Ian Kolaja PhD Exit Talk

Advanced Fuel Measurement and Operation Modeling for Pebble Bed Reactors

November 2025



Overview

Pebble bed reactors (PBRs) present unique challenges in burnup measurement and operational modeling.

My work explores a novel method for measuring discharged fuel pebbles and a ML framework for predicting the complex, time-dependent reactivity behavior of PBRs.

Outline

- 1. Introduction
- 2. Pebble Assessment with Bent Crystal Diffraction Spectrometers
- 3. Core State Prediction with a LSTM

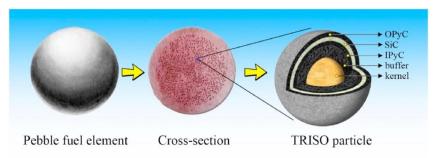


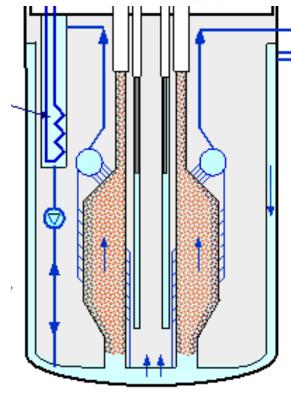
1) Introduction



Pebble Bed Reactor (PBR) Overview

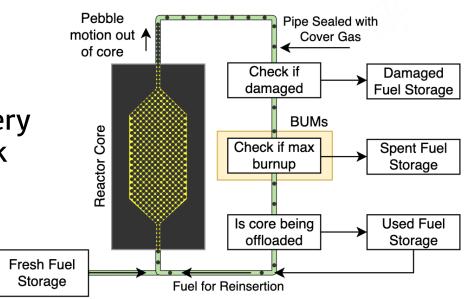
- Use fuel "pebbles" instead of fuel rods
 - 10⁴−10⁵ pebbles in the core
 - Constant fuel circulation
- Features coolants other than water
 - Nonreactive gas (i.e. Helium)
 - Molten Salt (i.e. FLiBe)



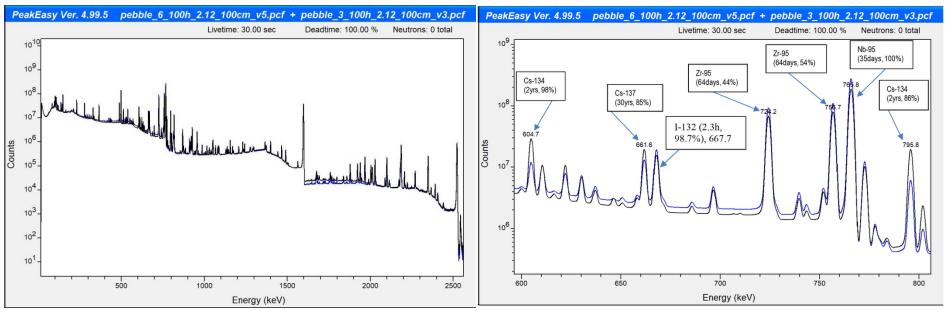


Burnup Measurement in PBRs

- ¹³⁷Cs is good burnup marker (661 keV gamma via ^{137m}Ba)
- Measuring burnup for PBR pebbles is hard
 - Pebbles leave the core every~20s in Kairos benchmark
 - High activity (10¹³ Bq) can cause dead time in many detectors
 - Compton scattering and spectrum crowding can mask 661 keV peak



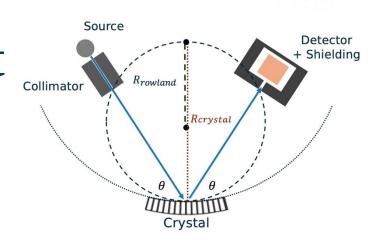
Example Gamma Spectra from discharged PBR fuel



Synthetic HPGe spectrum generated with GADRAS by Don Kovacic [3]. The wide spectrum is shown (a) and the region around the 137Cs peak (b). Note the 30 second measurement time, 100% deadtime, and bin counts ranging from 106 to 108.



2) Pebble Assessment with Bent Crystal Diffraction Spectrometers





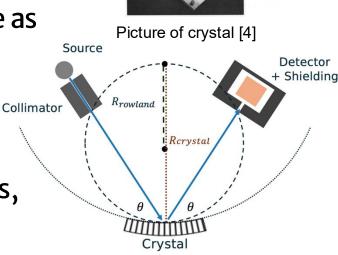
Bent Crystal Diffraction Spectrometers

 BCD Spectrometers offer a potential solution by acting as an energy filter

Uses perfect or mosaic crystal lattice as a diffraction grating

 Constructively diffracts and focuses gammas entering the crystal at a certain angle and energy

Used in nuclear physics, astrophysics, synchrotrons, and nuclear forensics

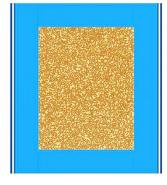


Schematic of BCD spectrometer for PBR



Pebble Data Generation

- Pebble-wise depletion performed with HxF
 - Kairos gFHR model
 - 250,000 pebbles in core, average 8 passes
- History, parameters of interest, and nuclide inventory predicted for each pebble
- Serpent used to generate emitted gamma spectra for each pebble
 - 1.5 day decay time assumed



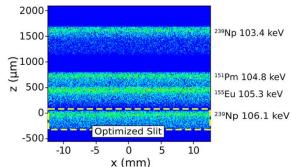
gFHR benchmark diagram



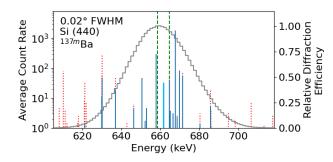


Generating Synthetic Measured Spectra

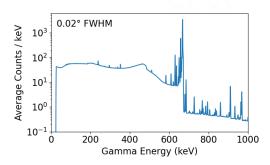
- SHADOW and GADRAS used
- Selected gammas: 661keV from ^{137m}Ba,
 106 keV from ²³⁹Np, 133 keV from ¹⁴⁴Ce,
 414 keV from ^{148m}Pm, 1596 keV from ¹⁴⁰La

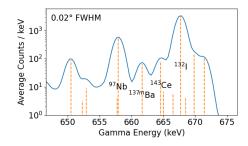


Example diffraction pattern incident on detector with slit shielding



Pebble emission spectra with spectrometer filter overlay

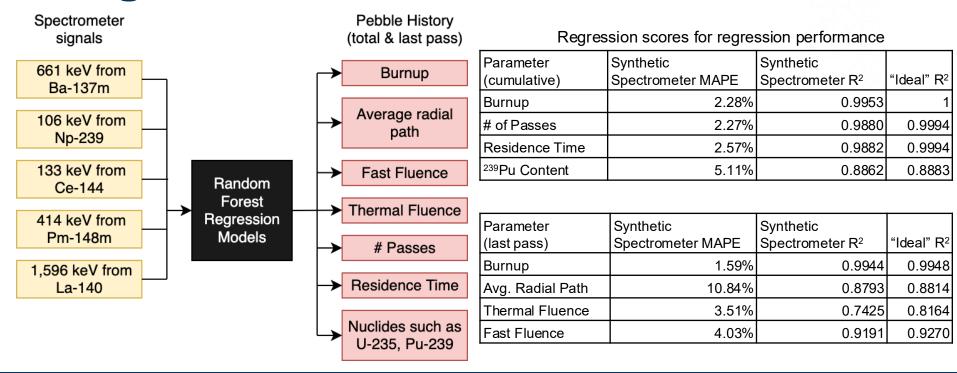




GADRAS simulation from incident ^{137m}Ba spectrum



Regression for Pebble Assessment





Conclusions and Future Work

- BCD spectrometers are a powerful tool for rapid fuel pebble assessment
- ML-powered regression enables accurate prediction of many pebble properties and history parameters
- Future design optimization based on footprint or cost constraints recommended
- Experiments verifying the BCD spectrometer properties and performance in relevant environments needed



Core State Prediction with a LSTM



PBR Operation Challenges

- In-core measurements limited
 - High temperature/flux causes thermocouple drift
 - Dynamic bed leaves little room for flux detectors
- Reactivity management more complex
 - Fuel handling and operation affect reactivity on multiple time scales
 - Excess reactivity kept low and nearly constant
 - "Running-in" to equilibrium can be achieved in various ways



Factors that affect reactivity in PBRs

Short Term

Long Term

Control rod movement

Pebble circulation rate change

Change to fuel insertion pattern

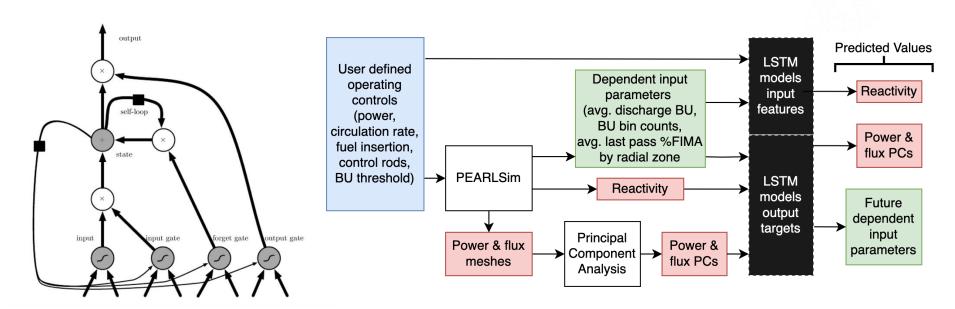
Power change

Change to burnup limit

Fuel depletion, or burnup



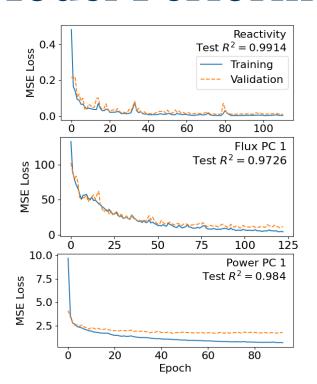
Long-Short Term Memory (LSTM) Network

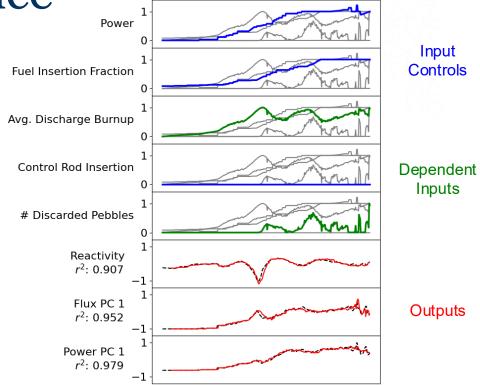


This block diagram shows the structure of an LSTM recurrent network "cell," illustrated by lan Goodfellow et al. [5]



Model Performance



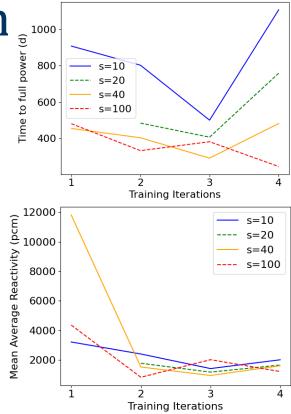


Performance on unseen sequence



Running-In Optimization

- LSTM used to control core simulator
- Controls moved towards "goal" state (i.e. 100% power, 0% graphite pebbles, rods fully withdrawn)
- Impact on reactivity predicted
- Controls selected so reactor is critical
- Different minimum number of adjustments, s, used
- Model retrained each time





Conclusions and Future Work

- LSTMs offer a strong tool for predicting reactivity
- Coupling core model with thermal hydraulics
- Running-in with multiple enrichments needed
- Feature engineering can be expanded
 - Reduced order models (i.e. infinite lattice k_{∞})
- Other ML model options (i.e. autoencoder)



Acknowledgements

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Thank you to:
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My committee: Dr. Massimiliano Fratoni, Dr. Lee Bernstein, Dr. Kai Vetter, and Dr. Benjamin Nachman

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My D&D group My cohort My research group

My friends from undergrad My friends from Civ/EnvE

The senior members of NucE Berkeley Hope Scholars

Engineering Student Services My chosen family

My family: Theresa Heitkamp, Kaley and Tierney Kolaja





References

[1] M. Liu, C. Zeng, Z. Luo, H. Gu, and J. Deng, 'Optimization of the TRISO fuel particle distribution based on octahedral and icosahedral-based segmentation methods in the pebble-bed nuclear core', *International Journal of Advanced Nuclear Reactor Design and Technology*, vol. 2, pp. 103–110, 2020.

[2] C. Andreades *et al.*, 'Design Summary of the Mark-I Pebble-Bed, Fluoride Salt-Cooled, High-Temperature Reactor Commercial Power Plant', *Nuclear Technology*, vol. 195, no. 3, pp. 223–238, 2016.

[3] D. N. Kovacic *et al.*, 'Nuclear Material Control & Accounting for Pebble Bed Reactors (FY 2023 Summary Report)', Oak Ridge National Laboratory (ORNL), Oak Ridge, TN (United States), 11 2023.

[4] B. W. Wehring and M. E. Wyman, 'A bent-crystal spectrometer for the measurement of KX-rays coincident with fission', *Nuclear Instruments and Methods*, vol. 61, no. 2, pp. 189–197, 1968.

[5] I. Goodfellow, Y. Bengio, and A. Courville, Deep Learning. MIT Press, 2016.

