Machine Learning in Safeguards at Pebble Bed Reactors

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Motivation of the Work

- MC&A at pebble bed reactors is challenging
  - Fuel pebbles require a different accountancy approach than traditional large fuel assemblies
  - Difficult to verify inventory esp. in reactor vessel
  - No unique identifications to distinguish individual pebbles
  - MC&A at single pebble level is almost impossible, but at what levels in terms of items and accuracy are needed from safeguards and security perspective?
- Goal of the project
  - Investigate the feasibility of machine learning in improving effectiveness and efficiency of safeguards at PBRs
- Objectives
  - Identify areas in safeguards implementation where machine learning (ML) can improve the safeguards effectiveness and efficiency, and
  - Develop/test machine learning algorithm to address the top priority need in this application

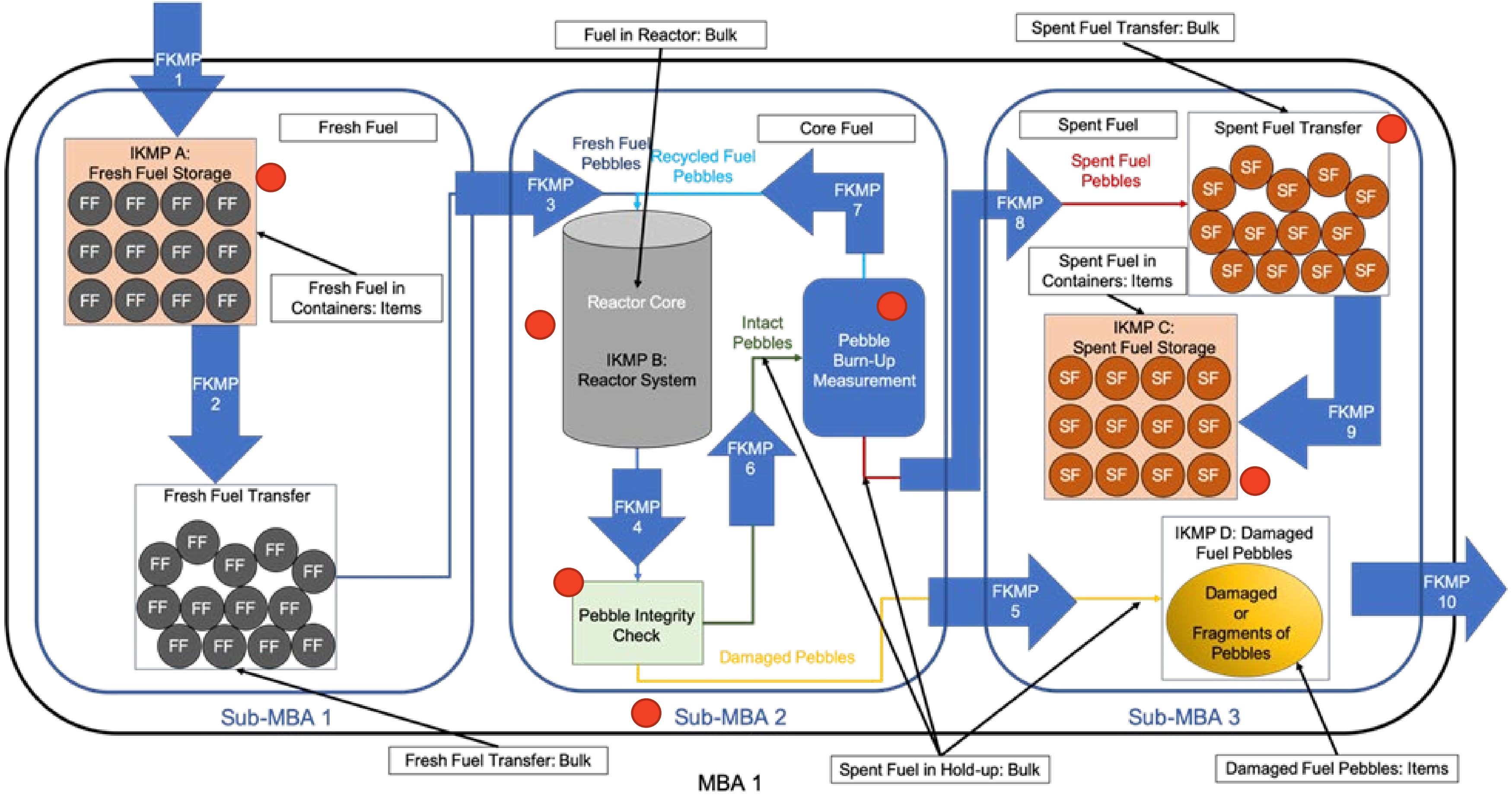
Project Workplan

- Work with stakeholders to examine current safeguards at PBRs and identify areas that machine learning can help strengthen safeguards approaches.
- Develop machine learning tasks to address these potential application areas – task definition, test bed and test datasets, etc.
- Down-select high priority tasks.
- Develop and test machine learning algorithms.

Potential Applications of ML for Safeguards at PBRs

We worked with Safeguards SMEs and PBR designers to identify the following areas that ML could potentially help improve efficiency and/or effectiveness of MC&A.

- **Improve burn-up measurements**
- Pebble integrity check
- Use transit times of selected pebbles to estimate/verify inventory in a reactor core
- Verify pebble inventory in the spent fuel containers
- Video surveillance in storage areas
- Using remote neutron measurement and operation log to estimate reactor power



Use Machine Learning to Improve Burnup Measurement

Decision point for fuel to be removed or reloaded from the core. Measurement uncertainty affecting decision remains to be determined. It will affect declared values for MC&A, safety, and operations. (P. Gibbs' presentation)

- Objective – reduce uncertainty of the measurement while maintaining or shortening the measurement time
- Gamma spectra (measured or simulated) - 1D vector (~8196 bins)

Standard approach

- Measure known photo-peaks (e.g. Cs-137)
- Perform regression to predict burnup rate

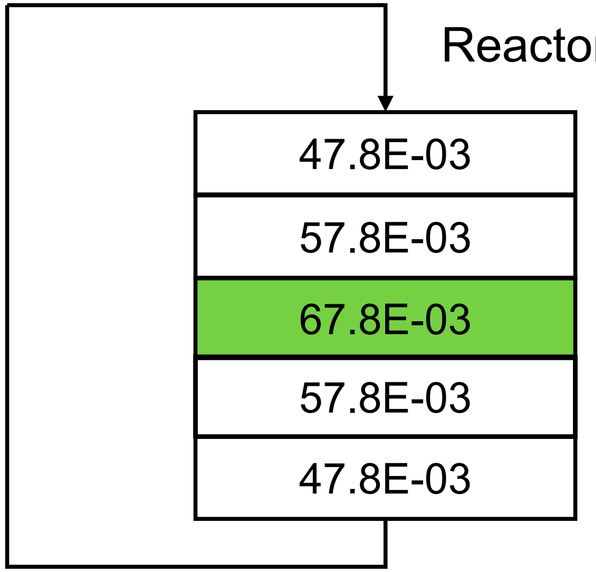
ML approach

- No manual feature selection/engineering
- Robust, data-driven feature learning

Simulation Model

6 Passes

$1\ pass \cong 30\ GWD/T$

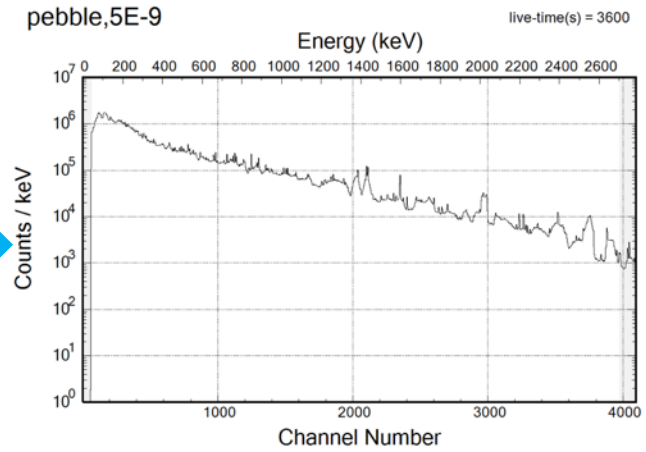


Serpent MC simulation

Parameters: transit time, power and profile

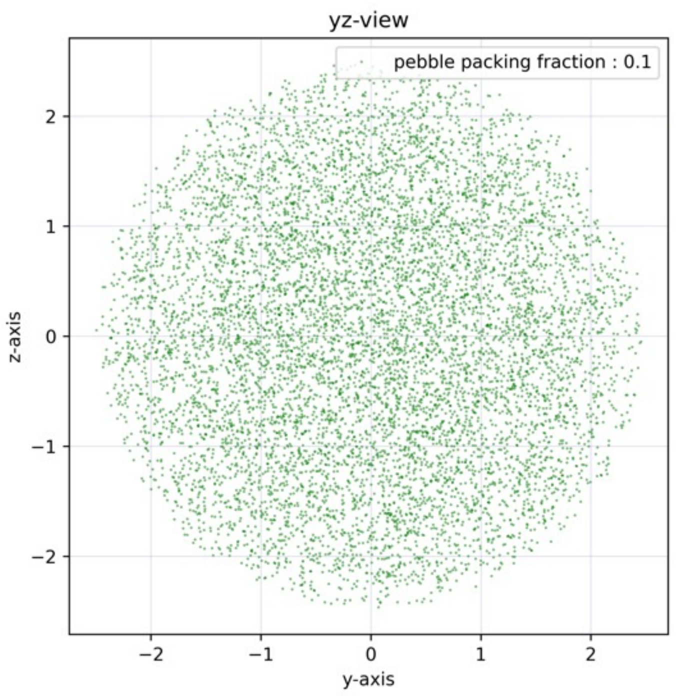
Photon emission results

GADRAS-DRF

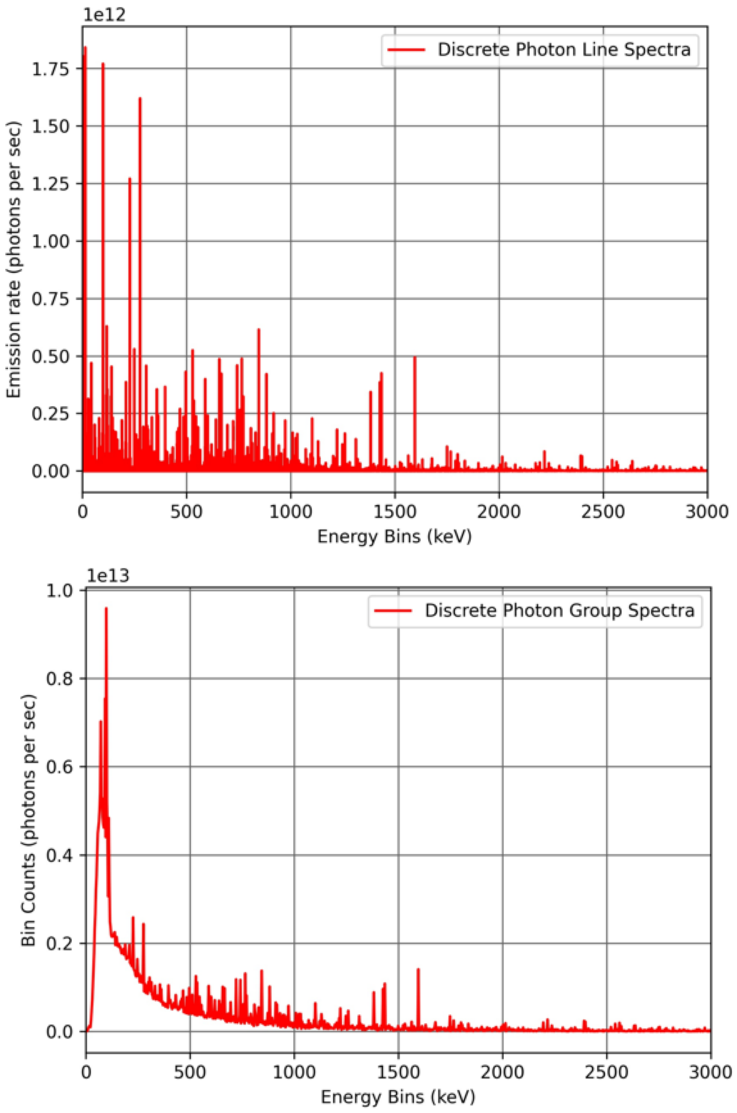


Gamma-ray spectrum

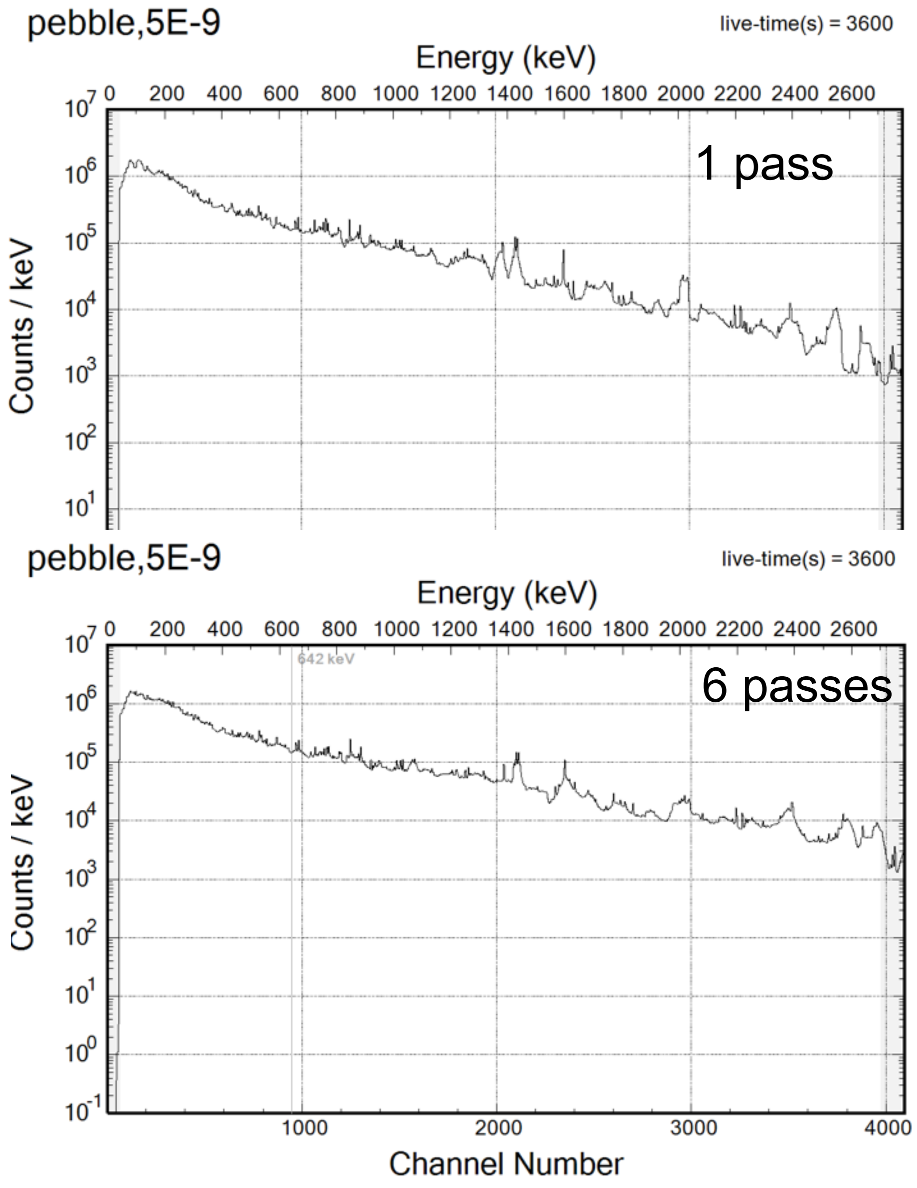
Simulation Results



Simulated pebble with 19,000 kernels



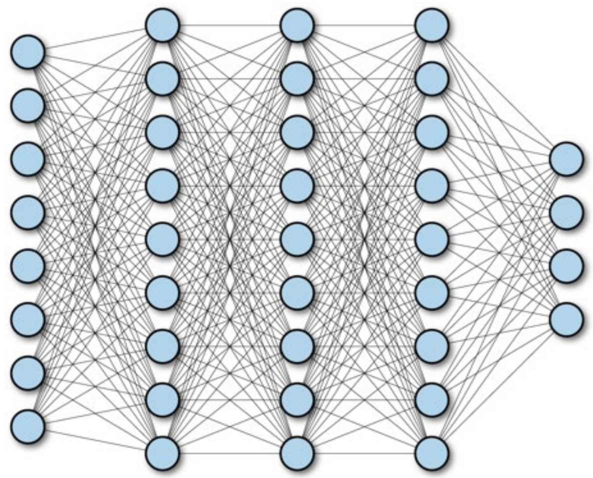
Photon emission of a pebble



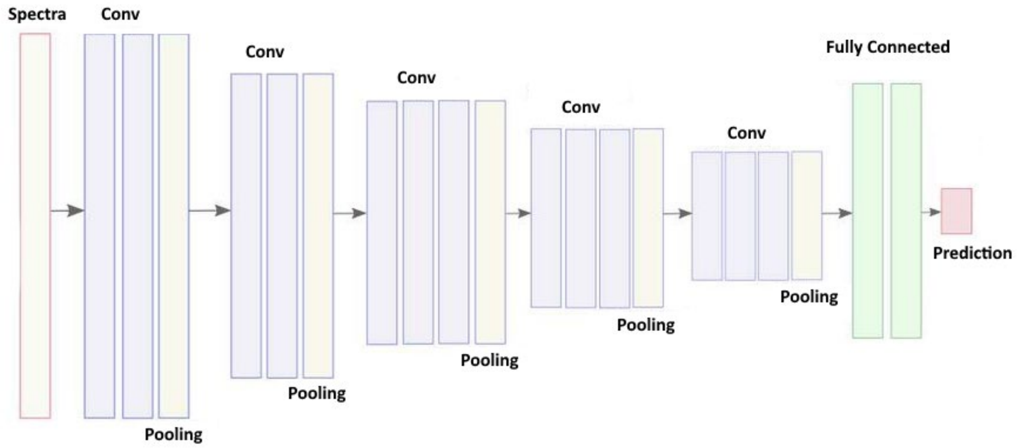
Gamma-ray spectra

ML Methods

- Fully connected network / "Multi-layer Perceptron" (MLP)
  - Global feature representations
  - Architecturally simple

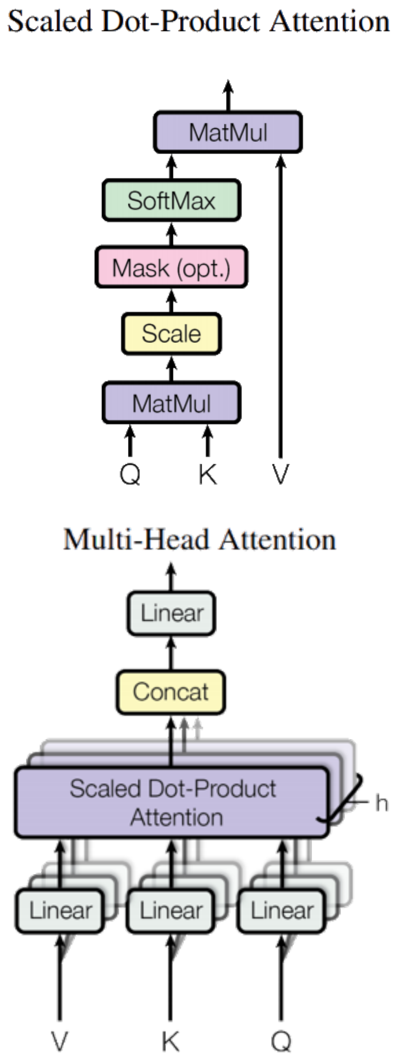


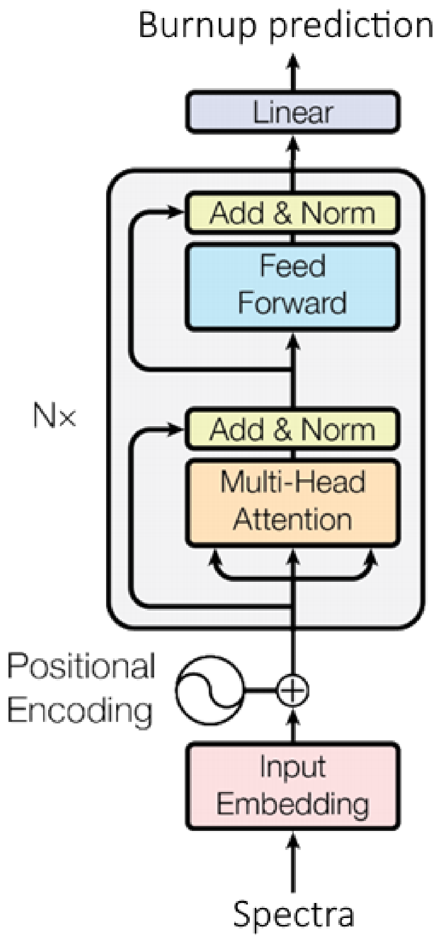
- Convolutional Neural Network (CNN)
  - Local feature representations
  - Incrementally grown receptive field via Max Pooling
  - Simultaneous deeper feature representation
  - Fully connected network head for prediction
  - Efficient inference



ML Methods (cont.)

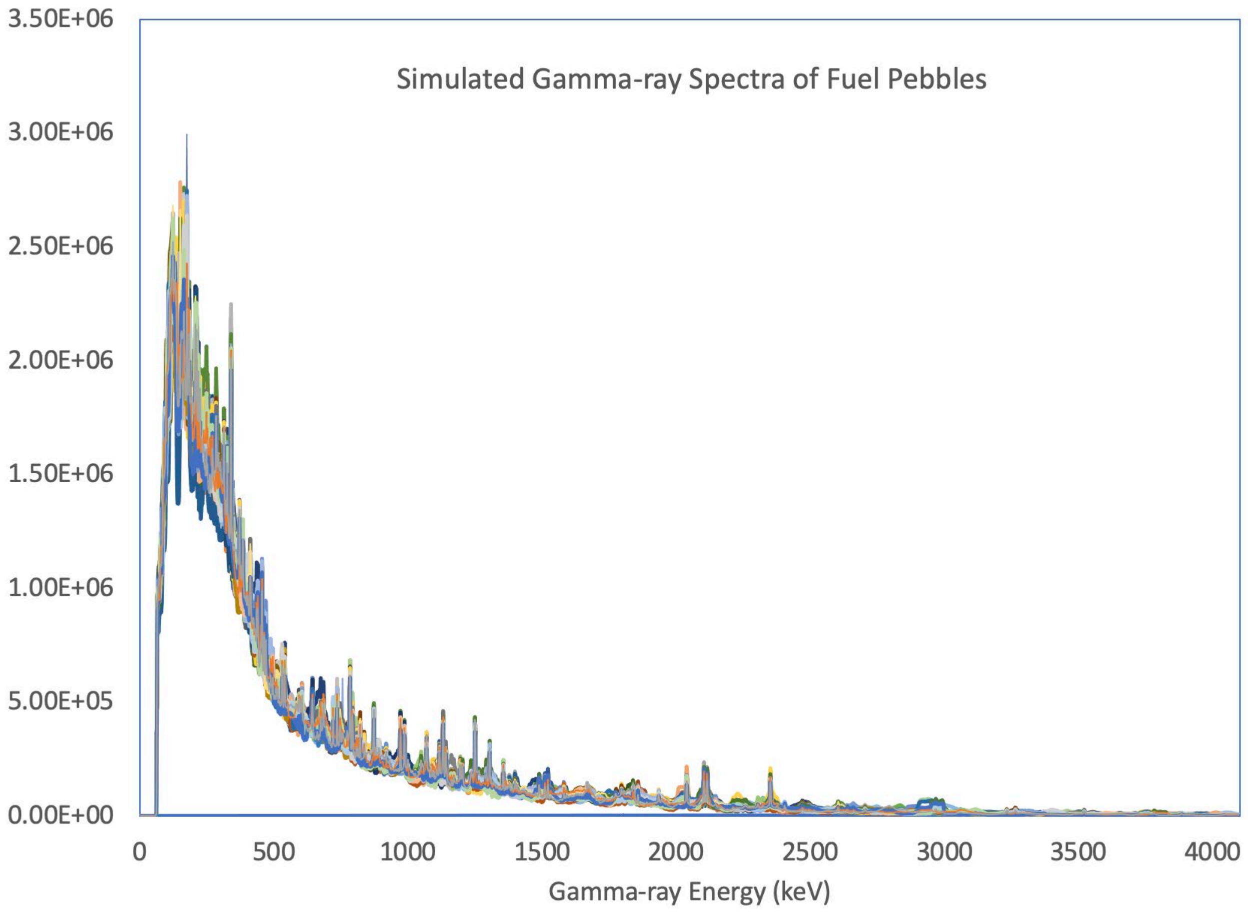
- Transformer
  - Dynamic feature representations
  - Multi-head attention mechanism simultaneously captures local & global data relationships
  - Positional encoding enables sequence processing without recursion
  - Transformer layers can be stacked for deeper representations, accommodating more data





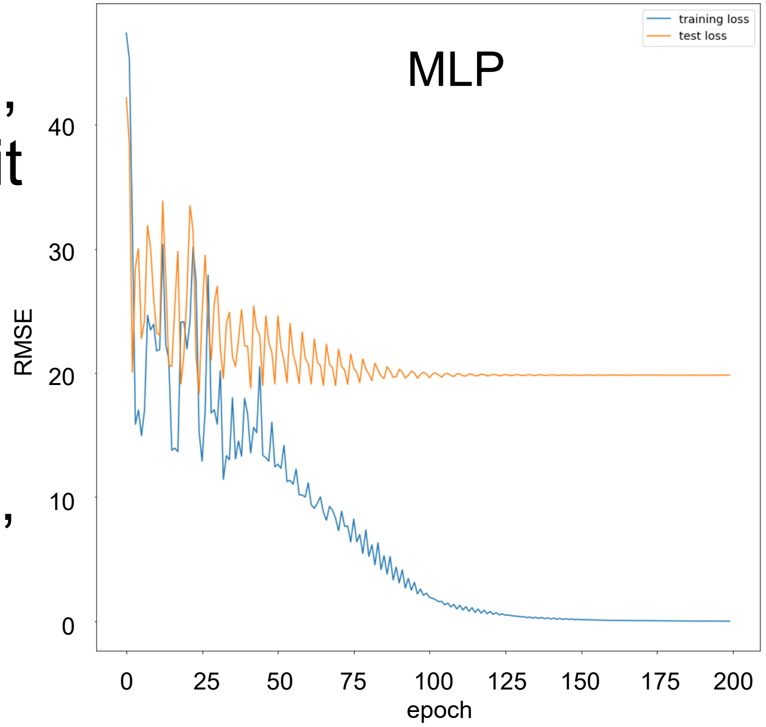
Preliminary Results of ML for Burnup Measurement

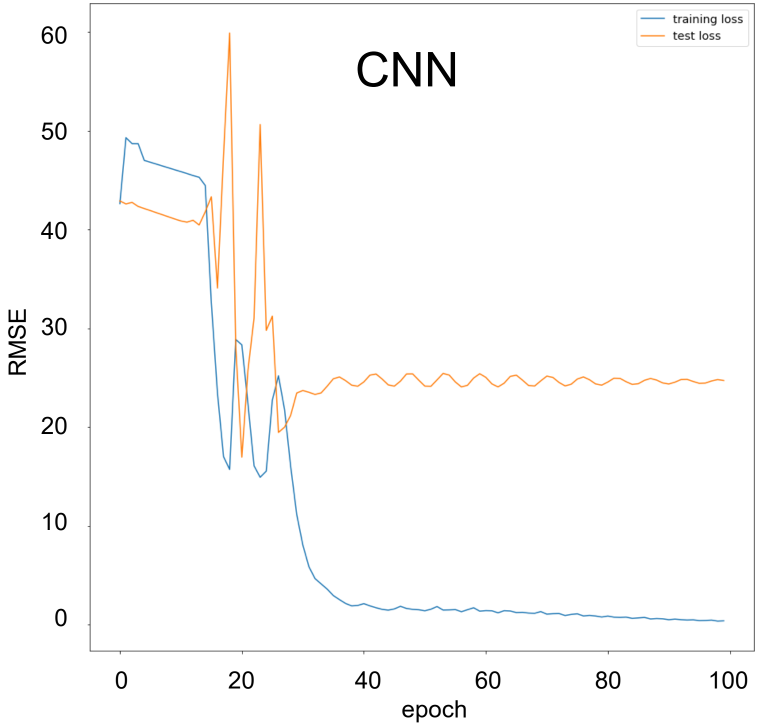
- Initial small training sample of 56 simulated spectra
- Trained 2 baseline models
  - MLP with 2 hidden layers
    - Layer 1 hidden nodes = [128-1024]
    - Layer 2 hidden nodes = 128
  - 2-layer 1D CNN with 1 or 2 prediction layers
    - Kernel size = [3, 5, 21, 41]
    - 4-8 kernels
  - 80:20 train/test split



Preliminary Results of ML for Burnup Measurement (cont.)

- Due to small training data, both models rapidly overfit
- Models plateau at:
  19.8 RMSE (MLP)
  24.5 RMSE (CNN)
  - With 10 model ensemble, CNN improves to 17.4 RMSE
- Model optimization underway
  - Expect CNN improve more rapidly than MLP with additional data





Conclusion

- Machine learning methods are data-driven solutions to complex problems. Potential ML use cases in safeguards of PBRs have been identified in the early phase of the research and then prioritized.
- The current focus of the study is on burnup measurement, a critical parameter for both operation and MC&A.
- Our preliminary results showed that ML methods can be used to improve accuracy and timeliness of estimate burnup of fuel pebbles. However, the accuracy is limited to the simulation dataset.
- We plan to improve the accuracy by expanding the simulation dataset. Working with designers to add additional datasets will be considered as well.

Acknowledgement

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