Feasibility study on AI-based prediction for CRUD induced power shift in PWRs

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ABSTRACT

In this study, feasibility of AI-based CIPS prediction method has been assessed. Recently, observation of CIPS (also known as AOA) has increased in PWRs due to increased cycle length and power uprates. To reduce the operation cost in NPP caused by AOA, AI-based CIPS prediction method was suggested. A simulation-based framework for data generation was established by using RAST-K. Based on OPR-1000 type reactor, training dataset for 52,373 core models with CRUD were generated. Three type of ML models (RF, LGBM, XGB) were trained to make up an ensemble model. Given testing datasets, it predicted CIPS occurrence with high accuracy over 95%, and high precision and recall scores over 85%.

Introduction

- With recent of PWR (increased cycle length, power uprates), observation of CIPS (also known as AOA) has increased.
- By affecting axial power distribution, CIPS makes nuclear reactor core operation more difficult, decreasing shutdown margin.
- This study has been carried out to assess feasibility of AI-based CIPS prediction method for purpose of early diagnostics of CIPS before the ASI to violate design limit.

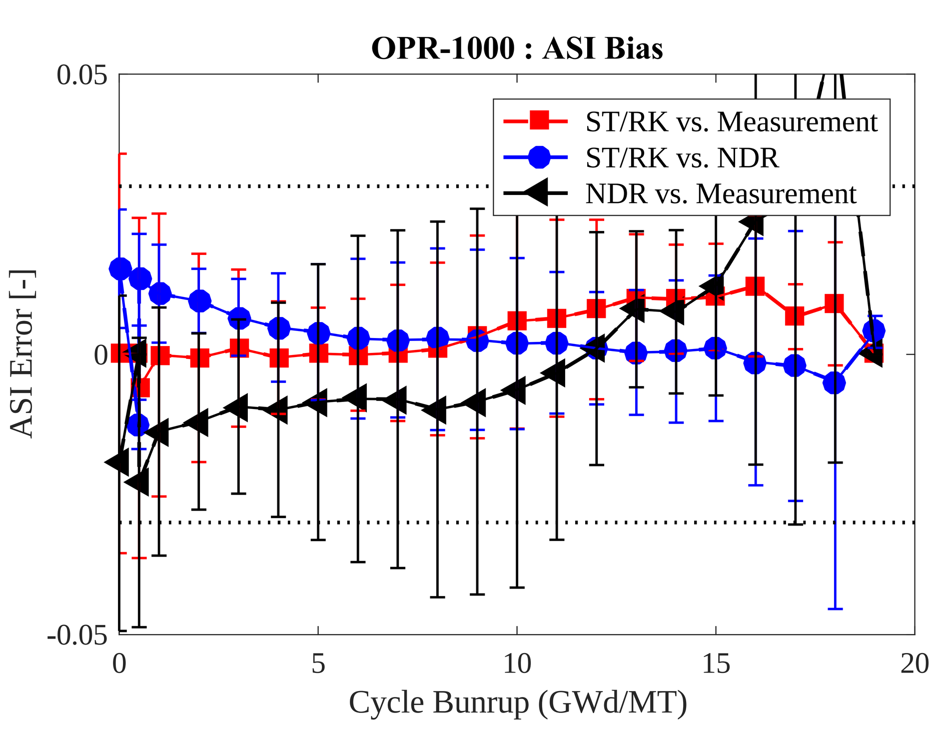
Simulation Code & CRUD Model

- To overcome the challenges of obtaining CIPS data, simulation-based train dataset is generated by using RAST-K.
- RAST-K is a nodal diffusion code which has been V&V with respect to the commercial PWRs including OPR-1000, APR-1400, WH2L, and WH3L.
- RAST-K can calculate both in-core instrument (ICI) and ex-core detector signals which are used to train ML models.
- RAST-K has capability to simulate CRUD accumulation during the operation by solving the CRUD balance equation within the RCS.

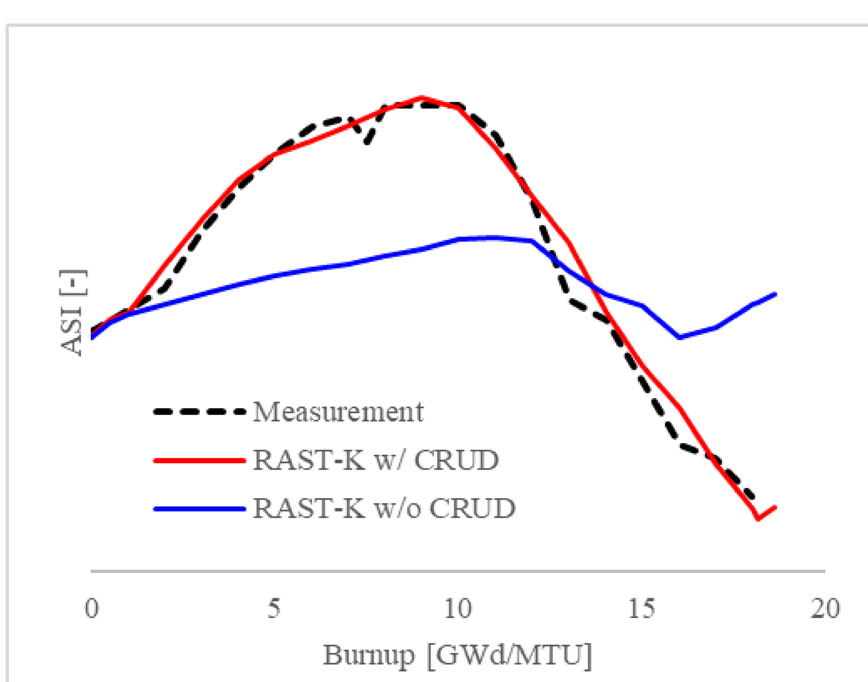
$$\frac{dC_{CRUD}(t')}{dt'} = \frac{1}{M_{RCS}}\left(S_{CRUD}^{RCS} + S_{CRUD}^{reload}(t') - \sum_{i=1}^{I}\frac{dM_{CRUD,i}(t')}{dt'} - \varepsilon \dot{M}_{letdown}C_{CRUD}(t')\right)$$

$$\frac{dM_{CRUD,i}(t')}{dt'} = C_{CRUD}(t')\bar{R}_{i,b} - K_{erosion}$$

$$S_{CRUD}^{reload}(t') = \lambda_{src}M_{CRUD,b-1}^{reload}\exp(-\lambda_{src}t')$$



V&V Results of RAST-K on OPR0-1000 type reactor



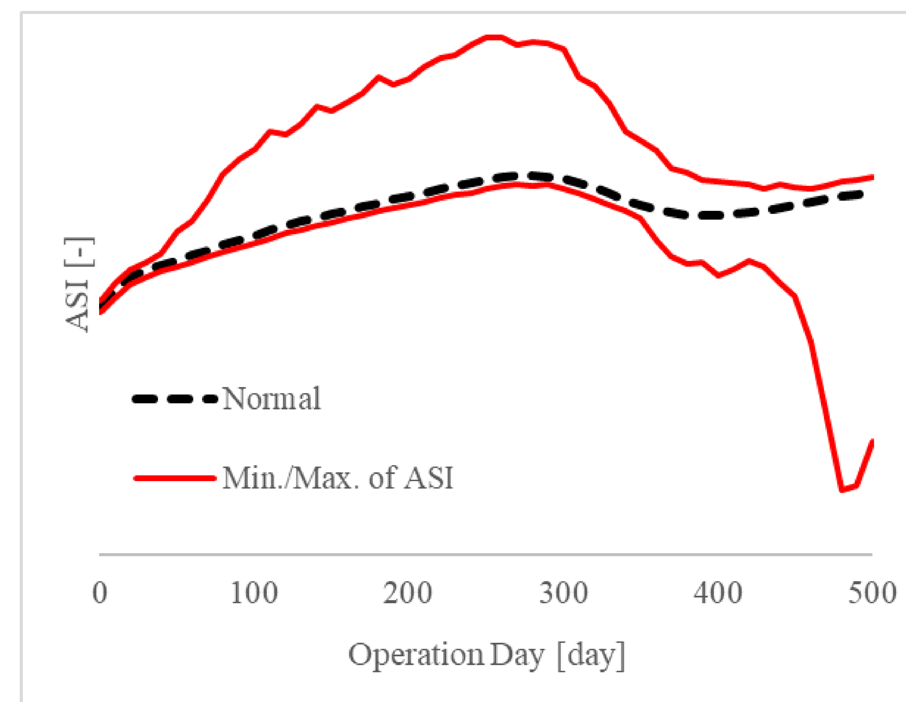
Validation Results of CRUD model (vs. OPR-1000)

Generation of Train Datasets

- Cycle 4 of OPR-1000 type reactor is used as base input model.
- To simulate deposit of CRUD, 500 days of depletion calculation with 52 burnup steps is performed with full power (100%) condition.
- Procedure to generate CRUD accumulation core model:
  1) *For every burnup step, core power is sampled 99.0%~101.0%.*
  2) *Parameters relating CRUD accumulation and boron hold-up rate are sampled.*
  3) *A core input model constructed at 1) and 2) is solved using RAST-K to compute in-core and ex-core detector signals.*
  4) *Each burnup step's data of the core model is labeled by comparing ASI computed at 3) with reference core model (HFP with no CRUD accumulation). If the ASI difference is larger than 2%, the data burnup point is labeled as CIPS occurrence.*
  5) *Procedure from 1) to 4) is repeated.*
- In total, 52,373 core models are generated and simulated with 52 burnup steps, taking 80 mins of calculation time for each core model.
- Out of the generated core models, 27,906 core models are normal (no CIPS occurred) and 24,467 core models are abnormal.

Parameter	Lower	Upper
Core power rate [%]	99	101
Threshold thickness [micron]	20	30
Source in RCS [kg/sec]	0.3E-7	4.3E-7
CRUD in reloaded fuel [kg]	4.0	11.0
CRUD release time constant [1/sec]	1.0E-7	6.0E-7

Sampled parameter and sampling range



Maximum/minimum envelope of ASI

Training ML model

- Problem definition: Supervised learning. The ML problem is classification where a class label (Y) is predicted for a given input data (X).
- Data: CSV file format. First column is a label (Y), referring 'day to CIPS occurrence' or not. Rest are ICI, ECI, CR position used for input data (X).
- Pre-processing: The label is converted to binary number, 1 (CIPS occurrence within coverage days) or 0 (no CIPS within coverage days). Data is normalized such that it has 0 mean and unit variance
- The dataset is divided into three training set (60%), validation set (20%), and testing set (20%).
- Three types of ML models such as RF, XGB, LGBM are combined with soft-voting method establishing an ensemble model. Hyper parameters of the ML models are tuned by using GridSearch method.

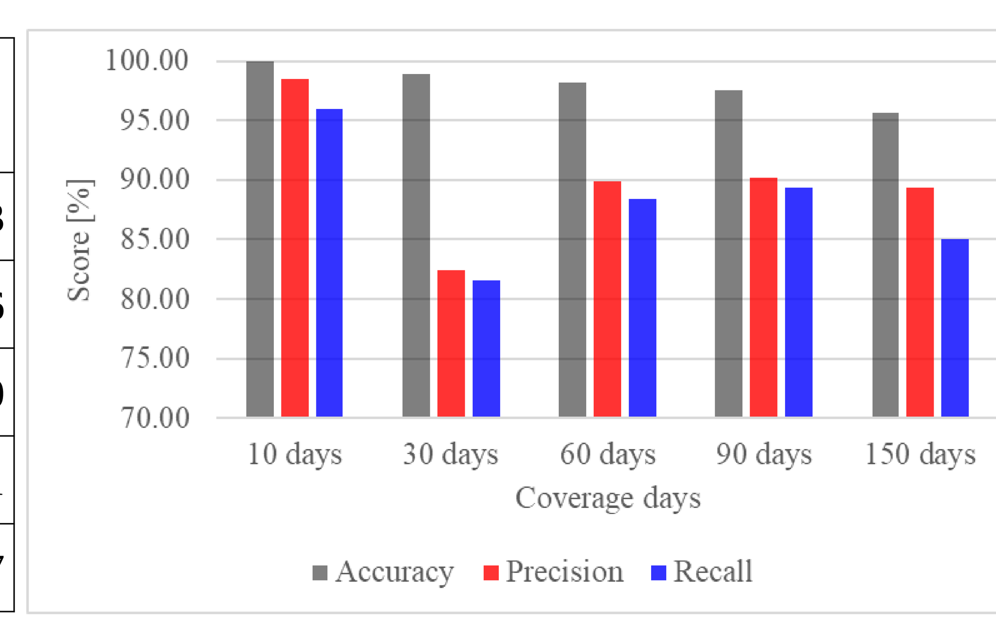
Results

- The binary classification of the ensemble model on testing dataset
- It predicts CIPS occurrence with high accuracy (95%<)
- precision and recall scores are lower than accuracy (80%<)
- This is because data label is imbalance, such as the fraction of positive labeled data is only 1.39% for dataset concerning 10 days to predict CIPS

$$accuracy = \frac{TP+TN}{TP+TN+FP+FN} \qquad precision = \frac{TP}{TP+FP} \qquad recall = \frac{TP}{TP+FN}$$

coverage days	TN	FP	FN	TP
10 days	0.9860	0.0002	0.0006	0.0133
30 days	0.9631	0.0054	0.0058	0.0256
60 days	0.9092	0.0082	0.0096	0.0730
90 days	0.8672	0.0117	0.0129	0.1081
150 days	0.8102	0.0174	0.0257	0.1467

Ensemble model's prediction results



Performance metrics of the ensemble

CONCLUSIONS

- Feasibility of AI-based CIPS prediction method has been assessed.
- Framework for simulation-based training method has been established.
- Three types of ML models (RF, LGBM, XGB) are trained, and they are combined with soft-voting method resulting in an ensemble model.
- The CIPS prediction results shows high accuracy score (95% <) and high precision and recall scores (80% <).
- However, there is limitation with imbalanced dataset.
- In future work, more dataset is generated with adjusted sampling range for balanced data label. Also, future study will train ML model with 'time series' data to learn gradual effect of CRUD on core over time progress.