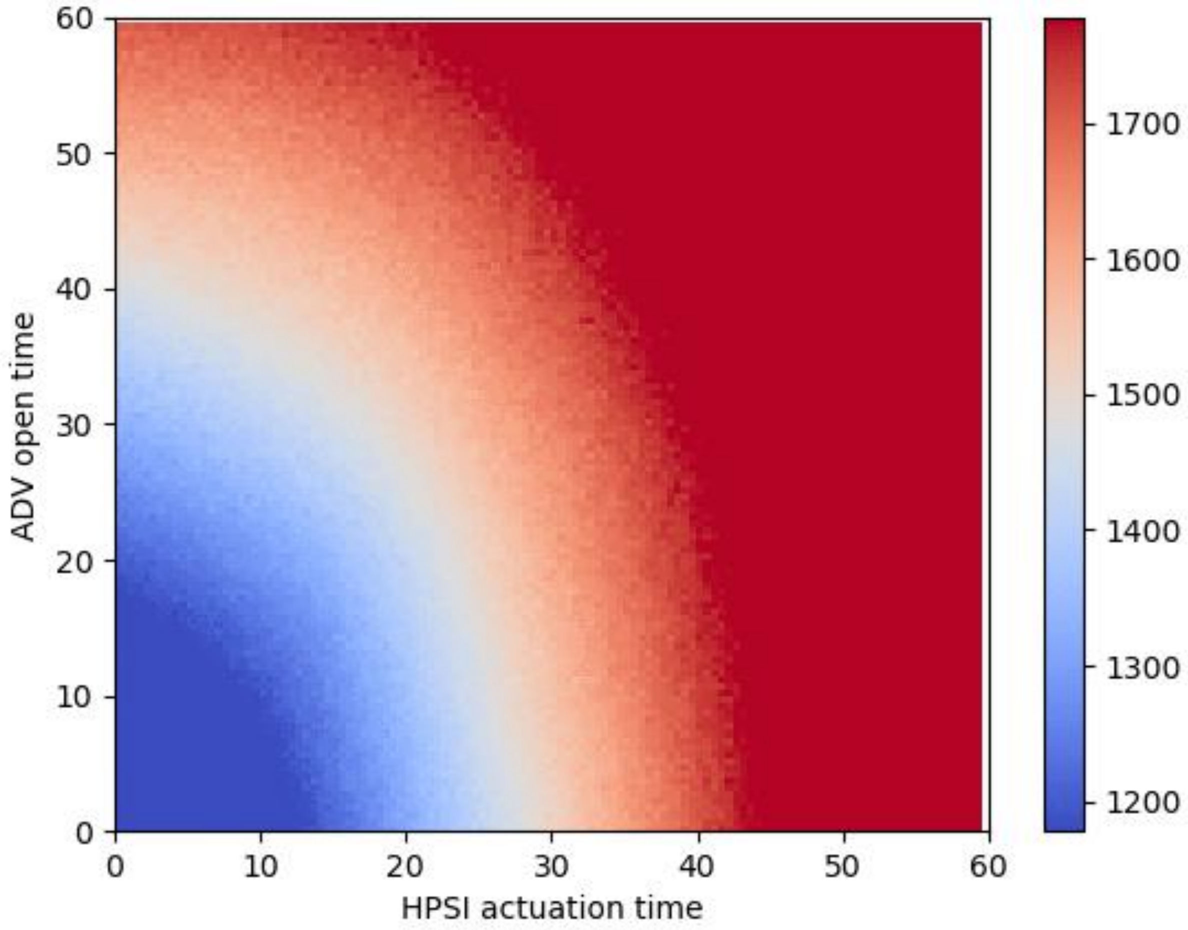
Case study (1) : SB-LOCA

- 10,143 scenarios

- When *D* (Range of suspicion) = 2.0
  - ✓ Scenarios : 10,143
  - ✓ Simulation : 1,129

  - ✓ non-CD to non-CD : 3,776
  - ✓ non-CD to CD : 1
  - ✓ CD to CD : 6,365
  - ✓ CD to non-CD : 1

  - ✓ Error rate : 0.02%
  - ✓ Simulation : 9.36%



Limit surface estimated by
the deep learning model for each iteration

(Assume HPSI performance = 75%)
(14,400 predictions per frame)

Case study (1) : SB-LOCA

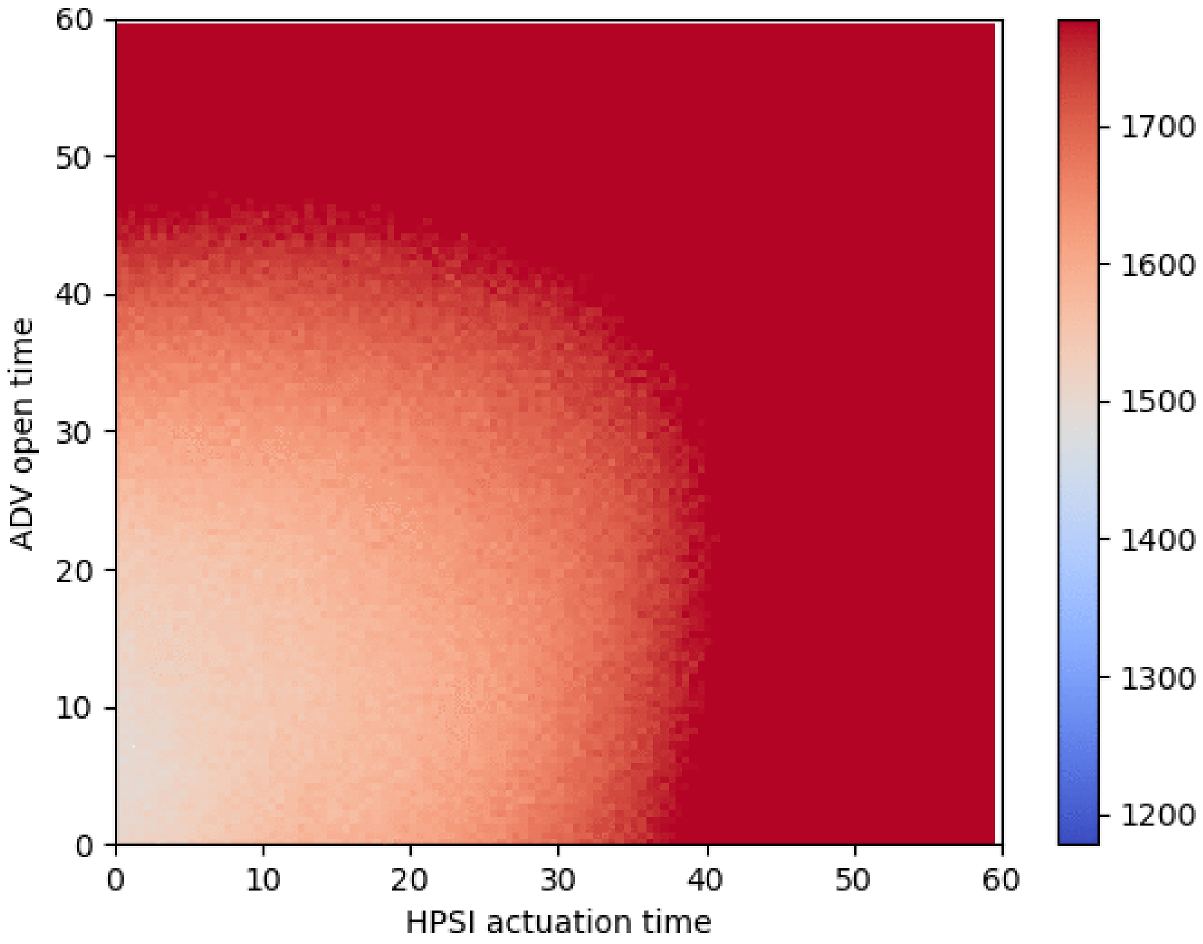
- 10,143 scenarios

- When D (Range of suspicion) = 2.0

✓ Scenarios : 10,143
✓ Simulation : 949

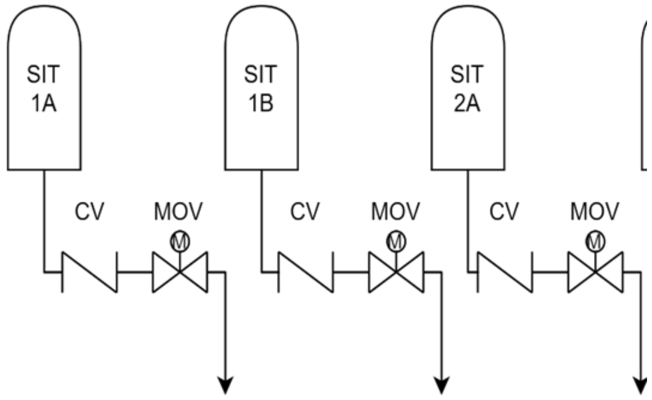
✓ non-CD to non-CD : 3,776
✓ non-CD to CD : 1
✓ CD to CD : 6,365
✓ CD to non-CD : 1

✓ Accuracy : 99.98%
✓ Simulation : 9.36%



Limit surface estimated by
the deep learning model for each iteration

(Assume HPSI performance = 25%)
(14,400 predictions per frame)



Case study (2) : LB-LOCA

- 40,250 scenarios
  - ✓ SIT performance : partial opening of cascading two valves.

Parameter	Unit	Uncertain domain	Discretization
SIT-1 performance	%	(0, 100)	5 (0, 25, 50, 75, 100)
SIT-2 performances	%	(0, 100)	5 (0, 25, 50, 75, 100)
SIT-3 performances	%	(0, 100)	5 (0, 25, 50, 75, 100)
ESFAS delayed time	s	(0, 400)	14 (0, 30, 60, 90, 120, 150, 180, 210, 240, 270, 300, 330, 360, 40
LPSI performance	%	(0, 100)	23 (100, 92, 88, 83, 79, 75, 71, 67, 63, 58, 54, 50, 46, 42, 38, 33, 2 25, 21, 17, 13, 8, 0)

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Case study (2) : LB-LOCA

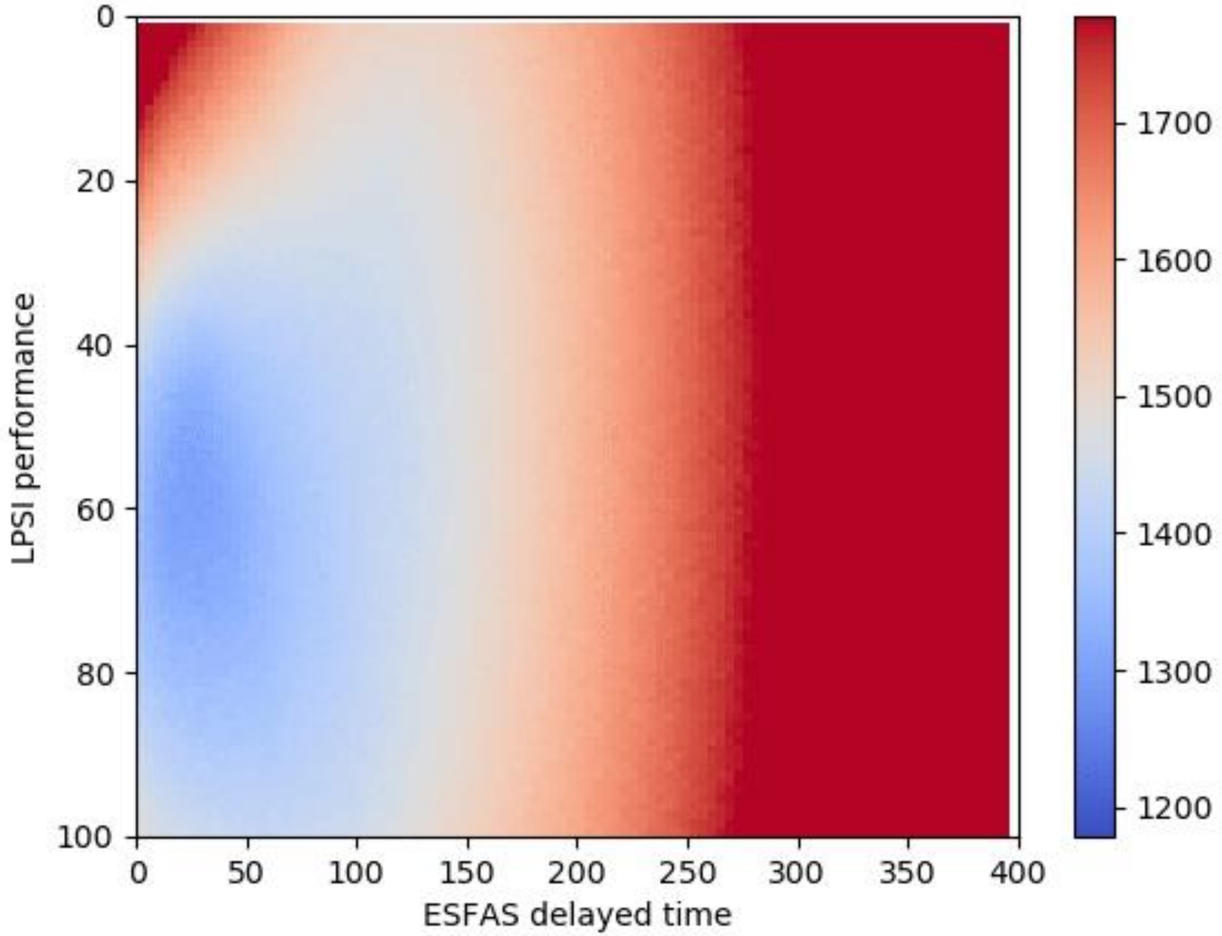
- 40,250 scenarios

- When D (Range of suspicion) = 2.0

✓ Scenarios : 40,250
✓ Simulation : 6,140

✓ non-CD to non-CD : 17,725
✓ non-CD to CD : 31
✓ CD to CD : 22,488
✓ CD to non-CD : 6

✓ Accuracy : 99.91%
✓ Simulation : 15.25%



Limit surface estimated by
the deep learning model for each iteration

(Assume SIT performances = 50%)
(14,400 predictions per frame)

Case study (2) : LB-LOCA

- 40,250 scenarios

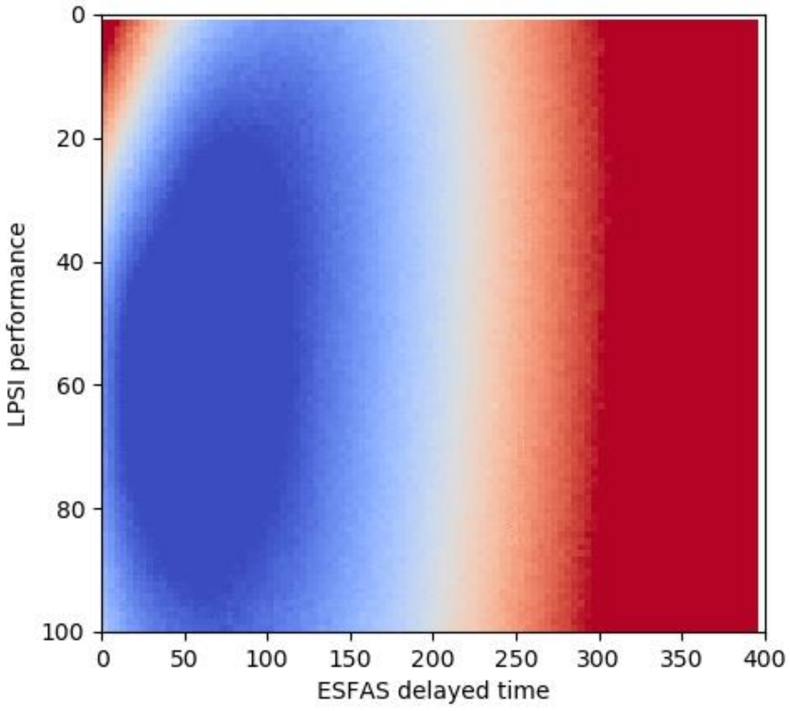
- Trade off relationship between accuracy and simulation according to D (range of suspicion)

	D = 0.5	D = 2.0	D = 5.0
Scenarios	40,250	40,250	40,250
Simulation	4,412	6,140	11,293
non-CD to non-CD	17,672	17,725	17,749
non-CD to CD	84	31	7
CD to CD	22,462	22,488	22,494
CD to non-CD	32	6	0
Accuracy	**99.71%**	**99.91%**	**99.98%**
Simulation (%)	**10.96%**	**15.25%**	**28.06%**

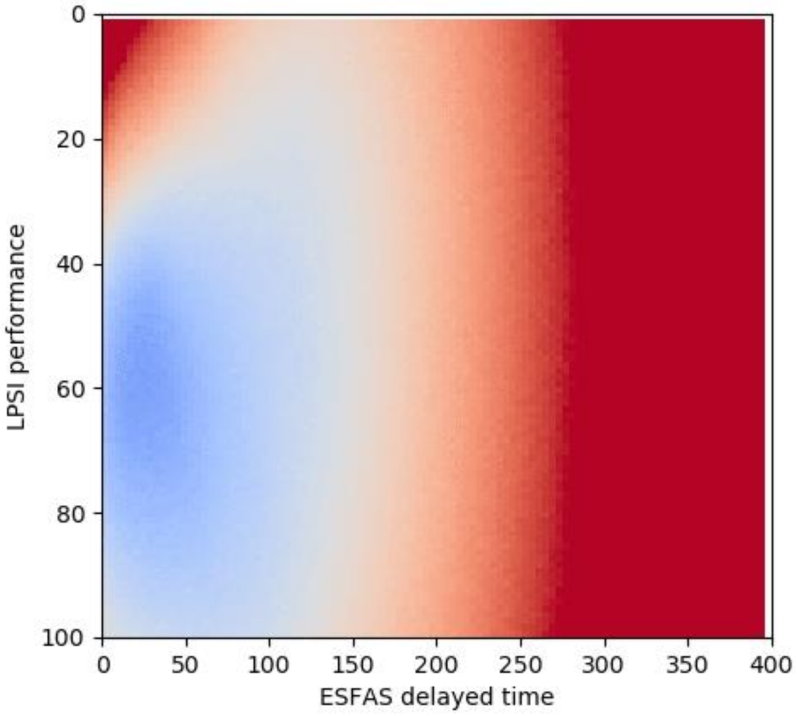
Case study (2) : LB-LOCA

- 40,250 scenarios

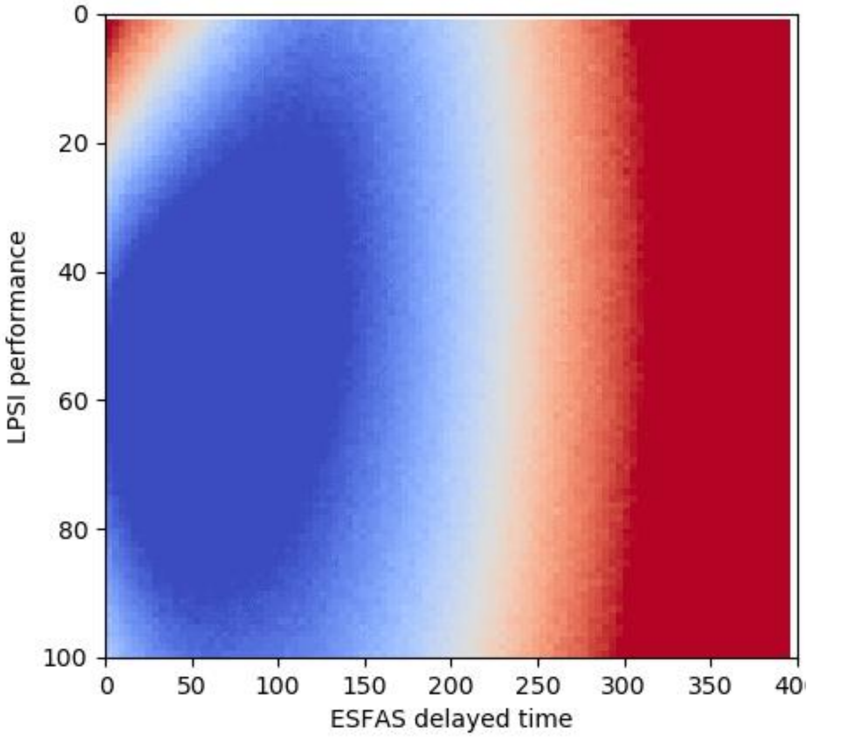
- Trade off relationship between accuracy and simulation according to D (range of suspicion)



D = 0.5



D = 2.0

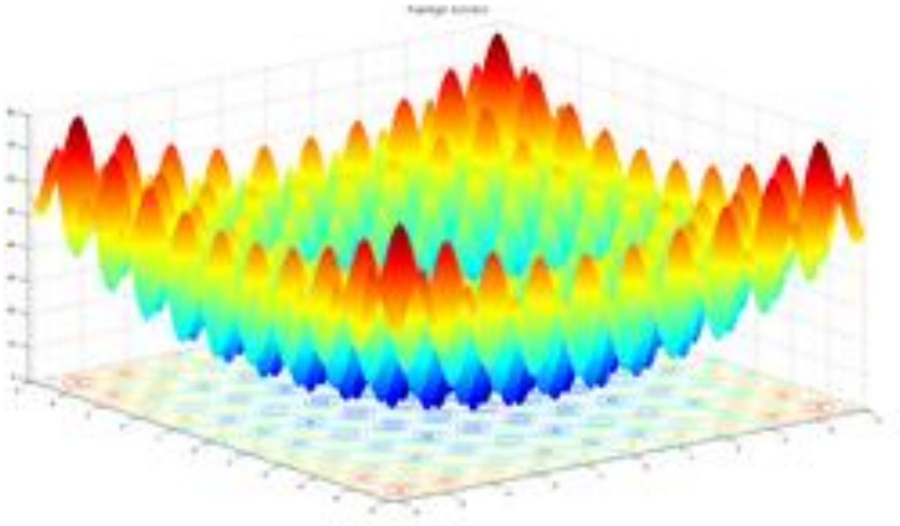


D = 5.0

Case study (3) : Modified Rastrign function

- 1,771,561 scenarios

- $f(x) = 60 + \sum_{i=1}^{6}[x_i^2 - 10\cos(2\pi x_i)]$
  - ✓ $x_i \in \{-5, -4, -3, -2, -1, 0, 1, 2, 3, 4, 5\}$
  - ✓ 6 factors with 11 performances = 1,771,561



- Assume $f(x) > 90$ as failure criteria
  - ✓ 158,640 fail scenarios
  - ✓ Failure rate (assume constant sampling distribution) = 0.0899

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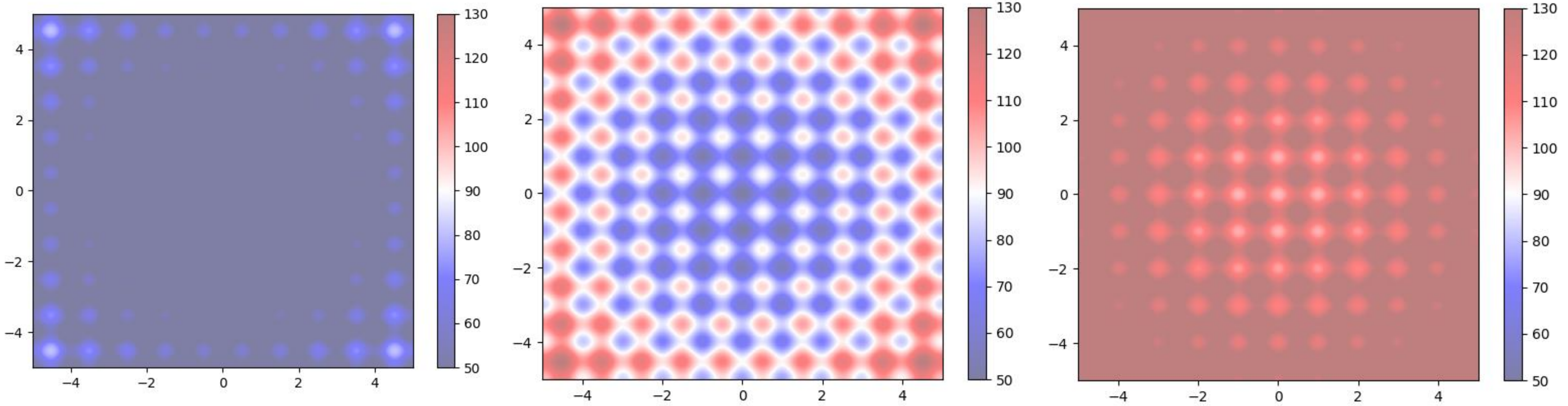
Case study (3) : Modified Rastrign function

- 1,771,561 scenarios



$x_3, x_4, x_5, x_6 = 0, 0, 0, 0$ $x_3, x_4, x_5, x_6 = 0, 0, 5, 5$ $x_3, x_4, x_5, x_6 = 5, 5, 5, 5$

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Case study (3) : Modified Rastrign function

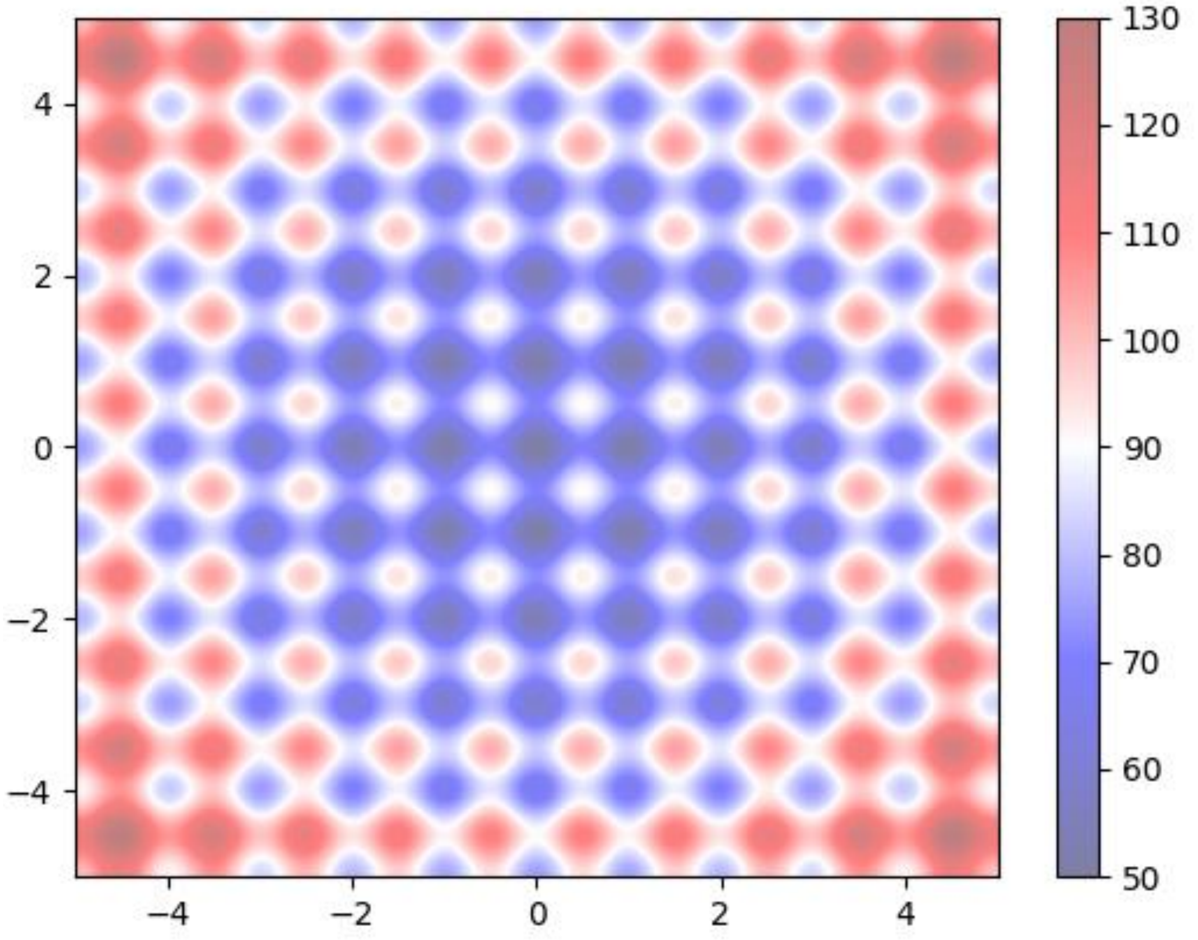
- 1,771,561 scenarios

- When D (Range of suspicion) = 2.0

✓ Scenarios : 1,771,561
✓ Simulation : 60,525

✓ non-CD to non-CD : 1,605,241
✓ non-CD to CD : 0
✓ CD to CD : 158,640
✓ CD to non-CD : 6

✓ Accuracy : 100.00%
✓ Simulation : 3.431%



Note : Division by zero problem for U-learning function exists

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04 Conclusion

Remark

- This research introduced a guided simulation algorithm of a dynamic PRA, named **Deep-SAILS**.
- To overcome the limitation of previous including AK-MCS, the algorithm employed a **deep-learning model** as a high-fidelity surrogate model.
- In addition, the algorithm retains the strong point of AK-MCS, that is **utilization of uncertainty information for a meticulous sampling of scenarios**. To this end, the predictive uncertainty is quantified by the **Monte Carlo Dropout** technique.
- This algorithm aims to sample and simulate **the scenarios close to the limit surface** and train **a dep learning model that can estimate the consequence of the non-simulated scenarios.**
- Consequently, Deep-SAILS can accurately identify the success and failure of the scenarios with the **minimized number of physical model runs.**
- Case study result shows the effectiveness of Deep-SAILS

- Detailed information can be found in following articles:
  - ✓ Junyong Bae et. al., *Limit surface/states searching algorithm with a deep neural network and Monte Carlo dropout for nuclear power plant safety assessment (2022)*
  - ✓ Jong Woo Park et. al., *Simulation optimization framework for dynamic probabilistic safety assessment (2022)*

Thank you

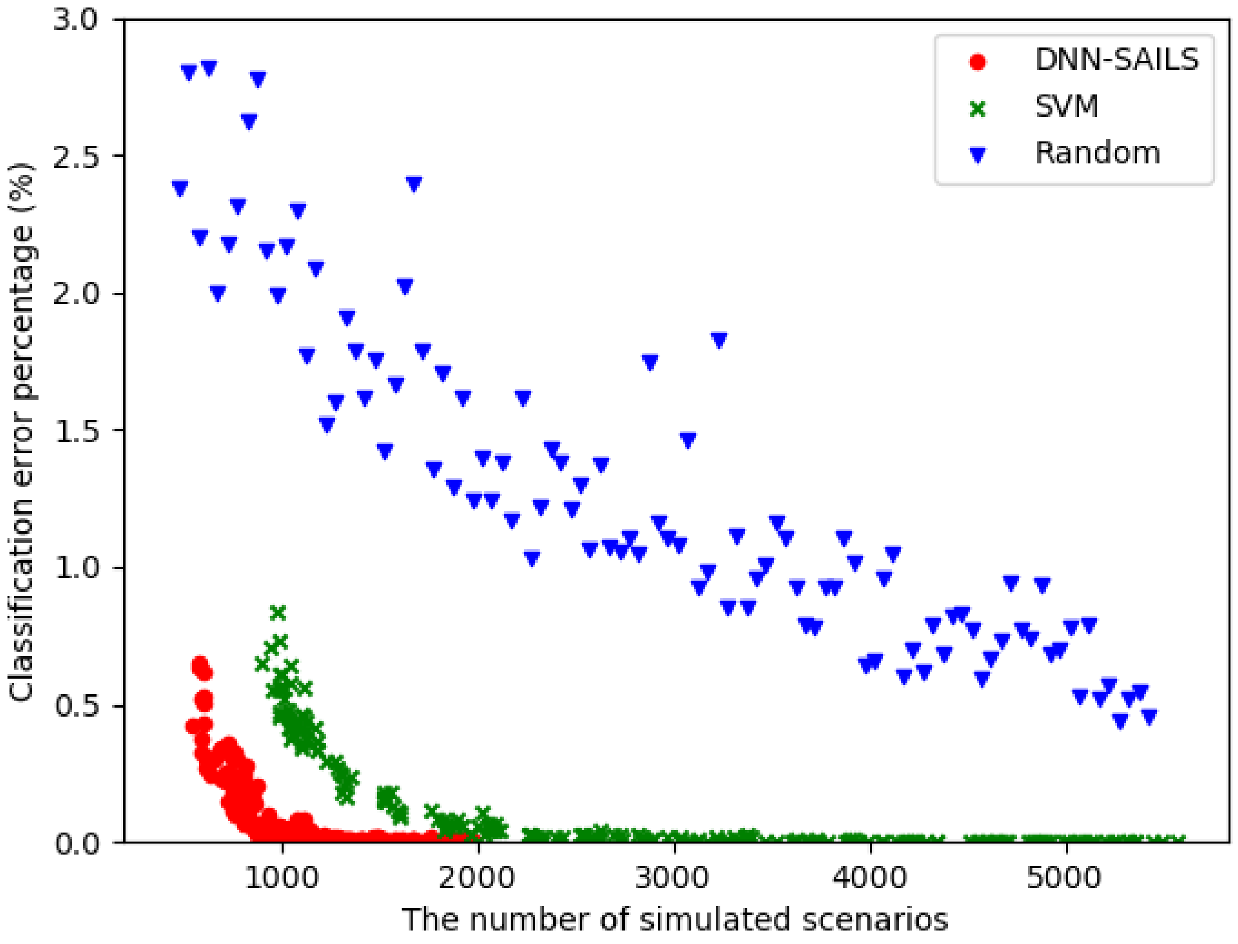
Any Questions?

SAILS across a sea of dynamic scenarios…

Case study (1) : SB-LOCA

- 10,143 scenarios

- Comparison with other method
  - ✓ Random sampling (Random)
  - ✓ Support vector machine (SVM)
    - ▪ ~ Adaptive sampler of RAVEN



01 Deep-SAILS

Deep-learning based Searching Algorithm of Informative Limit Surface/Scenarios/States

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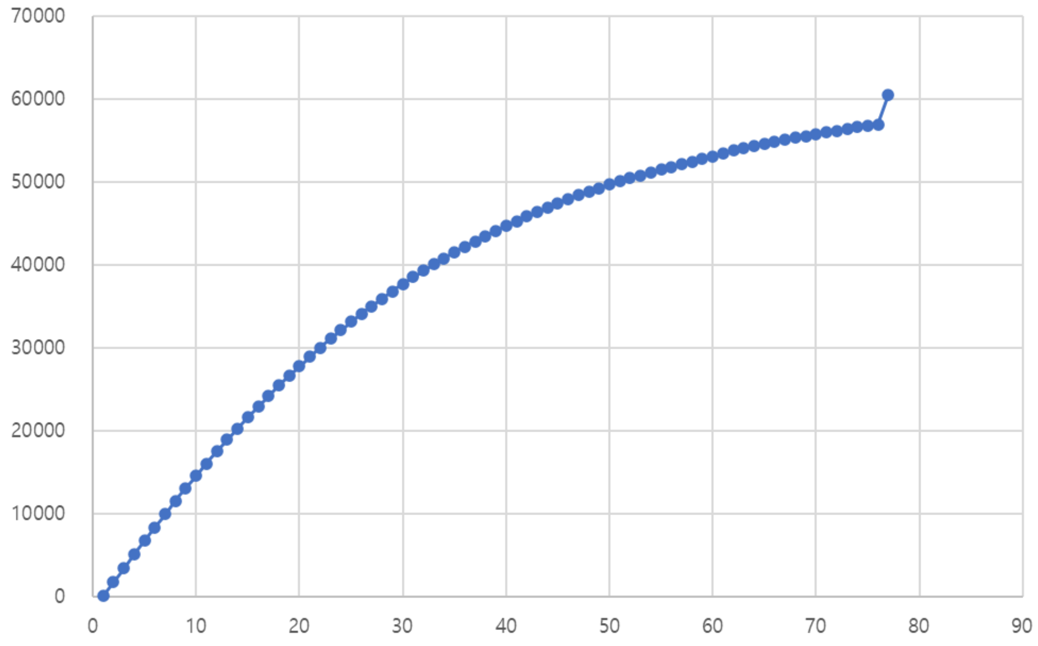
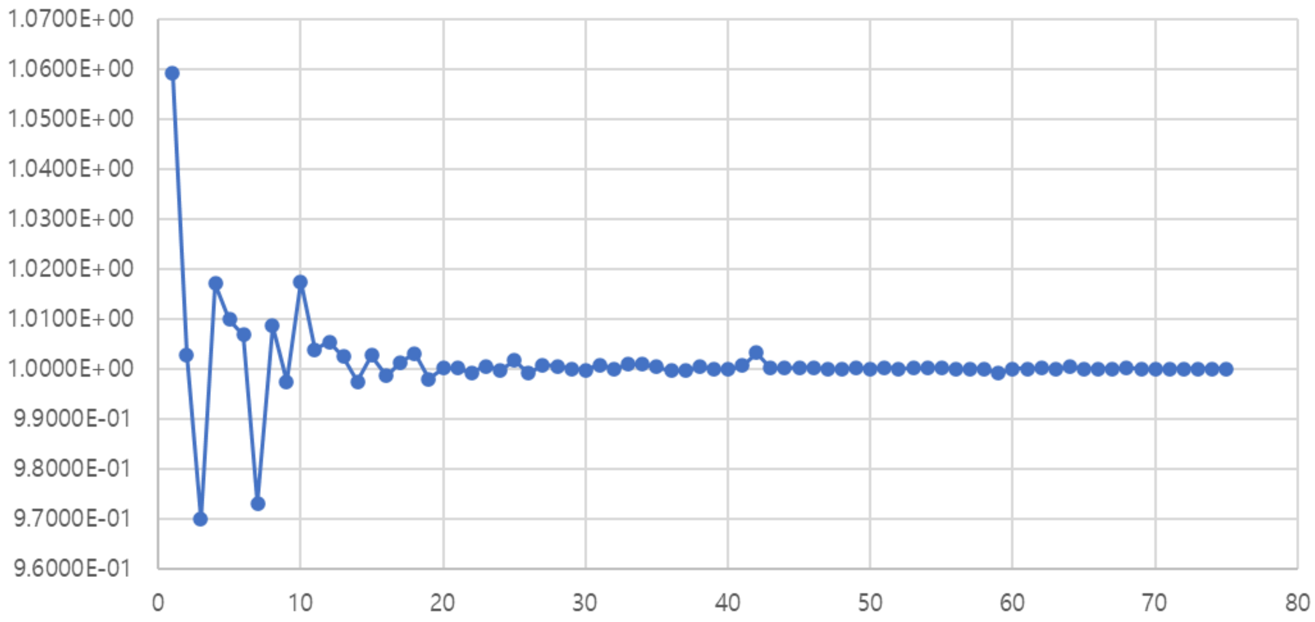
Case study (3) : Modified Rastrign function

- 1,771,561 scenarios
  - ✓ Number of simulated scenarios for each iteration
  - ✓ Normalized failure scenarios (Estimated number / Real number)





Note : Division by zero problem for U-learning function exists