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

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1. Introduction

As recent trend of pressurized water reactors (PWRs) has increased cycle length and undergone power uprates, CRUD induced power shift (CIPS), which is also known as axial offset anomaly (AOA), occurs in many commercial PWRs. In U.S, it has been reported 18 cases of AOA since 2004, and it has been observed at the OPR-1000 reactor in Korea in 2015. CIPS is an axial power shift towards the bottom half of the core resulting from deposited corrosion product at upper part the core called CRUD and boron hold-up within the CRUD. By affecting axial power distribution, CIPS makes nuclear reactor core operation more difficult, decreasing shutdown margin. A reactor core which exceeds acceptable limits is required to reduce operation power or shutdown. Since that, early diagnostics of CIPS, and follow-up measures such as water chemistry management can reduce costs caused by AOA during the operation. This study has been carried out to predict CIPS occurrence in commercial PWR during operation by using machine learning (ML) technique. Developing a high-performance ML model requires huge amount of training data which is, in this study, nuclear reactor operation data with CIPS occurrence. However, it is challenging to obtain real operation data from nuclear reactors due to safety and security issues. To overcome the challenges, this study employs a nuclear core analysis code, RAST-K [1] to generate simulation data which is used to train ML model predicting CIPS occurrence. A CRUD model solving CRUD balance equation in a reactor coolant system (RCS) is used to simulate CRUD accumulation and following power shift (CIPS). The simulation data is used to train a ML model to predict CIPS. The feasibility of the AI-based CIPS prediction method is assessed in this study.

2. AI-based CIPS prediction method

In this section, the suggested AI-based CIPS prediction methodology is described. At first, prediction of CIPS by using ML algorithm is described, and framework of simulation-based data generation including simulation code description and CRUD model is presented.

2.1 Prediction of CIPS

During nuclear reactor operation, the corrosion products such as Ni, Fe, and Co formed in RCS are deposited on fuel rod cladding surface by subcooled nucleate boiling, resulting in chalk river undefined deposit (CRUD) accumulation with porous media. The porous structure provokes precipitation of ions dissolved in coolant such as boron and lithium. The boron hold-up within the CRUD leads to neutron flux depression at the upper part of the core, bringing axial power shift toward the bottom, called CIPS. With growing of CRUD from the beginning of cycle (BOC), the effect of CRUD on the axial power shape increases gradually during operation. Meanwhile, to detect the AOA occurrence, axial offset (AO) or axial shape index (ASI) is monitored. If the difference between the measured and design values are greater than 3 percent, it is diagnosed with AOA. The suggested method is developed to predict CIPS before the nuclear reactor operation violates the ASI limit with help of ML technique. Since ML model can deal with large and complex problem, it is expected that it can catch anomalies in nuclear reactor core operation caused by CRUD earlier than existing method by monitoring local power shape of all ICI signals and ex-core detector signals in real time.

2.2 Simulation Code & CRUD Model

In this study, ML models learn with simulation data due to challenges of obtaining massive labeled datasets from real nuclear reactor. To make the CIPS prediction method practically usable in operation system, it is necessary to close the gap between 'real' and 'simulated' dataset. A nuclear reactor analysis core, RAST-K [1], is employed to produce simulation datasets. It is a nodal diffusion code developed for in-core fuel management study, core design calculation, load follow calculation and transient analysis of PWRs. It uses multi-group neutron cross section data computed by a lattice physics code, STREAM [2], which adopts pin-based slowing down method (PSM) for resonance treatment to obtain accurate numerical solutions. RAST-K has been verified and validated with respect to the commercial PWRs including OPR-1000, APR-1400, Westinghouse 2-Loop (WH2L), and Westinghouse 3-Loop (WH3L) showing good agreement in nuclear core parameters such as ASI, CBC, and fuel assembly power distributions. In addition, RAST-K can calculate both in-core instrument (ICI) and ex-core detector signals which are used to train ML models. Meanwhile, RAST-K has capability to simulate CRUD accumulation during the operation by solving the CRUD balance equation within the RCS. The balance equation for time $t' = t_b - t_{b-1} \in [0, \Delta t]$ is written as follow:

$$\frac{dC_{CRUD}(t')}{dt'} = \tag{1}$$

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

$$\frac{dM_{CRUD,i}(t')}{dt'} = C_{CRUD}(t')\bar{R}_{i,b} - K_{erosion}, \qquad (2)$$

$$S_{CRUD}^{reload}(t') = \lambda_{src} M_{CRUD,b-1}^{reload} \exp(-\lambda_{src} t'), \qquad (3)$$

where $C_{CRUD}(t')$ is CRUD mass concentration in RCS coolant, M_{RCS} is total mass of RCS coolant, S_{CRUD}^{RCS} is CRUD source from corrosion of RCS component walls, S_{CRUD}^{reload} is CRUD source from reloaded fuels, $M_{CRUD,i}$ is mass of CRUD deposited at node i, ε is purification filter efficient, $\dot{M}_{letdown}$ is RCS letdown flow rate for purification, $\bar{R}_{i,b}$ is average subcooled nucleate boiling rate at node i during time $t' \in [0, \Delta t]$, $K_{erosion}$ is CRUD erosion rate and λ_{src} is CRUD source time constant from reloaded fuels.

Given the CRUD mass deposited on cladding surface by solving Eq. (1) ~ (3), CRUD thickness (τ_{CRUD}) is calculated as:

$$\tau_{CRUD,i}(t_b) = \sqrt{\frac{M_{CRUD,i}(t_b)}{\pi \rho_{CRUD} \Delta z N_{fuel/node}} + R_{clad}^2} - R_{clad}, \qquad (4)$$

where R_{clad} is cladding outer radius, ρ_{CRUD} is CRUD density, Δz is node axial length, $N_{fuel/node}$ is number of fuel rods in a node.

The boron number density increase in CRUD during time $t' \in [0, \Delta t]$ (dN_B) can be calculated with boron number density in borated water ($N_{D,B}$) and CRUD volume increase (dV_{CRUD}):

$$dN_B = N_{D,B} \times dV_{CRUD} \ (\tau_{CRUD} > \tau_{threshold}). \qquad (5)$$

Since AOA is first observed in plants where CRUD deposits are believed to have built up to 20~30 micron [3], threshold CRUD thickness ($\tau_{threshold}$) for boron hold-up in CRUD porous is introduced.

To validate the CRUD accumulation model in ASI calculation, it is compared with measured ASI of the OPR-1000 reactor where AOA has beend observed. Fig. 1 shows the ASI comparison between measurement and computed one by RAST-K. The computed ASI with the CRUD model is well follow the trend of measured ASI comparing to that without the CRUD model.
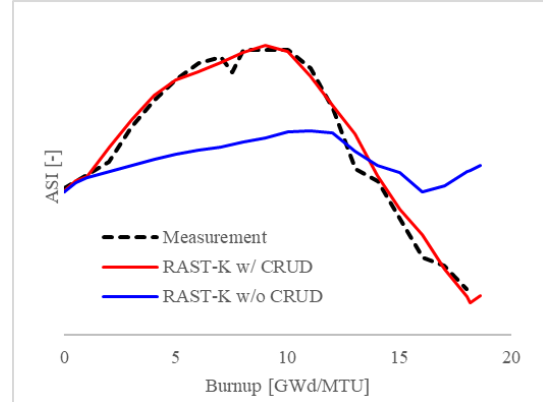

Fig. 1. Comparison of ASI for OPR-1000 where AOA has been observed

2.3 Generation of Train Datasets

In this study, datasets are generated by simulation of the nuclear reactor analysis code, RAST-K. A data generation system in which RAST-K is embedded has been established [4]. An equilibrium core (Cycle 4) of OPR-1000 type reactor is used as base input model. Since it simulates deposit of CRUD on cladding surface during the operation, 500 days of depletion calculation with 52 burnup steps is performed to produce every single core model data, and full power (100%) operation is assumed for depletion.

To make ML model practically usable in NPP, it should cover various core conditions being confronted with during the operation. Thus, train datasets are generated with random numbers to perturbate input parameters relating to operation condition and CRUD accumulation rate. Sampling ranges are set to make the generated core model to be occurrable. The data generation procedure is as follow:

1) For every burnup step, core power is determined by randomly sampling a number from 99.0 to 101 .0 with uniform probability.
2) Input parameters which determine CRUD accumulation rate and boron hold-up are determined. The input parameters are sampled with normal distribution as Table 1.
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) A procedure from 1) to 4) is repeated.

In generation of an input model, core power is perturbed for ±1% from full power (100%) operation condition to consider 2% of uncertainty to detect core thermal power during operation. To avoid a core model

out of normal operation range, sampling range for CRUD accumulation rate is set to be near the nominal values which is used to model the OPR-1000 core model where AOA has been observed. Input parameters which affect CRUD accumulation and boron hold-up rate are sampled with uniform distribution. The parameters are CRUD threshold thickness for boron hold-up, CRUD source in RCS coolant, CRUD in reloaded fuel, and CRUD release constant from reloaded fuel. Because this study is in purpose of developing ML predicting and diagnosing CIPS occurrence earlier than current method, criterion for labelling CIPS occurrence is set to be 2%. Once ASI difference is greater than 2% at a certain burnup step, the core model is labeled as CIPS occurred and snap data prior to the burnup step are labeled as 'day to CIPS occurrence'. The reference core model to compare ASI is hot full power (HFP) condition without CRUD.

Table I: Sampled input parameters and sampling range for uniform distribution

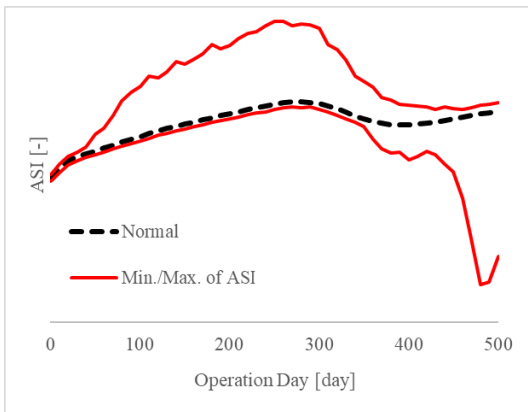| Parameter	Nominal	Lower	Upper
Core power rate [%]	100	99	101
Threshold thickness [micron]	25	20	30
Source in RCS [kg/sec]	1.3E-7	0.3E-7	4.3E-7
CRUD in reloaded fuel [kg]	6.5	4.0	11.0
CRUD release time constant [1/sec]	2.0E-7	1.0E-7	6.0E-7

Fig. 2. Minimum and maximum envelope of ASI over 52,373 core models with CRUD model

In total, 52,373 core models with randomly selected input parameters are generated and simulated with 52 burnup steps. In Linux cluster system with Intel(R) Xeon(R) CPU E5-2680 v4 @ 2.40GHz, it takes 80 mins to calculate a single core model. Out of the generated core models, 27,906 core models are normal (no CIPS occurred) and 24,467 core models are abnormal with

CIPS occurrence. Fig.2 shows minimum envelope and maximum envelope of ASI over 52,373 core models.

3. Training ML model and result

3.1 Training ML model

Since the train datasets are labeled in data generation procedure and it is used in training ML, it is supervised learning. With given label of data, CIPS or not, the ML problem is classification where a class label (Y) is predicted for a given input data (X). The CSV file format is used for train datasets and Fig. 3 shows an example of train dataset. First column is a label, referring 'day to CIPS occurrence' or not, and rest of data in row are control rods positions, ICI signals, and ex-core detector signals being used for input data of ML model. Each row represents a snap data of single burnup step.
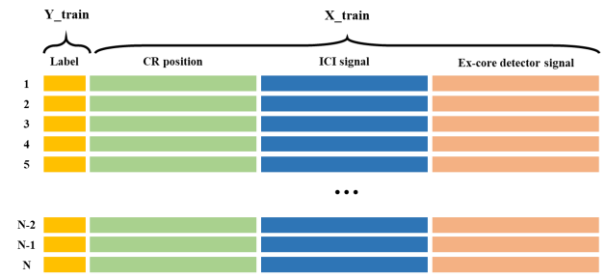

Fig. 3. Example of train datasets to train ML model

Before training, it is preprocessed that labelling is converted to binary number, 1 (CIPS occurrence within coverage days) and 0 (no CIPS within coverage days), according to the number of days to predict. Hence, the trained ML model can provide judgement if CIPS will occur within the coverage days. The coverage days are 10, 30, 60, 90, and 150 days. Data is normalized such that it has 0 mean and unit variance. The dataset is divided into three part to avoid overfitting and model selection bias called training set, validation set, and testing set, taking 60%, 20%, and 20% of dataset, respectively.

Three types of ML models such as Random Forest (RF) [5], XGBoost (XGB) [6], and Light GBM (LGBM) [7] are selected for binary classification of CIPS prediction. Hyper parameters of the ML models are tuned by using GridSearch method. To make it robust, the three trained ML models are combined with soft-voting method called an ensemble model.

3.2 CIPS prediction results

The binary classification result of the ensemble (combined RF, XGB, LGBM) model on testing dataset is shown in Table II including true positive (*TP*), false negative (*FN*), false positive (*FP*), and true negative (*TN*) rates. 'Positive or negative' represents ML model's prediction and 'true or false' represents right and wrong of ML model's decision.

Table II: Ensemble model's prediction results for
CIPS occurrence within coverage days

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

Performance of the trained ML model is tested by using performance metrics such as accuracy, precision (also known as positive predictive value), and recall (also called as sensitivity). The performance metrics are defined as follows:

$$accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (6)$$

$$precision = \frac{TP}{TP+FP} \quad (7)$$

$$recall = \frac{TP}{TP+FN} \quad (8)$$

Fig. 4 shows performance metrics of the ensemble model on predicting CIPS occurrence. Given testing datasets, it predicts CIPS occurrence with high accuracy over 95%. However, precision and recall scores, which are ratio of correctly predicted positive data to all data predicted as positive and all actual positive data, are lower than accuracy in all cases. This is because data label is imbalance. In train dataset, the fraction of positive (CIPS occurred) data (*TP+FN*) is only 1.39% in case where it concerns 10 days for CIPS occurrence. Nevertheless, precision and recall also greater than 80% in all cases. Furthermore, in case where it predicts CIPS occurrence within 10 days, precision and recall score is over 95%. It assures that ML model can recognize CIPS in advance to current method monitoring ASI by learning patterns of power distribution stemming from CRUD accumulation.
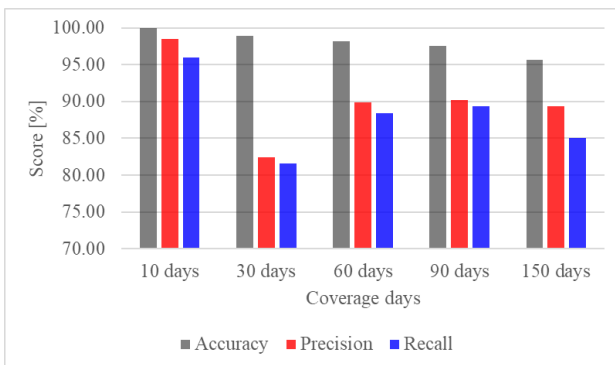

Fig. 4. Performance metrics of the ensemble model on predicting CIPS according to the coverage days

3. Conclusions

In this study, feasibility of AI-based CIPS prediction method has been assessed. Simulation-based dataset is generated by reactor core analysis code, RAST-K. Three types of ML models such as RF, XGB, and LGBM are trained. And then, an ensemble model which combines the three models is established by soft-voting method. The CIPS prediction results shows high accuracy score greater than 95% and high precision and recall scores greater than 80%. However, there is limitation with imbalanced dataset. The ratio of CIPS occurrence data is small if it concerns short-term future such as 10 days. Future work will generate more CIPS datasets to balance the normal and CIPS dataset even for short-term prediction. Also, unlike to this study which trains ML model with 'snap' data of a burnup step, future study will train ML model with 'time series' data for ML model to learn effect of CRUD on power distributions over time progress.

Acknowledgement

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