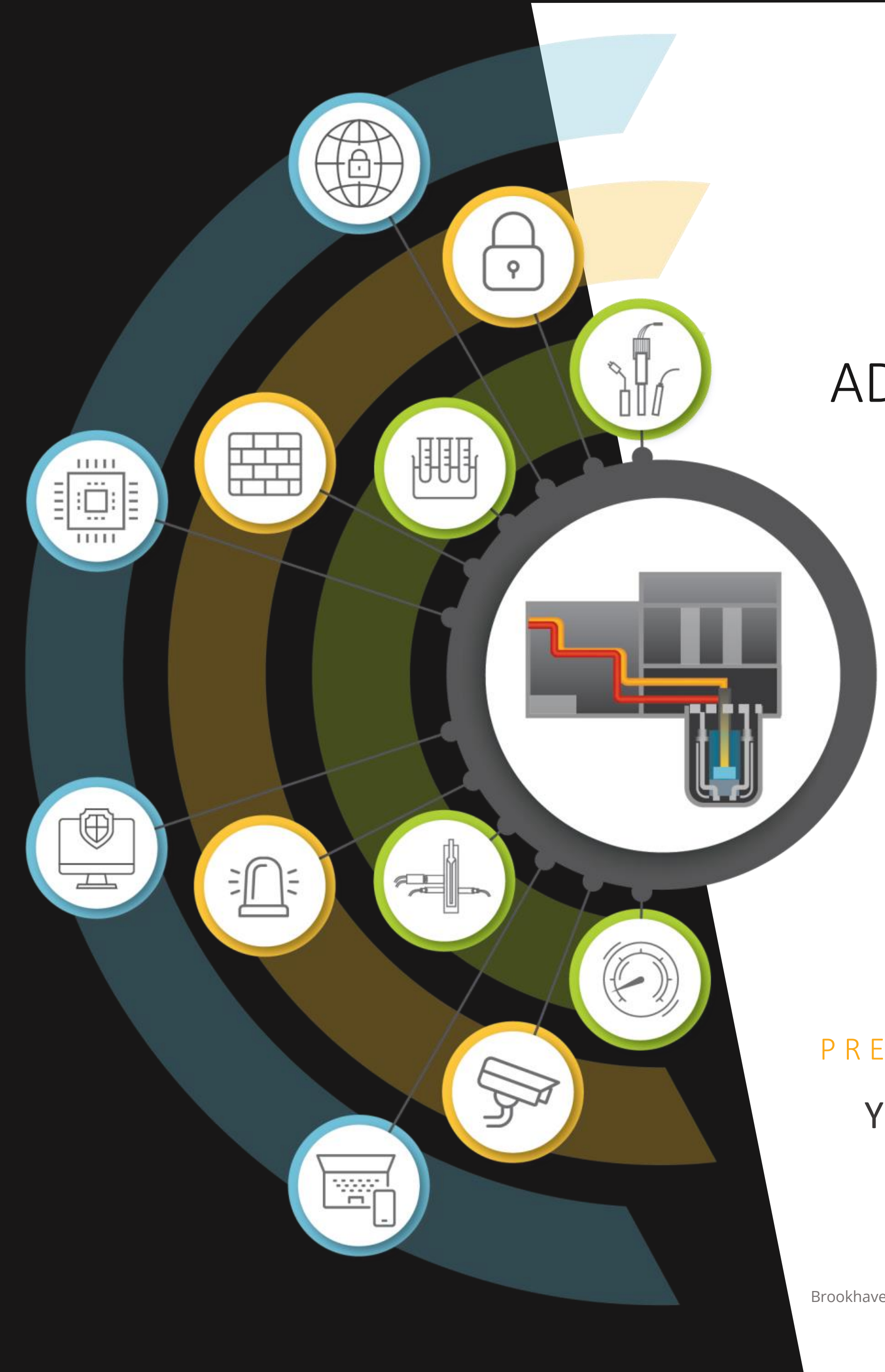


ADVANCED REACTOR SAFEGUARDS & SECURITY

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

PRESENTED BY

Yonggang Cui, Odera Dim, and Carlos Soto

5/14/2024

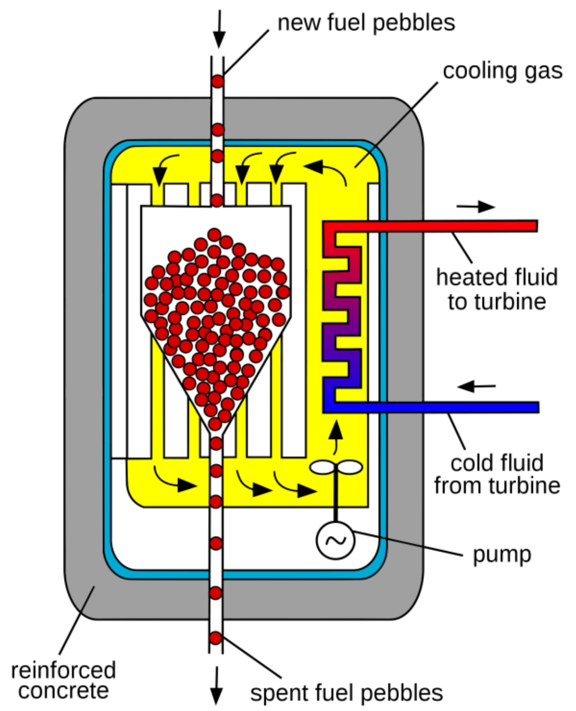
Brookhaven National Laboratory (BNL) is managed on behalf of DOE by Brookhaven Science Associates (BSA), a partnership between the Research Foundation for the State University of New York on behalf of Stony Brook University, and Battelle under contract DE-SC00127045.

BNL-NN-20240506-0024-00-INRE

Motivations of the Work

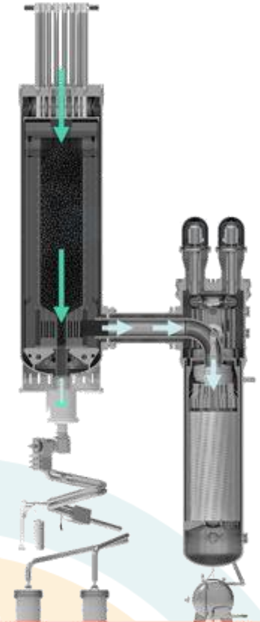
- Burnup measurement is the key to deciding if the pebble should be discharged or recycled during the operation of a PBR reactor
- Burnup measurement faces two challenges:
  - High throughput
  - High accuracy
- Objectives
  - Create and validate a workflow for modeling and simulation of both burnup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

Pebble bed reactor scheme



[Pebble-bed reactor - Wikipedia]

Modeling and Simulation Workflow

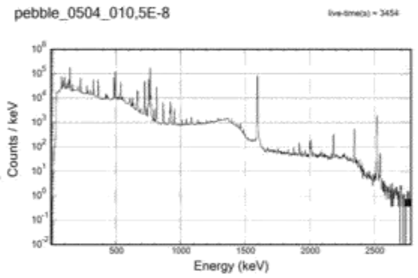


SERPENT SIMULATION

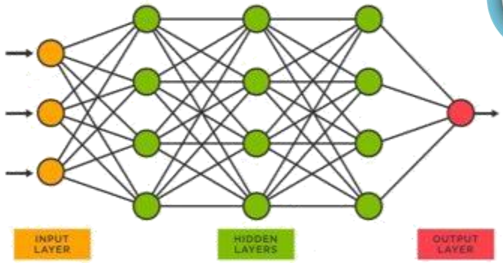
Include burnup model and collimation

GAMMA SOURCE

GADRAS SOFTWARE



GAMMA SPECTRA

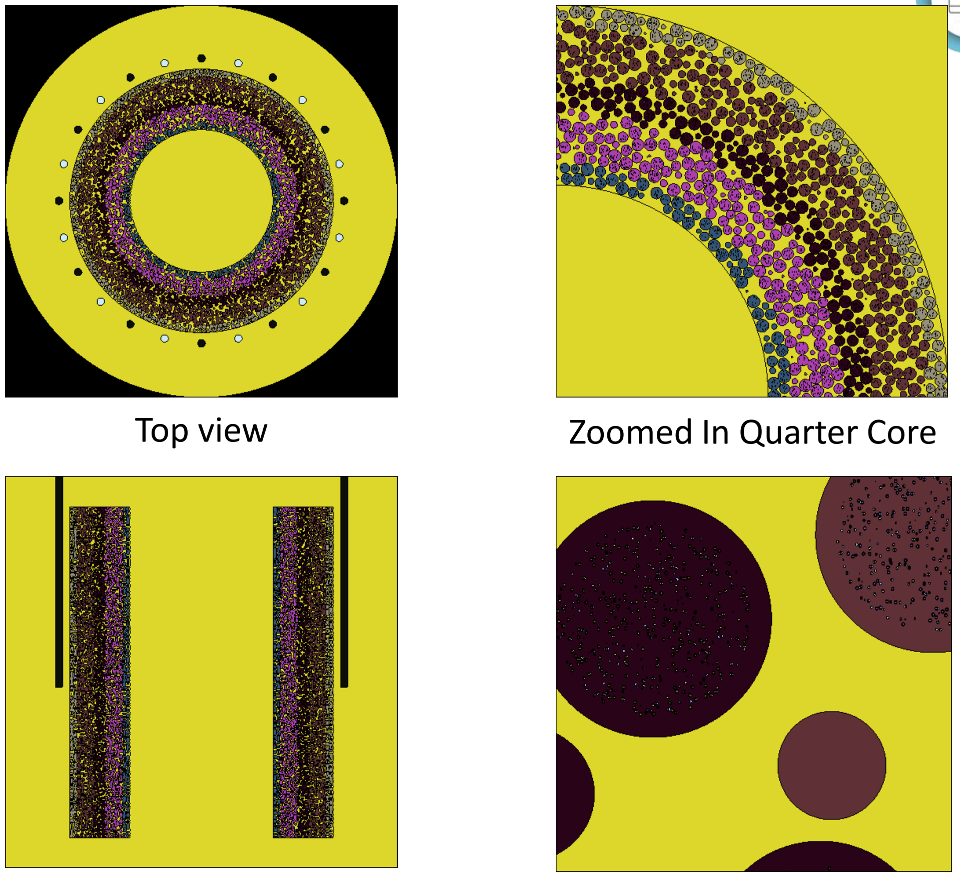


ML ALGORITHM

PREDICTION

Full-core Burnup Model

- Extended the simple lattice model into a full PBMR model
- *Validate the Serpent simulation results with the ones generated in Oak Ridge Isotope GENeration (ORIGEN)*
- Add collimator to the workflow to reduce the photon flux


Top view

Zoomed In Quarter Core

Cut through Side View

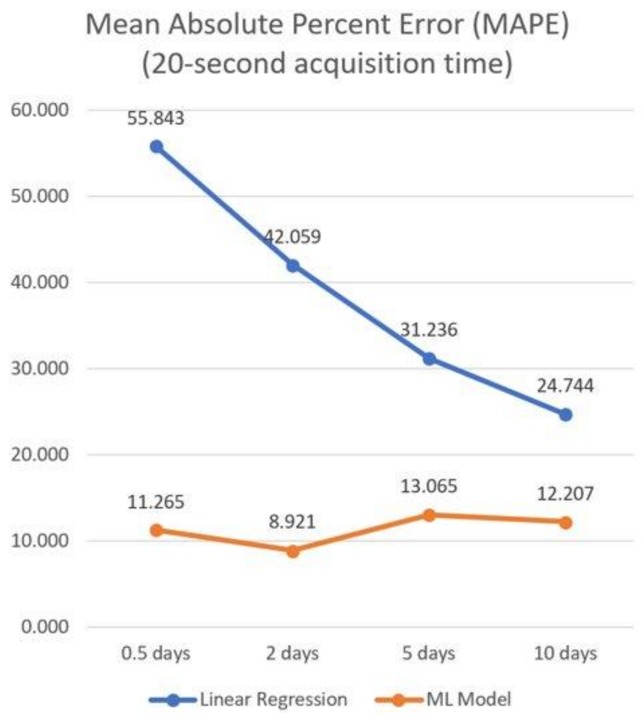
Pebble in Core

Full core model of a PBMR design

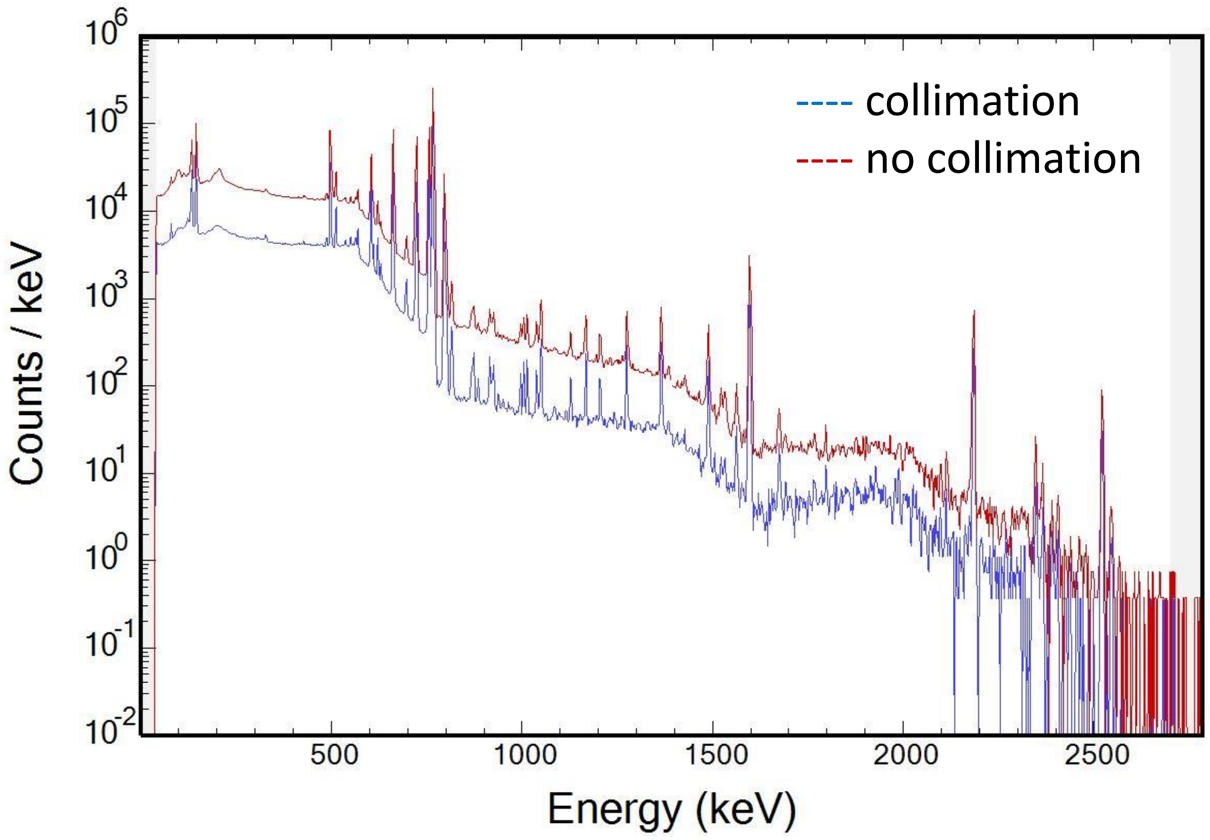
Machine Learning for Burnup Measurement

- We have demonstrated promising results with our ML models
  - Significantly outperforming linear regression method
  - Specifically, high performance at short cooling
- Results were published last year

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



Example Gamma Spectra of a Pebble



Explainability of the MLP Model

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

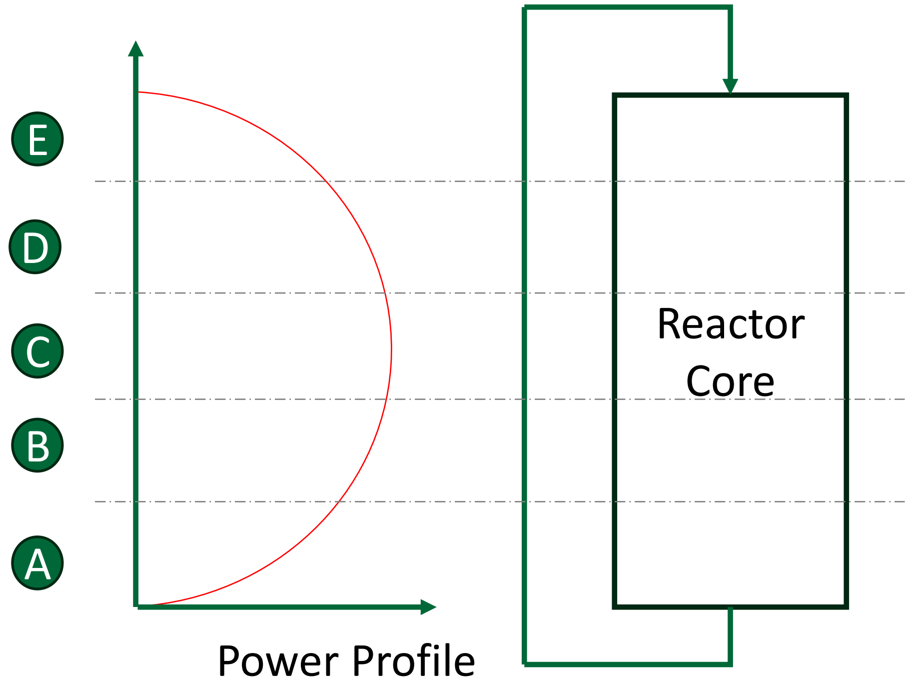
Rank	Energy (keV)	Energy (keV)	Rank	Energy (keV)	Energy (keV)
1	891.153	2740.737	13	61.281	389.433
2	446.385	2754.297	14	318.921	348.753
3	443.673	888.441	15	58.569	584.697
4	337.905	308.073	16	340.617	354.177
5	118.233	118.233	17	280.953	421.977
6	278.241	2735.313	18	893.865	66.705
7	180.609	337.905	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

Updates in the Burnup Model in FY24

- The initial simulation of the spent fuel pebbles was simplified and lacked some of the required complexity of pebble traveling through a core.
- Some of the key parameters that needed some additional complexity include:
  - Consideration of the radial flux and irregular travel path of a pebble down the core.
  - Variation in the flux and power on each pass/cycle of a pebble through the core.
  - Slight variation in cooling time to simulate real reactor operation.
  - Other local power/flux considerations such as proximity of pebble to control rod position.

Simulation

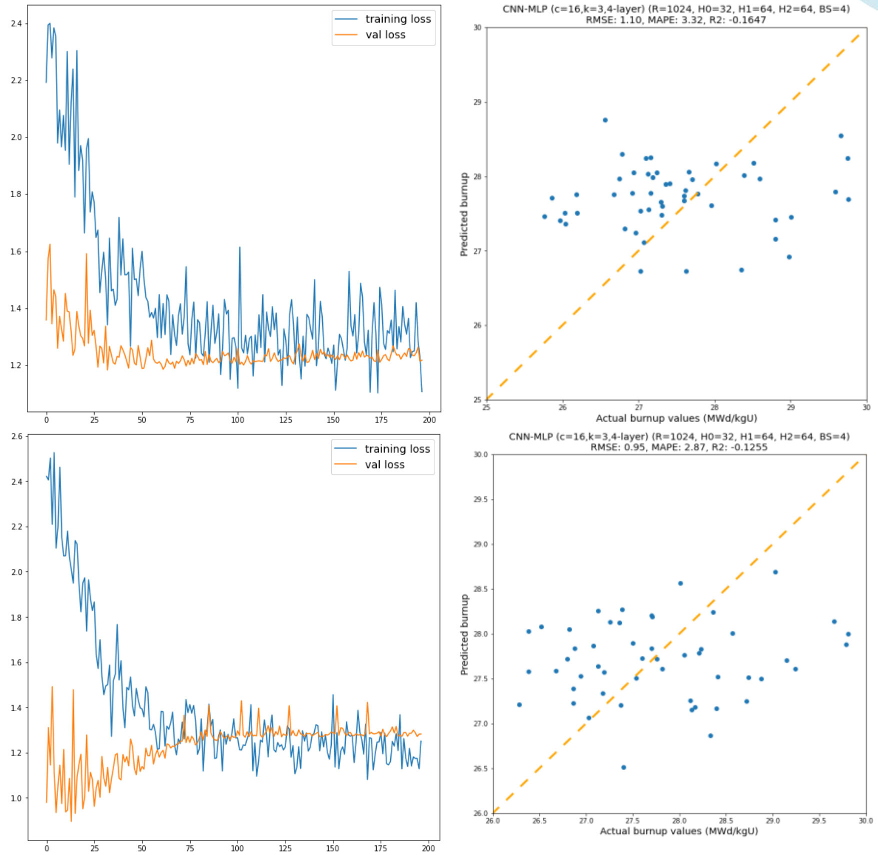
- Each pebble cycled/passed through the core 8 times (for a total of about 100 days per cycle).
- Cooling time was set to 12±1% hours.
- Each pebble has a slightly different time to travel from top to bottom of the core.
- To simulate this effect, we used an average of 100 day with ±25-day variation in residence time.
- The power density on a pebble was set at a peak of 0.057kW/g.
- This power density was resampled to follow the cosine shape of the power profile in a generic core depending on the zone the pebble is in for that step.



- Spectra of 500 used pebbles were generated.

Results from the First ML Test

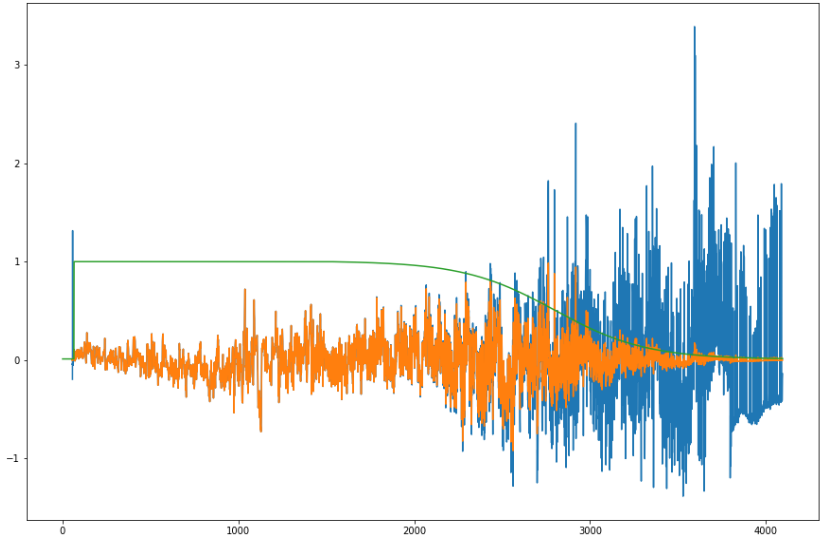
- Initial ML model training on new data results in significant convergence challenges
- We know the expected model capacity (i.e., sensible model hyperparameters) of the ML model for gamma spectra data from previous results
  - Convergence failures are likely because of the **significant increase in data variance**
  - Attempts to model increased variance with larger ML models result in rapid overfitting due to limited data
- Conclusion: ML training is currently data-starved



Left: Samples of training runs for nominal (*top*) and moderately increased-capacity (*bottom*) models (results for CNN-MLP hybrid shown here). Validation loss quickly plateaus, or climbs then plateaus (**indicative of convergence and overfitting issues**). *Right*: samples of uncorrelated model predictions with **regression to mean value**; indicates training failure.

Ongoing ML Model Work

- We anticipate NN model convergence issues may be resolved with increased data volume
  - Conclusion supported by our experience in the previous datasets and quality of training failures observed in the recent trainings
- Potential resolutions being considered
  - Generate more data through modeling and simulation
  - Explore ML architectures that do not rely on learned embeddings, i.e., those that operate in original feature space
  - Experiment with dimensionality reduction techniques and data projections for classical regression
  - Quantify variance changes relative to previous datasets and their effects on ML model training



Preliminary exploration of variance contributions to ML model training by transforming data with a dampening factor

Next Steps

- Continue modeling and simulation to produce more spectra for ML trainings.
- Tune and train ML models.
- Report the results in a journal paper

Acknowledgement

The work presented in this paper was funded through the Advanced Reactor Safeguards (ARS) program, Office of Nuclear Energy U.S. Department of Energy.