BNL-NN-20230717-0188-00-FORE

ADVANCED REACTOR SAFEGUARDS Using Machine Learning to Improve Efficiency and Accuracy of Burnup Measurements at PBR Reactors

PRESENTED BY

Ŷ

HH

=

Yonggang Cui, Odera Dim, and Carlos Soto

11/02/2023





Motivations of the Work

- Burnup measurement is the key to deciding if the pebble should be discharged or recycled during the operation of a PBR reactor
- Burnup measurement faces two challenges:
 - High throughput
 - High accuracy
- Objectives
 - Create and validate a workflow for modeling and simulation of both burnup and gamma-ray detection
 - Build ML models
 - Study performance of ML models





Pebble-bed reactor - Wikipedia



FY23 Technical Tasks

- Modeling and simulation
 - Add collimator to the workflow to reduce the flux
 - Validation of the simulation workflow
 - Develop full PBMR model
 - Automate result generation
 - Validate the Serpent simulation results with the ones generated in Oak Ridge Isotope GENeration (ORIGEN)
- Explore the explainability of the ML model



Modeling and Simulation

BNL-NN-20230717-0188-00-FORE



BNL-NN-20230717-0188-00-FORE

Collimation Analysis

- Ejected pebbles from the core are highly radioactive, so collimator is needed to reduce the flux seen by the detector.
- A few options (MCNP, Geant4, Serpent) were considered based on ease of implementation, efficiency of simulation and accuracy.
- We decided to model the collimator directly into the source model in Serpent, eliminating the need to validate data translation to/from an external code.







Full Core Model for Burnup Validation

- Compared to the lattice model, a fullcore model allows
 - More realistic flux and power distribution, hence resulting in more accurate burnup on a pebble per its location.
 - Full core modeling generates a potential to describe the effects of pebble flow path on the overall burnup
 - More accurate simulation to validate or compare to experimental data
 - The effect of control and burnup poisons are better described in a full core model



Top view



Pebble in Core

Zoomed In Quarter Core

Full core model of a PBMR design



Ο

Serpent

0

ORIGEN

Simulation Results – (isotope verification)





0

Serpent

0

ORIGEN

Simulation Results – (emission verification)





Explainability of ML Model

BNL-NN-20230717-0188-00-FORE

11



9.008

7.382

10 days

Machine Learning for Burnup Measurement

- We have demonstrated promising results with our ML models
 - Significantly outperforming linear regression method
 - Specifically, high performance at short cooling
- Results accepted for publication

12

C. X. Soto et al. "A Better Method to Calculate Fuel Burnup in Pebble Bed Reactors Using Machine Learning," Nuclear Technology, DOI 10.1080/00295450.2023.2200573



- However, Neural Network-based ML models are inherently opaque
 - Learned feature representations are not easily interpretable
 - Therefore, confidence and downstream impact of this work may be limited in its present state
 - Also, short-cooling performance merits deeper investigation



Approaches to ML Explainability/Interpretation

- Criteria of tool selection
 - Support the data and models
 - Output explainability insights identifying simple features related to gamma spectra that are most responsible for the ML predictions
- Two selected tools

13

- LIME: Linear Interpretable Model-agnostic Explanations
- SHAP: SHapley Additive exPlanations



LIME works by creating linear decision boundaries using perturbed feature values



SHAP works by creating an ensemble of tree models based on Shapley-value estimations for feature contributions



An Iterative Approach to Explore Explainability



14

StageNarrow down
thresholdExplainability125%88.74%225%78.95%337.5%96.71%

15







ADVA FEGUX

LIME Results

16



Top 24 energies identified by our LIME-based explainability analysis, for the 12-hour and 120-hour cooling condition dataset

Rank	Energy (keV)	Energy (keV)	Rank	Energy (keV)	Energy (keV)
1	891.153	2740.737	13	61.281	389.433
2	446.385	2754.297	14	318.921	348.753
3	443.673	888.441	15	58.569	584.697
4	337.905	308.073	16	340.617	354.177
5	118.233	118.233	17	280.953	421.977
6	278.241	2735.313	18	893.865	66.705
7	180.609	337.905	19	205.017	2770.569
8	286.377	58.569	20	899.289	405.705
9	36.873	446.385	21	272.817	61.281
10	55.857	443.673	22	888.441	351.465
11	896.577	2751.585	23	316.209	69.417
12	66.705	55.857	24	69.417	454.521

LIME Results

17

Validation of LIME-selected features with new MLP and LR models. Arrows indicate direction of better performance per metric: RMSE (root mean square error), MAPE (mean absolute percent error), R² (correlation coefficient)

		I RMSE	↓ MAPE (%)	1 R ²
MLP	Original	0.66	2.04	0.9995
	spectra			
	Stage 1	0.37	1.61	0.9998
	features			
	Stage 2	0.27	1.33	0.9999
	features			
	Stage 3	0.28	1.07	0.9999
	features			
Linear	Original	0.74	7.93	0.9992
Regression	spectra			
	Stage 3	0.53	5.16	0.9996
	features			

Linear regression on top-N LIME features (all features ~3 keV wide)

	↓ RMSE	I MAPE (%)	Î R ²
Top-24 (all)	0.528	5.16	0.9996
Тор-8	0.698	6.81	0.9994
Top-4	3.424	20.99	0.9848
Top-2	6.113	58.74	0.9533



Next Steps



- Improve burnup model towards realistic operational conditions by varying
 - Transient time
 - Cooling time

18

- Measurement time
- Study the performance of the ML models with the new datasets
- Validate the burnup model with measured spectra as new burnup experiments go through and gamma spectra of newly burned TRISO particles become available



- The work presented in this paper was funded through the Advanced Reactor Safeguards (ARS) program, Office of Nuclear Energy U.S. Department of Energy.
- Thanks for Drs. Jianwei Hu and Donny Hartanto from ORNL for discussions on modeling and simulation of PBMR400 reactor.