

Prediction of Fuel Debris Location in Fukushima Nuclear Power Plant using Machine Learning

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Abstract. Accurate fuel debris location is crucial part of the decommissioning of the Fukushima Nuclear Power plants. Conventional methods face challenges due to extreme radiation and complex structure of the materials involved. In this study, we propose a novel approach utilising neutron detection and machine learning to estimate fuel material location. Geant4 simulations and pythonTM scripts have been used to generate a comprehensive dataset to train a machine learning model using MATLAB's regression learner. A Gaussian Process Regression model was chosen for training and prediction. The results show excellent prediction performance to estimate the corium thickness effectively and to locate the nuclear fuel material with a mean square error (MSE) of 0.01. By combining the machine learning with nuclear simulation codes, this promises to enhance the nuclear decommissioning efforts to retrieve nuclear fuel debris.

1 Introduction

Locating fuel debris in the Fukushima Daiichi Nuclear Power Plant Stations (FDNPS) has proven to be a complex challenge during their decommissioning, primarily due to extreme radiation levels that makes visual inspection impractical. Whilst several attempts have utilised gamma-ray spectroscopy, the presence of activated structural materials and the dispersion of ¹³⁷Cs throughout the primary containment vessels (PCVs) has complicated efforts to locate the exact location of the fuel debris with sufficient accuracy [1]. Neutron detection is a promising alternative, as neutrons emitted solely from nuclear fuel material offer a more direct indicator of its presence. However, to leverage neutron detection effectively, it is essential to understand the neutron intensity and spectrum, which can vary dependent on the composition of the corium mixture [2].

The corium resulting from the 2011 accident comprises various materials, including the fuel (UO₂), Zircaloy cladding, control rods (B₄C), concrete, and stainless steel. Accurately quantifying the mass of each component is crucial for estimating the location and quantity of the fuel material [3]. Previous studies have employed severe accident codes such as MELCOR (MELtdown Core Response) and MAAP (Modular Accident Analysis Program) to estimate the mass distribution of corium components, providing valuable insights that inform the selection of component masses summarised in **Table 1**[4].

The proposed approach focuses on using neutron detectors capable of withstanding extreme radiation environments, particularly diamond detectors. The computations throughout the study have been calculated using the High-End Computer (HEC) cluster of Lancaster University [5]. Subsequently, pythonTM scripts are developed to analyse and visualise the results, providing valuable insight into the relationship between neutron spectra and fuel material characteristics.

In this paper, the determination of the location and the quantity of nuclear fuel material based on neutron energy spectra and source intensity is described. Thousands of different fuel debris scenarios have been generated using pythonTM computer code and then simulated using Geant4 Monte Carlo code to calculate the neutron energy spectra for each scenario. Subsequently, machine learning algorithms have been utilised to analyse the spectra implemented using MATLAB to predict the location of the fuel material. The focus of this is to predict the thickness of the corium layers above the nuclear fuel material to speed up the nuclear decommission process to retrieve fuel debris. The work flow is illustrated in details in the diagram.

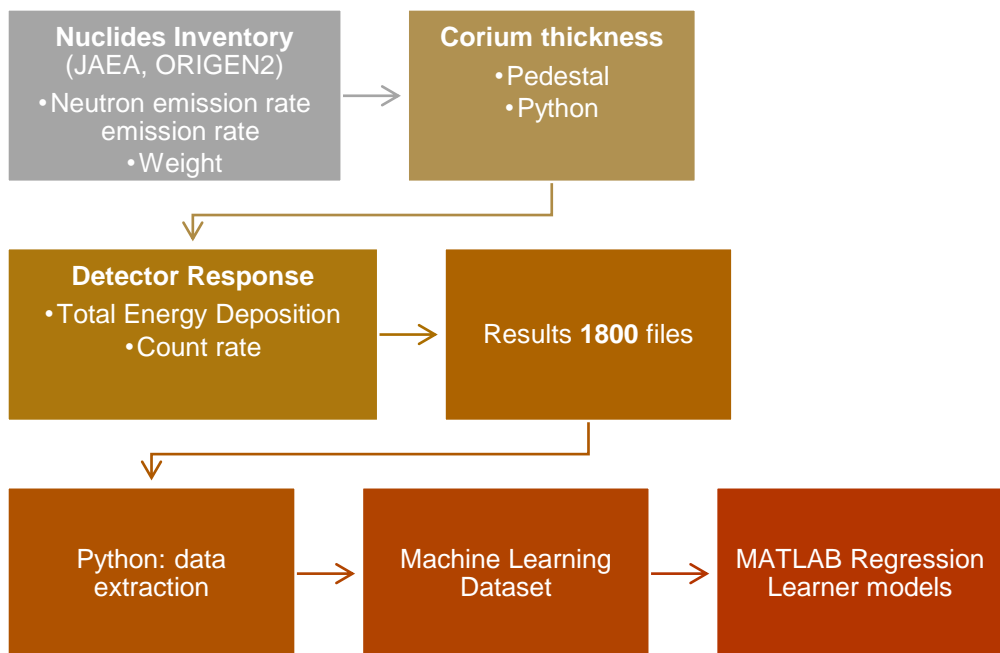


Table 1. This table presents the inventory of corium mixture components after 10 years of the accident, as simulated by MELCOR, MAAP, and MCNPX models (tons) [4].

Material	MELCOR	MAAP	MCNPX
UO2	69.4	76.15	75.77
Zr	25.8	16.59	17.8
ZrO2	16.6	14.14	13.82
B4C	0	0.502	0.59
Cr	5.9	1.13	1.1
Cr2O3	0.03	2.732	2.73
FeO	0.23	11.2	11.2
Ni	2.53	0.55	0.556
NiO	0.03	1.2	1.2

2 Methodology

The investigation begins by obtaining the fuel composition and radionuclides inventories from the Japan Atomic Energy (JAEA) data [6]. These datasets, calculated using ORIGEN2 isotope generation and depletion code, serve as the foundation of our analysis. This dataset provides crucial information such as mass, radioactivity, and neutron and photon emission rates [7]. A significant aspect of the methodology involves determining the proportion of the primary neutron emission source, identified as the ²⁴⁴Cm spontaneous fission nuclide [8].

Using this information, we model various scenarios by assuming the corium is located in the pedestal area with a known diameter and mass [9,10,11,12]. Geant4 simulations are then used to calculate the detector response for each scenario, including neutron count rate and total energy deposition in the detector. Utilising the High-End Computing (HEC) cluster at Lancaster University, our simulations are performed efficiently, with 256 cores to compute 1800 simulations, each completed in approximately 20 minutes.

For corium thickness prediction, we deployed a machine learning algorithm, specifically an Optimisable Gaussian Process Regression (GPR) model with Bayesian optimisation taking the advantage of the build-in MATLAB algorithms. GPR is chosen for its ability to model complex relationships between datasets and complicated patterns between input and output variables [13].

In preparing the GPR model for training, the features and target variables should be selected. Neutron count rate, neutron source intensity, and total energy deposited in the detector are identified as features, with corium thickness above the neutron source serving as the target variable. The features and target variables have been extracted using a pythonTM script to automate the simulation process. The resultant dataset is then organised and stored in CSV file format, and constitutes the input for training the GPR model in MATLAB. **Table 2** present a sight of the sample data comprising the target and feature variables, demonstrating the scope of the dataset used for training the machine learning model.

Table 2. This table represents the dataset used to train the Gaussian Process Regression (GPR) model, including neutron source intensity, total energy deposited in the detector, detector count rate, and corium thickness.

Neutron source / 10^7 n/s	Total energy deposited in the detector / MeV	Detector count rate / s^{-1}	Corium thickness cm
6.5	5.7	2.1	2
6.7	5.8	2.1	2
0.11	97.6	0.3	2.1
1.8	1.6	6.0	2.1
3.5	3.0	11.0	2.1
5.2	4.5	17.0	2.1
6.9	5.9	22.0	2.1

3 Results and Discussion

After training the GPR model using MATLAB, the response and the prediction plots against true response have been generated. **Figure 1** provides the response plot, indicating the accuracy and precision of the prediction model. The nearly perfect alignment observed in the plot demonstrates the reliability and high performance of the GPR model in capturing the relationship within the data. We further assessed the model’s performance using evaluation metrics. The Root Mean Squared Error (RMSE) value of 0.09 and Mean Squared Error (MSE) value of 0.009 signify a high level of prediction accuracy. **Table 3** presents the model parameters and performance metrics in detail.

In addition to the response plot, a scatter plot is presented to compare the predicted corium thickness values against their true response. **Figure 2** displays the total observations used to train the machine learning model, where true corium thickness values plotted along the x -axis and their corresponding predicted values along the y -axis. The observations cluster closely along the line of perfect prediction, indicating an excellent agreement between the true and predicted values. This suggests that the model performs exceptionally well in estimating corium thickness based on the input parameters.

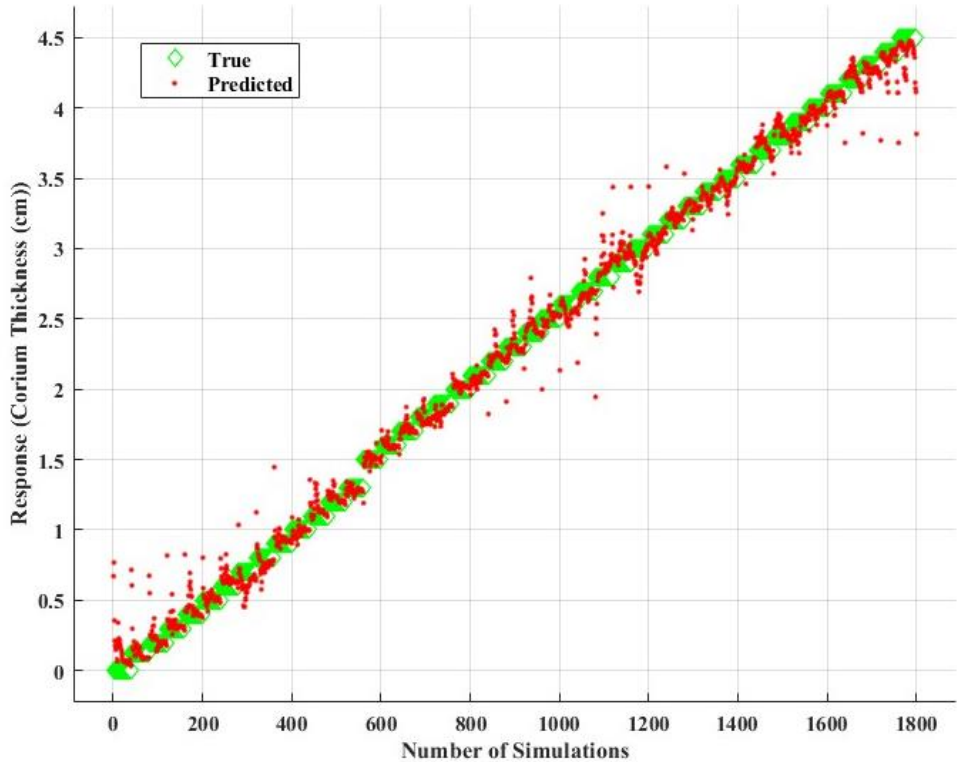


Fig. 1. The response plot of GPR training results. This figure illustrates the response generated from the Gaussian Process Regression (GPR) training process. The x -axis represents the record number, corresponding to the total observations, while the y -axis denotes corium thickness in centimetres (cm).

Table 3. This table summarises the optimization parameters and results of the GPR training model.

Parameter	Value
Model	Optimizable GPR
Kernel function	Nonisotropic Exponential
RMSE (Validation)	0.098685
MSE (Validation)	0.009738
Prediction speed	41000 obs/sec
Optimiser	Bayesian optimisation

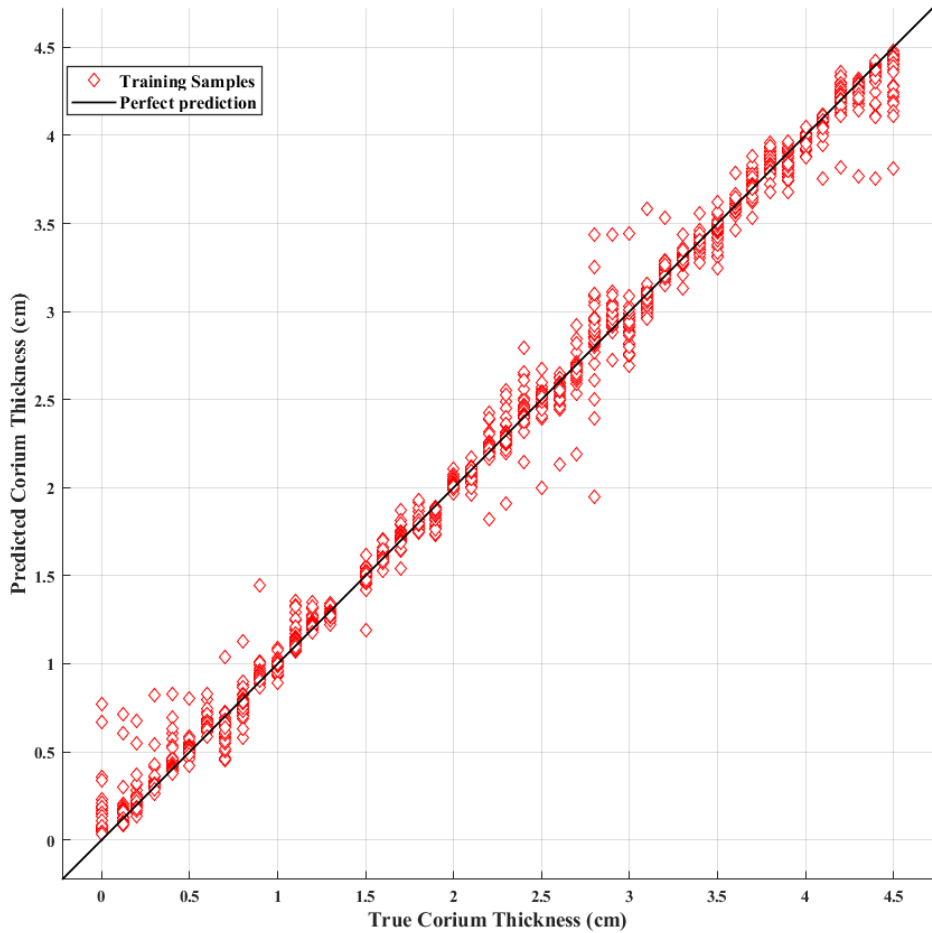


Fig. 2. Scatter plot of True and Predicted Corium Thickness Values. This figure depicts the comparison between true and predicted corium thickness values, displaying the training points alongside a line representing perfect prediction. The x-axis denotes true thickness values (in cm), while the y-axis represents corresponding predicted values.

4 Conclusion

This study shows the applicability of machine learning algorithms to predict the corium thickness above the neutron source with potential application to locate the fuel debris within the Fukushima Daiichi Nuclear Power Plant. The optimizable Gaussian Process Regression model in MATLAB was chosen for the prediction, and shows a high degree of accuracy in predicting corium thickness. This is a critical part of the decommissioning process where the nuclear fuel debris needs to be located for effective retrieval.

In the future, different machine learning algorithms will be used to estimate the quantity of the neutron source and to produce a map showing its location and extent.

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