Fuel Channel Bore Estimation for Onload Pressurised Fuel Grab Load Trace Data

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Abstract

Fuel channel bore estimation enables information about the health of the graphite core of an advanced gas-cooled reactor to be inferred. This was extensively explored previously for offload depressurised fuel grab load trace (FGLT) data: by isolating the frictional component of the FGLT and using inspection data as a ground truth, a linear regression model was trained to estimate the fuel channel bore. However, when data gathered during onload refuelling has the added contribution from the aerodynamic effects caused by the coolant gas, the same process cannot be used.

This paper describes the process for removing the aerodynamic effects of the coolant gas in the core from onload pressurised FGLT data. This effect cannot be directly measured, so initially, an empirical model was created by comparing the response from both offload depressurised and onload pressurised events. This model is then used to estimate the offload equivalent FGLT response, and by using a bore estimation model, trained on offload data, it is possible to produce bore estimations for onload FGLT data.

Keywords

Fuel Grab Load Trace (FGLT), bore estimation, modelling, advanced gas-cooled reactor (AGR), monitoring

INTRODUCTION

Currently, there are seven Advanced Gas-cooled reactor (AGR) nuclear power stations in operation within the UK. As the graphite core in these types of nuclear power station cannot be repaired or replaced this is one of the major life-limiting factors. To ensure their continued safe operation, information about the health of the graphite core is vital and currently, there are two main ways of gathering information about the health of the fuel channel within the core. The first approach is through inspection, which typically occurs every 12 months to 3 years, depending on the age of the station, during planned outages. The bore measurements are collected using either a New In Core Inspection Equipment mark 2 (NICIE 2) or a Channel Bore Inspection Unit (CBIU) (Cole-Baker & Reed, 2007). Monitoring data collected during refuelling events, called Fuel Grab Load Trace (FGLT) data, is used for the second approach. An FGLT is a measure of the perceived load of the fuel assembly as it is being removed (discharge) or inserted (charge) into the graphite core. Originally this data was mainly used to inform the reactor trip protection system (Skelton,

2007). For offload depressurised FGLT data (data gathered when the reactor is offline), it has been shown in (Berry, et al., 2016) that bore estimations can be produced. As the offload depressurised data is gathered at the same time the higher fidelity inspection data is collected the usefulness of these estimations is limited. Bore estimations produced from onload pressurised FGLT would be far more useful, however, due to the added aerodynamic effects of coolant gas during the collection of the data, the same process cannot be applied.

This paper presents an approach for the removal of the aerodynamic effects of the coolant gas in the core from onload pressurised FGLT data. This effect cannot be directly measured, so initially, an empirical model was created by comparing the response from both offload depressurised and onload pressurised events occurring within 5 years of each other. Several approaches are then discussed on how to calculate the offset necessary to apply this gas flow model to the onload data to remove the gas flow effects. Each approach is then used to estimate the offload equivalent FGLT response, and by using the current bore estimation model, trained on offload data, it was possible to produce bore estimations for onload pressurised FGLT data for each approach. The onload bore estimations from all three approaches are then compared with the corresponding offload bore estimations in regards to the root mean square error (RMSE) to determine the optimal approach.

FUEL GRAB LOAD TRACE

Part of the data collected during the refuelling process of AGRs is called an FGLT, this is gathered typically every 6 to 8 weeks. Originally this data was used for safety purposes to detect any faults that may occur during the refuelling process. As the fuel assembly is removed (discharge) or inserted (charge) into the fuel channel load values are recorded and stored (West, et al., 2007). Each FGLT can be split up into four contributions, which is discussed in more detail in (Berry, et al., 2016), these are; the frictional contribution from the lower stabilizing brushes being in contact with the channel wall, the frictional contribution from the upper stabilizing brushes being in contact with the refuelling guide tube, the fuel stringer deadweight and the aerodynamic contributions from coolant gas within the core. Both the contributions from the fuel stringer deadweight and aerodynamic effects act as a positive contribution to the FGLT in both discharge and charge FGLTs. However, the frictional contributions act in opposite directions, for a discharge FGLT,

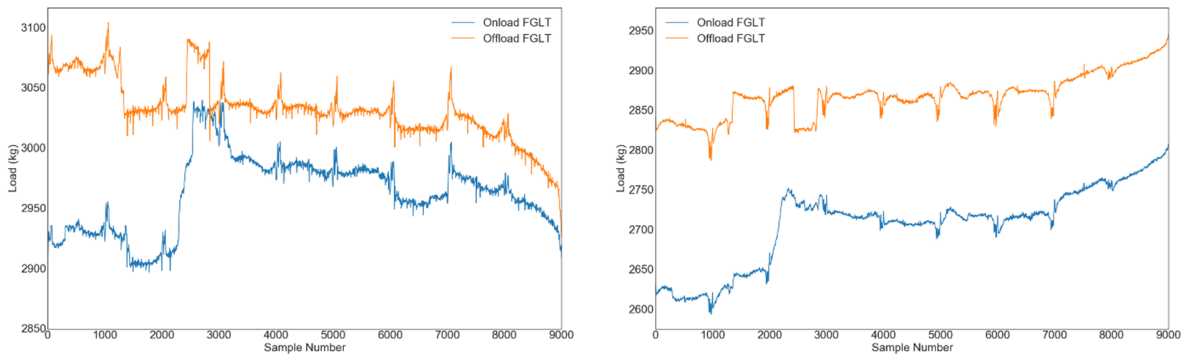


Fig. 1 - Example of offload depressurised and onload pressurised FGLT data, (a) Discharge, (b) Charge

a narrowing in a brick layer (BL) will cause an increased frictional contribution due to it being more difficult to pull the fuel assembly through the brick. For a charge FGLT, the friction will support some of the fuel assembly weight causing a decrease in frictional contribution. In offload depressurised data, the aerodynamic effects are minimal due to the station being offline and the coolant gas can dissipate, however, for onload pressurised FGLT data the effects are much more evident. Fig. 1 shows an example of both charge, discharge, onload and offload FGLTs.

FGLT analysis is currently an active research area as it allows for more frequent information to be gathered about the health of the graphite core than through inspection alone. In (West, et al., 2014) and (Berry, et al., 2016) it has been shown that through a physical understanding of the graphite core, FGLT data can be used to produce estimates of the dimensional changes within the fuel channels. Other work has also looked into automated approaches for the analysis of FGLT data for the purpose of classifying defects or cracks within the fuel channels, (West, et al., 2007) explored a data-mining approach to develop a deeper understanding of the behaviour of FGLT data and define a set of envelopes for normal behaviour which can be used to automatically analyse new FGLT data. (Berry, et al., 2017) proposed a semi-supervised approach to crack detection that exploits the large amount of unlabeled data to improve the classification accuracy.

METHODOLOGY

AVAILABLE DATA

Fig. 1 shows an example of two FGLTs taken from the same channel at different times, the orange is the offload depressurised FGLT, and the blue is the onload pressurised FGLT. While the main features, such as the brick interfaces, USB notch and the step change in brick layers 3 and 4 are all still present in both sets of data, the load values and overall shape of the onload data is distorted due to the aerodynamic effects. To determine if this effect was consistent across all data, each onload FGLT was paired with the closest offload FGLT, as the offload and onload data are always gathered at different times the time between each of these traces vary substantially. To determine how far apart data can be selected that only shows the effects of the gas flow, and nothing else, e.g. dimensional change in the graphite, each of these pairs of data was split up for an increment in the year, from 1 year up to 7 years. By subtracting the onload data from the offload data for each subset it was possible to produce a set of residuals for each pair of FGLTs. Fig. 2

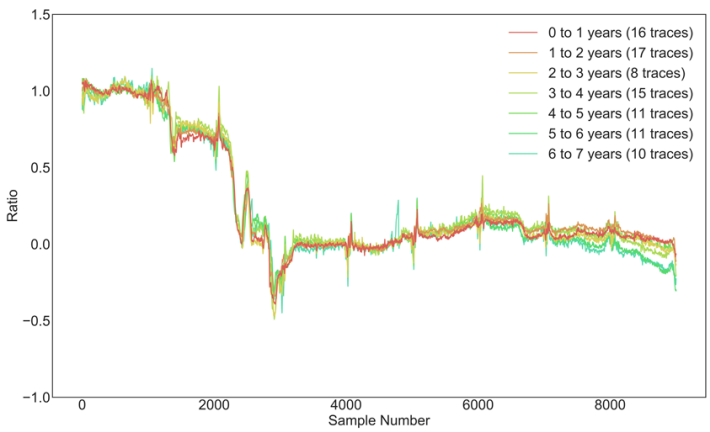


Fig. 2 – Estimated gas effects using data collected up to 7 years apart

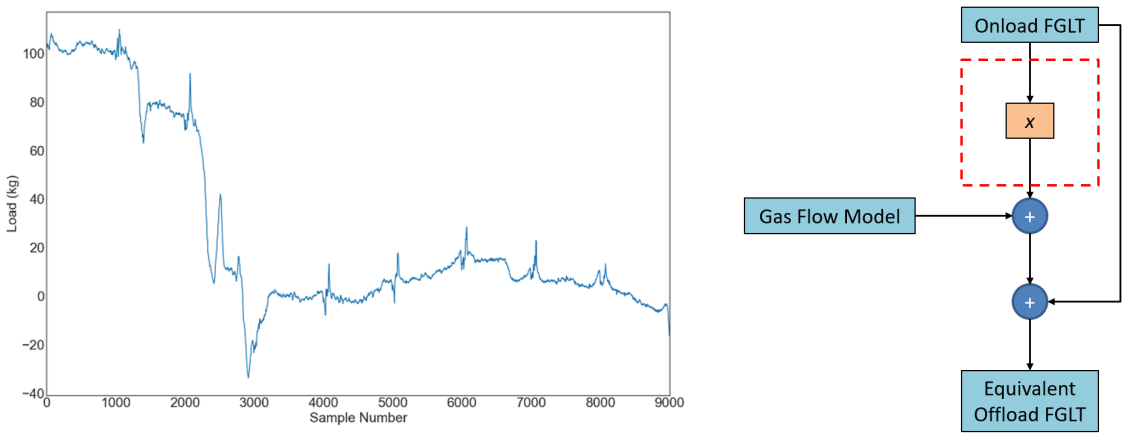
shows the average of each of these residuals and based on this it was selected that the aerodynamic effects were consistent when the data was spaced a maximum of 5 years apart. Given this constraint, the training dataset contained 216 pairs of onload pressurised and offload depressurised FGLTs and the testing dataset contained 15 traces, from a recent outage, each of these offload traces was paired with the closest onload pressurised FGLT data available.

DATA-DRIVEN GAS FLOW MODEL

Using the same technique used in (Berry, et al., 2016) the load value for each trace between the double peak region was calculated, this is a region in the trace where the fuel stringer is hanging freely. These values allow for the normalisation of each onload and offload FGLT. Comparing each pair individually the only variation that should now remain is due to the aerodynamic effects (additional variation may occur due to graphite dimensional change). By subtracting the normalised traces, a residual was produced for each pair which is an estimation of the aerodynamic effects for that FGLT. Further analysis of the residuals show that the general shape of the residuals were the same for all traces analysed and also the step change in load between the bottom region (BLs 3 and 4) and the top region (BL6 to BL11) is approximately 100kg, this is shown in Fig. 3a. This provided the confidence that there was an underlying repeatable response, which was likely to be attributed to the gas effects. As this was consistent throughout all data tested in the next section several approaches are proposed to calculate the gas flow model offset according to the given data.

OFFSET ESTIMATION

Fig. 3b shows the process for producing an equivalent offload FGLT from an onload FGLT. First, the offset (x) must be derived from specific regions of the onload trace, this offset is then applied to the gas flow model. Having completed this, the scaled gas flow model is then added to the onload FGLT to produce an equivalent offload FGLT.



(a) *(b)*

Fig. 3 – (a) Residuals from subtraction of onload and offload pairs of data, (b) Flowchart for producing equivalent offload FGLT

The first approach to estimate the gas flow model offset uses the average load value for specific BLs within the FGLT to calculate the offset. For each BL, the average load of the middle 80% was calculated for both the onload and offload FGLT. By creating a scatter plot between the average load of the onload FGLT and the offset (the difference between offload and onload), a linear trend can be found between these two

variables. By using linear regression, it is possible to produce a linear model that can be used to estimate the offset given the average load for only the onload FGLT. An example of two of these scatter plots, with the corresponding linear model is shown in Fig. 4. This was done for all BLs between BL 6 and 11 to determine the optimal BL. The greatest advantage of using this approach is that it allows for a simple, and quick way of producing the offset for a given FGLT, however, should the selected BL contain a defect which affects the average load the estimated offset would also be affected. Additionally, the linear model does not provide a perfect fit to the data, there is a significant amount of error, however, for simplicity and explicability, the relationship has been assumed to be linear.

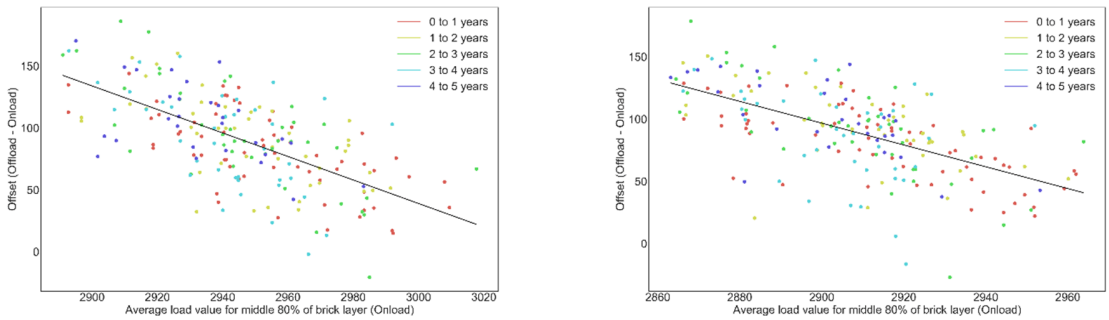


Fig. 4 – Relationship between average load value for middle 80% of brick layer vs. difference in load between onload and offload for the same region, (a) BL 6, (b) BL 11

As discussed, the main drawback with the previous approach is that in the presence of cracks the estimations will likely be poor. Based on this issue, the second approach was to estimate the offset for all BLs between BL 6 and 11, using the same method as the previous approach. These six values can then can be averaged or the median taken to produce a result. The inclusion of additional BLs may potentially reduce the overall accuracy of specific FGLTs without defects, however, will produce more robust estimations for BLs with defects present.

A neural network is used for the final approach, rather than attempting to select regions or BLs, that can be used to estimate the offset, a neural network can be used to learn regions in the trace that are best suited to calculating the offset. The neural network is a shallow network with an architecture of "10000-512-1". The first layer contains 10000 neurons, 1000 for each of the 9 BLs and 1000 for the double peak region, the next layer contains 512 this value was produced using a brute force approach to determine the optimal number of neurons for the training dataset, the final layer contains 1 neuron which will produce the offset to scale the gas flow model. A disadvantage of this approach is that it loses the explicability that the previous two approaches have, with the need to provide supporting evidence in an industrial application this may present an issue. However, this problem is well suited to machine learning techniques and is likely to produce more accurate results than the previous two approaches and will also be quick to calculate the offset after the initial training.

EVALUATION

Before producing, results for any of the approaches discussed above it was necessary to first determine what the optimal results would be. Equation 1 shows the RMSE between the equivalent offload FGLT (the onload trace after removal of the gas effects) and the offload FGLT. By applying an optimization algorithm to the function shown in Equation 1, where x is the offset, n is the number of data points, on is the onload FGLT trace, GF is the empirical gas flow model, and off is the offload FGLT trace, it was possible to calculate what the optimal value for the offset (x) was for each test case. These offsets were used to produce the best estimation of aerodynamic effects using the current gas flow model.

$$minimize: f(x) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\left(on_i + (GF + x)\right) - off_i\right)^2} \tag{1}$$

For the first proposed approach, a linear model was produced for each BL between 6 and 11, using the approach shown in Fig. 4, for all 216 FGLT pairs in the training dataset. Using these linear models, the offset was calculated for the 15 test FGLTs which were then applied as previously discussed to produce an equivalent offload FGLT. The RMSE (in kg) was calculated between each equivalent offload FGLT and the corresponding offload FGLT, see Table 1.

Table 1 – RMSE for single brick layer approach

	Optimal	BL6	BL7	BL8	BL9	BL10	BL11
Avg. RMSE	10.687	19.886	17.806	22.485	25.575	19.947	19.099

From these results, using this approach the best BL to select for the offset estimation is BL7, with BLs 6, 10 and 11 also producing acceptable results. As mentioned previously the issue with using a single BL to calculate the offset is that if there were to be a crack present in this BL this would affect the estimation. Taking this into consideration for the second approach a linear model was produced for all BLs between 6 and 11, therefore producing six offsets for each FGLT. Firstly, the mean and median of all these values were taken which produced results similar to the results produced for BLs 6, 10 and 11 individually but was noticeably worse than BL 7 individually. To improve the results, as BL 8 and 9 produced the worst results individually these were removed from the calculation, all these results are shown in Table 2. Using only BLs 6, 7, 10 and 11 produces results close to only using BL 7 but also has the added robustness of not using a single BL to calculate the offset.

Table 2 – RMSE for multiple brick layer approach

	Optimal	BL6-BL11 (Mean)	BL6-BL11 (Median)	BL6,7,10,11 (Mean)	BL6,7,10,11 (Median)
Avg. RMSE	10.687	19.676	19.640	18.440	18.147

The final approach uses a completely different technique from the first two approaches, using the design for the neural network discussed earlier and the optimal offset values calculated for the 216 training FGLTs. It was possible to train the network to produce an offset given a single onload FGLT. The 15 test FGLTs were then input into this trained network, and as before the RMSE (in kg) was calculated for each. Table 3

shows the results for the neural network, the best results from the two previous approaches and the optimal results. As expected, the neural network outperforms the best option from the two previous approaches and produces results very close to the optimal results, for our chosen metric of average RMSE.

Table 3 – RMSE for best result from each approach

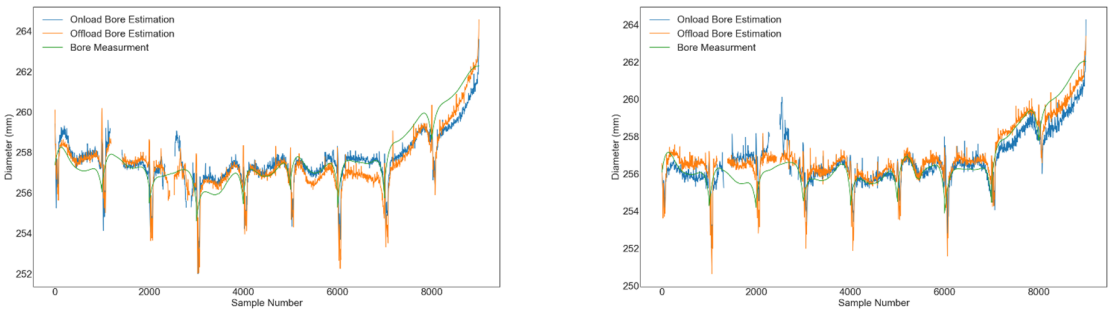
	Optimal	BL7	BL6,7,10,11 (Median)	Neural Network
Avg. RMSE	10.687	17.806	18.147	11.244

ONLOAD BORE ESTIMATION

Using the neural network approach for all 15 test onload FGLTs an equivalent offload trace was created. Both the equivalent offload and the actual offload FGLT were then input into the model designed by (Berry, et al., 2016) to produce a bore estimation for both the onload and offload data. The RMSE for both estimations were then calculated against the nearest channel bore measurement data to produce an error for each estimation. Table 4 shows the average RMSE (in mm) for each brick layer for both sets of estimations, and also the average for the complete estimation. These results show that the offload bore estimation is only slightly more accurate than the onload estimation, however, this could be due to the difference in time between the bore measurement and the onload FGLT being collected. As the load to bore model for both approaches is the same, this suggests that the gas flow removal algorithm correctly removes the aerodynamic contributions to the onload pressurised FGLT. Two examples of both onload and offload bore estimations are shown in Fig. 5, with the corresponding bore measurements.

Table 4 – RMSE for both onload and offload bore estimation compared with nearest bore measurements

	BL3	BL4	BL5	BL6	BL7	BL8	BL9	BL10	BL11	Average
Onload	1.31	1.42	1.62	1.18	0.94	0.94	0.88	0.91	1.15	1.15
Offload	1.14	1.25	1.10	0.96	1.07	0.81	1.02	1.05	1.20	1.07



(a) *(b)*

Fig. 5 - Onload pressurised and offload depressurised bore estimations from the test dataset

CONCLUSION

This paper has shown that the aerodynamic contribution to onload pressurised FGLT data can be estimated by examining the variation between offload and onload data. Through analysis of several pairs of data it

was found that the general shape of the gas effects were consistent, however, a single offset was present in each. Various techniques were then proposed to estimate this offset, these included using a single BL to calculate the offset, using multiple BLs or using a neural network. It was found that the best approach was to use a neural network that had been trained to estimate the offset required from the onload data. An equivalent offload FGLT can be produced by applying the scaled gas flow model to the onload data, which can then be input into the previously designed bore estimation model to produce an estimate of the fuel channel bore. Comparison of the offload and onload bore estimations with the bore measurements showed that the RMSE of each approach was relatively close with the offload estimations only producing a slightly better estimate, however, this is likely due to the graphite dimensional change between the time the bore measurements were taken and the onload trace was gathered.

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