

Random Forest Regression and Shapley Additive Explanation for Effective Dose Rate Estimation in High-Energy Neutron Fields Based on Bonner Spectrometer Measurements

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### Introduction

- Individual dosimetric occupational monitoring is based on the results of dosimetric monitoring of workplaces, which consists of determining the energy distribution of **neutron flux density** when monitoring continuous radiation fields, as well as the time a worker spends in these conditions.
- Radiation fields behind the protective shields of the JINR nuclear physics facilities (particle accelerator, nuclear reactors) are formed mainly by **neutrons** of a wide energy spectrum.
- Radiation monitoring at accelerators cannot be carried out using standard dosimeters and neutron radiometers alone, since their operating range is limited by a maximum neutron energy of about 10-20 MeV.
- **Bonner Multisphere Spectrometer** is a common used tool for radiation monitoring at accelerators.









### **Bonner Multi-sphere Spectrometer**

- A multi-sphere Bonner spectrometer is used to measure the neutron flux density.
- The measurement method is based on the moderation of fast neutrons in polyethylene moderator spheres of various diameters.
- Various detectors are used to detect thermal neutrons, e.g., inorganic scintillators such as <sup>6</sup>LiI.



### **Response functions of moderator spheres**



Martinkovic, J., and G. N. Timoshenko. *Calculation of multisphere neutron spectrometer response functions in energy range up to 20 MeV*. No. JINR-R--16-2005-105. Division of Radiation and Radiobiological Research, 2005.



# **Unfolding the neutron spectra**

System of Fredholm integral equations of the 1st kind:

$$\begin{cases} \int_{E_{\min}}^{E_{\max}} K_1(E) \varphi(E) dE = Q_1, \\ \vdots \\ \int_{E_{\min}}^{E_{\max}} K_M(E) \varphi(E) dE = Q_M, \end{cases}$$

where:

- $Q_j$  is the Bonner spectrometer reading for the *j*-th sphere,
- $\varphi(E)$  neutron spectrum,
- $K_j(E)$  is the kernel of the *j*-th equation, which is a response function of the detector to neutrons of various energies,
- *M* is the number of spheres used to measure the spectrum.
- The integration limits  $E_{\min}$  and  $E_{\max}$  are specified by the domain of definition of the neutron spectrum *E* and the set of detectors used for measurements.

## **Direct and inverse problems of spectrum unfolding**



- Direct task: to obtain "effective" readings of the Bonner spectrometer based on the given spectra.
- Inverse task: to obtain the initial spectra based on the measurement results.

### **Dose estimation for spectrum**

The Bonner multi-sphere spectrometer is used to measure neutron spectra in stationary fields to assess irradiation of personnel.



 $\dot{H}$  – dose rate ( $\dot{E}_{eff\_AP}$ , $\dot{E}_{eff\_ISO}$ ,  $\dot{H}$ \*(10),  $\dot{H}_{p}$ (10,0°))

h(w) – corresponding conversion factor [pSv·cm2] for monoenergetic particles in different irradiation geometries, ICRP Publication 116\*



\*Petoussi-Henss, Nina, et al. "ICRP Publication 116—the first ICRP/ICRU application of the male and female adult reference computational phantoms." Physics in Medicine & Biology 59.18 (2014): 5209.

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# **Previously developed methods**

- 1. Regularization (Tikhonov,...)
- 2. Statistical regularization
- 3. Maximum entropy principle
- 4. Maximum likehood
- 5. Genetic
- 6. Iterative
- 7. Parametric
- 8. Bayesian parameter estimation
- 9. Machine learning + neural networks
- 10. Combinations of methods

11....



- Gómez-Ros, J. M., et al. "Results of the EURADOS international comparison exercise on neutron spectra unfolding in Bonner spheres spectrometry." *Radiation Measurements* 153 (2022): 106755.
- Barros, S., et al. "Comparison of unfolding codes for neutron spectrometry with Bonner spheres." *Radiation protection dosimetry* 161.1-4 (2014): 46-52.
- Chizhov, K., L. Beskrovnaya, and A. Chizhov. "Neutron Spectra Unfolding from Bonner Spectrometer Readings by the Regularization Method Using the Legendre Polynomials." *Physics of Particles and Nuclei* 55.3 (2024): 532-534.

# Methodology

#### **ML** method & implementation

The random forest machine learning algorithm is a model consisting of an ensemble of decision trees. In a regression problem, the method is used to predict numerical values, the responses of each tree are averaged, while when constructing trees, a random sample of elements from the data set occurs, and when dividing nodes, random sets of parameters are selected.

- Implementation in Python + Sklearn + optuna + NumPy + pandas + matplotlib;
- Calculation on the multifunctional information and computing complex of the JINR Information Technology Laboratory, http://hlit.jinr.ru/.



DOI: <u>10.9734/air/2020/v21i930238</u>

# Dataset (80/20% train/test)

- 1. IAEA dataset\* (251 spectra)
  - 1. Input features:
    - a. Numerical: 7 measurements
    - b. Category: one-hot encoding, 8 categories
  - 2. Output target: Spectre values for 60 energy bins  $(10^{-8} 3.98 \cdot 10^2 \text{ MeV}, \text{ logscale})$

#### 2. Synthetic based on FRUIT\*\* method (10<sup>4</sup> spectra)

- 1. Input features: numerical, 7 measurements
- 2. Output target: Spectre values for 60 energy bins  $(10^{-8} 3.98 \cdot 10^2 \text{ MeV}, \text{ logscale})$



\*Compendium of Neutron Spectra and Detector Response for Radiation Protection Purposes: Technical Report Series. Vienna: IAEA, 2001. No. 403. \*\* Frascati Unfolding Interactive Tool, doi: 10.1016/J.NIMA.2007.07.033

### **Generated and real spectra**

#### Spectrum representation in FRUIT method:

 $\varphi(E) = P_{th}\varphi_{th}(E) + P_e\varphi_e(E) + P_f\varphi_f(E) + P_{hi}\varphi_{hi}(E),$ 

 $P_{th} + P_e + P_f + P_{hi} = 1$ 

- $\varphi_{th}$  Maxwell thermal
- $\varphi_e$  epitermal
- $\varphi_f$  fast
- $\varphi_{hi}$  high-energy



### **ML model for IAEA dataset**



### **ML model for synthetic spectra**

M = 7 S = 60



# **Optimization of the algorithm**

The criterion for measuring the quality of separation is the root mean square error. Optimization criterion: negative mean maximum error.



- the number of trees in the forest (n\_estimators) = 169;
- the maximum tree depth (max\_depth) = 39;
- the minimum number of samples required to split an internal node (min\_samples\_split) = 2;
- the minimum number of samples required to be at a leaf node (Min\_samples\_leaf) = 1.

### **Results**



uncertainty of spectrum unfolding for  $\xi = 5\%$  error in measurements

# **SHAP (Shapley Additive Explanation)**

A method for explaining individual forecasts. SHAP is based on the game of theoretically optimal Shapley values. The technical definition of the Shapley value is "the average marginal contribution of a feature value to all possible coalitions..."



# **SHAP (Shapley Additive Explanation)**

Impact of the measurement with moderator sphere to the dose rate assessment



### Auto ML

AutoML solutions automatically develop ML-based models. We used *lightautoml*\* package.

Automatic fine-tuning of the model hyperparameters and blending of different models:

- 1. Linear regression with L2 regularization
- 2. LightGBM
- 3. CatBoost

LOSS = MAE METRIC = MSE

```
Final prediction for new objects =
0.22569 * (5 averaged models Lvl_0_Pipe_2_Mod_0_CatBoost) +
0.77431 * (5 averaged models Lvl_0_Pipe_2_Mod_1_Tuned_CatBoost)
```

Prediction metrics: MAE:  $4.2 \cdot 10^{-3}$ MSE:  $2.0 \cdot 10^{-4}$ R<sup>2</sup> score: 0.80

\*Vakhrushev, Anton, et al. "Lightautoml: Automl solution for a large financial services ecosystem", *arXiv preprint arXiv:2109.01528* (2021).



### **Discussion**

- Development of a training set using Monte Carlo simulations (Geant4).
- Improving the set of moderator spheres in the **high-energy region** (adding composite spheres with lead and other materials).
- Other metrics metrics of the discrepancy between the true and unfolded distributions: Kolmogorov-Smirnov statistic, maximum mean discrepancy.
- Combine the algorithm with other methods to improve accuracy

### Conclusions

- This study presents a machine learning-based approach for neutron spectrum unfolding and effective dose rate estimation using Bonner spectrometer measurements.
- Comparison of two Random Forest Regression models trained on a small real spectres dataset and on a large synthetic dataset is presented. Both models showed strong correlation between actual and unfolded spectra and in dose rate assessment.
- The SHAP method enabled the optimization of BSS moderator sphere selection, it is showed that measurements with the 10" moderator sphere make are the most important to the dose assessment.
- The proposed method could be used for improving radiation protection in high-energy neutron fields.

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# Thank you!

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Publications:

- 1. Chizhov, K., L. Beskrovnaya, and A. Chizhov. "Neutron Spectra Unfolding from Bonner Spectrometer Readings by the Regularization Method Using the Legendre Polynomials." *Physics of Particles and Nuclei* 55.3 (2024): 532-534.
- 2. Chizhov K, Chizhov A. Dose assessment of personnel neutron irradiation on high-energy accelerators using a multi-sphere Bonner spectrometer. *Mathematical Modeling* 7 (2), 63-64, 2023.