

Introduction and Motivation

- As a reactor generates power via fissions in the core, it also breeds plutonium, which can be removed by foreign actors for use in nuclear weapons proliferation For this reason it is important to
- be able to verify the time that the reactor has been running, in order to account for expected reactor inventory



This work seeks to improve methods of international Non-Proliferation Treaty (NPT) verification by the IAEA Response to the 1994 North Korean crisis could have been aided by such technology



Survey of Machine Learning Methods for Antineutrino-Based Reactor Burnup Time Prediction

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Technical Approach

This work is performed on fission rates generated fro simulations by Christophe The models operate on an the reactor and do not inc The investigated methods time in Effective Full-Powe

- Regression (linear and
- Support Vector Regres
- Neural Network (with loss)

Results

Currently, the linear performing the best the difference betwe and algorithm-predi



Currently, the result neural network are not demonstrably optimized. The current performance of these methods are shown in Table 1

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	Table 1
n AFR-100 isotopic om REBUS/MCC	TrueLinear Regression PredictionLinear SVR (scaled)Neural Network PredictionEFPY(and deviation)Prediction (and deviation)(and deviation)
er Stewart	13.5 13.500 (2.300e-07) 13.534 (-0.034) 13.461 (0.038) 10 10.000 (1.122a 07) 18.041 (0.058) 18.004 (0.005)
ntineutrino vields from	1919.000 (1.122e-07)18.941 (0.058)18.994 (0.005) 8.75 $8.749 (5.569e-07)$ $8.634 (0.115)$ $8.730 (0.019)$
cludo dotoctor	25.25 25.249 (6.408e-07) 24.718 (0.531) 25.240 (0.009)
	29.25 29.250 (4.484e-07) 28.223 (1.026) 29.243 (0.006)
s for predicting burnup	
er Years (EFPY) are:	 These results represent one given rul
polynomial)	as the neural network and SVM will
ssion (SVR)	predict slightly different values for
mean-squared error	every run due to the random nature
	the training process
	The line on meaning between the second second
	• The linear regression nowever, predic
	the exact same values every time
	Conclusion
r regression is	
t hy measure of	
L, by measure of	 Currently, without definitively optimize
een the actual	
icted values	models, the linear regression predicts t
	closest to the correct estimates for rea
ion with scaling None	hurnun time demonstrating the
	burnup time, demonstrating the
	effectiveness of simple models over
	complex ones for tasks with a simple
	mathematical relationship
	Novt Stope
	Next Steps
15 20 25 30 EFPY	 Verify optimization of hyperparameter
c of the CV/D and	for the neural network and SVR
sor the SVR and	 Test polynomial regression and
not demonstrably	



cts

the ctor

nonlinear kernels for the SVR

