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 materials. In this study, we propose a novel approach utilising neutron detection and machine learning to estimate fuel material location. Geant4 simulations and Python scripts have been used to generate a comprehensive dataset to train a machine learning model using MATLAB's regression learner. Gaussian Process Regression model was chosen for training and prediction. The results show excellent prediction performance to effectively estimate the corium thickness and locating the nuclear fuel material with MSE value of 0.009738. By combining the machine learning with ~~the~~ nuclear simulation codes, it promising to enhancing the nuclear decommissioning efforts and fuel debris retrieval.

1 Introduction

Locating the fuel debris within the Fukushima Daiichi Nuclear Power Plant Stations FDNPS has proven to be a complex challenge during the decommissioning process, primarily due to the extreme radiation levels that makes the visual inspection impractical. While several attempts have utilised gamma spectroscopy, the presence of activated structural material and the dispersion of Cs137 within the primary containment vessel PCV have complicated efforts to accurately locate the exact location of the fuel debris [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 depending on the composition of the corium mixture [2].

The corium resulting from the 2011 accident comprises various materials, including UO_2, Zircaloy cladding, control rods (B_4C), 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 and MAAP to estimate the mass distribution of corium components, providing valuable insights that inform the selection of component masses~~ where they are~~ summarised in **Table 1**[4].

The proposed approach focuses on using robust neutron detectors ~~which capable to withstand~~ extreme radiation environment, particularly diamond detectors. The computations throughout the study have been calculated ~~at the cluster at~~ Lancaster University. Subsequently, Python 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, we aim to determine the location and the quantity of nuclear fuel material based on neutron energy spectra and source intensity. Thousands of different fuel debris scenarios have been generated using Python computer code and then simulated ~~them~~ using Geant4 Monte Carlo to calculate the neutron energy spectra for each scenario. Subsequently, machine learning algorithms have been utilised to analyse the spectral data implemented ~~un~~ MATLAB to predict the location of the fuel material. ~~This study focus is predicting~~ the thickness of corium layers above the nuclear fuel material to speed up the nuclear decommission process to retrieve the fuel debris.

Table 1. Corium mixture components inventory at the time of accident.

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 study begins by obtaining ~~by obtaining~~ the fuel composition and radionuclides inventories from JAEA data, which were calculated using ORIGEN2 code. This dataset provides crucial information such as weight, radioactivity, and neutron and photon emission rates [5]. The primary neutron emission source considered in our investigation is the Cm244 spontaneous fission nuclide [6].

With the assumption that the corium is situated in the pedestal area with a diameter of 500 cm, and its mass is known, various cases can be investigated [7,8,9,10]. Using a Python script, thousands of possibilities of corium thicknesses and neutron source locations were generated.

To obtain the necessary data, Geant4 simulations have been produced to calculate the detector response for each case, specifically the neutron count rate and the total energy deposited in the detector. Taking the advantage of the supercomputer cluster at Lancaster

University, 256 cores have been used to calculate 1800 simulations where each simulation completed in approximately 20 minutes.

To predict the corium thickness based on these parameters, a machine learning algorithm has been used, taking the advantage of the MATLAB ~~built-in~~ algorithm~~s~~, ~~an~~ Optimisable Process Regression (GPR) model with Bayesian optimisation ~~is~~ chosen. ~~Gaussian Process Regression~~ ~~has been~~ selected due to its powerful technique for modelling complex relationship between datasets and a complex pattern between input and output variables [11].

To feed the GPR model with training data, the features and target variables should be selected with a sample data shown in **Table 2** for demonstration. The features selecti~~on~~ ~~is~~: neutron count rate, neutron source intensity, and total energy deposited in the detector~~,~~ ~~While the~~ target variable is the corium thickness above the neutron source. The features and target variables have been extracted using a Python script to efficiently automate the simulation process. This dataset is then organised and stored in an Excel file format providing an input for training the machine learning GPR model in MATLAB.

Table 2. Sample dataset used to feed the GPR model.

Neutron source n/s	**Corium thickness cm**	**Total energy deposited in the detector MeV**	**Detector count rate cts/sec**
65281000	2	56718.77938	213279
66996000	2	58191.5405	218888
111000	2.1	97.57484927	345
1826000	2.1	1575.446575	5876
3541000	2.1	3042.774188	11422
5256000	2.1	4520.044424	16918
6971000	2.1	5954.856039	22394

3 Results and Discussion

After training the GPR model using MATLAB, the response plot and the prediction ~~vs.~~ ~~T~~rue response plots have been produced. The response plot~~ as~~ shown in **Figure 1** represents the accuracy and precision of the prediction model~~. From the figure, it is clearly shown the~~ perfect alignment~~. This perfect alignment shows~~ the reliability and high performance of the GPR model in observing the relationship within the data. It was found that the Root Mean Squared Error (RMSE) value of 0.098~~685~~ and Mean Squared Error (MSE) value of 0.009~~738~~ which clearly indicate a high prediction accuracy. **Table 3** shows the model parameters and prediction performance values.

In addition to the response plot, a scatter plot is presented to compare the predict~~ion~~ corium thickness values against their true response.

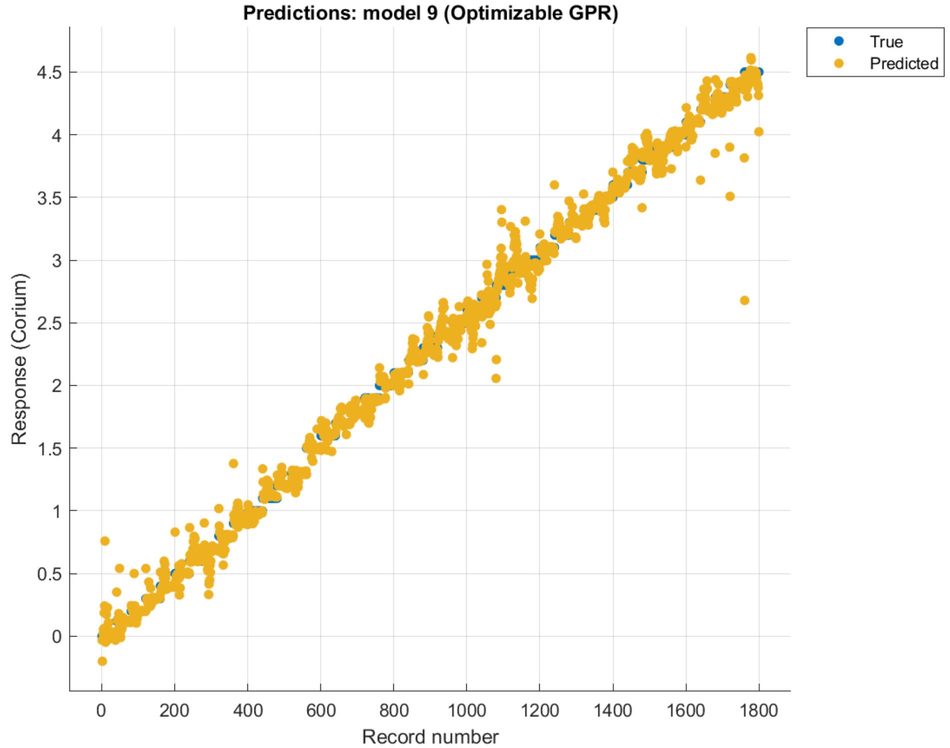

Fig. 1. Response plot results from the GPR training.

Figure 2 shows the total observations ~~that~~ used to train the machine learning model, with the true corium thickness values plotted along the x-axis and the corresponding predictions ~~values~~ along the y-axis. From **Figure 2**, the observations are gathered along the line of perfect prediction, which indicates an excellent agreement between the true and predicted values ~~which imply the~~ high performance of the model to estimate the corium thickness based on the input parameters.

Table 3. ~~m~~odel optimization parameters and results.

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

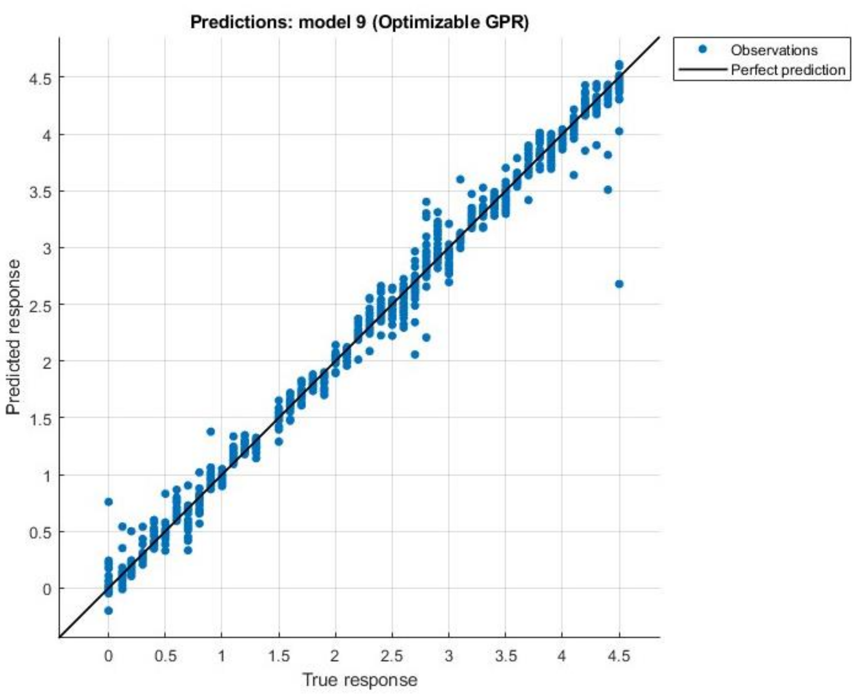

Fig. 1. Prediction plot for the true and prediction response with the observation points and ~~perfect~~ prediction line

4 Conclusion

This study shows the applicability of machine learning algorithms to predict the corium thickness above the neutron source, ~~in another word,~~ locate the fuel ~~material~~ within the Fukushima Daiichi Nuclear Power Plant. The optimizable Gaussian Process Regression model in MATLAB ~~is~~ chosen for prediction, ~~which shows~~ a high prediction accuracy of the corium thickness. This is a critical part of the decommissioning process where the nuclear fuel ~~material~~ needed to be located ~~to effectively retrieve the fuel debris~~.

In the future, different machine learning algorithm will be used to estimate the quantity of the neutron source and produce a map ~~shows~~ the location and the quantity.

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