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VERIFICATION OF TRISO FUEL BURNUP USING MACHINE LEARNING ALGORITHMS

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Verification of TRISO fuel burnup using machine learning algorithms

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Background

- Pebble Bed Reactors operate on pebbles circulated multiple times through the reactor vessel before discharge.
- Determining the burnup level of a pebble is the key to deciding if the pebble should be discharged or recycled.
- Height of photopeaks in gamma spectra related to various indicator isotopes such as ^{137}Cs, ^{154}Eu etc. are often used for this application.
- These techniques suffer several challenges:
  - Source is complex and measurements are performed in less-than-ideal environment with self-shielding effects, strong radiation backgrounds and intervening material effects.
  - Also, due to operational constraints, high pebble throughput necessitate lower acquisition times which results in noisier spectra.

Objectives

- Develop a process for generating gamma spectra, which is representative of the burnup levels of a reference pebble.
- Establish baseline gamma spectra dataset as well as spectra data that represents typical operational condition for a PBR.
- Compare the performance of a multilayer perceptron's (MLP) model to standard linear regression for burnup prediction.
    - For both an ideal and operation type measurement times.
    - Also, for multiple pebble cooling times that range between typical operational cooling times to ideal cooling times (i.e., which produce cleaner spectra).

Gamma Spectra Data Generation

Presenter : Odera Dim

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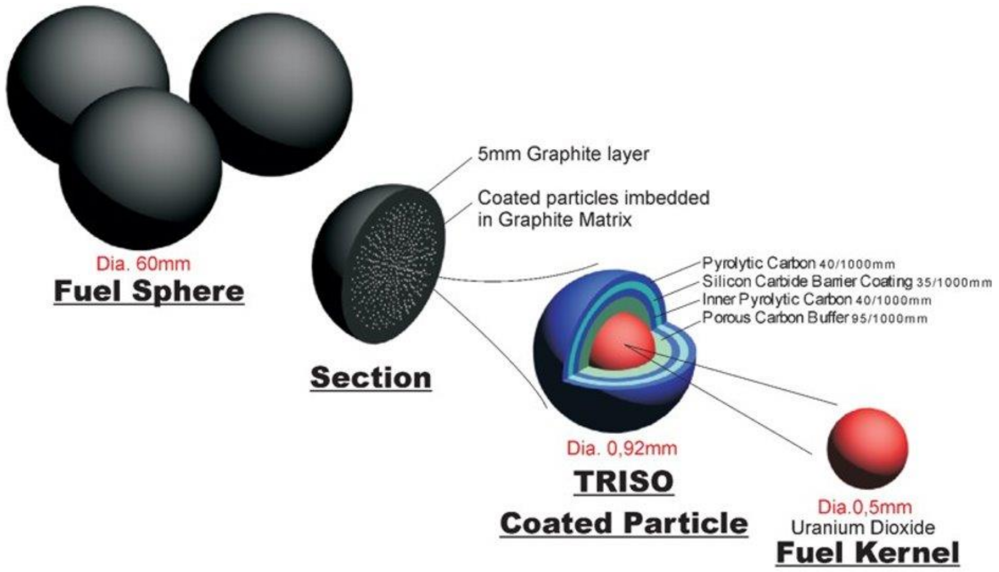
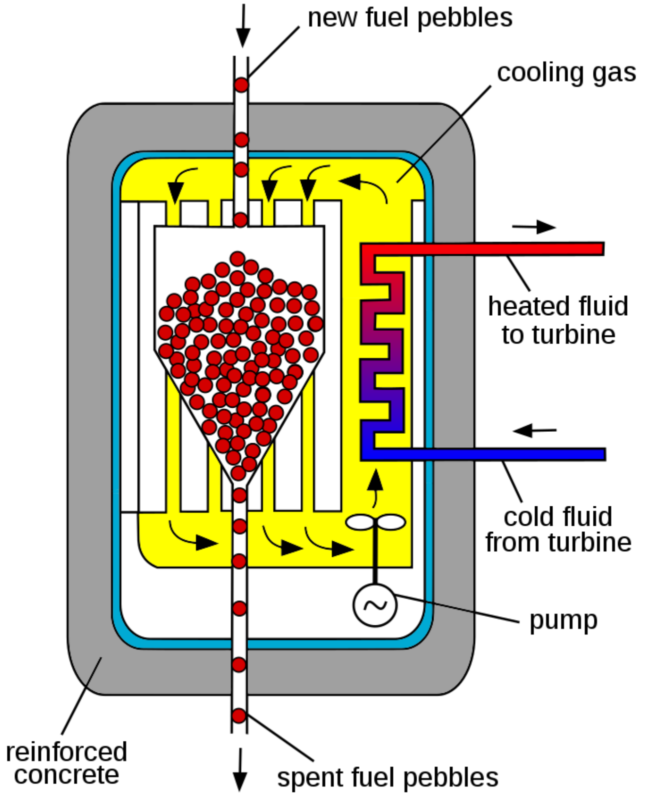
Structure of a Pebble & PBR core

Images from:
www.nuclearstreet.com (left)
www.wikipedia.org (right)



Typical structure of a pebble and TRISO

Pebble bed reactor scheme



PBR reactor core

Overall Process Flow

5 - 8 Passes

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

Reactor Core

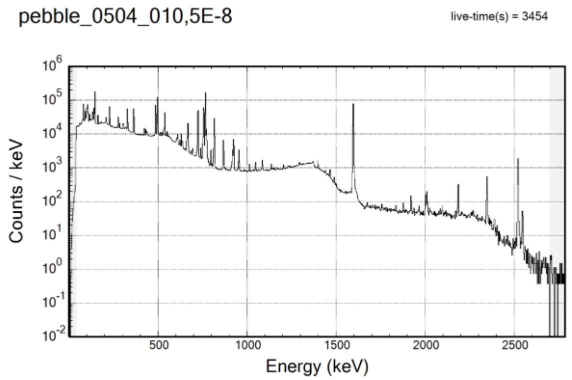
47.8E-03
57.8E-03
67.8E-03
57.8E-03
47.8E-03

Serpent MC simulation

Parameters: transit time, power and profile

Photon emission results

GADRAS-DRF



Gamma-ray spectrum

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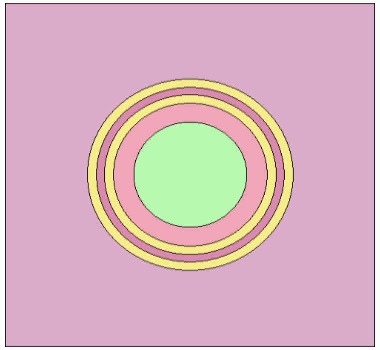
Burnup and Source Modeling

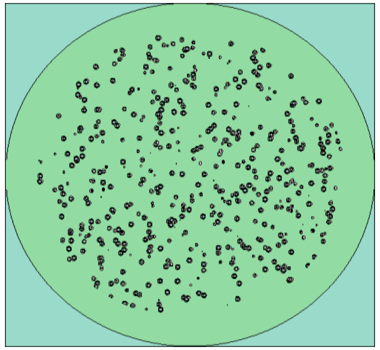
- Burnup and source modeling of the pebble was done in SERPENT Monte Carlo.
- Two separate Models were created:
  - To perform burnup and obtain burnup level specific isotope composition.
  - To transport the gamma source from the TRISO kernels through the coatings to the pebble surfaces.
- A 3x3x3 lattice of pebbles was designed and the center pebble was regarded as the reference pebble for burnup and source definitions.

Burnup and Source Modeling (cont'd)

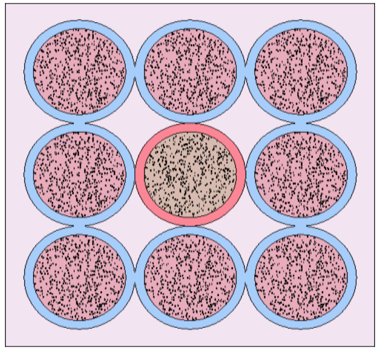
Parameter	Value
Uranium Oxy-Carbide (UCO) Density (atoms/b-cm)	6.9924E-02
Buffer (C) Density (atoms/b-cm)	5.2644E-02
Polycarbonate (PyC)/ Silicon Carbide (SiC) Density (atoms/b-cm)	~9.5262E-02
Number of Pebble/TRISO	27/18857
Pebble/TRISO radius (cm)	3.000/0.0455
Lattice configuration	3 x 3 x 3
Power (MW_{th})	280
Boundary condition	Reflected/Periodic
Pebble/TRISO PF	0.5200/0.1137
Average residence time (days)/Cycles(passes)	522/8
Cooling time before spectral measurement (days)	0, 0.5, 1, 2, 5, 10
Data acquisition time (s)	20, 3600



TRISO Kernel



Single Pebble



3x3x3 Pebble Lattice

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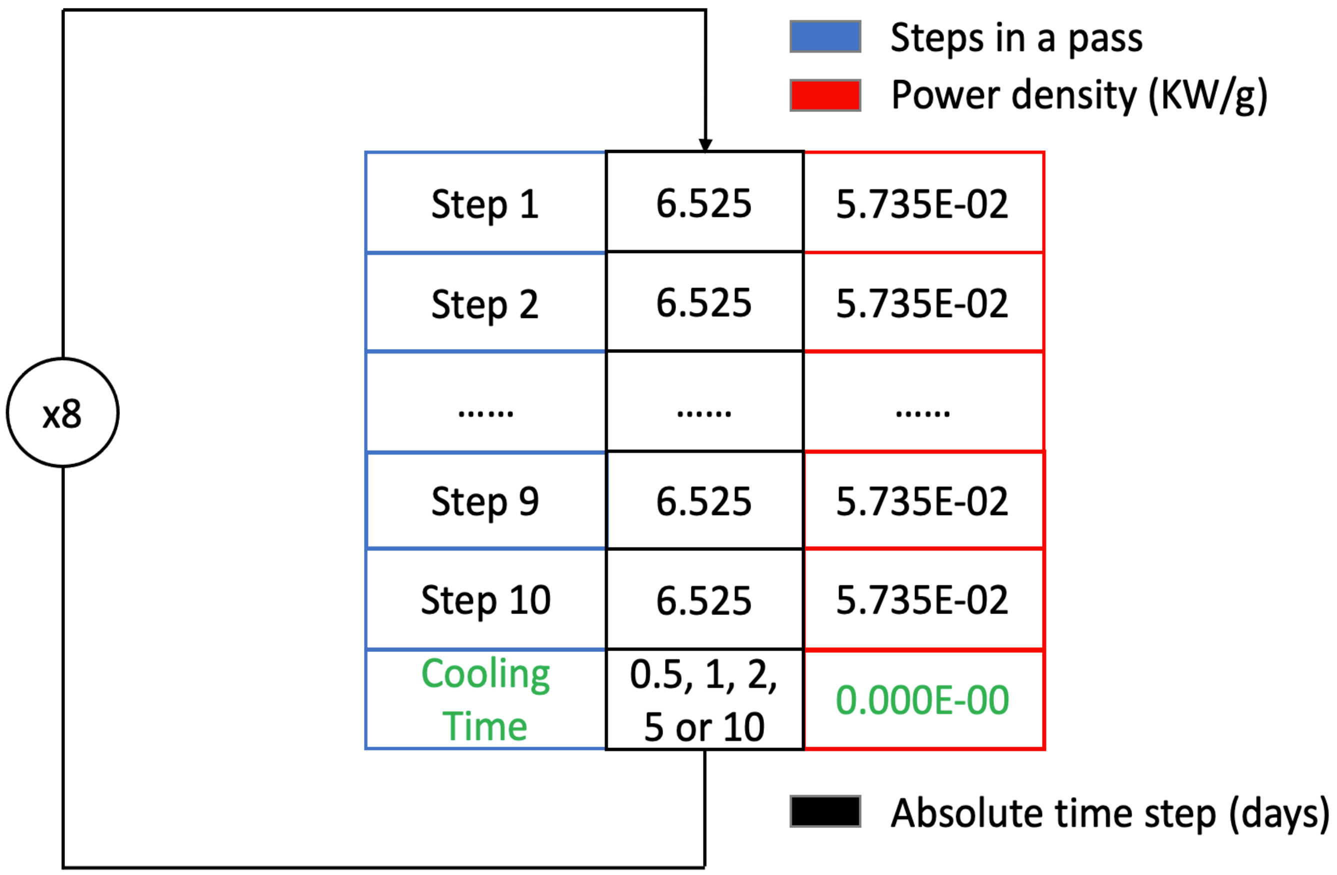
Burnup and Source Modeling (cont'd)



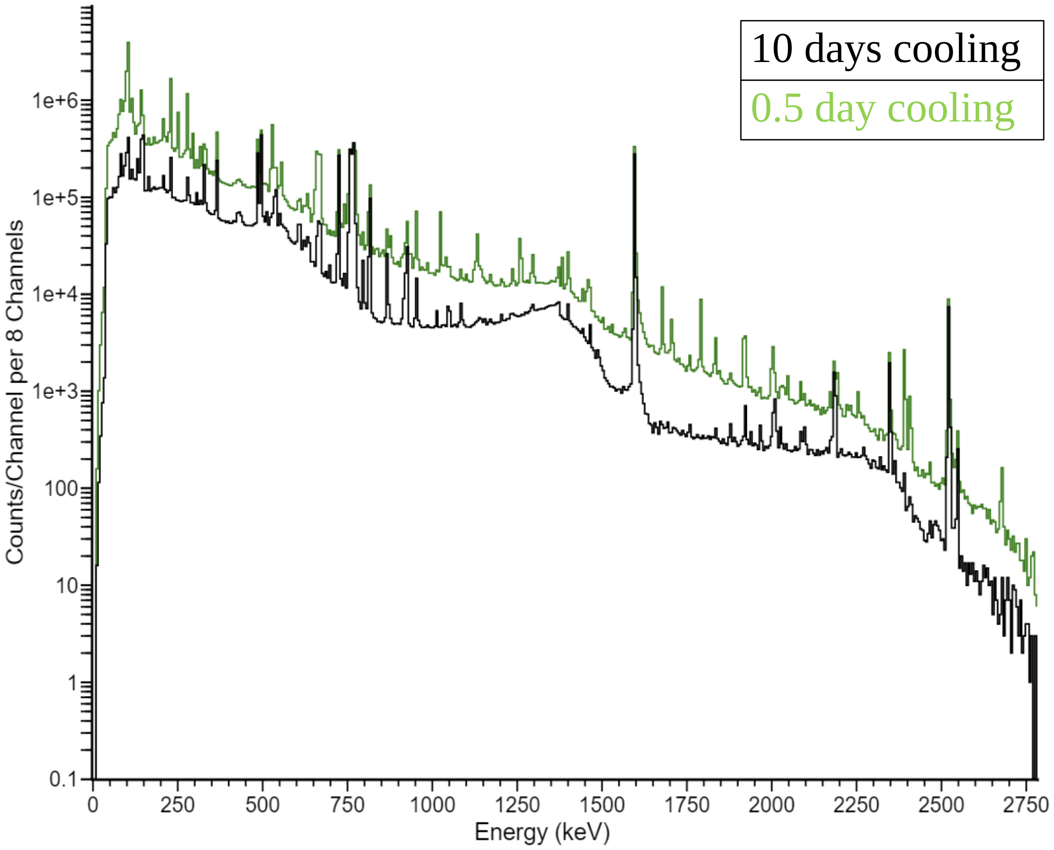
Pebble burnup process

- Although the axial power profile is roughly cosine, an average pebble power is used in this work.
- Spectra relevant output is extracted after the cooling time step shown in the Figure.

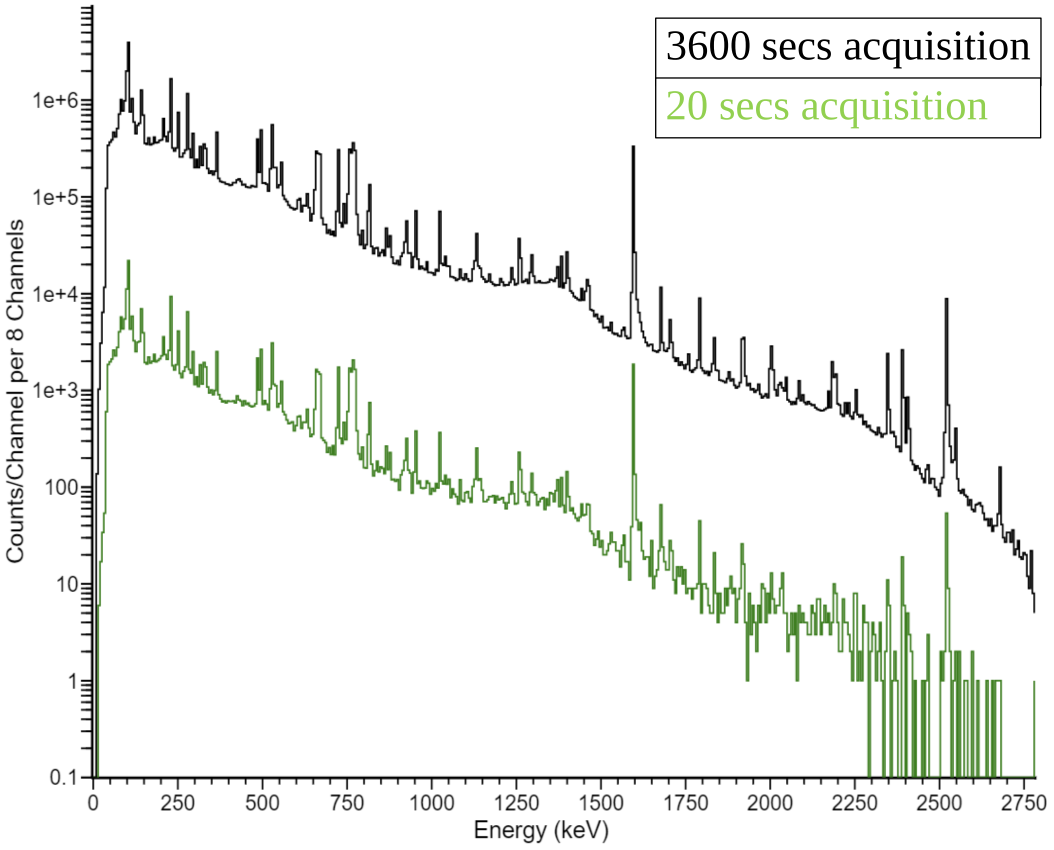
Generation of Spectra in GADRAS

- The source information and output generated by SERPENT is fed into GADRAS to generate spectra data.
- A burnup steps produced in the SERPENT, after appropriate cooling time is converted into a GADRAS readable file format known as .GAM files.
- A HPGe detector with 95% efficiency is selected in GADRAS and calibrated with spectroscopic pair that span the energy spectra (i.e., about 0 – 2500 keV).
- The .GAM files are then injected in batch mode to produce spectra data in .N42 format. (no simulated background was injected into the data sets)

Generation of Spectra in GADRAS (cont'd)



Similar residence and acquisition times



Similar residence and cooling times

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Performance of ML Algorithm

Presenter : Carlos Soto

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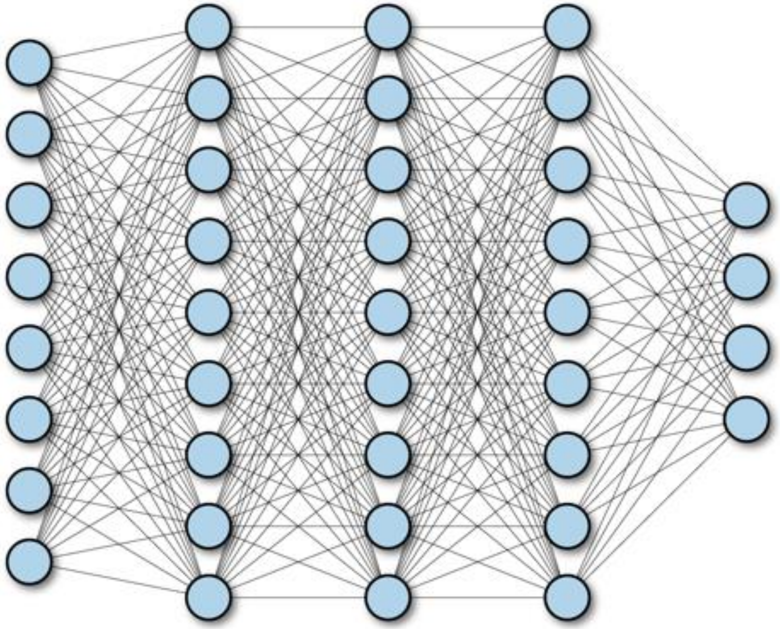
Baseline and ML approaches

- Standard approach to burnup prediction is linear regression with known photopeak (e.g. ^{137}Cs 662 keV)
  - More complex algorithms may be used; but key is hand-selected features (may be multiple photopeaks)
  - Accuracy is limited by pronounced effects of self-shielding, background radiation, short acquisition time, etc. on spectrum signal
- Machine learning (ML) methods can use full spectra, with no need for manual feature selection or engineering (data-driven)
  - More robust to background effects, as full signal is used
  - Feature extraction can be done with many ML methods; most direct is a multi-layer perceptron (MLP), also called a fully-connected neural network

MLP and parameters



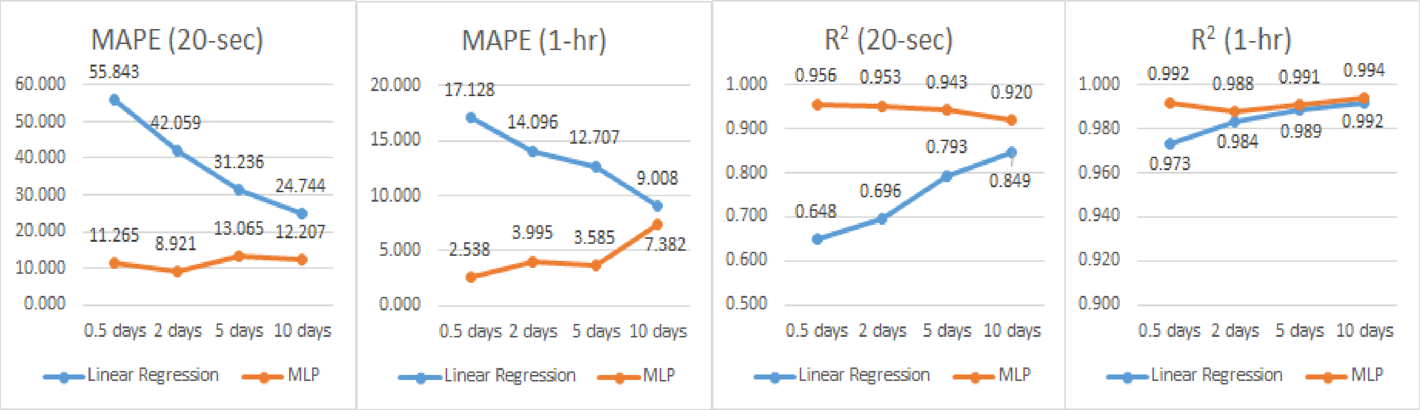
- MLP is "classic" neural network
  - Architecturally simple
  - Extracts global features representations (because layers are fully connected)
- Parameters and hyperparameters
  - Connection weights and biases are learned during model training from annotated data (like standard regression)
  - Network shape (number and size of hidden layers) is architectural choice ("hyperparameter") determined empirically
    - Other hyperparameters: learning rate, rate schedule, activation function, optimization algorithm and parameters, binning rate, dropout rate
    - 3-layer network with hidden layers of size 256 and 32 worked well

^{137}Cs Regression vs ML results

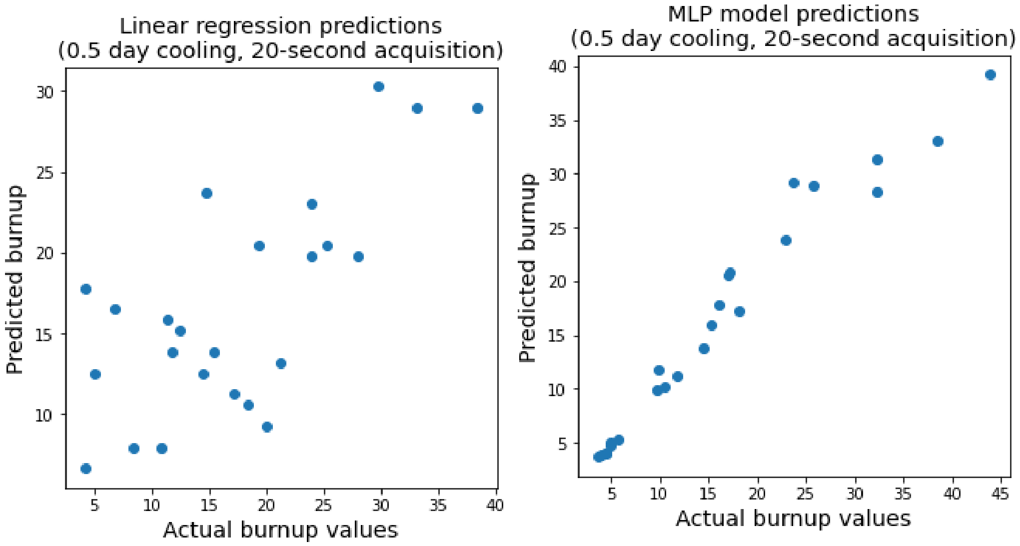
- MLP significantly outperforms regression, particularly in challenging conditions
  - ^{137}Cs regression performance drops dramatically with reduced cooling time and acquisition time
  - MLP performance largely unaffected, even appears to improve (likely due to under-optimized model)

Performance @0.5 day cooling, 20-sec acquisition

	^{137}Cs regression	MLP model
Mean average percent error (MAPE)	55.8%	11.3%
Correlation (R^2)	0.648	0.956



Mean average percent error (MAPE) and correlation (R^2) performance of ^{137}Cs regression and MLP model over differing conditions. (lower is better for MAPE, higher is better for R^2)



True vs predicted burnup (perfect predictions would lay along main diagonal)

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Conclusion

- The preliminary tests in this work showed that both ML-based methods and the photopeak-based linear regression method achieved higher accuracy when the gamma-ray spectra contained negligible background radiation caused by short-lived fission products and minimal statistical errors.
- Under the conditions that the PBR designers are considering today, e.g., 2 days or less cooling time and 20-s acquisition time, the gamma spectra from burnup measurement is noisy.
- The proposed ML methods outperformed the conventional linear regression method significantly under these conditions.

Acknowledgement

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Thanks

Questions

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